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November 5, 2015

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Attorney General's Office
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**RE: Docket No. 58-0102-1201 - Negotiated Rulemaking
Human Health Water Quality Criteria (HHWQC)**

Dear Ms. Wilson:

Clearwater Paper offers this comment letter on the subject rulemaking. We appreciate the Idaho Department of Environmental Quality's (IDEQ) work on this very important matter and look forward to our continued participation in this rulemaking process.

This rulemaking has been particularly complex and we highly commend IDEQ for their technical and policy work on this subject. Our company, industry and ultimately Idaho's economic, social and public health systems must rely on using the best available science and making viable policy choices to ensure the protection of human health and a reasonable allocation of resources while preserving a fully functioning economy. We understand the varied, external pressures IDEQ must address in regards to this matter. Clearly and unfortunately, some of the dialogue around the subject is not always based on rational risk policy choices or science but rather optics and politics that are not the best, nor an appropriate, prism through which to make highly technical decisions for the good of the people and state of Idaho. As IDEQ considers final HHWQC, we urge you to use sound science, to exercise the flexibility allowed under the Clean Water Act (CWA) in making risk policy decisions and to consider the long-term view of the resources that would be required by the state, municipalities and industry to meet the proposed HHWQC. There is clearly a balance between the cost and benefits associated with implementing any final criteria that IDEQ must consider before finalizing the proposed rule.

Best Available Science

IDEQ's use of a state-based fish consumption survey, correction of the data used in the analysis for fish not found in Idaho waters or the waters of nearby states, assumption of minimal anadromous fish and use of a probabilistic risk assessment approach are commendable and scientifically sound. The demand by some to include all market and anadromous fish in Idaho appears to be motivated by factors other than science or human health concerns for Idahoans. Furthermore, it is not based on the data gathered via the Idaho fish consumption survey. We strongly advocate for a science-based outcome on these issues.

Risk Policy Choices

We urge IDEQ to reassess its proposed risk policy choices on carcinogens and non-carcinogens.

Based on material previously submitted by ARCADIS, a nationally recognized environmental consulting firm, there is no measurable difference in the number of excess cancers expected for Idaho residents under criteria based on a 10^{-5} versus 10^{-6} excess lifetime cancer risk (ELCR). Specifically, deriving criteria based on a 10^{-5} (instead of 10^{-6}) allowable ELCR management goal for the population size of Idaho would be expected to lead to an increase of 0.23 cancers in total per year—from 2570.00 to 2570.23 (based on the 2012 Idaho population). If a $1x10^{-6}$ ELCR were used, the increase would be 0.023—from 2570.00 to 2570.023 (based on the 2012 Idaho population). The difference in the number of excess cancers resulting from the application of criteria based on the different risk levels is so small that it is basically immeasurable and statistically without meaning because of the year-to-year variation in cancer incidence. Moreover, as noted in the IACI comments, these calculations do not reflect that IDEQ is currently proposing to apply the $1x10^{-6}$ risk management goal to the 95th percentile of the general population, an <u>even more</u> stringent benchmark than used in the above example and much more stringent than the EPA's national risk policy guidance.

Clearwater Paper urges IDEQ to modify the ELCR used in selecting carcinogenic HHWQC's to the more stringent of 1 in a 100,000 at the 95^{th} risk percentile of either the general population or the tribal risk distributions <u>assuming</u> the very important statistical correction discussed below (and in *Attachment* A) is adopted by IDEQ. With this adjustment, spurious 303(d) listings will be avoided and only those water bodies posing elevated and unacceptable risk would be listed thereby avoiding unneeded TMDL's and unwarranted NPDES allocations that provide no measureable improvement in public health. To provide some perspective, the added risk from the proposed risk policy change is the equivalent of the average Idahoan *driving an additional 11 miles a year*.

Noted below is a discussion of the cost implication of the proposed standard—**<u>$16 billion</u>** over the next 25 years for municipal and industrial dischargers in Idaho, with no guarantee of even achieving the de minimis benefit represented by the proposed HHWQC based on an ELCR of 10^{-6} (when compared to 10^{-5}).

EPA Risk Policy Objective for Idaho

Based on the EPA's comment letters in regards to this matter, the EPA is not aligned with the their existing HHWQC risk policy guidance, case law nor how risk-based levels are established by the federal agency under other programs

Idaho, as do all states, has the primary role in setting water quality criteria for its citizens. This point is established in the CWA and long recognized by federal courts.

The federal appellate court in *NRDC v. EPA*, 16 F.3rd 1395 (4th Cir. 1993) emphasized that the states have the primary role in setting water quality criteria and that the EPA's role is to review those criteria for sufficiency under the CWA, not to impose its own views on what the standards should be. That court, along with the district court, upheld the EPA's approval of Maryland's and Virginia's use of a 1 in 100,000 (10^{-5}) excess lifetime cancer risk factor in establishing dioxin criteria (using a 6.5 grams per day fish consumption rate). Another federal appellate court, the 9th Circuit, upheld the EPA's use of 1 in

1,000,000 (10^{-6}) risk factor applied to a 6.5 grams per day fish consumption rate, which resulted (based on the evidence presented in that case) in a 23 in 1,000,000 risk factor for high-fish consumers. *Dioxin Organochlorine Center v. Clarke, 57 F.3d 1517, at 1524* (9th Cir. 1995).

Essentially, the federal courts deferred to the EPA and the states as to the appropriate risk factors. Given the role of the states in establishing water quality criteria, and given that the courts have held that a 1 in 100,000 risk factor is within the appropriate range, the burden would be on the EPA to explain why the use of a 1 in 100,000 risk factor would produce unacceptable levels of risk in Idaho but not in Maryland or Virginia.

In *State Of Ohio v. U.S.E.P.A*, 997 F.2d 1520 (D.C. Cir. 1993) , which was cited favorably in the 9th Circuit decision, another federal appellate court upheld the use of a variable risk factor ranging from 1 in 10,000 to 1 in 1,000,000, based on site-specific factors. Although this was an environmental clean-up case, it supports the proposition that different risk factors may be used in different circumstances--a single risk factor need not be used in all circumstances. [1]

In summary, under the CWA each state is provided a broad amount of flexibility to choose risk management policies when setting human health criteria. One of these risk management policies involves setting a level for excess cancer risks. The EPA specifically instructs that states may use a cancer risk range of either 10^{-6} or 10^{-5} to protect the general population so long as highly exposed populations are protected at a 10^{-4} cancer risk level. *See* Methodology for Deriving Ambient Water Quality Criteria for the Protection of Human Health (EPA 2000), 65 Fed. Reg. 66444 (November 3, 2000). While today's EPA seemingly may not like this guidance or the judicial cases confirming the state's discretion in this area, they remain the authoritative interpretation of the state's discretion under the CWA.

Because the appropriate level of risk is a matter of policy, IDEQ and the Idaho Legislature represent the appropriate bodies to establish the state's policy on risk.

IDEQ's Risk Policy Choices and Idaho Stringency Requirements

In the proposed rule, IDEQ has applied certain risk policy decisions in setting the proposed criteria that appear contrary to the spirit if not the specific intent of state law. Idaho Code 39-3602 prohibits IDEQ from adopting water quality standards that "impose requirements" beyond the minimum requirements of the CWA. Additionally, Idaho Code 39-107D requires IDEQ to specifically identify those provisions in proposed rules that are "broader in scope or more stringent than" the requirements under the CWA. We believe that these two provisions explicitly or implicitly create a directive to IDEQ to exercise

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[1] Please note *Attachment B* which demonstrates how states have adopted different risk factors for their clean-up programs. While different than HHWQC, clean-up programs generally deal with "real-life" exposure to citizens. It is not realistic to assume that the average Idahoan drinks untreated surface water and eats extraordinary amounts of local fish, especially given that approximately 90% of all Idahoans receive their primary drinking water from groundwater sources.

whatever flexibility is afforded the state under the CWA when promulgating water quality standards to avoid overregulation of Idaho citizens.

As noted above, the CWA provides each state a broad amount of flexibility to choose risk management policies when setting human health criteria and the EPA specifically instructs that states may use a cancer risk range of either 10^{-6} or 10^{-5} to protect the general population so long as highly exposed populations are protected at a 10^{-4} cancer risk level.

This range of risk (10^{-6} to 10^{-4}) is not unique to setting human health criteria under the CWA. Under the Safe Drinking Water Act for example, maximum contaminant levels (MCLs) are set using this same range of risk levels (which are incorporated into Idaho's Ground Water Rule). Similarly these same risk levels are used to set clean-up standards at contaminated sites under the Federal Superfund law (CERCLA). It is important to note that the Idaho Legislature has sanctioned the same range of risks allowed under CERCLA to apply to IDEQ supervised clean-ups in the Idaho Land Remediation Act, Idaho Code 39-7210(1).

It was therefore disappointing that, and perplexing as to why, IDEQ has proposed the application of a 10^{-6} cancer risk level to protect a very small, higher fish-consuming portion of the Idaho population for setting criteria for all Idahoans. We believe such a decision would result in overly stringent criteria being adopted. As noted above applying a risk level between 10^{-6} to 10^{-4} is well established under Idaho law, federal law and the EPA's own guidance. IDEQ should exercise the flexibility allowed by the EPA guidance and sanctioned by the courts and adopt a risk level at 10^{-5} that would also protect those who consume fish at higher levels with a 10^{-4} level. We believe such a policy choice is what the Idaho Legislature had in mind when it passed laws directing IDEQ not to adopt water quality rules that are more stringent than EPA minimum requirements.

Relative Source Contribution (RSC)

Please refer to *Attachment C*, which presents an assessment of IDEQ's choices to set more reasonable than "default" RSC's in establishing the HHWQC for non-carcinogens. Clearwater Paper urges IDEQ to use the best available science in setting RSC's that reflect actual (not defaulting to worst case) risks to the citizens of Idaho from drinking untreated surface water and eating local fish.

Market Fish

Clearwater Paper supports IDEQ's scientifically justified choice of limiting the level of market fish by including only those fish reared naturally or purposefully in Idaho to set HHWQC. To include species not grown in Idaho or Pacific Northwest states in a fish consumption rate would be overly stringent and quite frankly result in risk assessments not rooted in reality. Because it is scientifically based and defensible and would result in an accurate risk assessment outcome, we strongly urge IDEQ to maintain the treatment of market fish as proposed.

Anadromous Fish

As with the issue of market fish, including anadromous fish that spend a negligible amount of time in Idaho waters would result in an overly stringent risk calculation and would have a negligible difference on the actual risk to those eating large amounts of anadromous fish. Forcing Idaho to adopt overly and unnecessarily stringent controls would not affect contaminants in anadromous fish: so to include such fish in the determination of HHWQC is not following a science-based decision process. Because it is scientifically based and defensible and would result in an accurate risk assessment outcome, we strongly urge IDEQ to maintain the treatment of anadromous fish as proposed.

Probabilistic Risk Assessment (PRA)

Using a probabilistic risk assessment approach for HHWQC criteria represents the best available science for setting HHWQC. EPA has endorsed PRA as noted in our comment later dated April 18, 2014, and as shown in *Attachment D*.

Even the EPA's website advocates for the use of PRA. *See http://www2.epa.gov/osa/probabilistic-risk-assessment-white-paper-and-supporting-documents*. Because it is scientifically based and defensible and would result in an accurate risk assessment outcome, we strongly urge IDEQ to maintain the use of PRA as proposed.

Tribal Survey Results

As noted above *Attachment A* describes a statistically necessary adjustment to the tribal fish consumption data set used by DEQ in setting HHWQC. This data only became available from the EPA last week but should be reflected in the final HHWQC criteria that IDEQ adopts and proposes for approval by the IDEQ board and Idaho Legislature. Some of the HHWQC as proposed are now inconsistent with IDEQ's stated risk policy choices.

Disconnect Between Proposed HHWQC and Drinking Water MCL's

The human health risk levels used to set MCL's under the Safe Drinking Water Act should be the same risk levels used to set HHWQC's. To manage drinking water (where the general population is being exposed every day) at a less stringent risk level than HHWQC based on drinking untreated surface water and eating local fish would defy common sense and set grossly inconsistent public policy. Drinking water MCL's are based on the feasibility of treatment and are a well-considered balance of public health concerns and resources. To set HHWQC using risk levels more stringent than drinking water standards would also result in a serious misallocation of public and private resources. For those contaminants that have MCL's, we strongly urge IDEQ not to set HHWQC more stringent than the equivalent risk associated with the applicable MCL's.

Cost of Implementation

Please note *Attachment E* which presents an estimated summary of capital and operating costs to Idaho municipalities and businesses if Idaho were to adopt a PCB criterion of 61 pg/l. This analysis represents the costs when the state follows the expected CWA processes of 303(d) impairment listings, TMDL's and NDPES permit limitations associated with a 61 pg/l PCB criterion.

Based on the proposed regulatory framework, the estimated cost to Idaho cities would be $13.8 billion over the next 25 years plus $2.6 billion more to Idaho businesses, with an infinitesimal, to potentially no, reduction in risk to Idaho citizens from building and operating these systems. This is not sound public policy and does not represent a reasonable allocation of public and private resources.

We believe IDEQ may not have properly accounted for the compliance costs of the proposed rule. Additionally, the cost to the state involved in the development of TMDLs, TMDL implementation plans and modification of NPDES and storm water permits would be substantial. Given the nature of this rulemaking and the costs involved, IDEQ is required to estimate the costs, economic impact and evaluation of benefits for the proposed rule. *See* Idaho Code 67-5223. We do not believe IDEQ has adequately fulfilled that obligation here. Because of the flexibility IDEQ has in the proposed rule to establish a range of risk levels (as discussed above) we believe that to adequately fulfill IDEQ's obligations to notify the public and the Idaho Legislature on the costs and benefits of a proposed rule, a comparison should be made of the costs (and benefits) associated with applying a risk level of 10^{-6} to 10^{-5}. We believe such a comparison would truly allow the public and the Legislature to evaluate the proposed rule. We are confident that if IDEQ evaluated the public health benefits associated with the human health criteria at both 10^{-6} and 10^{-5} risk levels and compared these to the associated costs, it would conclude that the added costs do not justify the very incidental human health benefits potentially associated with choosing a 10^{-6} cancer risk level.

Downstream Waters

We urge IDEQ to withdraw this provision (IDAPA 58.01.02.070.08) for the reasons specified in our letter of August 20, 2015. In short, we believe this provision raises too many questions as to how it will be implemented and may complicate approval of this rule by the EPA in light of conflicting state and tribal criteria in this area.

On behalf of Clearwater Paper, we appreciate the opportunity to provide comments on this important matter and look forward to participating in this process as this rulemaking goes forward.

Please contact me at 509-344-5956 or marv.lewallen@clearwaterpaper.com with questions.

Sincerely yours,

Marvin A. Lewallen
Vice President – Environmental, Energy & Sustainability

Encl. Attachment A
Attachment B
Attachment C
Attachment D
Attachment E

FISH CONSUMPTION RATE DISTRIBUTION FITTING FOR IDAHO HUMAN HEALTH CRITERIA

November 5, 2015

FISH CONSUMPTION RATE DISTRIBUTION FITTING FOR IDAHO HUMAN HEALTH CRITERIA

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APPENDICES

A Interpolated Fish Consumption Distributions

ACRONYMS AND ABBREVIATIONS

ELCR	excess lifetime cancer risk
FCR	fish consumption rate
FFQ	food frequency questionnaire
g/day	grams per day
HHAWQC	human health ambient water quality criteria
HI	hazard index
IDEQ	Idaho Department of Environmental Quality
NCI	National Cancer Institute
USEPA	United States Environmental Protection Agency

1 INTRODUCTION

On October 7, 2015, the Idaho Department of Environmental Quality (IDEQ) released its draft human health ambient water quality criteria (HHAWQC) rule. The draft HHAWQC were calculated using probabilistic risk assessment methods, using distributions capturing the variability in fish consumption rate (FCR), drinking water intake, and body weight across the Idaho population. IDEQ derived two sets of HHAWQC: one set focused on the general Idaho population and the other set focused on high consuming subpopulations, represented by Nez Perce tribal members. The 95th percentile of the general population and arithmetic mean of the high consuming subpopulation were targeted with an acceptable excess lifetime cancer risk (ELCR) of 1×10^{-6} and non-carcinogenic hazard index (HI) of 1.0.

The process used to derive IDEQ's draft HHAWQC is described in greater detail by Windward (2015). This report focuses specifically on the FCR distributions used to derive the draft HHAWQC, both for the general and tribal populations of Idaho.

2 EMPIRICAL FISH CONSUMPTION RATE DISTRIBUTIONS

IDEQ recently completed a state-wide survey on fish consumption in Idaho (NWRG 2015). National Cancer Institute (NCI)-adjusted usual intake distributions for fish consumption, as reported by Buckman et al. (2015), were used to develop FCR distributions for the general population of Idaho. IDEQ chose to base its draft HHAWQC on consumption of resident freshwater fish, referred to as Idaho fish[1] (IDEQ 2015, NWRG 2015). Buckman et al. (2015) reports summary statistics for the empirical NCI-adjusted distribution of general population Idaho fish consumption, including the mean and each integer percentile (**Table 1**).

The empirical Idaho fish distribution includes a 100th percentile[2] value of 1,261 grams per day (g/day), equivalent to approximately 1,000-2,000 calories per day, depending on the species. This estimated value has a reported standard error of 612 g/day and is more than two times larger than the 100th percentile value reported for consumption of all fish (533 g/day), of which Idaho fish is by definition a subset (Buckman et al. 2015). The 99th percentile reported for consumption of Idaho fish is 40.6 g/day, over 30 times lower than the 100th percentile estimate. This increase between the 99th and 100th percentiles is extreme; in comparison, the 99th and 100th percentile estimates for consumption of all fish (118 g/day and 553 g/day, respectively) only differ by a factor of five. Therefore, this 100th percentile estimate is highly uncertain and should either be used with great caution or not used at all in the derivation of a FCR distribution for the purpose of establishing HHAWQC for Idaho.

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[1] Idaho fish is defined as freshwater fish resident to Idaho waters. Idaho fish includes all trout, regardless of where acquired, as well as the following species when caught in an Idaho lake or stream: whitefish, yellow perch, walleye, catfish, bass, bluegill, black crappie, northern pike, white sturgeon, crayfish, Kokanee Salmon, or Sockeye Salmon (also known as Blueback Salmon).

[2] The SAS macros used in the NCI method do not routinely report estimates beyond the 99th percentile of the distribution due to the inherent uncertainty of this value. This 100th percentile value was generated at the request of IDEQ.

The United States Environmental Protection Agency (USEPA), in collaboration with the Nez Perce and Shoshone-Bannock Tribes, recently completed a survey of tribal fish consumption (Ridolfi and Pacific Market Research 2015). Similar methods were used to survey both tribes, and NCI modelling was conducted using data from both tribes with a tribal identifier used as a covariate in the modelling. Information from this survey was used by IDEQ to develop FCR distributions for the Nez Perce tribal population of Idaho. The Nez Perce were chosen to represent the tribal population of Idaho as their estimated mean FCR is the highest among the tribes. The following is a brief discussion of the Nez Perce survey report.

Estimates of the FCR, given as edible mass of uncooked finfish and/or shellfish in g/day, are presented based on two different survey methods resulting in two data sets collected from the same set of respondents. One set of data is provided by a food frequency questionnaire (FFQ), wherein for each species survey respondents directly provide estimates of frequency of consumption, portion sizes and duration of their consumption seasons during the past year. The second method, a statistical method developed by the National Cancer Institute ("NCI method"), uses responses to questions asked on two separate days, about fish consumption "yesterday" (a 24-hour recall period).The survey covered adult members (age 18 and over) of the Nez Perce residing within approximately 50 miles of two major tribal centers, Lapwai and Kamiah. A stratified (gender, age) random sample was drawn from tribal enrolment files. Tribal interviewers were employed and trained to administer the questionnaire in person. Interviews were conducted from May 2014 to May 2015 either at the respondent's home or an agreed upon location. Due to the difficulty in locating and contacting sampled members, a survey design change resulted in interviews and/or initial contacts taking place at special tribal events. The second 24-hour dietary recall interview was conducted sometime after the first interview by telephone. Respondents were offered an incentive for participation in the survey, financed by the Tribe, that included a raffle drawing (approximately $1000 worth of prizes were available), t-shirts and paid time off for Tribal employees who were sampled. Respondents to the survey answered questions about species consumed (frequency and quantity), covering consumption over the past year, as well as answering questions about fish consumption "yesterday" (the 24-hour recall).

The tribe has 2,727 recorded adult members. A sample of 1,250 was drawn but only 38% (460 members) responded, 98% of whom (451) were fish consumers. Due to differences in the response rate among demographic subgroups within the Tribe, statistical weighting was used to estimate FCRs so as to be unbiased and representative of the entire Tribe. The authors described the following limitations of the study:

- A number of cases had missing data which had to be imputed in order for the respondent's other responses to be included. However, they also report that a sensitivity analysis indicates little effect on FCRs due to imputation.
- With an interview-guided survey, there is a possibility of a social desirability bias, where individuals tend to over- or under-report consumption due to perceived social norms.
- The survey had a "modest" response rate, 38% which is low among tribal fish consumption surveys. It is possible that those who were either not reached or reached but did not agree to an interview have different consumption rates than those included.

While the first limitation did not appear to have an effect on the FCRs it is unclear how the second and third limitations affect FCR. However, given that the Tribe has emphasized the cultural importance of fish, it is unlikely that under-reporting bias would be an issue.

Ridolfi and Pacific Market Research (2015) reports summary statistics for the empirical NCI-adjusted distribution of Nez Perce tribal population fish consumption for all fish (i.e., Group 1) and Group 2 fish, a subset of Group 1. Although species level data were recorded by the interviewers for dietary recall, these data were not reported or modelled using NCI methods. The mean and each fifth percentile of Group 2 FCR are given in **Table 2**.

The Nez Perce fish consumption survey data were reported based on different species groupings than the state-wide Idaho fish consumption survey (**Table 3**). While the Nez Perce species Group 2 consumption is more similar to the species group defined as Idaho fish than Group 1, it includes some species excluded from Idaho fish. Therefore, IDEQ had to derive an adjustment factor to apply to the Group 2 fish consumption distribution to estimate the Nez Perce Idaho fish consumption distribution. IDEQ derived this Idaho fish adjustment factor using data from the FFQ. Rather than subtracting species from Group 2, IDEQ subtracted Chinook, Coho, and other salmon from Group 3; subtracted tilapia from Group 5; and summed these modified Groups with the existing Group 4. The resulting mean consumption rate, expressed as a ratio of reported Group 2 fish consumption, is 24.2%. Calculations were done by respondent and were appropriately weighted by the demographic based statistical weighting variable. This process is described in greater detail by IDEQ (2015). IDEQ applied the adjustment factor to the mean and each fifth percentile of the empirical distribution of Nez Perce Group 2 fish consumption to derive the estimated distribution of Nez Perce Idaho fish consumption (**Table 2**). Given that NCI-based Idaho fish FCRs were not reported for the tribes, IDEQ's approach is appropriate but should have been conducted using dietary recall data rather than the FFQ data. The FFQ data rely on one's memory over an entire year and involve mental averaging over that period. The authors of the survey report state the following:

> *"The NCI method results are probably closer to the true consumption rate distribution for the Tribe, but the FFQ consumption rates are also plausible. The truth probably lies somewhere in between, though likely closer to the NCI-method rates, which are based on consumption 'yesterday' (24-hour recall) rather than on memory of the preceding year's consumption. (A report on the OPEN study by Subar et al, 2003, found that 24-hour recall data were more accurate than FFQ data in predicting total energy and protein intake.)"*

Arcadis followed the process outlined by IDEQ (2015) to derive a Group 2 adjustment factor using the Nez Perce dietary recall data rather than the FFQ data.[3] The calculations were conducted separately for each of the two dietary recalls since there were some missing responses for the second recall. The NCI methodology for estimating usual intake distributions for fish consumption rely on the dietary recall data, and therefore deriving a Group 2 adjustment factor from these data is more appropriate than relying on

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[3] The dietary recall data were obtained by Arcadis via the expedited Freedom of Information Act process mentioned in USEPA's August 6, 2015 presentation given at the IDEQ Negotiated Rulemaking meeting.

the FFQ data[4]. The mean adjustment factor for the two recall events is 7.04%.[5] Arcadis applied the alternate adjustment factor to the mean and each fifth percentile of the empirical distribution of Nez Perce Group 2 fish consumption to derive an alternate estimated distribution of Nez Perce Idaho fish consumption (**Table 2**). A similar analysis was conducted for the Shoshone-Bannock data set as a check of the assumption that their mean Idaho fish FCR is not greater than that of the Nez Perce, which would result in the Shoshone-Bannock Tribe being the more sensitive population. The mean Group 2 FCR for the Shoshone-Bannock is 18.6 grams per day. The percentage of Group 2 fish that are Idaho fish based on dietary recall data is 22.8%, resulting in a mean Idaho fish FCR of 4.2 grams per day. Therefore, it can still be assumed that the Nez Perce Tribe have a higher Idaho fish FCR than the Shoshone-Bannock Tribe.

3 IDEQ DISTRIBUTION FITTING

Although empirical distributions are available from the abovementioned sources for both Idaho populations, the software used to conduct probabilistic derivation of HHAWQC (i.e., @Risk; Palisade [2013]) requires that, in the absence of an empirical dataset, each distribution be described formulaically. Because the empirical distributions were produced by NCI modelling and individual data points are not available, theoretical distributions must be “fit” to the empirical distributions to conduct the probabilistic analysis.

The @Risk software allows users to fit distributions to data using the “Distribution Fitting” tool. This tool generates numerous potential “fits” to the data (i.e., theoretical distributions with inherent statistics, such as arithmetic mean and percentiles, comparable to those associated with the empirical data) and ranks them in order of increasing error. Additional goodness-of-fit tests, such as the chi-square goodness-of-fit test, can be performed to determine whether the theoretical distribution’s inherent statistics are consistent with the empirical distribution. The distribution fitting process should focus on the bulk of the distribution rather than the extreme tails of the distribution. This is particularly true in cases such as the general

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[4] IDEQ recognized that use of the FFQ is not the preferred data set from which to derive the adjustment factor and that species-specific data from the dietary recall survey would be preferred as indicated in the footnote to the FCR summary table prepared by IDEQ for the August 6, 2105 Negotiated Rulemaking meeting: “Because the Idaho FFQ does not provide species level data, Idaho fish is based on a survey question that asks respondents to say what percentage of the fish they ate over the past year came from Idaho waters. It thus includes Chinook and Coho salmon, and likely excludes some rainbow trout purchased rather than caught. THEREFORE IT IS NOT COMPRABLE TO THE DIETARY RECALL IDAHO FISH GROUP.” (Emphasis in the original). IDEQ used the FFQ data to derive the adjustment factor because species-specific data for the Idaho fish group from the dietary recall survey were not available to IDEQ at the time they had to develop FCR distributions and derive draft HHAWQC.

[5] The survey data included two weighting variables to adjust for missing responses in the data. The calculations were conducted twice, once for each of the two survey weight variables. The effect on the adjustment factor was minimal. Using the variable “survey_wt1” resulted in an estimate of 7.03% compared to the adjustment factor of 7.04% presented in the text of this report.

population distribution for consumption of Idaho fish, which, as described above in **Section 2**, has an extreme upper percentile value that has great uncertainty and appears inconsistent with the remainder of the distribution.

The distribution fitting approach used by IDEQ for each distribution is discussed below.

3.1 General Population

Rather than fitting a continuous theoretical distribution to the empirical FCR distribution using the @Risk software, Windward (2015) used linear interpolation to estimate the FCR at each tenth-of-a-percentile increment and used the resulting empirical and interpolated values in a discrete @Risk distribution, assigning equal probability to each tenth-of-a-percentile estimate (**Appendix A**, **Figure 1**). While the individual percentiles of the discrete distribution fit the empirical distribution quite well, the arithmetic mean of the discrete distribution is nearly four times greater than that of the empirical distribution (8.74 g/day versus 2.34 g/day), driven upward by the inclusion of the estimated 100th percentile value of 1,261 g/day and the interpolated tenth-of-a-percentile estimates between the 99th and 100th percentiles. In addition, using linear interpolation between percentiles of a positively skewed distribution increases the likelihood of less probable values, particularly in the upper tail of the distribution, and therefore is not an ideal method for estimating between the percentiles of the FCR distribution.

3.2 Nez Perce Tribal Population

As with the general population, Windward (2015) used linear interpolation to estimate the FCR at each tenth-of-a-percentile increment and used the resulting empirical and interpolated values in a discrete @Risk distribution, assigning equal probability to each tenth-of-a-percentile estimate (**Appendix A**, **Figure 2**). Ridolfi and Pacific Market Research (2015) only reported every fifth percentile through the 95th because the higher percentiles were considered to be too uncertain to report.[6] In the absence of such

[6] The authors noted the following with respect to the upper percentiles of the distribution: "The NCI method as implemented in SAS software provides integer percentiles of usual consumption rates up to the 99th percentile. However, an analysis of species Group 1 and species Group 2 consumption for the NPT (all respondents) showed a lower calculated 99th percentile consumption rate for Group 1 (373.2 g/day) than for Group 2 (409.6 g/day), even though the nearby 95th percentile values were in the order expected (232.1 g/day and 221.8 g/day, respectively). The number of respondents in the two analyses was very similar (though small for the NCI method), and Group 2 is a subset of the species in Group 1 and would be expected to have a smaller true 99th percentile in the population. However, it is not an error for these two estimated values of the 99th percentiles to be in an unexpected order. These are both estimates—not population values—for the 99th percentile for each group of species, and—as indicated by the width of the confidence interval for the 99th percentile for Group 1 (276.2-692.7g/day)—there is a range of plausible values for these kinds of estimates. Among the plausible estimates for each of the two 99th percentiles, some of the plausible choices will have the 99th in the expected order (Group 2 having a smaller 99th percentile than Group 1). In order to avoid confusion in presentation of results, all NCI-method percentiles for Group 1 and Group 2 have been reported only up to the 95th percentile."

percentiles Windward (2015) assumed the maximum tribal FCR was equal to the 100th percentile Idaho fish FCR for the general population (i.e., 1,261 g/day), multiplied by the 24.2% adjustment factor for Idaho fish. This approach is not appropriate for at least two reasons. First, Ridolfi and Pacific Market Research (2015) evaluated the higher percentiles of tribal consumption and believed those to be too uncertain to report. Substituting general population FCRs for those percentiles using a highly uncertain maximum general population FCR contradicts the findings of Ridolfi and Pacific Market Research (2015) and suggests tribal and general population consumption are interchangeable. Second, the 1,261 g/day FCR for the general population already represents consumption of Idaho fish. Therefore, the adjustment of 24.2% to estimate the Idaho fish FCR from the tribal Group 2 fish is not necessary for this maximum value.

While the individual percentiles of the discrete distribution fit the empirical distribution quite well, the arithmetic mean of the discrete distribution is approximately 20% greater than that of the empirical distribution (19.2 g/day versus 16.1 g/day), driven upward by the inclusion of a maximum value derived from the highly uncertain 100th percentile value reported for the general population. The overestimation of the arithmetic mean is of particular importance for the Nez Perce tribal distribution, because the draft HHAWQC for the tribal population are derived by targeting the arithmetic mean of the Nez Perce population. Using a FCR distribution that overestimates the arithmetic mean in a probabilistic approach that targets the arithmetic mean will result in HHAWQC that are more stringent than warranted based on the tribal FCR data.

4 ALTERNATIVE DISTRIBUTION FITTING

Arcadis used the same data used by IDEQ to develop FCR distributions for the general and Nez Perce tribal populations of Idaho. Arcadis fit continuous theoretical curves to the data in @Risk as well as alternate discrete distributions. This process is described below.

4.1 General Population

After investigating alternative fits to the empirical data using the @Risk “Distribution Fitting” function, Arcadis found that no single theoretical distribution matched all percentiles of the empirical distribution well. Therefore, Arcadis used the “RiskSplice” function within @Risk, which enabled Arcadis to fit two theoretical distributions to the empirical distribution reported by Buckman et al. (2015) – one fitting well to the lower percentiles (i.e., 0 to 75th) and the other fitting well to the upper percentiles (i.e., 76th to 100th) – and combine the two. Samples below the “splice point” (in this case, the 75th percentile) are selected from the first distribution (a lognormal distribution), and samples above the “splice point” are selected from the second distribution (an inverse Gaussian distribution). This approach of describing the tail of a distribution with a separate function is supported by USEPA probabilistic risk assessment guidance (USEPA 2001), which discusses an example of extending the tails of a distribution using an exponential distribution, stating that this method is “based on extreme value theory, and the observation that extreme values for many continuous, unbounded distributions follow an exponential distribution.” The resulting theoretical distribution provides a close fit to the individual percentiles of the empirical distribution, comparable to IDEQ’s discrete distribution, but provides a much closer fit to the arithmetic mean (2.28 g/day versus 2.34 g/day) (**Table 4**, **Figure 1**).

Arcadis also developed two alternate discrete distributions using the empirical data. First, Arcadis used the empirical percentile values in a discrete @Risk distribution, assigning equal probability to each empirical percentile value and excluding the highly uncertain 100th percentile responsible for driving up the arithmetic mean of IDEQ's discrete distribution. While the individual percentiles of the discrete distribution fit the empirical distribution quite well, the arithmetic mean of the discrete distribution is approximately 23% lower than that of the empirical distribution (1.81 g/day versus 2.34 g/day). Next, Arcadis followed the interpolation approach used by Windward (2015), however instead of using linear interpolation between each empirical percentile, Arcadis used logarithmic interpolation to estimate the FCR at each tenth-of-a-percentile increment and used the resulting values in a discrete @Risk distribution, assigning equal probability to each tenth-of-a-percentile estimate (**Appendix A**). Again, the individual percentiles of the discrete distribution fit the empirical distribution quite well, but the arithmetic mean of the distribution is 2.5 times greater than that of the empirical distribution (5.81 g/day versus 2.34 g/day).

These multiple attempts at trying to create a discrete distribution that tries to address the highly uncertain maximum FCR highlight both the uncertainty of the FCR and its inconsistency with remainder of the FCR distribution for the general population, as well as the sensitivity of the discrete function to the assumptions used to interpolate tenths of percentiles between reported percentiles. While it is possible that tenths of percentiles could eventually be estimated that fit both the percentiles of the FCR distribution and its arithmetic mean, neither the linear interpolation used to derive the draft HHAWQC nor the logarithmic interpolation used as an alternative by Arcadis do so. Rather, the combination of two continuous distributions developed by Arcadis provide the best fit of both the percentiles and arithmetic mean of the empirical FCR distribution and should be used to derive HHAWQC for Idaho.

4.2 Nez Perce Tribal Population

Arcadis used the @Risk "Distribution Fitting" function to fit a theoretical distribution to the IDEQ estimated (i.e., based on 24.2% adjustment factor) empirical Nez Perce Idaho fish consumption distribution. The best fitting single theoretical distribution (i.e., the theoretical distribution with the lowest root mean square error) was an inverse Gaussian distribution, which provides a close fit to the individual percentiles of the empirical distribution, comparable to IDEQ's discrete distribution, but provides a much closer fit to the arithmetic mean (16.6 g/day versus 16.1 g/day) (**Table 5**, **Figure 2**).

Arcadis also used the @Risk "Distribution Fitting" function to fit a theoretical distribution to the alternate estimated (i.e., based on 7.04% adjustment factor) empirical Nez Perce Idaho fish consumption distribution. The best fitting single theoretical distribution was an inverse Gaussian distribution, which fits the empirical percentiles well as well as the arithmetic mean (4.81 g/day versus 4.68 g/day) (**Table 6**, **Figure 3**). This tribal Idaho fish FCR distribution based on the recall survey adjustment factor (7.04%) should be used to derive HHAWQC for the tribal population in lieu of a distribution based on the FFQ (24.2%) because, as noted by the authors of the tribal FCR survey report (Ridolfi and Pacific Market Research 2015), the recall survey results are likely closer to the true tribal consumption rate than the FFQ results.

5 CONCLUSION

To derive probabilistically based HHAWQC using @Risk, empirical FCR distributions must be modelled using theoretical distributions defined within the @Risk software. Windward (2015) used discrete distributions to model FCR in @Risk, incorporating a highly uncertain 100th percentile FCR estimate reported by Buckman et al. (2015). This approach results in theoretical distributions that fit the individual percentiles of the empirical distributions well but overestimate the arithmetic means of the empirical distributions by nearly a factor of four for the general population and approximately 20% for the Nez Perce tribal population. While the overestimation of the mean for the general population is the larger of the two, the overestimation of the mean for the Nez Perce population is of particular practical importance because IDEQ is targeting the arithmetic mean of the Nez Perce population to derive draft HHAWQC. Using FCR distributions that overestimate the arithmetic mean results in draft HHAWQC that are more stringent than warranted based on the tribal FCR data.

In lieu of the discrete distributions used by the draft HHAWQC that overestimate the arithmetic mean of the empirical FCR data substantially and which require interpolation between existing percentiles with no basis to determine if the interpolation model is correct, Arcadis recommends that IDEQ use continuous theoretical curves to model FCR distributions in @Risk when deriving probabilistic HHAWQC. This approach, as described in detail in **Section 4** of this report, results in theoretical distributions that fit the individual percentiles of the empirical distributions as well as IDEQ's discrete distribution, but provide a much closer fit to the arithmetic means. It is crucial that both of these statistics be accurately represented when developing distributions to derive probabilistic HHAWQC so that risk managers can knowledgeably and appropriately manage risk for the average member of the population as well as any given percentile.

6 REFERENCES

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TABLES

Table 1. General Population Empirical Idaho Fish Consumption Distribution

Statistic	Idaho Fish FCR (g/day)
Mean	2.34
0%	0
1%	0.00000918
2%	0.0000377
3%	0.000078
4%	0.000131
5%	0.000196
6%	0.000277
7%	0.000371
8%	0.000484
9%	0.000617
10%	0.000766
11%	0.000951
12%	0.00116
13%	0.00140
14%	0.00167
15%	0.00199
16%	0.00234
17%	0.00273
18%	0.00317
19%	0.00366
20%	0.00420
21%	0.00480
22%	0.00545
23%	0.00618
24%	0.0070
25%	0.00791
26%	0.00891
27%	0.0100
28%	0.0112
29%	0.0125
30%	0.0140
31%	0.0156
32%	0.0173
33%	0.0191
34%	0.0212
35%	0.0234
36%	0.0258
37%	0.0285
38%	0.0313
39%	0.0345
40%	0.0379
41%	0.0415
42%	0.0455
43%	0.0500
44%	0.0546
45%	0.0597
46%	0.0653
47%	0.0714
48%	0.0780
49%	0.0852

Statistic	Idaho Fish FCR (g/day)
50%	0.0928
51%	0.101
52%	0.111
53%	0.121
54%	0.131
55%	0.143
56%	0.156
57%	0.170
58%	0.185
59%	0.202
60%	0.220
61%	0.239
62%	0.261
63%	0.285
64%	0.310
65%	0.339
66%	0.370
67%	0.403
68%	0.442
69%	0.483
70%	0.529
71%	0.580
72%	0.635
73%	0.698
74%	0.765
75%	0.840
76%	0.923
77%	1.02
78%	1.12
79%	1.24
80%	1.38
81%	1.53
82%	1.71
83%	1.91
84%	2.15
85%	2.42
86%	2.74
87%	3.09
88%	3.53
89%	4.03
90%	4.66
91%	5.42
92%	6.36
93%	7.53
94%	9.14
95%	11.2
96%	14.1
97%	18.2
98%	25.3
99%	40.5
100%	1261

Table 2. Nez Perce Empirical Fish Consumption Distributions

Statistic	Group 2 FCR (g/day)	IDEQ Estimated Idaho Fish FCR (g/day)[a]	Alternate Estimated Idaho Fish FCR (g/day)[b]
Mean	66.5	16.1	4.68
5%	4.10	0.992	0.289
10%	6.80	1.65	0.479
15%	9.40	2.27	0.662
20%	12.2	2.95	0.859
25%	15.1	3.65	1.06
30%	18.3	4.43	1.29
35%	21.9	5.30	1.54
40%	26.1	6.32	1.84
45%	30.8	7.45	2.17
50%	36.0	8.71	2.53
55%	42.1	10.2	2.96
60%	49.5	12.0	3.48
65%	58.0	14.0	4.08
70%	68.7	16.6	4.84
75%	81.7	19.8	5.75
80%	98.2	23.8	6.91
85%	122	29.5	8.57
90%	159	38.6	11.2
95%	234	56.6	16.5

Notes:

Both Group 2 to Idaho fish adjustment factors were derived using the process outlined by IDEQ (2015).

a. Estimated as 24.2% of the Group 2 FCR, derived from Nez Perce food frequency questionnaire.

b. Estimated as 7.04% of the Group 2 FCR, derived from the Nez Perce dietary recall data.

Table 3. Nez Perce Tribal Survey Species Groups

Group	Description	Species and Groups Included
Group 1	All finfish and shellfish	Combination of Groups 3, 4, 5, 6, and 7
Group 2	Near coastal, estuarine, freshwater, and anadromous	All species in Groups 3, 4, and 5 as well as <u>lobster, crab, shrimp, marine clams or mussels, octopus, and scallops</u>
Group 3	Salmon or steelhead	<u>Chinook, coho,</u> sockeye, kokanee, steelhead, <u>other salmon,</u> and any unspecified salmon species
Group 4	Resident trout	Rainbow, cutthroat, cutbow, bull, brook, lake, brown, other trout, and any unspecified trout species.
Group 5	Other freshwater finfish or shellfish	Lamprey, sturgeon, whitefish, sucker, bass, bluegill, carp, catfish, crappie, sunfish, <u>tilapia,</u> walleye, yellow perch, crayfish, freshwater clams or mussels, other freshwater finfish, and any unspecified freshwater species
Group 6	Marine finfish or shellfish	Cod, halibut, pollock, tuna, lobster, crab, marine clams or mussels, shrimp, other marine fish, or shellfish
Group 7	Unspecified finfish or shellfish	Any response where the species was not specified sufficiently to be placed into Groups 3, 4, 5, or 6

Notes:
Species <u>underlined</u> in Groups 2 through 5 are not considered Idaho fish (IDEQ 2015).

Table 4. General Population Alternate Theoretical Distribution

Statistic	Empirical Idaho Fish FCR (g/day)	Continuous Theoretical Idaho Fish FCR (g/day)[a]
Mean	2.34	2.28
1%	0.00000918	0.00003814
5%	0.000196	0.000326
10%	0.000766	0.00107
15%	0.00199	0.00244
20%	0.00420	0.00473
25%	0.00791	0.00837
30%	0.0140	0.0140
35%	0.0234	0.0226
40%	0.0379	0.0356
45%	0.0597	0.0552
50%	0.0928	0.0851
55%	0.143	0.131
60%	0.220	0.203
65%	0.339	0.319
70%	0.529	0.511
75%	0.840	0.847
80%	1.38	1.43
85%	2.42	2.48
90%	4.66	4.70
95%	11.2	11.3
99%	40.5	44.2

Notes:

a. This continuous theoretical distribution fits the arithmetic mean of the empirical distribution better than the IDEQ discrete theoretical distribution.
@Risk formula: =RiskSplice(RiskLognorm(49.066,27171.1,RiskShift(-0.0000285067),RiskTruncate(0.0000285067)),RiskInvgauss(2.698,0.19327,RiskShift(-0.49512),RiskTruncate(0.49512)),0.84)

Table 5. Nez Perce Alternate Theoretical Distribution for IDEQ Estimated Idaho Fish

Statistic	IDEQ Estimated Empirical Idaho Fish FCR (g/day)	Continuous Theoretical Idaho Fish FCR (g/day)[a]
Mean	16.1	16.6
5%	0.992	1.01
10%	1.65	1.72
15%	2.27	2.40
20%	2.95	3.09
25%	3.65	3.82
30%	4.43	4.61
35%	5.30	5.47
40%	6.32	6.44
45%	7.45	7.53
50%	8.71	8.78
55%	10.2	10.2
60%	12.0	12.0
65%	14.0	14.0
70%	16.6	16.6
75%	19.8	19.8
80%	23.8	24.2
85%	29.5	30.3
90%	38.6	39.9
95%	56.6	58.7

Notes:

a. This continuous theoretical distribution fits the arithmetic mean of the empirical distribution better than the IDEQ discrete theoretical distribution.

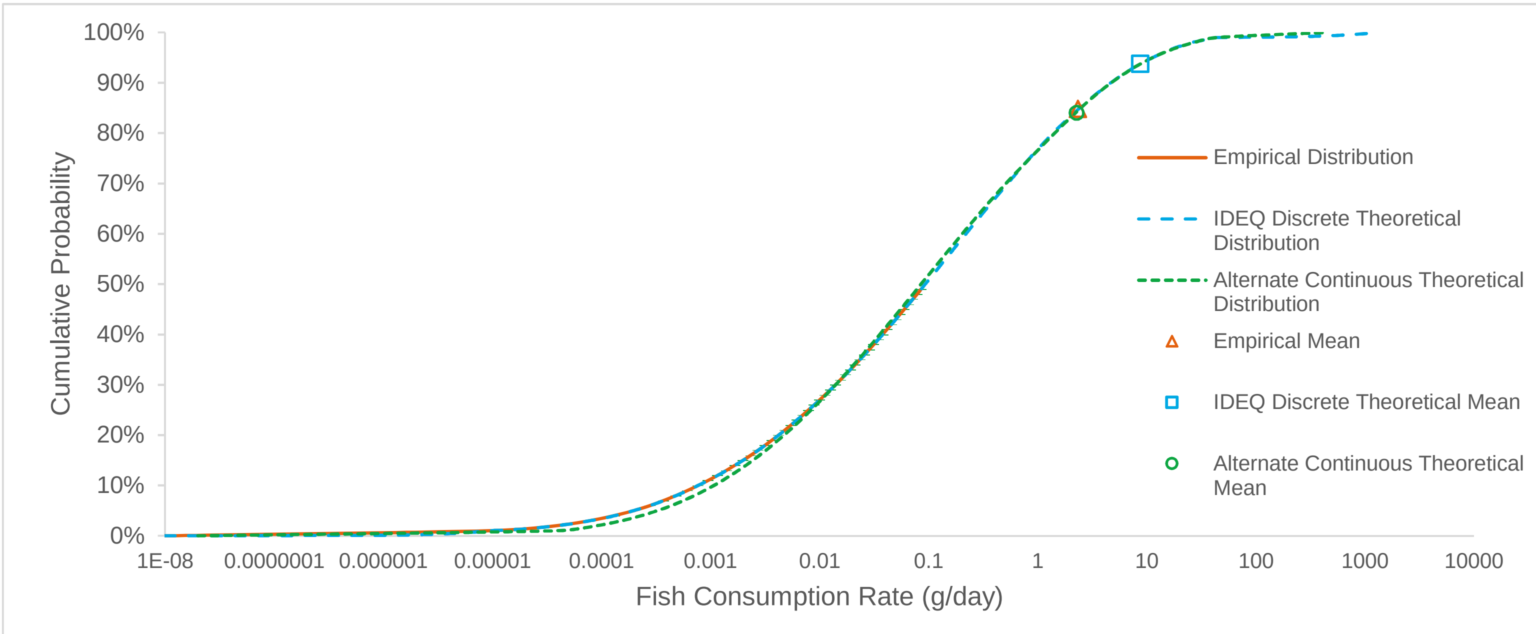
@Risk formula: =RiskInvgauss(17.802,10.944,RiskShift(-1.3888),RiskTruncate(1.3888))

Table 6. Nez Perce Theoretical Distribution for Alternate Estimated Idaho Fish

Statistic	Alternate Estimated Empirical Idaho Fish FCR (g/day)	Continuous Theoretical Idaho Fish FCR (g/day)[a]
Mean	4.67	4.82
5%	0.288	0.294
10%	0.478	0.502
15%	0.661	0.699
20%	0.858	0.899
25%	1.06	1.11
30%	1.29	1.34
35%	1.54	1.59
40%	1.83	1.87
45%	2.17	2.19
50%	2.53	2.56
55%	2.96	2.98
60%	3.48	3.48
65%	4.08	4.08
70%	4.83	4.82
75%	5.74	5.77
80%	6.90	7.03
85%	8.56	8.80
90%	11.2	11.6
95%	16.4	17.1

Notes:
a. @Risk formula: =RiskInvgauss(5.1782,3.1855,RiskShift(-0.40434),RiskTruncate(0.40434))

FIGURES



ARCADIS

Figure 1
General Population Idaho Fish Consumption Distributions

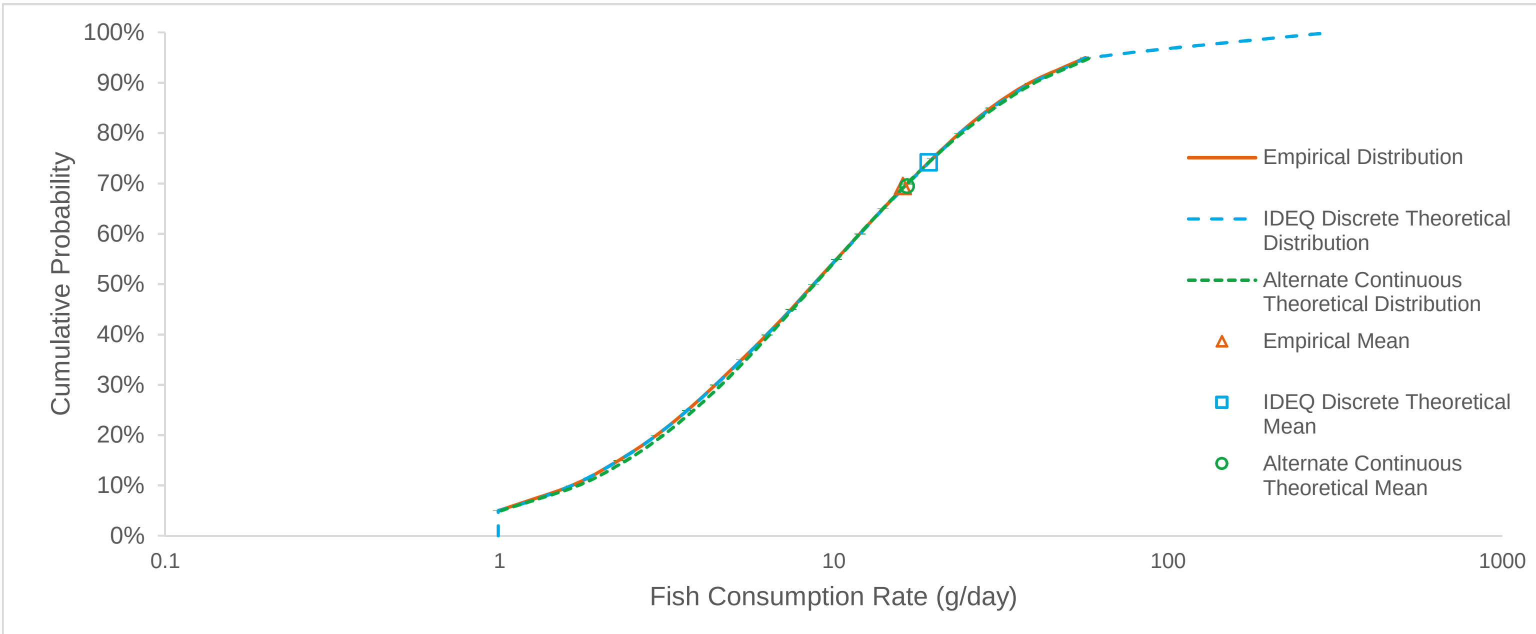


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Figure 2
Nez Perce Tribal Population IDEQ Estimated Idaho Fish Consumption Distributions

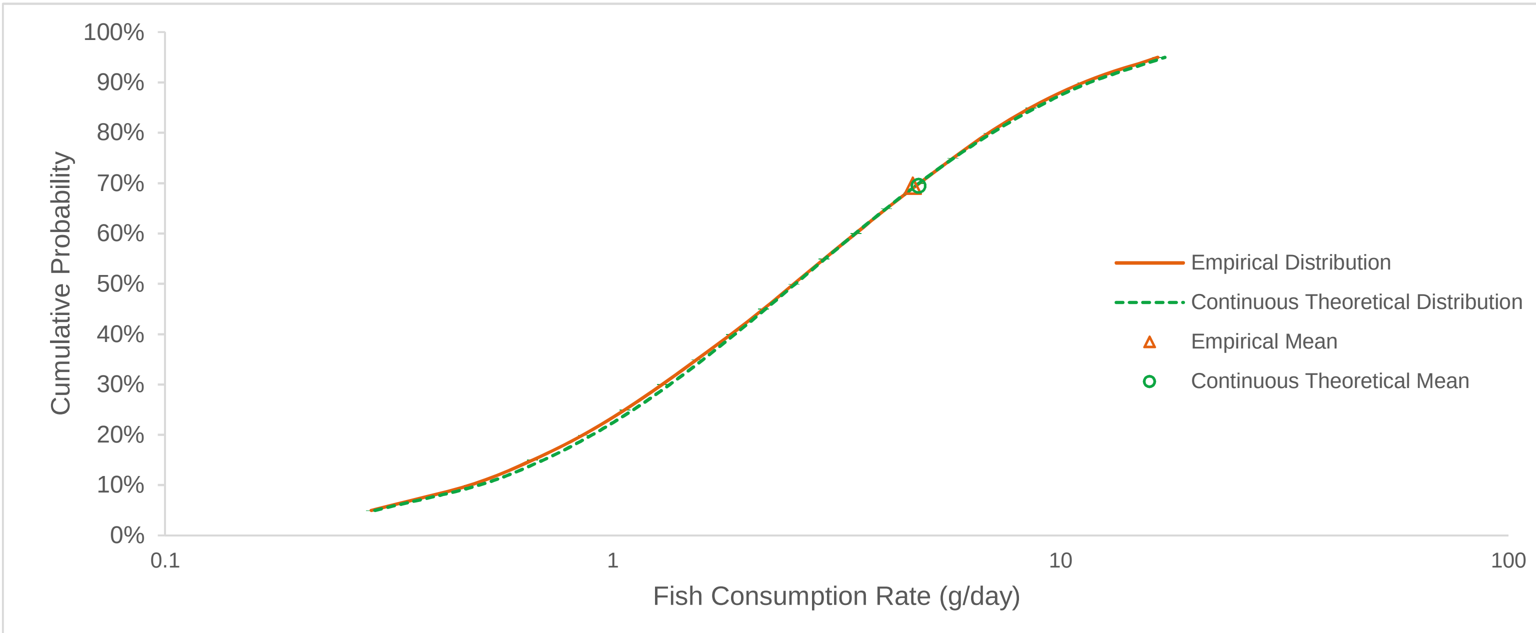

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Figure 3
Nez Perce Tribal Population Alternate Estimated Idaho Fish Consumption Distributions

APPENDIX A

Interpolated Fish Consumption Distributions

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
Mean	--	8.47	arithmetic mean of discrete distribution
0%	0.0999%	0	estimate from Buckman et al. (2015) using the NCI method
0.1%	0.0999%	0.000000918	linear interpolation
0.2%	0.0999%	0.00000184	linear interpolation
0.3%	0.0999%	0.00000275	linear interpolation
0.4%	0.0999%	0.00000367	linear interpolation
0.5%	0.0999%	0.00000459	linear interpolation
0.6%	0.0999%	0.00000551	linear interpolation
0.7%	0.0999%	0.00000642	linear interpolation
0.8%	0.0999%	0.00000734	linear interpolation
0.9%	0.0999%	0.00000826	linear interpolation
1.0%	0.0999%	0.00000918	estimate from Buckman et al. (2015) using the NCI method
1.1%	0.0999%	0.0000120	linear interpolation
1.2%	0.0999%	0.0000149	linear interpolation
1.3%	0.0999%	0.0000177	linear interpolation
1.4%	0.0999%	0.0000206	linear interpolation
1.5%	0.0999%	0.0000234	linear interpolation
1.6%	0.0999%	0.0000263	linear interpolation
1.7%	0.0999%	0.0000291	linear interpolation
1.8%	0.0999%	0.0000320	linear interpolation
1.9%	0.0999%	0.0000348	linear interpolation
2.0%	0.0999%	0.0000377	estimate from Buckman et al. (2015) using the NCI method
2.1%	0.0999%	0.0000417	linear interpolation
2.2%	0.0999%	0.0000458	linear interpolation
2.3%	0.0999%	0.0000498	linear interpolation
2.4%	0.0999%	0.0000538	linear interpolation
2.5%	0.0999%	0.0000579	linear interpolation
2.6%	0.0999%	0.0000619	linear interpolation
2.7%	0.0999%	0.0000659	linear interpolation
2.8%	0.0999%	0.0000700	linear interpolation
2.9%	0.0999%	0.0000740	linear interpolation
3.0%	0.0999%	0.0000780	estimate from Buckman et al. (2015) using the NCI method
3.1%	0.0999%	0.0000834	linear interpolation
3.2%	0.0999%	0.0000887	linear interpolation
3.3%	0.0999%	0.0000941	linear interpolation
3.4%	0.0999%	0.0000994	linear interpolation
3.5%	0.0999%	0.000105	linear interpolation
3.6%	0.0999%	0.000110	linear interpolation
3.7%	0.0999%	0.000115	linear interpolation
3.8%	0.0999%	0.000121	linear interpolation
3.9%	0.0999%	0.000126	linear interpolation
4.0%	0.0999%	0.000131	estimate from Buckman et al. (2015) using the NCI method
4.1%	0.0999%	0.000138	linear interpolation
4.2%	0.0999%	0.000144	linear interpolation
4.3%	0.0999%	0.000151	linear interpolation
4.4%	0.0999%	0.000157	linear interpolation
4.5%	0.0999%	0.000164	linear interpolation
4.6%	0.0999%	0.000170	linear interpolation
4.7%	0.0999%	0.000177	linear interpolation
4.8%	0.0999%	0.000183	linear interpolation
4.9%	0.0999%	0.000189	linear interpolation
5.0%	0.0999%	0.000196	estimate from Buckman et al. (2015) using the NCI method
5.1%	0.0999%	0.000204	linear interpolation
5.2%	0.0999%	0.000212	linear interpolation
5.3%	0.0999%	0.000220	linear interpolation
5.4%	0.0999%	0.000228	linear interpolation
5.5%	0.0999%	0.000236	linear interpolation
5.6%	0.0999%	0.000245	linear interpolation
5.7%	0.0999%	0.000253	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
5.8%	0.0999%	0.000261	linear interpolation
5.9%	0.0999%	0.000269	linear interpolation
6.0%	0.0999%	0.000277	estimate from Buckman et al. (2015) using the NCI method
6.1%	0.0999%	0.000286	linear interpolation
6.2%	0.0999%	0.000296	linear interpolation
6.3%	0.0999%	0.000305	linear interpolation
6.4%	0.0999%	0.000315	linear interpolation
6.5%	0.0999%	0.000324	linear interpolation
6.6%	0.0999%	0.000333	linear interpolation
6.7%	0.0999%	0.000343	linear interpolation
6.8%	0.0999%	0.000352	linear interpolation
6.9%	0.0999%	0.000362	linear interpolation
7.0%	0.0999%	0.000371	estimate from Buckman et al. (2015) using the NCI method
7.1%	0.0999%	0.000382	linear interpolation
7.2%	0.0999%	0.000394	linear interpolation
7.3%	0.0999%	0.000405	linear interpolation
7.4%	0.0999%	0.000416	linear interpolation
7.5%	0.0999%	0.000428	linear interpolation
7.6%	0.0999%	0.000439	linear interpolation
7.7%	0.0999%	0.000450	linear interpolation
7.8%	0.0999%	0.000461	linear interpolation
7.9%	0.0999%	0.000473	linear interpolation
8.0%	0.0999%	0.000484	estimate from Buckman et al. (2015) using the NCI method
8.1%	0.0999%	0.000497	linear interpolation
8.2%	0.0999%	0.000511	linear interpolation
8.3%	0.0999%	0.000524	linear interpolation
8.4%	0.0999%	0.000537	linear interpolation
8.5%	0.0999%	0.000551	linear interpolation
8.6%	0.0999%	0.000564	linear interpolation
8.7%	0.0999%	0.000577	linear interpolation
8.8%	0.0999%	0.000590	linear interpolation
8.9%	0.0999%	0.000604	linear interpolation
9.0%	0.0999%	0.000617	estimate from Buckman et al. (2015) using the NCI method
9.1%	0.0999%	0.000632	linear interpolation
9.2%	0.0999%	0.000647	linear interpolation
9.3%	0.0999%	0.000662	linear interpolation
9.4%	0.0999%	0.000677	linear interpolation
9.5%	0.0999%	0.000692	linear interpolation
9.6%	0.0999%	0.000706	linear interpolation
9.7%	0.0999%	0.000721	linear interpolation
9.8%	0.0999%	0.000736	linear interpolation
9.9%	0.0999%	0.000751	linear interpolation
10.0%	0.0999%	0.000766	estimate from Buckman et al. (2015) using the NCI method
10.1%	0.0999%	0.000785	linear interpolation
10.2%	0.0999%	0.000803	linear interpolation
10.3%	0.0999%	0.000822	linear interpolation
10.4%	0.0999%	0.000840	linear interpolation
10.5%	0.0999%	0.000859	linear interpolation
10.6%	0.0999%	0.000877	linear interpolation
10.7%	0.0999%	0.000896	linear interpolation
10.8%	0.0999%	0.000914	linear interpolation
10.9%	0.0999%	0.000933	linear interpolation
11.0%	0.0999%	0.000951	estimate from Buckman et al. (2015) using the NCI method
11.1%	0.0999%	0.000972	linear interpolation
11.2%	0.0999%	0.000993	linear interpolation
11.3%	0.0999%	0.00101	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
11.4%	0.0999%	0.00104	linear interpolation
11.5%	0.0999%	0.00106	linear interpolation
11.6%	0.0999%	0.00108	linear interpolation
11.7%	0.0999%	0.00110	linear interpolation
11.8%	0.0999%	0.00112	linear interpolation
11.9%	0.0999%	0.00114	linear interpolation
12.0%	0.0999%	0.00116	estimate from Buckman et al. (2015) using the NCI method
12.1%	0.0999%	0.00119	linear interpolation
12.2%	0.0999%	0.00121	linear interpolation
12.3%	0.0999%	0.00123	linear interpolation
12.4%	0.0999%	0.00126	linear interpolation
12.5%	0.0999%	0.00128	linear interpolation
12.6%	0.0999%	0.00131	linear interpolation
12.7%	0.0999%	0.00133	linear interpolation
12.8%	0.0999%	0.00135	linear interpolation
12.9%	0.0999%	0.00138	linear interpolation
13.0%	0.0999%	0.00140	estimate from Buckman et al. (2015) using the NCI method
13.1%	0.0999%	0.00143	linear interpolation
13.2%	0.0999%	0.00146	linear interpolation
13.3%	0.0999%	0.00148	linear interpolation
13.4%	0.0999%	0.00151	linear interpolation
13.5%	0.0999%	0.00154	linear interpolation
13.6%	0.0999%	0.00156	linear interpolation
13.7%	0.0999%	0.00159	linear interpolation
13.8%	0.0999%	0.00162	linear interpolation
13.9%	0.0999%	0.00165	linear interpolation
14.0%	0.0999%	0.00167	estimate from Buckman et al. (2015) using the NCI method
14.1%	0.0999%	0.00171	linear interpolation
14.2%	0.0999%	0.00174	linear interpolation
14.3%	0.0999%	0.00177	linear interpolation
14.4%	0.0999%	0.00180	linear interpolation
14.5%	0.0999%	0.00183	linear interpolation
14.6%	0.0999%	0.00186	linear interpolation
14.7%	0.0999%	0.00189	linear interpolation
14.8%	0.0999%	0.00192	linear interpolation
14.9%	0.0999%	0.00195	linear interpolation
15.0%	0.0999%	0.00199	estimate from Buckman et al. (2015) using the NCI method
15.1%	0.0999%	0.00202	linear interpolation
15.2%	0.0999%	0.00206	linear interpolation
15.3%	0.0999%	0.00209	linear interpolation
15.4%	0.0999%	0.00213	linear interpolation
15.5%	0.0999%	0.00216	linear interpolation
15.6%	0.0999%	0.00220	linear interpolation
15.7%	0.0999%	0.00223	linear interpolation
15.8%	0.0999%	0.00227	linear interpolation
15.9%	0.0999%	0.00230	linear interpolation
16.0%	0.0999%	0.00234	estimate from Buckman et al. (2015) using the NCI method
16.1%	0.0999%	0.00238	linear interpolation
16.2%	0.0999%	0.00242	linear interpolation
16.3%	0.0999%	0.00246	linear interpolation
16.4%	0.0999%	0.00250	linear interpolation
16.5%	0.0999%	0.00254	linear interpolation
16.6%	0.0999%	0.00258	linear interpolation
16.7%	0.0999%	0.00262	linear interpolation
16.8%	0.0999%	0.00266	linear interpolation
16.9%	0.0999%	0.00269	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
17.0%	0.0999%	0.00273	estimate from Buckman et al. (2015) using the NCI method
17.1%	0.0999%	0.00278	linear interpolation
17.2%	0.0999%	0.00282	linear interpolation
17.3%	0.0999%	0.00286	linear interpolation
17.4%	0.0999%	0.00291	linear interpolation
17.5%	0.0999%	0.00295	linear interpolation
17.6%	0.0999%	0.00299	linear interpolation
17.7%	0.0999%	0.00304	linear interpolation
17.8%	0.0999%	0.00308	linear interpolation
17.9%	0.0999%	0.00312	linear interpolation
18.0%	0.0999%	0.00317	estimate from Buckman et al. (2015) using the NCI method
18.1%	0.0999%	0.00322	linear interpolation
18.2%	0.0999%	0.00327	linear interpolation
18.3%	0.0999%	0.00331	linear interpolation
18.4%	0.0999%	0.00336	linear interpolation
18.5%	0.0999%	0.00341	linear interpolation
18.6%	0.0999%	0.00346	linear interpolation
18.7%	0.0999%	0.00351	linear interpolation
18.8%	0.0999%	0.00356	linear interpolation
18.9%	0.0999%	0.00361	linear interpolation
19.0%	0.0999%	0.00366	estimate from Buckman et al. (2015) using the NCI method
19.1%	0.0999%	0.00371	linear interpolation
19.2%	0.0999%	0.00377	linear interpolation
19.3%	0.0999%	0.00382	linear interpolation
19.4%	0.0999%	0.00388	linear interpolation
19.5%	0.0999%	0.00393	linear interpolation
19.6%	0.0999%	0.00399	linear interpolation
19.7%	0.0999%	0.00404	linear interpolation
19.8%	0.0999%	0.00409	linear interpolation
19.9%	0.0999%	0.00415	linear interpolation
20.0%	0.0999%	0.00420	estimate from Buckman et al. (2015) using the NCI method
20.1%	0.0999%	0.00426	linear interpolation
20.2%	0.0999%	0.00432	linear interpolation
20.3%	0.0999%	0.00438	linear interpolation
20.4%	0.0999%	0.00444	linear interpolation
20.5%	0.0999%	0.00450	linear interpolation
20.6%	0.0999%	0.00456	linear interpolation
20.7%	0.0999%	0.00462	linear interpolation
20.8%	0.0999%	0.00468	linear interpolation
20.9%	0.0999%	0.00474	linear interpolation
21.0%	0.0999%	0.00480	estimate from Buckman et al. (2015) using the NCI method
21.1%	0.0999%	0.00487	linear interpolation
21.2%	0.0999%	0.00493	linear interpolation
21.3%	0.0999%	0.00500	linear interpolation
21.4%	0.0999%	0.00506	linear interpolation
21.5%	0.0999%	0.00513	linear interpolation
21.6%	0.0999%	0.00519	linear interpolation
21.7%	0.0999%	0.00526	linear interpolation
21.8%	0.0999%	0.00532	linear interpolation
21.9%	0.0999%	0.00539	linear interpolation
22.0%	0.0999%	0.00545	estimate from Buckman et al. (2015) using the NCI method
22.1%	0.0999%	0.00553	linear interpolation
22.2%	0.0999%	0.00560	linear interpolation
22.3%	0.0999%	0.00567	linear interpolation
22.4%	0.0999%	0.00574	linear interpolation
22.5%	0.0999%	0.00582	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
22.6%	0.0999%	0.00589	linear interpolation
22.7%	0.0999%	0.00596	linear interpolation
22.8%	0.0999%	0.00603	linear interpolation
22.9%	0.0999%	0.00610	linear interpolation
23.0%	0.0999%	0.00618	estimate from Buckman et al. (2015) using the NCI method
23.1%	0.0999%	0.00626	linear interpolation
23.2%	0.0999%	0.00634	linear interpolation
23.3%	0.0999%	0.00642	linear interpolation
23.4%	0.0999%	0.00651	linear interpolation
23.5%	0.0999%	0.00659	linear interpolation
23.6%	0.0999%	0.00667	linear interpolation
23.7%	0.0999%	0.00675	linear interpolation
23.8%	0.0999%	0.00684	linear interpolation
23.9%	0.0999%	0.00692	linear interpolation
24.0%	0.0999%	0.00700	estimate from Buckman et al. (2015) using the NCI method
24.1%	0.0999%	0.00709	linear interpolation
24.2%	0.0999%	0.00718	linear interpolation
24.3%	0.0999%	0.00727	linear interpolation
24.4%	0.0999%	0.00736	linear interpolation
24.5%	0.0999%	0.00746	linear interpolation
24.6%	0.0999%	0.00755	linear interpolation
24.7%	0.0999%	0.00764	linear interpolation
24.8%	0.0999%	0.00773	linear interpolation
24.9%	0.0999%	0.00782	linear interpolation
25.0%	0.0999%	0.00791	estimate from Buckman et al. (2015) using the NCI method
25.1%	0.0999%	0.00801	linear interpolation
25.2%	0.0999%	0.00811	linear interpolation
25.3%	0.0999%	0.00821	linear interpolation
25.4%	0.0999%	0.00831	linear interpolation
25.5%	0.0999%	0.00841	linear interpolation
25.6%	0.0999%	0.00851	linear interpolation
25.7%	0.0999%	0.00861	linear interpolation
25.8%	0.0999%	0.00871	linear interpolation
25.9%	0.0999%	0.00881	linear interpolation
26.0%	0.0999%	0.00891	estimate from Buckman et al. (2015) using the NCI method
26.1%	0.0999%	0.00902	linear interpolation
26.2%	0.0999%	0.00913	linear interpolation
26.3%	0.0999%	0.00924	linear interpolation
26.4%	0.0999%	0.00935	linear interpolation
26.5%	0.0999%	0.00946	linear interpolation
26.6%	0.0999%	0.00956	linear interpolation
26.7%	0.0999%	0.00967	linear interpolation
26.8%	0.0999%	0.00978	linear interpolation
26.9%	0.0999%	0.00989	linear interpolation
27.0%	0.0999%	0.0100	estimate from Buckman et al. (2015) using the NCI method
27.1%	0.0999%	0.0101	linear interpolation
27.2%	0.0999%	0.0102	linear interpolation
27.3%	0.0999%	0.0104	linear interpolation
27.4%	0.0999%	0.0105	linear interpolation
27.5%	0.0999%	0.0106	linear interpolation
27.6%	0.0999%	0.0107	linear interpolation
27.7%	0.0999%	0.0109	linear interpolation
27.8%	0.0999%	0.0110	linear interpolation
27.9%	0.0999%	0.0111	linear interpolation
28.0%	0.0999%	0.0112	estimate from Buckman et al. (2015) using the NCI method
28.1%	0.0999%	0.0114	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
28.2%	0.0999%	0.0115	linear interpolation
28.3%	0.0999%	0.0116	linear interpolation
28.4%	0.0999%	0.0118	linear interpolation
28.5%	0.0999%	0.0119	linear interpolation
28.6%	0.0999%	0.0120	linear interpolation
28.7%	0.0999%	0.0121	linear interpolation
28.8%	0.0999%	0.0123	linear interpolation
28.9%	0.0999%	0.0124	linear interpolation
29.0%	0.0999%	0.0125	estimate from Buckman et al. (2015) using the NCI method
29.1%	0.0999%	0.0127	linear interpolation
29.2%	0.0999%	0.0128	linear interpolation
29.3%	0.0999%	0.0130	linear interpolation
29.4%	0.0999%	0.0131	linear interpolation
29.5%	0.0999%	0.0133	linear interpolation
29.6%	0.0999%	0.0134	linear interpolation
29.7%	0.0999%	0.0136	linear interpolation
29.8%	0.0999%	0.0137	linear interpolation
29.9%	0.0999%	0.0139	linear interpolation
30.0%	0.0999%	0.0140	estimate from Buckman et al. (2015) using the NCI method
30.1%	0.0999%	0.0142	linear interpolation
30.2%	0.0999%	0.0143	linear interpolation
30.3%	0.0999%	0.0145	linear interpolation
30.4%	0.0999%	0.0146	linear interpolation
30.5%	0.0999%	0.0148	linear interpolation
30.6%	0.0999%	0.0149	linear interpolation
30.7%	0.0999%	0.0151	linear interpolation
30.8%	0.0999%	0.0152	linear interpolation
30.9%	0.0999%	0.0154	linear interpolation
31.0%	0.0999%	0.0156	estimate from Buckman et al. (2015) using the NCI method
31.1%	0.0999%	0.0157	linear interpolation
31.2%	0.0999%	0.0159	linear interpolation
31.3%	0.0999%	0.0161	linear interpolation
31.4%	0.0999%	0.0163	linear interpolation
31.5%	0.0999%	0.0164	linear interpolation
31.6%	0.0999%	0.0166	linear interpolation
31.7%	0.0999%	0.0168	linear interpolation
31.8%	0.0999%	0.0170	linear interpolation
31.9%	0.0999%	0.0171	linear interpolation
32.0%	0.0999%	0.0173	estimate from Buckman et al. (2015) using the NCI method
32.1%	0.0999%	0.0175	linear interpolation
32.2%	0.0999%	0.0177	linear interpolation
32.3%	0.0999%	0.0178	linear interpolation
32.4%	0.0999%	0.0180	linear interpolation
32.5%	0.0999%	0.0182	linear interpolation
32.6%	0.0999%	0.0184	linear interpolation
32.7%	0.0999%	0.0185	linear interpolation
32.8%	0.0999%	0.0187	linear interpolation
32.9%	0.0999%	0.0189	linear interpolation
33.0%	0.0999%	0.0191	estimate from Buckman et al. (2015) using the NCI method
33.1%	0.0999%	0.0193	linear interpolation
33.2%	0.0999%	0.0195	linear interpolation
33.3%	0.0999%	0.0197	linear interpolation
33.4%	0.0999%	0.0199	linear interpolation
33.5%	0.0999%	0.0201	linear interpolation
33.6%	0.0999%	0.0203	linear interpolation
33.7%	0.0999%	0.0206	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
33.8%	0.0999%	0.0208	linear interpolation
33.9%	0.0999%	0.0210	linear interpolation
34.0%	0.0999%	0.0212	estimate from Buckman et al. (2015) using the NCI method
34.1%	0.0999%	0.0214	linear interpolation
34.2%	0.0999%	0.0216	linear interpolation
34.3%	0.0999%	0.0219	linear interpolation
34.4%	0.0999%	0.0221	linear interpolation
34.5%	0.0999%	0.0223	linear interpolation
34.6%	0.0999%	0.0225	linear interpolation
34.7%	0.0999%	0.0227	linear interpolation
34.8%	0.0999%	0.0230	linear interpolation
34.9%	0.0999%	0.0232	linear interpolation
35.0%	0.0999%	0.0234	estimate from Buckman et al. (2015) using the NCI method
35.1%	0.0999%	0.0237	linear interpolation
35.2%	0.0999%	0.0239	linear interpolation
35.3%	0.0999%	0.0241	linear interpolation
35.4%	0.0999%	0.0244	linear interpolation
35.5%	0.0999%	0.0246	linear interpolation
35.6%	0.0999%	0.0248	linear interpolation
35.7%	0.0999%	0.0251	linear interpolation
35.8%	0.0999%	0.0253	linear interpolation
35.9%	0.0999%	0.0255	linear interpolation
36.0%	0.0999%	0.0258	estimate from Buckman et al. (2015) using the NCI method
36.1%	0.0999%	0.0261	linear interpolation
36.2%	0.0999%	0.0263	linear interpolation
36.3%	0.0999%	0.0266	linear interpolation
36.4%	0.0999%	0.0269	linear interpolation
36.5%	0.0999%	0.0271	linear interpolation
36.6%	0.0999%	0.0274	linear interpolation
36.7%	0.0999%	0.0277	linear interpolation
36.8%	0.0999%	0.0279	linear interpolation
36.9%	0.0999%	0.0282	linear interpolation
37.0%	0.0999%	0.0285	estimate from Buckman et al. (2015) using the NCI method
37.1%	0.0999%	0.0288	linear interpolation
37.2%	0.0999%	0.0291	linear interpolation
37.3%	0.0999%	0.0293	linear interpolation
37.4%	0.0999%	0.0296	linear interpolation
37.5%	0.0999%	0.0299	linear interpolation
37.6%	0.0999%	0.0302	linear interpolation
37.7%	0.0999%	0.0305	linear interpolation
37.8%	0.0999%	0.0308	linear interpolation
37.9%	0.0999%	0.0310	linear interpolation
38.0%	0.0999%	0.0313	estimate from Buckman et al. (2015) using the NCI method
38.1%	0.0999%	0.0316	linear interpolation
38.2%	0.0999%	0.0320	linear interpolation
38.3%	0.0999%	0.0323	linear interpolation
38.4%	0.0999%	0.0326	linear interpolation
38.5%	0.0999%	0.0329	linear interpolation
38.6%	0.0999%	0.0332	linear interpolation
38.7%	0.0999%	0.0335	linear interpolation
38.8%	0.0999%	0.0338	linear interpolation
38.9%	0.0999%	0.0342	linear interpolation
39.0%	0.0999%	0.0345	estimate from Buckman et al. (2015) using the NCI method
39.1%	0.0999%	0.0348	linear interpolation
39.2%	0.0999%	0.0352	linear interpolation
39.3%	0.0999%	0.0355	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
39.4%	0.0999%	0.0358	linear interpolation
39.5%	0.0999%	0.0362	linear interpolation
39.6%	0.0999%	0.0365	linear interpolation
39.7%	0.0999%	0.0369	linear interpolation
39.8%	0.0999%	0.0372	linear interpolation
39.9%	0.0999%	0.0375	linear interpolation
40.0%	0.0999%	0.0379	estimate from Buckman et al. (2015) using the NCI method
40.1%	0.0999%	0.0382	linear interpolation
40.2%	0.0999%	0.0386	linear interpolation
40.3%	0.0999%	0.0390	linear interpolation
40.4%	0.0999%	0.0393	linear interpolation
40.5%	0.0999%	0.0397	linear interpolation
40.6%	0.0999%	0.0400	linear interpolation
40.7%	0.0999%	0.0404	linear interpolation
40.8%	0.0999%	0.0408	linear interpolation
40.9%	0.0999%	0.0411	linear interpolation
41.0%	0.0999%	0.0415	estimate from Buckman et al. (2015) using the NCI method
41.1%	0.0999%	0.0419	linear interpolation
41.2%	0.0999%	0.0423	linear interpolation
41.3%	0.0999%	0.0427	linear interpolation
41.4%	0.0999%	0.0431	linear interpolation
41.5%	0.0999%	0.0435	linear interpolation
41.6%	0.0999%	0.0439	linear interpolation
41.7%	0.0999%	0.0443	linear interpolation
41.8%	0.0999%	0.0447	linear interpolation
41.9%	0.0999%	0.0451	linear interpolation
42.0%	0.0999%	0.0455	estimate from Buckman et al. (2015) using the NCI method
42.1%	0.0999%	0.0460	linear interpolation
42.2%	0.0999%	0.0464	linear interpolation
42.3%	0.0999%	0.0469	linear interpolation
42.4%	0.0999%	0.0473	linear interpolation
42.5%	0.0999%	0.0477	linear interpolation
42.6%	0.0999%	0.0482	linear interpolation
42.7%	0.0999%	0.0486	linear interpolation
42.8%	0.0999%	0.0491	linear interpolation
42.9%	0.0999%	0.0495	linear interpolation
43.0%	0.0999%	0.0500	estimate from Buckman et al. (2015) using the NCI method
43.1%	0.0999%	0.0504	linear interpolation
43.2%	0.0999%	0.0509	linear interpolation
43.3%	0.0999%	0.0514	linear interpolation
43.4%	0.0999%	0.0518	linear interpolation
43.5%	0.0999%	0.0523	linear interpolation
43.6%	0.0999%	0.0528	linear interpolation
43.7%	0.0999%	0.0532	linear interpolation
43.8%	0.0999%	0.0537	linear interpolation
43.9%	0.0999%	0.0541	linear interpolation
44.0%	0.0999%	0.0546	estimate from Buckman et al. (2015) using the NCI method
44.1%	0.0999%	0.0551	linear interpolation
44.2%	0.0999%	0.0556	linear interpolation
44.3%	0.0999%	0.0561	linear interpolation
44.4%	0.0999%	0.0567	linear interpolation
44.5%	0.0999%	0.0572	linear interpolation
44.6%	0.0999%	0.0577	linear interpolation
44.7%	0.0999%	0.0582	linear interpolation
44.8%	0.0999%	0.0587	linear interpolation
44.9%	0.0999%	0.0592	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
45.0%	0.0999%	0.0597	estimate from Buckman et al. (2015) using the NCI method
45.1%	0.0999%	0.0603	linear interpolation
45.2%	0.0999%	0.0609	linear interpolation
45.3%	0.0999%	0.0614	linear interpolation
45.4%	0.0999%	0.0620	linear interpolation
45.5%	0.0999%	0.0625	linear interpolation
45.6%	0.0999%	0.0631	linear interpolation
45.7%	0.0999%	0.0636	linear interpolation
45.8%	0.0999%	0.0642	linear interpolation
45.9%	0.0999%	0.0647	linear interpolation
46.0%	0.0999%	0.0653	estimate from Buckman et al. (2015) using the NCI method
46.1%	0.0999%	0.0659	linear interpolation
46.2%	0.0999%	0.0665	linear interpolation
46.3%	0.0999%	0.0671	linear interpolation
46.4%	0.0999%	0.0677	linear interpolation
46.5%	0.0999%	0.0683	linear interpolation
46.6%	0.0999%	0.0689	linear interpolation
46.7%	0.0999%	0.0695	linear interpolation
46.8%	0.0999%	0.0702	linear interpolation
46.9%	0.0999%	0.0708	linear interpolation
47.0%	0.0999%	0.0714	estimate from Buckman et al. (2015) using the NCI method
47.1%	0.0999%	0.0720	linear interpolation
47.2%	0.0999%	0.0727	linear interpolation
47.3%	0.0999%	0.0734	linear interpolation
47.4%	0.0999%	0.0740	linear interpolation
47.5%	0.0999%	0.0747	linear interpolation
47.6%	0.0999%	0.0754	linear interpolation
47.7%	0.0999%	0.0760	linear interpolation
47.8%	0.0999%	0.0767	linear interpolation
47.9%	0.0999%	0.0774	linear interpolation
48.0%	0.0999%	0.0780	estimate from Buckman et al. (2015) using the NCI method
48.1%	0.0999%	0.0788	linear interpolation
48.2%	0.0999%	0.0795	linear interpolation
48.3%	0.0999%	0.0802	linear interpolation
48.4%	0.0999%	0.0809	linear interpolation
48.5%	0.0999%	0.0816	linear interpolation
48.6%	0.0999%	0.0823	linear interpolation
48.7%	0.0999%	0.0831	linear interpolation
48.8%	0.0999%	0.0838	linear interpolation
48.9%	0.0999%	0.0845	linear interpolation
49.0%	0.0999%	0.0852	estimate from Buckman et al. (2015) using the NCI method
49.1%	0.0999%	0.0860	linear interpolation
49.2%	0.0999%	0.0867	linear interpolation
49.3%	0.0999%	0.0875	linear interpolation
49.4%	0.0999%	0.0883	linear interpolation
49.5%	0.0999%	0.0890	linear interpolation
49.6%	0.0999%	0.0898	linear interpolation
49.7%	0.0999%	0.0905	linear interpolation
49.8%	0.0999%	0.0913	linear interpolation
49.9%	0.0999%	0.0921	linear interpolation
50.0%	0.0999%	0.0928	estimate from Buckman et al. (2015) using the NCI method
50.1%	0.0999%	0.0937	linear interpolation
50.2%	0.0999%	0.0945	linear interpolation
50.3%	0.0999%	0.0954	linear interpolation
50.4%	0.0999%	0.0963	linear interpolation
50.5%	0.0999%	0.0971	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
50.6%	0.0999%	0.0980	linear interpolation
50.7%	0.0999%	0.0988	linear interpolation
50.8%	0.0999%	0.0997	linear interpolation
50.9%	0.0999%	0.101	linear interpolation
51.0%	0.0999%	0.101	estimate from Buckman et al. (2015) using the NCI method
51.1%	0.0999%	0.102	linear interpolation
51.2%	0.0999%	0.103	linear interpolation
51.3%	0.0999%	0.104	linear interpolation
51.4%	0.0999%	0.105	linear interpolation
51.5%	0.0999%	0.106	linear interpolation
51.6%	0.0999%	0.107	linear interpolation
51.7%	0.0999%	0.108	linear interpolation
51.8%	0.0999%	0.109	linear interpolation
51.9%	0.0999%	0.110	linear interpolation
52.0%	0.0999%	0.111	estimate from Buckman et al. (2015) using the NCI method
52.1%	0.0999%	0.112	linear interpolation
52.2%	0.0999%	0.113	linear interpolation
52.3%	0.0999%	0.114	linear interpolation
52.4%	0.0999%	0.115	linear interpolation
52.5%	0.0999%	0.116	linear interpolation
52.6%	0.0999%	0.117	linear interpolation
52.7%	0.0999%	0.118	linear interpolation
52.8%	0.0999%	0.119	linear interpolation
52.9%	0.0999%	0.120	linear interpolation
53.0%	0.0999%	0.121	estimate from Buckman et al. (2015) using the NCI method
53.1%	0.0999%	0.122	linear interpolation
53.2%	0.0999%	0.123	linear interpolation
53.3%	0.0999%	0.124	linear interpolation
53.4%	0.0999%	0.125	linear interpolation
53.5%	0.0999%	0.126	linear interpolation
53.6%	0.0999%	0.127	linear interpolation
53.7%	0.0999%	0.128	linear interpolation
53.8%	0.0999%	0.129	linear interpolation
53.9%	0.0999%	0.130	linear interpolation
54.0%	0.0999%	0.131	estimate from Buckman et al. (2015) using the NCI method
54.1%	0.0999%	0.132	linear interpolation
54.2%	0.0999%	0.133	linear interpolation
54.3%	0.0999%	0.134	linear interpolation
54.4%	0.0999%	0.136	linear interpolation
54.5%	0.0999%	0.137	linear interpolation
54.6%	0.0999%	0.138	linear interpolation
54.7%	0.0999%	0.139	linear interpolation
54.8%	0.0999%	0.140	linear interpolation
54.9%	0.0999%	0.142	linear interpolation
55.0%	0.0999%	0.143	estimate from Buckman et al. (2015) using the NCI method
55.1%	0.0999%	0.144	linear interpolation
55.2%	0.0999%	0.145	linear interpolation
55.3%	0.0999%	0.147	linear interpolation
55.4%	0.0999%	0.148	linear interpolation
55.5%	0.0999%	0.149	linear interpolation
55.6%	0.0999%	0.151	linear interpolation
55.7%	0.0999%	0.152	linear interpolation
55.8%	0.0999%	0.153	linear interpolation
55.9%	0.0999%	0.155	linear interpolation
56.0%	0.0999%	0.156	estimate from Buckman et al. (2015) using the NCI method
56.1%	0.0999%	0.157	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
56.2%	0.0999%	0.159	linear interpolation
56.3%	0.0999%	0.160	linear interpolation
56.4%	0.0999%	0.161	linear interpolation
56.5%	0.0999%	0.163	linear interpolation
56.6%	0.0999%	0.164	linear interpolation
56.7%	0.0999%	0.166	linear interpolation
56.8%	0.0999%	0.167	linear interpolation
56.9%	0.0999%	0.168	linear interpolation
57.0%	0.0999%	0.170	estimate from Buckman et al. (2015) using the NCI method
57.1%	0.0999%	0.171	linear interpolation
57.2%	0.0999%	0.173	linear interpolation
57.3%	0.0999%	0.174	linear interpolation
57.4%	0.0999%	0.176	linear interpolation
57.5%	0.0999%	0.177	linear interpolation
57.6%	0.0999%	0.179	linear interpolation
57.7%	0.0999%	0.180	linear interpolation
57.8%	0.0999%	0.182	linear interpolation
57.9%	0.0999%	0.183	linear interpolation
58.0%	0.0999%	0.185	estimate from Buckman et al. (2015) using the NCI method
58.1%	0.0999%	0.186	linear interpolation
58.2%	0.0999%	0.188	linear interpolation
58.3%	0.0999%	0.190	linear interpolation
58.4%	0.0999%	0.192	linear interpolation
58.5%	0.0999%	0.193	linear interpolation
58.6%	0.0999%	0.195	linear interpolation
58.7%	0.0999%	0.197	linear interpolation
58.8%	0.0999%	0.198	linear interpolation
58.9%	0.0999%	0.200	linear interpolation
59.0%	0.0999%	0.202	estimate from Buckman et al. (2015) using the NCI method
59.1%	0.0999%	0.204	linear interpolation
59.2%	0.0999%	0.205	linear interpolation
59.3%	0.0999%	0.207	linear interpolation
59.4%	0.0999%	0.209	linear interpolation
59.5%	0.0999%	0.211	linear interpolation
59.6%	0.0999%	0.213	linear interpolation
59.7%	0.0999%	0.214	linear interpolation
59.8%	0.0999%	0.216	linear interpolation
59.9%	0.0999%	0.218	linear interpolation
60.0%	0.0999%	0.220	estimate from Buckman et al. (2015) using the NCI method
60.1%	0.0999%	0.222	linear interpolation
60.2%	0.0999%	0.224	linear interpolation
60.3%	0.0999%	0.226	linear interpolation
60.4%	0.0999%	0.228	linear interpolation
60.5%	0.0999%	0.229	linear interpolation
60.6%	0.0999%	0.231	linear interpolation
60.7%	0.0999%	0.233	linear interpolation
60.8%	0.0999%	0.235	linear interpolation
60.9%	0.0999%	0.237	linear interpolation
61.0%	0.0999%	0.239	estimate from Buckman et al. (2015) using the NCI method
61.1%	0.0999%	0.241	linear interpolation
61.2%	0.0999%	0.243	linear interpolation
61.3%	0.0999%	0.246	linear interpolation
61.4%	0.0999%	0.248	linear interpolation
61.5%	0.0999%	0.250	linear interpolation
61.6%	0.0999%	0.252	linear interpolation
61.7%	0.0999%	0.254	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
61.8%	0.0999%	0.256	linear interpolation
61.9%	0.0999%	0.258	linear interpolation
62.0%	0.0999%	0.261	estimate from Buckman et al. (2015) using the NCI method
62.1%	0.0999%	0.263	linear interpolation
62.2%	0.0999%	0.265	linear interpolation
62.3%	0.0999%	0.268	linear interpolation
62.4%	0.0999%	0.270	linear interpolation
62.5%	0.0999%	0.273	linear interpolation
62.6%	0.0999%	0.275	linear interpolation
62.7%	0.0999%	0.277	linear interpolation
62.8%	0.0999%	0.280	linear interpolation
62.9%	0.0999%	0.282	linear interpolation
63.0%	0.0999%	0.285	estimate from Buckman et al. (2015) using the NCI method
63.1%	0.0999%	0.287	linear interpolation
63.2%	0.0999%	0.290	linear interpolation
63.3%	0.0999%	0.292	linear interpolation
63.4%	0.0999%	0.295	linear interpolation
63.5%	0.0999%	0.297	linear interpolation
63.6%	0.0999%	0.300	linear interpolation
63.7%	0.0999%	0.303	linear interpolation
63.8%	0.0999%	0.305	linear interpolation
63.9%	0.0999%	0.308	linear interpolation
64.0%	0.0999%	0.310	estimate from Buckman et al. (2015) using the NCI method
64.1%	0.0999%	0.313	linear interpolation
64.2%	0.0999%	0.316	linear interpolation
64.3%	0.0999%	0.319	linear interpolation
64.4%	0.0999%	0.322	linear interpolation
64.5%	0.0999%	0.325	linear interpolation
64.6%	0.0999%	0.328	linear interpolation
64.7%	0.0999%	0.331	linear interpolation
64.8%	0.0999%	0.333	linear interpolation
64.9%	0.0999%	0.336	linear interpolation
65.0%	0.0999%	0.339	estimate from Buckman et al. (2015) using the NCI method
65.1%	0.0999%	0.342	linear interpolation
65.2%	0.0999%	0.345	linear interpolation
65.3%	0.0999%	0.348	linear interpolation
65.4%	0.0999%	0.352	linear interpolation
65.5%	0.0999%	0.355	linear interpolation
65.6%	0.0999%	0.358	linear interpolation
65.7%	0.0999%	0.361	linear interpolation
65.8%	0.0999%	0.364	linear interpolation
65.9%	0.0999%	0.367	linear interpolation
66.0%	0.0999%	0.370	estimate from Buckman et al. (2015) using the NCI method
66.1%	0.0999%	0.373	linear interpolation
66.2%	0.0999%	0.377	linear interpolation
66.3%	0.0999%	0.380	linear interpolation
66.4%	0.0999%	0.383	linear interpolation
66.5%	0.0999%	0.387	linear interpolation
66.6%	0.0999%	0.390	linear interpolation
66.7%	0.0999%	0.393	linear interpolation
66.8%	0.0999%	0.397	linear interpolation
66.9%	0.0999%	0.400	linear interpolation
67.0%	0.0999%	0.403	estimate from Buckman et al. (2015) using the NCI method
67.1%	0.0999%	0.407	linear interpolation
67.2%	0.0999%	0.411	linear interpolation
67.3%	0.0999%	0.415	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
67.4%	0.0999%	0.419	linear interpolation
67.5%	0.0999%	0.423	linear interpolation
67.6%	0.0999%	0.427	linear interpolation
67.7%	0.0999%	0.430	linear interpolation
67.8%	0.0999%	0.434	linear interpolation
67.9%	0.0999%	0.438	linear interpolation
68.0%	0.0999%	0.442	estimate from Buckman et al. (2015) using the NCI method
68.1%	0.0999%	0.446	linear interpolation
68.2%	0.0999%	0.450	linear interpolation
68.3%	0.0999%	0.454	linear interpolation
68.4%	0.0999%	0.459	linear interpolation
68.5%	0.0999%	0.463	linear interpolation
68.6%	0.0999%	0.467	linear interpolation
68.7%	0.0999%	0.471	linear interpolation
68.8%	0.0999%	0.475	linear interpolation
68.9%	0.0999%	0.479	linear interpolation
69.0%	0.0999%	0.483	estimate from Buckman et al. (2015) using the NCI method
69.1%	0.0999%	0.488	linear interpolation
69.2%	0.0999%	0.493	linear interpolation
69.3%	0.0999%	0.497	linear interpolation
69.4%	0.0999%	0.502	linear interpolation
69.5%	0.0999%	0.506	linear interpolation
69.6%	0.0999%	0.511	linear interpolation
69.7%	0.0999%	0.515	linear interpolation
69.8%	0.0999%	0.520	linear interpolation
69.9%	0.0999%	0.524	linear interpolation
70.0%	0.0999%	0.529	estimate from Buckman et al. (2015) using the NCI method
70.1%	0.0999%	0.534	linear interpolation
70.2%	0.0999%	0.539	linear interpolation
70.3%	0.0999%	0.544	linear interpolation
70.4%	0.0999%	0.549	linear interpolation
70.5%	0.0999%	0.554	linear interpolation
70.6%	0.0999%	0.559	linear interpolation
70.7%	0.0999%	0.564	linear interpolation
70.8%	0.0999%	0.570	linear interpolation
70.9%	0.0999%	0.575	linear interpolation
71.0%	0.0999%	0.580	estimate from Buckman et al. (2015) using the NCI method
71.1%	0.0999%	0.585	linear interpolation
71.2%	0.0999%	0.591	linear interpolation
71.3%	0.0999%	0.596	linear interpolation
71.4%	0.0999%	0.602	linear interpolation
71.5%	0.0999%	0.608	linear interpolation
71.6%	0.0999%	0.613	linear interpolation
71.7%	0.0999%	0.619	linear interpolation
71.8%	0.0999%	0.624	linear interpolation
71.9%	0.0999%	0.630	linear interpolation
72.0%	0.0999%	0.635	estimate from Buckman et al. (2015) using the NCI method
72.1%	0.0999%	0.642	linear interpolation
72.2%	0.0999%	0.648	linear interpolation
72.3%	0.0999%	0.654	linear interpolation
72.4%	0.0999%	0.660	linear interpolation
72.5%	0.0999%	0.667	linear interpolation
72.6%	0.0999%	0.673	linear interpolation
72.7%	0.0999%	0.679	linear interpolation
72.8%	0.0999%	0.685	linear interpolation
72.9%	0.0999%	0.692	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
73.0%	0.0999%	0.698	estimate from Buckman et al. (2015) using the NCI method
73.1%	0.0999%	0.705	linear interpolation
73.2%	0.0999%	0.711	linear interpolation
73.3%	0.0999%	0.718	linear interpolation
73.4%	0.0999%	0.725	linear interpolation
73.5%	0.0999%	0.731	linear interpolation
73.6%	0.0999%	0.738	linear interpolation
73.7%	0.0999%	0.745	linear interpolation
73.8%	0.0999%	0.751	linear interpolation
73.9%	0.0999%	0.758	linear interpolation
74.0%	0.0999%	0.765	estimate from Buckman et al. (2015) using the NCI method
74.1%	0.0999%	0.772	linear interpolation
74.2%	0.0999%	0.780	linear interpolation
74.3%	0.0999%	0.787	linear interpolation
74.4%	0.0999%	0.795	linear interpolation
74.5%	0.0999%	0.802	linear interpolation
74.6%	0.0999%	0.810	linear interpolation
74.7%	0.0999%	0.817	linear interpolation
74.8%	0.0999%	0.825	linear interpolation
74.9%	0.0999%	0.832	linear interpolation
75.0%	0.0999%	0.840	estimate from Buckman et al. (2015) using the NCI method
75.1%	0.0999%	0.848	linear interpolation
75.2%	0.0999%	0.857	linear interpolation
75.3%	0.0999%	0.865	linear interpolation
75.4%	0.0999%	0.873	linear interpolation
75.5%	0.0999%	0.882	linear interpolation
75.6%	0.0999%	0.890	linear interpolation
75.7%	0.0999%	0.898	linear interpolation
75.8%	0.0999%	0.906	linear interpolation
75.9%	0.0999%	0.915	linear interpolation
76.0%	0.0999%	0.923	estimate from Buckman et al. (2015) using the NCI method
76.1%	0.0999%	0.933	linear interpolation
76.2%	0.0999%	0.942	linear interpolation
76.3%	0.0999%	0.952	linear interpolation
76.4%	0.0999%	0.962	linear interpolation
76.5%	0.0999%	0.971	linear interpolation
76.6%	0.0999%	0.981	linear interpolation
76.7%	0.0999%	0.991	linear interpolation
76.8%	0.0999%	1.00	linear interpolation
76.9%	0.0999%	1.01	linear interpolation
77.0%	0.0999%	1.02	estimate from Buckman et al. (2015) using the NCI method
77.1%	0.0999%	1.03	linear interpolation
77.2%	0.0999%	1.04	linear interpolation
77.3%	0.0999%	1.05	linear interpolation
77.4%	0.0999%	1.06	linear interpolation
77.5%	0.0999%	1.07	linear interpolation
77.6%	0.0999%	1.08	linear interpolation
77.7%	0.0999%	1.09	linear interpolation
77.8%	0.0999%	1.10	linear interpolation
77.9%	0.0999%	1.11	linear interpolation
78.0%	0.0999%	1.12	estimate from Buckman et al. (2015) using the NCI method
78.1%	0.0999%	1.14	linear interpolation
78.2%	0.0999%	1.15	linear interpolation
78.3%	0.0999%	1.16	linear interpolation
78.4%	0.0999%	1.17	linear interpolation
78.5%	0.0999%	1.18	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
78.6%	0.0999%	1.20	linear interpolation
78.7%	0.0999%	1.21	linear interpolation
78.8%	0.0999%	1.22	linear interpolation
78.9%	0.0999%	1.23	linear interpolation
79.0%	0.0999%	1.24	estimate from Buckman et al. (2015) using the NCI method
79.1%	0.0999%	1.26	linear interpolation
79.2%	0.0999%	1.27	linear interpolation
79.3%	0.0999%	1.28	linear interpolation
79.4%	0.0999%	1.30	linear interpolation
79.5%	0.0999%	1.31	linear interpolation
79.6%	0.0999%	1.32	linear interpolation
79.7%	0.0999%	1.34	linear interpolation
79.8%	0.0999%	1.35	linear interpolation
79.9%	0.0999%	1.36	linear interpolation
80.0%	0.0999%	1.38	estimate from Buckman et al. (2015) using the NCI method
80.1%	0.0999%	1.39	linear interpolation
80.2%	0.0999%	1.41	linear interpolation
80.3%	0.0999%	1.42	linear interpolation
80.4%	0.0999%	1.44	linear interpolation
80.5%	0.0999%	1.45	linear interpolation
80.6%	0.0999%	1.47	linear interpolation
80.7%	0.0999%	1.48	linear interpolation
80.8%	0.0999%	1.50	linear interpolation
80.9%	0.0999%	1.51	linear interpolation
81.0%	0.0999%	1.53	estimate from Buckman et al. (2015) using the NCI method
81.1%	0.0999%	1.55	linear interpolation
81.2%	0.0999%	1.57	linear interpolation
81.3%	0.0999%	1.58	linear interpolation
81.4%	0.0999%	1.60	linear interpolation
81.5%	0.0999%	1.62	linear interpolation
81.6%	0.0999%	1.64	linear interpolation
81.7%	0.0999%	1.66	linear interpolation
81.8%	0.0999%	1.67	linear interpolation
81.9%	0.0999%	1.69	linear interpolation
82.0%	0.0999%	1.71	estimate from Buckman et al. (2015) using the NCI method
82.1%	0.0999%	1.73	linear interpolation
82.2%	0.0999%	1.75	linear interpolation
82.3%	0.0999%	1.77	linear interpolation
82.4%	0.0999%	1.79	linear interpolation
82.5%	0.0999%	1.81	linear interpolation
82.6%	0.0999%	1.83	linear interpolation
82.7%	0.0999%	1.85	linear interpolation
82.8%	0.0999%	1.87	linear interpolation
82.9%	0.0999%	1.89	linear interpolation
83.0%	0.0999%	1.91	estimate from Buckman et al. (2015) using the NCI method
83.1%	0.0999%	1.94	linear interpolation
83.2%	0.0999%	1.96	linear interpolation
83.3%	0.0999%	1.98	linear interpolation
83.4%	0.0999%	2.01	linear interpolation
83.5%	0.0999%	2.03	linear interpolation
83.6%	0.0999%	2.05	linear interpolation
83.7%	0.0999%	2.08	linear interpolation
83.8%	0.0999%	2.10	linear interpolation
83.9%	0.0999%	2.12	linear interpolation
84.0%	0.0999%	2.15	estimate from Buckman et al. (2015) using the NCI method
84.1%	0.0999%	2.17	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
84.2%	0.0999%	2.20	linear interpolation
84.3%	0.0999%	2.23	linear interpolation
84.4%	0.0999%	2.26	linear interpolation
84.5%	0.0999%	2.28	linear interpolation
84.6%	0.0999%	2.31	linear interpolation
84.7%	0.0999%	2.34	linear interpolation
84.8%	0.0999%	2.36	linear interpolation
84.9%	0.0999%	2.39	linear interpolation
85.0%	0.0999%	2.42	estimate from Buckman et al. (2015) using the NCI method
85.1%	0.0999%	2.45	linear interpolation
85.2%	0.0999%	2.48	linear interpolation
85.3%	0.0999%	2.51	linear interpolation
85.4%	0.0999%	2.55	linear interpolation
85.5%	0.0999%	2.58	linear interpolation
85.6%	0.0999%	2.61	linear interpolation
85.7%	0.0999%	2.64	linear interpolation
85.8%	0.0999%	2.67	linear interpolation
85.9%	0.0999%	2.70	linear interpolation
86.0%	0.0999%	2.74	estimate from Buckman et al. (2015) using the NCI method
86.1%	0.0999%	2.77	linear interpolation
86.2%	0.0999%	2.81	linear interpolation
86.3%	0.0999%	2.84	linear interpolation
86.4%	0.0999%	2.88	linear interpolation
86.5%	0.0999%	2.91	linear interpolation
86.6%	0.0999%	2.95	linear interpolation
86.7%	0.0999%	2.98	linear interpolation
86.8%	0.0999%	3.02	linear interpolation
86.9%	0.0999%	3.06	linear interpolation
87.0%	0.0999%	3.09	estimate from Buckman et al. (2015) using the NCI method
87.1%	0.0999%	3.13	linear interpolation
87.2%	0.0999%	3.18	linear interpolation
87.3%	0.0999%	3.22	linear interpolation
87.4%	0.0999%	3.27	linear interpolation
87.5%	0.0999%	3.31	linear interpolation
87.6%	0.0999%	3.35	linear interpolation
87.7%	0.0999%	3.40	linear interpolation
87.8%	0.0999%	3.44	linear interpolation
87.9%	0.0999%	3.48	linear interpolation
88.0%	0.0999%	3.53	estimate from Buckman et al. (2015) using the NCI method
88.1%	0.0999%	3.58	linear interpolation
88.2%	0.0999%	3.63	linear interpolation
88.3%	0.0999%	3.68	linear interpolation
88.4%	0.0999%	3.73	linear interpolation
88.5%	0.0999%	3.78	linear interpolation
88.6%	0.0999%	3.83	linear interpolation
88.7%	0.0999%	3.88	linear interpolation
88.8%	0.0999%	3.93	linear interpolation
88.9%	0.0999%	3.98	linear interpolation
89.0%	0.0999%	4.03	estimate from Buckman et al. (2015) using the NCI method
89.1%	0.0999%	4.10	linear interpolation
89.2%	0.0999%	4.16	linear interpolation
89.3%	0.0999%	4.22	linear interpolation
89.4%	0.0999%	4.28	linear interpolation
89.5%	0.0999%	4.35	linear interpolation
89.6%	0.0999%	4.41	linear interpolation
89.7%	0.0999%	4.47	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
89.8%	0.0999%	4.53	linear interpolation
89.9%	0.0999%	4.60	linear interpolation
90.0%	0.0999%	4.66	estimate from Buckman et al. (2015) using the NCI method
90.1%	0.0999%	4.73	linear interpolation
90.2%	0.0999%	4.81	linear interpolation
90.3%	0.0999%	4.89	linear interpolation
90.4%	0.0999%	4.96	linear interpolation
90.5%	0.0999%	5.04	linear interpolation
90.6%	0.0999%	5.11	linear interpolation
90.7%	0.0999%	5.19	linear interpolation
90.8%	0.0999%	5.27	linear interpolation
90.9%	0.0999%	5.34	linear interpolation
91.0%	0.0999%	5.42	estimate from Buckman et al. (2015) using the NCI method
91.1%	0.0999%	5.51	linear interpolation
91.2%	0.0999%	5.61	linear interpolation
91.3%	0.0999%	5.70	linear interpolation
91.4%	0.0999%	5.80	linear interpolation
91.5%	0.0999%	5.89	linear interpolation
91.6%	0.0999%	5.98	linear interpolation
91.7%	0.0999%	6.08	linear interpolation
91.8%	0.0999%	6.17	linear interpolation
91.9%	0.0999%	6.27	linear interpolation
92.0%	0.0999%	6.36	estimate from Buckman et al. (2015) using the NCI method
92.1%	0.0999%	6.48	linear interpolation
92.2%	0.0999%	6.60	linear interpolation
92.3%	0.0999%	6.71	linear interpolation
92.4%	0.0999%	6.83	linear interpolation
92.5%	0.0999%	6.94	linear interpolation
92.6%	0.0999%	7.06	linear interpolation
92.7%	0.0999%	7.18	linear interpolation
92.8%	0.0999%	7.29	linear interpolation
92.9%	0.0999%	7.41	linear interpolation
93.0%	0.0999%	7.53	estimate from Buckman et al. (2015) using the NCI method
93.1%	0.0999%	7.69	linear interpolation
93.2%	0.0999%	7.85	linear interpolation
93.3%	0.0999%	8.01	linear interpolation
93.4%	0.0999%	8.17	linear interpolation
93.5%	0.0999%	8.33	linear interpolation
93.6%	0.0999%	8.49	linear interpolation
93.7%	0.0999%	8.65	linear interpolation
93.8%	0.0999%	8.81	linear interpolation
93.9%	0.0999%	8.98	linear interpolation
94.0%	0.0999%	9.14	estimate from Buckman et al. (2015) using the NCI method
94.1%	0.0999%	9.35	linear interpolation
94.2%	0.0999%	9.56	linear interpolation
94.3%	0.0999%	9.77	linear interpolation
94.4%	0.0999%	9.98	linear interpolation
94.5%	0.0999%	10.2	linear interpolation
94.6%	0.0999%	10.4	linear interpolation
94.7%	0.0999%	10.6	linear interpolation
94.8%	0.0999%	10.8	linear interpolation
94.9%	0.0999%	11.0	linear interpolation
95.0%	0.0999%	11.2	estimate from Buckman et al. (2015) using the NCI method
95.1%	0.0999%	11.5	linear interpolation
95.2%	0.0999%	11.8	linear interpolation
95.3%	0.0999%	12.1	linear interpolation

Table A1. IDEQ Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
95.4%	0.0999%	12.4	linear interpolation
95.5%	0.0999%	12.6	linear interpolation
95.6%	0.0999%	12.9	linear interpolation
95.7%	0.0999%	13.2	linear interpolation
95.8%	0.0999%	13.5	linear interpolation
95.9%	0.0999%	13.8	linear interpolation
96.0%	0.0999%	14.1	estimate from Buckman et al. (2015) using the NCI method
96.1%	0.0999%	14.5	linear interpolation
96.2%	0.0999%	14.9	linear interpolation
96.3%	0.0999%	15.3	linear interpolation
96.4%	0.0999%	15.7	linear interpolation
96.5%	0.0999%	16.1	linear interpolation
96.6%	0.0999%	16.6	linear interpolation
96.7%	0.0999%	17.0	linear interpolation
96.8%	0.0999%	17.4	linear interpolation
96.9%	0.0999%	17.8	linear interpolation
97.0%	0.0999%	18.2	estimate from Buckman et al. (2015) using the NCI method
97.1%	0.0999%	18.9	linear interpolation
97.2%	0.0999%	19.6	linear interpolation
97.3%	0.0999%	20.4	linear interpolation
97.4%	0.0999%	21.1	linear interpolation
97.5%	0.0999%	21.8	linear interpolation
97.6%	0.0999%	22.5	linear interpolation
97.7%	0.0999%	23.2	linear interpolation
97.8%	0.0999%	23.9	linear interpolation
97.9%	0.0999%	24.6	linear interpolation
98.0%	0.0999%	25.3	estimate from Buckman et al. (2015) using the NCI method
98.1%	0.0999%	26.9	linear interpolation
98.2%	0.0999%	28.4	linear interpolation
98.3%	0.0999%	29.9	linear interpolation
98.4%	0.0999%	31.4	linear interpolation
98.5%	0.0999%	32.9	linear interpolation
98.6%	0.0999%	34.5	linear interpolation
98.7%	0.0999%	36.0	linear interpolation
98.8%	0.0999%	37.5	linear interpolation
98.9%	0.0999%	39.0	linear interpolation
99.0%	0.0999%	40.5	estimate from Buckman et al. (2015) using the NCI method
99.1%	0.0999%	163	linear interpolation
99.2%	0.0999%	285	linear interpolation
99.3%	0.0999%	407	linear interpolation
99.4%	0.0999%	529	linear interpolation
99.5%	0.0999%	651	linear interpolation
99.6%	0.0999%	773	linear interpolation
99.7%	0.0999%	895	linear interpolation
99.8%	0.0999%	1017	linear interpolation
99.9%	0.0999%	1139	linear interpolation
100%	0.0999%	1261	estimate from Buckman et al. (2015) using the NCI method

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
Mean	--	5.81	arithmetic mean of discrete distribution
0%	0.0999%	0	estimate from Buckman et al. (2015) using the NCI method
0.1%	0.0999%	0.000000020	logarithmic interpolation
0.2%	0.0999%	0.00000004	logarithmic interpolation
0.3%	0.0999%	0.00000008	logarithmic interpolation
0.4%	0.0999%	0.00000015	logarithmic interpolation
0.5%	0.0999%	0.00000030	logarithmic interpolation
0.6%	0.0999%	0.00000060	logarithmic interpolation
0.7%	0.0999%	0.00000119	logarithmic interpolation
0.8%	0.0999%	0.00000235	logarithmic interpolation
0.9%	0.0999%	0.00000464	logarithmic interpolation
1.0%	0.0999%	0.00000918	estimate from Buckman et al. (2015) using the NCI method
1.1%	0.0999%	0.0000106	logarithmic interpolation
1.2%	0.0999%	0.0000122	logarithmic interpolation
1.3%	0.0999%	0.0000140	logarithmic interpolation
1.4%	0.0999%	0.0000161	logarithmic interpolation
1.5%	0.0999%	0.0000186	logarithmic interpolation
1.6%	0.0999%	0.0000214	logarithmic interpolation
1.7%	0.0999%	0.0000247	logarithmic interpolation
1.8%	0.0999%	0.0000284	logarithmic interpolation
1.9%	0.0999%	0.0000327	logarithmic interpolation
2.0%	0.0999%	0.0000377	estimate from Buckman et al. (2015) using the NCI method
2.1%	0.0999%	0.0000405	logarithmic interpolation
2.2%	0.0999%	0.0000436	logarithmic interpolation
2.3%	0.0999%	0.0000469	logarithmic interpolation
2.4%	0.0999%	0.0000504	logarithmic interpolation
2.5%	0.0999%	0.0000542	logarithmic interpolation
2.6%	0.0999%	0.0000583	logarithmic interpolation
2.7%	0.0999%	0.0000627	logarithmic interpolation
2.8%	0.0999%	0.0000675	logarithmic interpolation
2.9%	0.0999%	0.0000726	logarithmic interpolation
3.0%	0.0999%	0.0000780	estimate from Buckman et al. (2015) using the NCI method
3.1%	0.0999%	0.0000822	logarithmic interpolation
3.2%	0.0999%	0.0000866	logarithmic interpolation
3.3%	0.0999%	0.0000913	logarithmic interpolation
3.4%	0.0999%	0.0000961	logarithmic interpolation
3.5%	0.0999%	0.000101	logarithmic interpolation
3.6%	0.0999%	0.000107	logarithmic interpolation
3.7%	0.0999%	0.000112	logarithmic interpolation
3.8%	0.0999%	0.000118	logarithmic interpolation
3.9%	0.0999%	0.000125	logarithmic interpolation
4.0%	0.0999%	0.000131	estimate from Buckman et al. (2015) using the NCI method
4.1%	0.0999%	0.000137	logarithmic interpolation
4.2%	0.0999%	0.000142	logarithmic interpolation
4.3%	0.0999%	0.000148	logarithmic interpolation
4.4%	0.0999%	0.000154	logarithmic interpolation
4.5%	0.0999%	0.000160	logarithmic interpolation
4.6%	0.0999%	0.000167	logarithmic interpolation
4.7%	0.0999%	0.000174	logarithmic interpolation
4.8%	0.0999%	0.000181	logarithmic interpolation
4.9%	0.0999%	0.000188	logarithmic interpolation
5.0%	0.0999%	0.000196	estimate from Buckman et al. (2015) using the NCI method
5.1%	0.0999%	0.000203	logarithmic interpolation
5.2%	0.0999%	0.000210	logarithmic interpolation
5.3%	0.0999%	0.000217	logarithmic interpolation
5.4%	0.0999%	0.000225	logarithmic interpolation
5.5%	0.0999%	0.000233	logarithmic interpolation
5.6%	0.0999%	0.000241	logarithmic interpolation
5.7%	0.0999%	0.000250	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
5.8%	0.0999%	0.000258	logarithmic interpolation
5.9%	0.0999%	0.000268	logarithmic interpolation
6.0%	0.0999%	0.000277	estimate from Buckman et al. (2015) using the NCI method
6.1%	0.0999%	0.000285	logarithmic interpolation
6.2%	0.0999%	0.000294	logarithmic interpolation
6.3%	0.0999%	0.000302	logarithmic interpolation
6.4%	0.0999%	0.000311	logarithmic interpolation
6.5%	0.0999%	0.000321	logarithmic interpolation
6.6%	0.0999%	0.000330	logarithmic interpolation
6.7%	0.0999%	0.000340	logarithmic interpolation
6.8%	0.0999%	0.000350	logarithmic interpolation
6.9%	0.0999%	0.000360	logarithmic interpolation
7.0%	0.0999%	0.000371	estimate from Buckman et al. (2015) using the NCI method
7.1%	0.0999%	0.000381	logarithmic interpolation
7.2%	0.0999%	0.000391	logarithmic interpolation
7.3%	0.0999%	0.000402	logarithmic interpolation
7.4%	0.0999%	0.000413	logarithmic interpolation
7.5%	0.0999%	0.000424	logarithmic interpolation
7.6%	0.0999%	0.000435	logarithmic interpolation
7.7%	0.0999%	0.000447	logarithmic interpolation
7.8%	0.0999%	0.000459	logarithmic interpolation
7.9%	0.0999%	0.000471	logarithmic interpolation
8.0%	0.0999%	0.000484	estimate from Buckman et al. (2015) using the NCI method
8.1%	0.0999%	0.000496	logarithmic interpolation
8.2%	0.0999%	0.000508	logarithmic interpolation
8.3%	0.0999%	0.000521	logarithmic interpolation
8.4%	0.0999%	0.000533	logarithmic interpolation
8.5%	0.0999%	0.000546	logarithmic interpolation
8.6%	0.0999%	0.000560	logarithmic interpolation
8.7%	0.0999%	0.000574	logarithmic interpolation
8.8%	0.0999%	0.000588	logarithmic interpolation
8.9%	0.0999%	0.000602	logarithmic interpolation
9.0%	0.0999%	0.000617	estimate from Buckman et al. (2015) using the NCI method
9.1%	0.0999%	0.000630	logarithmic interpolation
9.2%	0.0999%	0.000644	logarithmic interpolation
9.3%	0.0999%	0.000658	logarithmic interpolation
9.4%	0.0999%	0.000673	logarithmic interpolation
9.5%	0.0999%	0.000687	logarithmic interpolation
9.6%	0.0999%	0.000703	logarithmic interpolation
9.7%	0.0999%	0.000718	logarithmic interpolation
9.8%	0.0999%	0.000734	logarithmic interpolation
9.9%	0.0999%	0.000750	logarithmic interpolation
10.0%	0.0999%	0.000766	estimate from Buckman et al. (2015) using the NCI method
10.1%	0.0999%	0.000783	logarithmic interpolation
10.2%	0.0999%	0.000800	logarithmic interpolation
10.3%	0.0999%	0.000817	logarithmic interpolation
10.4%	0.0999%	0.000835	logarithmic interpolation
10.5%	0.0999%	0.000854	logarithmic interpolation
10.6%	0.0999%	0.000872	logarithmic interpolation
10.7%	0.0999%	0.000891	logarithmic interpolation
10.8%	0.0999%	0.000911	logarithmic interpolation
10.9%	0.0999%	0.000931	logarithmic interpolation
11.0%	0.0999%	0.000951	estimate from Buckman et al. (2015) using the NCI method
11.1%	0.0999%	0.000970	logarithmic interpolation
11.2%	0.0999%	0.000990	logarithmic interpolation
11.3%	0.0999%	0.00101	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
11.4%	0.0999%	0.00103	logarithmic interpolation
11.5%	0.0999%	0.00105	logarithmic interpolation
11.6%	0.0999%	0.00107	logarithmic interpolation
11.7%	0.0999%	0.00109	logarithmic interpolation
11.8%	0.0999%	0.00112	logarithmic interpolation
11.9%	0.0999%	0.00114	logarithmic interpolation
12.0%	0.0999%	0.00116	estimate from Buckman et al. (2015) using the NCI method
12.1%	0.0999%	0.00118	logarithmic interpolation
12.2%	0.0999%	0.00121	logarithmic interpolation
12.3%	0.0999%	0.00123	logarithmic interpolation
12.4%	0.0999%	0.00125	logarithmic interpolation
12.5%	0.0999%	0.00128	logarithmic interpolation
12.6%	0.0999%	0.00130	logarithmic interpolation
12.7%	0.0999%	0.00132	logarithmic interpolation
12.8%	0.0999%	0.00135	logarithmic interpolation
12.9%	0.0999%	0.00137	logarithmic interpolation
13.0%	0.0999%	0.00140	estimate from Buckman et al. (2015) using the NCI method
13.1%	0.0999%	0.00143	logarithmic interpolation
13.2%	0.0999%	0.00145	logarithmic interpolation
13.3%	0.0999%	0.00148	logarithmic interpolation
13.4%	0.0999%	0.00150	logarithmic interpolation
13.5%	0.0999%	0.00153	logarithmic interpolation
13.6%	0.0999%	0.00156	logarithmic interpolation
13.7%	0.0999%	0.00159	logarithmic interpolation
13.8%	0.0999%	0.00162	logarithmic interpolation
13.9%	0.0999%	0.00164	logarithmic interpolation
14.0%	0.0999%	0.00167	estimate from Buckman et al. (2015) using the NCI method
14.1%	0.0999%	0.00170	logarithmic interpolation
14.2%	0.0999%	0.00173	logarithmic interpolation
14.3%	0.0999%	0.00176	logarithmic interpolation
14.4%	0.0999%	0.00179	logarithmic interpolation
14.5%	0.0999%	0.00182	logarithmic interpolation
14.6%	0.0999%	0.00185	logarithmic interpolation
14.7%	0.0999%	0.00189	logarithmic interpolation
14.8%	0.0999%	0.00192	logarithmic interpolation
14.9%	0.0999%	0.00195	logarithmic interpolation
15.0%	0.0999%	0.00199	estimate from Buckman et al. (2015) using the NCI method
15.1%	0.0999%	0.00202	logarithmic interpolation
15.2%	0.0999%	0.00205	logarithmic interpolation
15.3%	0.0999%	0.00209	logarithmic interpolation
15.4%	0.0999%	0.00212	logarithmic interpolation
15.5%	0.0999%	0.00216	logarithmic interpolation
15.6%	0.0999%	0.00219	logarithmic interpolation
15.7%	0.0999%	0.00223	logarithmic interpolation
15.8%	0.0999%	0.00226	logarithmic interpolation
15.9%	0.0999%	0.00230	logarithmic interpolation
16.0%	0.0999%	0.00234	estimate from Buckman et al. (2015) using the NCI method
16.1%	0.0999%	0.00238	logarithmic interpolation
16.2%	0.0999%	0.00241	logarithmic interpolation
16.3%	0.0999%	0.00245	logarithmic interpolation
16.4%	0.0999%	0.00249	logarithmic interpolation
16.5%	0.0999%	0.00253	logarithmic interpolation
16.6%	0.0999%	0.00257	logarithmic interpolation
16.7%	0.0999%	0.00261	logarithmic interpolation
16.8%	0.0999%	0.00265	logarithmic interpolation
16.9%	0.0999%	0.00269	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
17.0%	0.0999%	0.00273	estimate from Buckman et al. (2015) using the NCI method
17.1%	0.0999%	0.00277	logarithmic interpolation
17.2%	0.0999%	0.00282	logarithmic interpolation
17.3%	0.0999%	0.00286	logarithmic interpolation
17.4%	0.0999%	0.00290	logarithmic interpolation
17.5%	0.0999%	0.00294	logarithmic interpolation
17.6%	0.0999%	0.00299	logarithmic interpolation
17.7%	0.0999%	0.00303	logarithmic interpolation
17.8%	0.0999%	0.00308	logarithmic interpolation
17.9%	0.0999%	0.00312	logarithmic interpolation
18.0%	0.0999%	0.00317	estimate from Buckman et al. (2015) using the NCI method
18.1%	0.0999%	0.00321	logarithmic interpolation
18.2%	0.0999%	0.00326	logarithmic interpolation
18.3%	0.0999%	0.00331	logarithmic interpolation
18.4%	0.0999%	0.00335	logarithmic interpolation
18.5%	0.0999%	0.00340	logarithmic interpolation
18.6%	0.0999%	0.00345	logarithmic interpolation
18.7%	0.0999%	0.00350	logarithmic interpolation
18.8%	0.0999%	0.00355	logarithmic interpolation
18.9%	0.0999%	0.00360	logarithmic interpolation
19.0%	0.0999%	0.00366	estimate from Buckman et al. (2015) using the NCI method
19.1%	0.0999%	0.00371	logarithmic interpolation
19.2%	0.0999%	0.00376	logarithmic interpolation
19.3%	0.0999%	0.00381	logarithmic interpolation
19.4%	0.0999%	0.00387	logarithmic interpolation
19.5%	0.0999%	0.00392	logarithmic interpolation
19.6%	0.0999%	0.00398	logarithmic interpolation
19.7%	0.0999%	0.00403	logarithmic interpolation
19.8%	0.0999%	0.00409	logarithmic interpolation
19.9%	0.0999%	0.00415	logarithmic interpolation
20.0%	0.0999%	0.00420	estimate from Buckman et al. (2015) using the NCI method
20.1%	0.0999%	0.00426	logarithmic interpolation
20.2%	0.0999%	0.00432	logarithmic interpolation
20.3%	0.0999%	0.00437	logarithmic interpolation
20.4%	0.0999%	0.00443	logarithmic interpolation
20.5%	0.0999%	0.00449	logarithmic interpolation
20.6%	0.0999%	0.00455	logarithmic interpolation
20.7%	0.0999%	0.00461	logarithmic interpolation
20.8%	0.0999%	0.00468	logarithmic interpolation
20.9%	0.0999%	0.00474	logarithmic interpolation
21.0%	0.0999%	0.00480	estimate from Buckman et al. (2015) using the NCI method
21.1%	0.0999%	0.00486	logarithmic interpolation
21.2%	0.0999%	0.00493	logarithmic interpolation
21.3%	0.0999%	0.00499	logarithmic interpolation
21.4%	0.0999%	0.00505	logarithmic interpolation
21.5%	0.0999%	0.00512	logarithmic interpolation
21.6%	0.0999%	0.00518	logarithmic interpolation
21.7%	0.0999%	0.00525	logarithmic interpolation
21.8%	0.0999%	0.00532	logarithmic interpolation
21.9%	0.0999%	0.00538	logarithmic interpolation
22.0%	0.0999%	0.00545	estimate from Buckman et al. (2015) using the NCI method
22.1%	0.0999%	0.00552	logarithmic interpolation
22.2%	0.0999%	0.00559	logarithmic interpolation
22.3%	0.0999%	0.00566	logarithmic interpolation
22.4%	0.0999%	0.00573	logarithmic interpolation
22.5%	0.0999%	0.00580	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
22.6%	0.0999%	0.00588	logarithmic interpolation
22.7%	0.0999%	0.00595	logarithmic interpolation
22.8%	0.0999%	0.00603	logarithmic interpolation
22.9%	0.0999%	0.00610	logarithmic interpolation
23.0%	0.0999%	0.00618	estimate from Buckman et al. (2015) using the NCI method
23.1%	0.0999%	0.00625	logarithmic interpolation
23.2%	0.0999%	0.00633	logarithmic interpolation
23.3%	0.0999%	0.00641	logarithmic interpolation
23.4%	0.0999%	0.00649	logarithmic interpolation
23.5%	0.0999%	0.00658	logarithmic interpolation
23.6%	0.0999%	0.00666	logarithmic interpolation
23.7%	0.0999%	0.00674	logarithmic interpolation
23.8%	0.0999%	0.00683	logarithmic interpolation
23.9%	0.0999%	0.00691	logarithmic interpolation
24.0%	0.0999%	0.00700	estimate from Buckman et al. (2015) using the NCI method
24.1%	0.0999%	0.00709	logarithmic interpolation
24.2%	0.0999%	0.00717	logarithmic interpolation
24.3%	0.0999%	0.00726	logarithmic interpolation
24.4%	0.0999%	0.00735	logarithmic interpolation
24.5%	0.0999%	0.00744	logarithmic interpolation
24.6%	0.0999%	0.00753	logarithmic interpolation
24.7%	0.0999%	0.00763	logarithmic interpolation
24.8%	0.0999%	0.00772	logarithmic interpolation
24.9%	0.0999%	0.00781	logarithmic interpolation
25.0%	0.0999%	0.00791	estimate from Buckman et al. (2015) using the NCI method
25.1%	0.0999%	0.00800	logarithmic interpolation
25.2%	0.0999%	0.00810	logarithmic interpolation
25.3%	0.0999%	0.00820	logarithmic interpolation
25.4%	0.0999%	0.00830	logarithmic interpolation
25.5%	0.0999%	0.00840	logarithmic interpolation
25.6%	0.0999%	0.00850	logarithmic interpolation
25.7%	0.0999%	0.00860	logarithmic interpolation
25.8%	0.0999%	0.00870	logarithmic interpolation
25.9%	0.0999%	0.00880	logarithmic interpolation
26.0%	0.0999%	0.00891	estimate from Buckman et al. (2015) using the NCI method
26.1%	0.0999%	0.00901	logarithmic interpolation
26.2%	0.0999%	0.00912	logarithmic interpolation
26.3%	0.0999%	0.00922	logarithmic interpolation
26.4%	0.0999%	0.00933	logarithmic interpolation
26.5%	0.0999%	0.00944	logarithmic interpolation
26.6%	0.0999%	0.00955	logarithmic interpolation
26.7%	0.0999%	0.00966	logarithmic interpolation
26.8%	0.0999%	0.00977	logarithmic interpolation
26.9%	0.0999%	0.00989	logarithmic interpolation
27.0%	0.0999%	0.0100	estimate from Buckman et al. (2015) using the NCI method
27.1%	0.0999%	0.0101	logarithmic interpolation
27.2%	0.0999%	0.0102	logarithmic interpolation
27.3%	0.0999%	0.0104	logarithmic interpolation
27.4%	0.0999%	0.0105	logarithmic interpolation
27.5%	0.0999%	0.0106	logarithmic interpolation
27.6%	0.0999%	0.0107	logarithmic interpolation
27.7%	0.0999%	0.0108	logarithmic interpolation
27.8%	0.0999%	0.0110	logarithmic interpolation
27.9%	0.0999%	0.0111	logarithmic interpolation
28.0%	0.0999%	0.0112	estimate from Buckman et al. (2015) using the NCI method
28.1%	0.0999%	0.0114	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
28.2%	0.0999%	0.0115	logarithmic interpolation
28.3%	0.0999%	0.0116	logarithmic interpolation
28.4%	0.0999%	0.0117	logarithmic interpolation
28.5%	0.0999%	0.0119	logarithmic interpolation
28.6%	0.0999%	0.0120	logarithmic interpolation
28.7%	0.0999%	0.0121	logarithmic interpolation
28.8%	0.0999%	0.0123	logarithmic interpolation
28.9%	0.0999%	0.0124	logarithmic interpolation
29.0%	0.0999%	0.0125	estimate from Buckman et al. (2015) using the NCI method
29.1%	0.0999%	0.0127	logarithmic interpolation
29.2%	0.0999%	0.0128	logarithmic interpolation
29.3%	0.0999%	0.0130	logarithmic interpolation
29.4%	0.0999%	0.0131	logarithmic interpolation
29.5%	0.0999%	0.0132	logarithmic interpolation
29.6%	0.0999%	0.0134	logarithmic interpolation
29.7%	0.0999%	0.0135	logarithmic interpolation
29.8%	0.0999%	0.0137	logarithmic interpolation
29.9%	0.0999%	0.0138	logarithmic interpolation
30.0%	0.0999%	0.0140	estimate from Buckman et al. (2015) using the NCI method
30.1%	0.0999%	0.0141	logarithmic interpolation
30.2%	0.0999%	0.0143	logarithmic interpolation
30.3%	0.0999%	0.0145	logarithmic interpolation
30.4%	0.0999%	0.0146	logarithmic interpolation
30.5%	0.0999%	0.0148	logarithmic interpolation
30.6%	0.0999%	0.0149	logarithmic interpolation
30.7%	0.0999%	0.0151	logarithmic interpolation
30.8%	0.0999%	0.0152	logarithmic interpolation
30.9%	0.0999%	0.0154	logarithmic interpolation
31.0%	0.0999%	0.0156	estimate from Buckman et al. (2015) using the NCI method
31.1%	0.0999%	0.0157	logarithmic interpolation
31.2%	0.0999%	0.0159	logarithmic interpolation
31.3%	0.0999%	0.0161	logarithmic interpolation
31.4%	0.0999%	0.0162	logarithmic interpolation
31.5%	0.0999%	0.0164	logarithmic interpolation
31.6%	0.0999%	0.0166	logarithmic interpolation
31.7%	0.0999%	0.0168	logarithmic interpolation
31.8%	0.0999%	0.0169	logarithmic interpolation
31.9%	0.0999%	0.0171	logarithmic interpolation
32.0%	0.0999%	0.0173	estimate from Buckman et al. (2015) using the NCI method
32.1%	0.0999%	0.0175	logarithmic interpolation
32.2%	0.0999%	0.0176	logarithmic interpolation
32.3%	0.0999%	0.0178	logarithmic interpolation
32.4%	0.0999%	0.0180	logarithmic interpolation
32.5%	0.0999%	0.0182	logarithmic interpolation
32.6%	0.0999%	0.0183	logarithmic interpolation
32.7%	0.0999%	0.0185	logarithmic interpolation
32.8%	0.0999%	0.0187	logarithmic interpolation
32.9%	0.0999%	0.0189	logarithmic interpolation
33.0%	0.0999%	0.0191	estimate from Buckman et al. (2015) using the NCI method
33.1%	0.0999%	0.0193	logarithmic interpolation
33.2%	0.0999%	0.0195	logarithmic interpolation
33.3%	0.0999%	0.0197	logarithmic interpolation
33.4%	0.0999%	0.0199	logarithmic interpolation
33.5%	0.0999%	0.0201	logarithmic interpolation
33.6%	0.0999%	0.0203	logarithmic interpolation
33.7%	0.0999%	0.0205	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
33.8%	0.0999%	0.0207	logarithmic interpolation
33.9%	0.0999%	0.0210	logarithmic interpolation
34.0%	0.0999%	0.0212	estimate from Buckman et al. (2015) using the NCI method
34.1%	0.0999%	0.0214	logarithmic interpolation
34.2%	0.0999%	0.0216	logarithmic interpolation
34.3%	0.0999%	0.0218	logarithmic interpolation
34.4%	0.0999%	0.0220	logarithmic interpolation
34.5%	0.0999%	0.0223	logarithmic interpolation
34.6%	0.0999%	0.0225	logarithmic interpolation
34.7%	0.0999%	0.0227	logarithmic interpolation
34.8%	0.0999%	0.0230	logarithmic interpolation
34.9%	0.0999%	0.0232	logarithmic interpolation
35.0%	0.0999%	0.0234	estimate from Buckman et al. (2015) using the NCI method
35.1%	0.0999%	0.0236	logarithmic interpolation
35.2%	0.0999%	0.0239	logarithmic interpolation
35.3%	0.0999%	0.0241	logarithmic interpolation
35.4%	0.0999%	0.0243	logarithmic interpolation
35.5%	0.0999%	0.0246	logarithmic interpolation
35.6%	0.0999%	0.0248	logarithmic interpolation
35.7%	0.0999%	0.0250	logarithmic interpolation
35.8%	0.0999%	0.0253	logarithmic interpolation
35.9%	0.0999%	0.0255	logarithmic interpolation
36.0%	0.0999%	0.0258	estimate from Buckman et al. (2015) using the NCI method
36.1%	0.0999%	0.0260	logarithmic interpolation
36.2%	0.0999%	0.0263	logarithmic interpolation
36.3%	0.0999%	0.0266	logarithmic interpolation
36.4%	0.0999%	0.0268	logarithmic interpolation
36.5%	0.0999%	0.0271	logarithmic interpolation
36.6%	0.0999%	0.0274	logarithmic interpolation
36.7%	0.0999%	0.0276	logarithmic interpolation
36.8%	0.0999%	0.0279	logarithmic interpolation
36.9%	0.0999%	0.0282	logarithmic interpolation
37.0%	0.0999%	0.0285	estimate from Buckman et al. (2015) using the NCI method
37.1%	0.0999%	0.0288	logarithmic interpolation
37.2%	0.0999%	0.0290	logarithmic interpolation
37.3%	0.0999%	0.0293	logarithmic interpolation
37.4%	0.0999%	0.0296	logarithmic interpolation
37.5%	0.0999%	0.0299	logarithmic interpolation
37.6%	0.0999%	0.0302	logarithmic interpolation
37.7%	0.0999%	0.0304	logarithmic interpolation
37.8%	0.0999%	0.0307	logarithmic interpolation
37.9%	0.0999%	0.0310	logarithmic interpolation
38.0%	0.0999%	0.0313	estimate from Buckman et al. (2015) using the NCI method
38.1%	0.0999%	0.0316	logarithmic interpolation
38.2%	0.0999%	0.0319	logarithmic interpolation
38.3%	0.0999%	0.0322	logarithmic interpolation
38.4%	0.0999%	0.0325	logarithmic interpolation
38.5%	0.0999%	0.0329	logarithmic interpolation
38.6%	0.0999%	0.0332	logarithmic interpolation
38.7%	0.0999%	0.0335	logarithmic interpolation
38.8%	0.0999%	0.0338	logarithmic interpolation
38.9%	0.0999%	0.0341	logarithmic interpolation
39.0%	0.0999%	0.0345	estimate from Buckman et al. (2015) using the NCI method
39.1%	0.0999%	0.0348	logarithmic interpolation
39.2%	0.0999%	0.0351	logarithmic interpolation
39.3%	0.0999%	0.0355	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
39.4%	0.0999%	0.0358	logarithmic interpolation
39.5%	0.0999%	0.0361	logarithmic interpolation
39.6%	0.0999%	0.0365	logarithmic interpolation
39.7%	0.0999%	0.0368	logarithmic interpolation
39.8%	0.0999%	0.0372	logarithmic interpolation
39.9%	0.0999%	0.0375	logarithmic interpolation
40.0%	0.0999%	0.0379	estimate from Buckman et al. (2015) using the NCI method
40.1%	0.0999%	0.0382	logarithmic interpolation
40.2%	0.0999%	0.0386	logarithmic interpolation
40.3%	0.0999%	0.0389	logarithmic interpolation
40.4%	0.0999%	0.0393	logarithmic interpolation
40.5%	0.0999%	0.0396	logarithmic interpolation
40.6%	0.0999%	0.0400	logarithmic interpolation
40.7%	0.0999%	0.0404	logarithmic interpolation
40.8%	0.0999%	0.0407	logarithmic interpolation
40.9%	0.0999%	0.0411	logarithmic interpolation
41.0%	0.0999%	0.0415	estimate from Buckman et al. (2015) using the NCI method
41.1%	0.0999%	0.0419	logarithmic interpolation
41.2%	0.0999%	0.0423	logarithmic interpolation
41.3%	0.0999%	0.0427	logarithmic interpolation
41.4%	0.0999%	0.0431	logarithmic interpolation
41.5%	0.0999%	0.0435	logarithmic interpolation
41.6%	0.0999%	0.0439	logarithmic interpolation
41.7%	0.0999%	0.0443	logarithmic interpolation
41.8%	0.0999%	0.0447	logarithmic interpolation
41.9%	0.0999%	0.0451	logarithmic interpolation
42.0%	0.0999%	0.0455	estimate from Buckman et al. (2015) using the NCI method
42.1%	0.0999%	0.0460	logarithmic interpolation
42.2%	0.0999%	0.0464	logarithmic interpolation
42.3%	0.0999%	0.0468	logarithmic interpolation
42.4%	0.0999%	0.0473	logarithmic interpolation
42.5%	0.0999%	0.0477	logarithmic interpolation
42.6%	0.0999%	0.0481	logarithmic interpolation
42.7%	0.0999%	0.0486	logarithmic interpolation
42.8%	0.0999%	0.0490	logarithmic interpolation
42.9%	0.0999%	0.0495	logarithmic interpolation
43.0%	0.0999%	0.0500	estimate from Buckman et al. (2015) using the NCI method
43.1%	0.0999%	0.0504	logarithmic interpolation
43.2%	0.0999%	0.0509	logarithmic interpolation
43.3%	0.0999%	0.0513	logarithmic interpolation
43.4%	0.0999%	0.0518	logarithmic interpolation
43.5%	0.0999%	0.0522	logarithmic interpolation
43.6%	0.0999%	0.0527	logarithmic interpolation
43.7%	0.0999%	0.0532	logarithmic interpolation
43.8%	0.0999%	0.0536	logarithmic interpolation
43.9%	0.0999%	0.0541	logarithmic interpolation
44.0%	0.0999%	0.0546	estimate from Buckman et al. (2015) using the NCI method
44.1%	0.0999%	0.0551	logarithmic interpolation
44.2%	0.0999%	0.0556	logarithmic interpolation
44.3%	0.0999%	0.0561	logarithmic interpolation
44.4%	0.0999%	0.0566	logarithmic interpolation
44.5%	0.0999%	0.0571	logarithmic interpolation
44.6%	0.0999%	0.0576	logarithmic interpolation
44.7%	0.0999%	0.0582	logarithmic interpolation
44.8%	0.0999%	0.0587	logarithmic interpolation
44.9%	0.0999%	0.0592	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
45.0%	0.0999%	0.0597	estimate from Buckman et al. (2015) using the NCI method
45.1%	0.0999%	0.0603	logarithmic interpolation
45.2%	0.0999%	0.0608	logarithmic interpolation
45.3%	0.0999%	0.0614	logarithmic interpolation
45.4%	0.0999%	0.0619	logarithmic interpolation
45.5%	0.0999%	0.0625	logarithmic interpolation
45.6%	0.0999%	0.0630	logarithmic interpolation
45.7%	0.0999%	0.0636	logarithmic interpolation
45.8%	0.0999%	0.0641	logarithmic interpolation
45.9%	0.0999%	0.0647	logarithmic interpolation
46.0%	0.0999%	0.0653	estimate from Buckman et al. (2015) using the NCI method
46.1%	0.0999%	0.0659	logarithmic interpolation
46.2%	0.0999%	0.0665	logarithmic interpolation
46.3%	0.0999%	0.0671	logarithmic interpolation
46.4%	0.0999%	0.0677	logarithmic interpolation
46.5%	0.0999%	0.0683	logarithmic interpolation
46.6%	0.0999%	0.0689	logarithmic interpolation
46.7%	0.0999%	0.0695	logarithmic interpolation
46.8%	0.0999%	0.0701	logarithmic interpolation
46.9%	0.0999%	0.0707	logarithmic interpolation
47.0%	0.0999%	0.0714	estimate from Buckman et al. (2015) using the NCI method
47.1%	0.0999%	0.0720	logarithmic interpolation
47.2%	0.0999%	0.0727	logarithmic interpolation
47.3%	0.0999%	0.0733	logarithmic interpolation
47.4%	0.0999%	0.0740	logarithmic interpolation
47.5%	0.0999%	0.0746	logarithmic interpolation
47.6%	0.0999%	0.0753	logarithmic interpolation
47.7%	0.0999%	0.0760	logarithmic interpolation
47.8%	0.0999%	0.0767	logarithmic interpolation
47.9%	0.0999%	0.0773	logarithmic interpolation
48.0%	0.0999%	0.0780	estimate from Buckman et al. (2015) using the NCI method
48.1%	0.0999%	0.0787	logarithmic interpolation
48.2%	0.0999%	0.0794	logarithmic interpolation
48.3%	0.0999%	0.0801	logarithmic interpolation
48.4%	0.0999%	0.0808	logarithmic interpolation
48.5%	0.0999%	0.0815	logarithmic interpolation
48.6%	0.0999%	0.0823	logarithmic interpolation
48.7%	0.0999%	0.0830	logarithmic interpolation
48.8%	0.0999%	0.0837	logarithmic interpolation
48.9%	0.0999%	0.0845	logarithmic interpolation
49.0%	0.0999%	0.0852	estimate from Buckman et al. (2015) using the NCI method
49.1%	0.0999%	0.0859	logarithmic interpolation
49.2%	0.0999%	0.0867	logarithmic interpolation
49.3%	0.0999%	0.0874	logarithmic interpolation
49.4%	0.0999%	0.0882	logarithmic interpolation
49.5%	0.0999%	0.0889	logarithmic interpolation
49.6%	0.0999%	0.0897	logarithmic interpolation
49.7%	0.0999%	0.0905	logarithmic interpolation
49.8%	0.0999%	0.0913	logarithmic interpolation
49.9%	0.0999%	0.0920	logarithmic interpolation
50.0%	0.0999%	0.0928	estimate from Buckman et al. (2015) using the NCI method
50.1%	0.0999%	0.0937	logarithmic interpolation
50.2%	0.0999%	0.0945	logarithmic interpolation
50.3%	0.0999%	0.0953	logarithmic interpolation
50.4%	0.0999%	0.0962	logarithmic interpolation
50.5%	0.0999%	0.0970	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
50.6%	0.0999%	0.0979	logarithmic interpolation
50.7%	0.0999%	0.0987	logarithmic interpolation
50.8%	0.0999%	0.0996	logarithmic interpolation
50.9%	0.0999%	0.100	logarithmic interpolation
51.0%	0.0999%	0.101	estimate from Buckman et al. (2015) using the NCI method
51.1%	0.0999%	0.102	logarithmic interpolation
51.2%	0.0999%	0.103	logarithmic interpolation
51.3%	0.0999%	0.104	logarithmic interpolation
51.4%	0.0999%	0.105	logarithmic interpolation
51.5%	0.0999%	0.106	logarithmic interpolation
51.6%	0.0999%	0.107	logarithmic interpolation
51.7%	0.0999%	0.108	logarithmic interpolation
51.8%	0.0999%	0.109	logarithmic interpolation
51.9%	0.0999%	0.110	logarithmic interpolation
52.0%	0.0999%	0.111	estimate from Buckman et al. (2015) using the NCI method
52.1%	0.0999%	0.112	logarithmic interpolation
52.2%	0.0999%	0.113	logarithmic interpolation
52.3%	0.0999%	0.114	logarithmic interpolation
52.4%	0.0999%	0.115	logarithmic interpolation
52.5%	0.0999%	0.116	logarithmic interpolation
52.6%	0.0999%	0.117	logarithmic interpolation
52.7%	0.0999%	0.118	logarithmic interpolation
52.8%	0.0999%	0.119	logarithmic interpolation
52.9%	0.0999%	0.120	logarithmic interpolation
53.0%	0.0999%	0.121	estimate from Buckman et al. (2015) using the NCI method
53.1%	0.0999%	0.122	logarithmic interpolation
53.2%	0.0999%	0.123	logarithmic interpolation
53.3%	0.0999%	0.124	logarithmic interpolation
53.4%	0.0999%	0.125	logarithmic interpolation
53.5%	0.0999%	0.126	logarithmic interpolation
53.6%	0.0999%	0.127	logarithmic interpolation
53.7%	0.0999%	0.128	logarithmic interpolation
53.8%	0.0999%	0.129	logarithmic interpolation
53.9%	0.0999%	0.130	logarithmic interpolation
54.0%	0.0999%	0.131	estimate from Buckman et al. (2015) using the NCI method
54.1%	0.0999%	0.132	logarithmic interpolation
54.2%	0.0999%	0.133	logarithmic interpolation
54.3%	0.0999%	0.134	logarithmic interpolation
54.4%	0.0999%	0.136	logarithmic interpolation
54.5%	0.0999%	0.137	logarithmic interpolation
54.6%	0.0999%	0.138	logarithmic interpolation
54.7%	0.0999%	0.139	logarithmic interpolation
54.8%	0.0999%	0.140	logarithmic interpolation
54.9%	0.0999%	0.142	logarithmic interpolation
55.0%	0.0999%	0.143	estimate from Buckman et al. (2015) using the NCI method
55.1%	0.0999%	0.144	logarithmic interpolation
55.2%	0.0999%	0.145	logarithmic interpolation
55.3%	0.0999%	0.147	logarithmic interpolation
55.4%	0.0999%	0.148	logarithmic interpolation
55.5%	0.0999%	0.149	logarithmic interpolation
55.6%	0.0999%	0.151	logarithmic interpolation
55.7%	0.0999%	0.152	logarithmic interpolation
55.8%	0.0999%	0.153	logarithmic interpolation
55.9%	0.0999%	0.155	logarithmic interpolation
56.0%	0.0999%	0.156	estimate from Buckman et al. (2015) using the NCI method
56.1%	0.0999%	0.157	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
56.2%	0.0999%	0.159	logarithmic interpolation
56.3%	0.0999%	0.160	logarithmic interpolation
56.4%	0.0999%	0.161	logarithmic interpolation
56.5%	0.0999%	0.163	logarithmic interpolation
56.6%	0.0999%	0.164	logarithmic interpolation
56.7%	0.0999%	0.165	logarithmic interpolation
56.8%	0.0999%	0.167	logarithmic interpolation
56.9%	0.0999%	0.168	logarithmic interpolation
57.0%	0.0999%	0.170	estimate from Buckman et al. (2015) using the NCI method
57.1%	0.0999%	0.171	logarithmic interpolation
57.2%	0.0999%	0.173	logarithmic interpolation
57.3%	0.0999%	0.174	logarithmic interpolation
57.4%	0.0999%	0.176	logarithmic interpolation
57.5%	0.0999%	0.177	logarithmic interpolation
57.6%	0.0999%	0.179	logarithmic interpolation
57.7%	0.0999%	0.180	logarithmic interpolation
57.8%	0.0999%	0.182	logarithmic interpolation
57.9%	0.0999%	0.183	logarithmic interpolation
58.0%	0.0999%	0.185	estimate from Buckman et al. (2015) using the NCI method
58.1%	0.0999%	0.186	logarithmic interpolation
58.2%	0.0999%	0.188	logarithmic interpolation
58.3%	0.0999%	0.190	logarithmic interpolation
58.4%	0.0999%	0.191	logarithmic interpolation
58.5%	0.0999%	0.193	logarithmic interpolation
58.6%	0.0999%	0.195	logarithmic interpolation
58.7%	0.0999%	0.197	logarithmic interpolation
58.8%	0.0999%	0.198	logarithmic interpolation
58.9%	0.0999%	0.200	logarithmic interpolation
59.0%	0.0999%	0.202	estimate from Buckman et al. (2015) using the NCI method
59.1%	0.0999%	0.204	logarithmic interpolation
59.2%	0.0999%	0.205	logarithmic interpolation
59.3%	0.0999%	0.207	logarithmic interpolation
59.4%	0.0999%	0.209	logarithmic interpolation
59.5%	0.0999%	0.211	logarithmic interpolation
59.6%	0.0999%	0.212	logarithmic interpolation
59.7%	0.0999%	0.214	logarithmic interpolation
59.8%	0.0999%	0.216	logarithmic interpolation
59.9%	0.0999%	0.218	logarithmic interpolation
60.0%	0.0999%	0.220	estimate from Buckman et al. (2015) using the NCI method
60.1%	0.0999%	0.222	logarithmic interpolation
60.2%	0.0999%	0.224	logarithmic interpolation
60.3%	0.0999%	0.225	logarithmic interpolation
60.4%	0.0999%	0.227	logarithmic interpolation
60.5%	0.0999%	0.229	logarithmic interpolation
60.6%	0.0999%	0.231	logarithmic interpolation
60.7%	0.0999%	0.233	logarithmic interpolation
60.8%	0.0999%	0.235	logarithmic interpolation
60.9%	0.0999%	0.237	logarithmic interpolation
61.0%	0.0999%	0.239	estimate from Buckman et al. (2015) using the NCI method
61.1%	0.0999%	0.241	logarithmic interpolation
61.2%	0.0999%	0.243	logarithmic interpolation
61.3%	0.0999%	0.245	logarithmic interpolation
61.4%	0.0999%	0.247	logarithmic interpolation
61.5%	0.0999%	0.250	logarithmic interpolation
61.6%	0.0999%	0.252	logarithmic interpolation
61.7%	0.0999%	0.254	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
61.8%	0.0999%	0.256	logarithmic interpolation
61.9%	0.0999%	0.258	logarithmic interpolation
62.0%	0.0999%	0.261	estimate from Buckman et al. (2015) using the NCI method
62.1%	0.0999%	0.263	logarithmic interpolation
62.2%	0.0999%	0.265	logarithmic interpolation
62.3%	0.0999%	0.268	logarithmic interpolation
62.4%	0.0999%	0.270	logarithmic interpolation
62.5%	0.0999%	0.272	logarithmic interpolation
62.6%	0.0999%	0.275	logarithmic interpolation
62.7%	0.0999%	0.277	logarithmic interpolation
62.8%	0.0999%	0.280	logarithmic interpolation
62.9%	0.0999%	0.282	logarithmic interpolation
63.0%	0.0999%	0.285	estimate from Buckman et al. (2015) using the NCI method
63.1%	0.0999%	0.287	logarithmic interpolation
63.2%	0.0999%	0.290	logarithmic interpolation
63.3%	0.0999%	0.292	logarithmic interpolation
63.4%	0.0999%	0.295	logarithmic interpolation
63.5%	0.0999%	0.297	logarithmic interpolation
63.6%	0.0999%	0.300	logarithmic interpolation
63.7%	0.0999%	0.302	logarithmic interpolation
63.8%	0.0999%	0.305	logarithmic interpolation
63.9%	0.0999%	0.308	logarithmic interpolation
64.0%	0.0999%	0.310	estimate from Buckman et al. (2015) using the NCI method
64.1%	0.0999%	0.313	logarithmic interpolation
64.2%	0.0999%	0.316	logarithmic interpolation
64.3%	0.0999%	0.319	logarithmic interpolation
64.4%	0.0999%	0.322	logarithmic interpolation
64.5%	0.0999%	0.324	logarithmic interpolation
64.6%	0.0999%	0.327	logarithmic interpolation
64.7%	0.0999%	0.330	logarithmic interpolation
64.8%	0.0999%	0.333	logarithmic interpolation
64.9%	0.0999%	0.336	logarithmic interpolation
65.0%	0.0999%	0.339	estimate from Buckman et al. (2015) using the NCI method
65.1%	0.0999%	0.342	logarithmic interpolation
65.2%	0.0999%	0.345	logarithmic interpolation
65.3%	0.0999%	0.348	logarithmic interpolation
65.4%	0.0999%	0.351	logarithmic interpolation
65.5%	0.0999%	0.354	logarithmic interpolation
65.6%	0.0999%	0.357	logarithmic interpolation
65.7%	0.0999%	0.360	logarithmic interpolation
65.8%	0.0999%	0.364	logarithmic interpolation
65.9%	0.0999%	0.367	logarithmic interpolation
66.0%	0.0999%	0.370	estimate from Buckman et al. (2015) using the NCI method
66.1%	0.0999%	0.373	logarithmic interpolation
66.2%	0.0999%	0.376	logarithmic interpolation
66.3%	0.0999%	0.380	logarithmic interpolation
66.4%	0.0999%	0.383	logarithmic interpolation
66.5%	0.0999%	0.386	logarithmic interpolation
66.6%	0.0999%	0.390	logarithmic interpolation
66.7%	0.0999%	0.393	logarithmic interpolation
66.8%	0.0999%	0.396	logarithmic interpolation
66.9%	0.0999%	0.400	logarithmic interpolation
67.0%	0.0999%	0.403	estimate from Buckman et al. (2015) using the NCI method
67.1%	0.0999%	0.407	logarithmic interpolation
67.2%	0.0999%	0.411	logarithmic interpolation
67.3%	0.0999%	0.415	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
67.4%	0.0999%	0.418	logarithmic interpolation
67.5%	0.0999%	0.422	logarithmic interpolation
67.6%	0.0999%	0.426	logarithmic interpolation
67.7%	0.0999%	0.430	logarithmic interpolation
67.8%	0.0999%	0.434	logarithmic interpolation
67.9%	0.0999%	0.438	logarithmic interpolation
68.0%	0.0999%	0.442	estimate from Buckman et al. (2015) using the NCI method
68.1%	0.0999%	0.446	logarithmic interpolation
68.2%	0.0999%	0.450	logarithmic interpolation
68.3%	0.0999%	0.454	logarithmic interpolation
68.4%	0.0999%	0.458	logarithmic interpolation
68.5%	0.0999%	0.462	logarithmic interpolation
68.6%	0.0999%	0.466	logarithmic interpolation
68.7%	0.0999%	0.471	logarithmic interpolation
68.8%	0.0999%	0.475	logarithmic interpolation
68.9%	0.0999%	0.479	logarithmic interpolation
69.0%	0.0999%	0.483	estimate from Buckman et al. (2015) using the NCI method
69.1%	0.0999%	0.488	logarithmic interpolation
69.2%	0.0999%	0.492	logarithmic interpolation
69.3%	0.0999%	0.497	logarithmic interpolation
69.4%	0.0999%	0.501	logarithmic interpolation
69.5%	0.0999%	0.506	logarithmic interpolation
69.6%	0.0999%	0.510	logarithmic interpolation
69.7%	0.0999%	0.515	logarithmic interpolation
69.8%	0.0999%	0.520	logarithmic interpolation
69.9%	0.0999%	0.524	logarithmic interpolation
70.0%	0.0999%	0.529	estimate from Buckman et al. (2015) using the NCI method
70.1%	0.0999%	0.534	logarithmic interpolation
70.2%	0.0999%	0.539	logarithmic interpolation
70.3%	0.0999%	0.544	logarithmic interpolation
70.4%	0.0999%	0.549	logarithmic interpolation
70.5%	0.0999%	0.554	logarithmic interpolation
70.6%	0.0999%	0.559	logarithmic interpolation
70.7%	0.0999%	0.564	logarithmic interpolation
70.8%	0.0999%	0.569	logarithmic interpolation
70.9%	0.0999%	0.574	logarithmic interpolation
71.0%	0.0999%	0.580	estimate from Buckman et al. (2015) using the NCI method
71.1%	0.0999%	0.585	logarithmic interpolation
71.2%	0.0999%	0.590	logarithmic interpolation
71.3%	0.0999%	0.596	logarithmic interpolation
71.4%	0.0999%	0.601	logarithmic interpolation
71.5%	0.0999%	0.607	logarithmic interpolation
71.6%	0.0999%	0.613	logarithmic interpolation
71.7%	0.0999%	0.618	logarithmic interpolation
71.8%	0.0999%	0.624	logarithmic interpolation
71.9%	0.0999%	0.630	logarithmic interpolation
72.0%	0.0999%	0.635	estimate from Buckman et al. (2015) using the NCI method
72.1%	0.0999%	0.641	logarithmic interpolation
72.2%	0.0999%	0.647	logarithmic interpolation
72.3%	0.0999%	0.654	logarithmic interpolation
72.4%	0.0999%	0.660	logarithmic interpolation
72.5%	0.0999%	0.666	logarithmic interpolation
72.6%	0.0999%	0.672	logarithmic interpolation
72.7%	0.0999%	0.678	logarithmic interpolation
72.8%	0.0999%	0.685	logarithmic interpolation
72.9%	0.0999%	0.691	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
73.0%	0.0999%	0.698	estimate from Buckman et al. (2015) using the NCI method
73.1%	0.0999%	0.704	logarithmic interpolation
73.2%	0.0999%	0.711	logarithmic interpolation
73.3%	0.0999%	0.717	logarithmic interpolation
73.4%	0.0999%	0.724	logarithmic interpolation
73.5%	0.0999%	0.730	logarithmic interpolation
73.6%	0.0999%	0.737	logarithmic interpolation
73.7%	0.0999%	0.744	logarithmic interpolation
73.8%	0.0999%	0.751	logarithmic interpolation
73.9%	0.0999%	0.758	logarithmic interpolation
74.0%	0.0999%	0.765	estimate from Buckman et al. (2015) using the NCI method
74.1%	0.0999%	0.772	logarithmic interpolation
74.2%	0.0999%	0.779	logarithmic interpolation
74.3%	0.0999%	0.787	logarithmic interpolation
74.4%	0.0999%	0.794	logarithmic interpolation
74.5%	0.0999%	0.801	logarithmic interpolation
74.6%	0.0999%	0.809	logarithmic interpolation
74.7%	0.0999%	0.817	logarithmic interpolation
74.8%	0.0999%	0.824	logarithmic interpolation
74.9%	0.0999%	0.832	logarithmic interpolation
75.0%	0.0999%	0.840	estimate from Buckman et al. (2015) using the NCI method
75.1%	0.0999%	0.848	logarithmic interpolation
75.2%	0.0999%	0.856	logarithmic interpolation
75.3%	0.0999%	0.864	logarithmic interpolation
75.4%	0.0999%	0.872	logarithmic interpolation
75.5%	0.0999%	0.881	logarithmic interpolation
75.6%	0.0999%	0.889	logarithmic interpolation
75.7%	0.0999%	0.897	logarithmic interpolation
75.8%	0.0999%	0.906	logarithmic interpolation
75.9%	0.0999%	0.914	logarithmic interpolation
76.0%	0.0999%	0.923	estimate from Buckman et al. (2015) using the NCI method
76.1%	0.0999%	0.932	logarithmic interpolation
76.2%	0.0999%	0.942	logarithmic interpolation
76.3%	0.0999%	0.951	logarithmic interpolation
76.4%	0.0999%	0.961	logarithmic interpolation
76.5%	0.0999%	0.970	logarithmic interpolation
76.6%	0.0999%	0.980	logarithmic interpolation
76.7%	0.0999%	0.990	logarithmic interpolation
76.8%	0.0999%	1.00	logarithmic interpolation
76.9%	0.0999%	1.01	logarithmic interpolation
77.0%	0.0999%	1.02	estimate from Buckman et al. (2015) using the NCI method
77.1%	0.0999%	1.03	logarithmic interpolation
77.2%	0.0999%	1.04	logarithmic interpolation
77.3%	0.0999%	1.05	logarithmic interpolation
77.4%	0.0999%	1.06	logarithmic interpolation
77.5%	0.0999%	1.07	logarithmic interpolation
77.6%	0.0999%	1.08	logarithmic interpolation
77.7%	0.0999%	1.09	logarithmic interpolation
77.8%	0.0999%	1.10	logarithmic interpolation
77.9%	0.0999%	1.11	logarithmic interpolation
78.0%	0.0999%	1.12	estimate from Buckman et al. (2015) using the NCI method
78.1%	0.0999%	1.14	logarithmic interpolation
78.2%	0.0999%	1.15	logarithmic interpolation
78.3%	0.0999%	1.16	logarithmic interpolation
78.4%	0.0999%	1.17	logarithmic interpolation
78.5%	0.0999%	1.18	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
78.6%	0.0999%	1.19	logarithmic interpolation
78.7%	0.0999%	1.21	logarithmic interpolation
78.8%	0.0999%	1.22	logarithmic interpolation
78.9%	0.0999%	1.23	logarithmic interpolation
79.0%	0.0999%	1.24	estimate from Buckman et al. (2015) using the NCI method
79.1%	0.0999%	1.26	logarithmic interpolation
79.2%	0.0999%	1.27	logarithmic interpolation
79.3%	0.0999%	1.28	logarithmic interpolation
79.4%	0.0999%	1.30	logarithmic interpolation
79.5%	0.0999%	1.31	logarithmic interpolation
79.6%	0.0999%	1.32	logarithmic interpolation
79.7%	0.0999%	1.34	logarithmic interpolation
79.8%	0.0999%	1.35	logarithmic interpolation
79.9%	0.0999%	1.36	logarithmic interpolation
80.0%	0.0999%	1.38	estimate from Buckman et al. (2015) using the NCI method
80.1%	0.0999%	1.39	logarithmic interpolation
80.2%	0.0999%	1.41	logarithmic interpolation
80.3%	0.0999%	1.42	logarithmic interpolation
80.4%	0.0999%	1.44	logarithmic interpolation
80.5%	0.0999%	1.45	logarithmic interpolation
80.6%	0.0999%	1.47	logarithmic interpolation
80.7%	0.0999%	1.48	logarithmic interpolation
80.8%	0.0999%	1.50	logarithmic interpolation
80.9%	0.0999%	1.51	logarithmic interpolation
81.0%	0.0999%	1.53	estimate from Buckman et al. (2015) using the NCI method
81.1%	0.0999%	1.55	logarithmic interpolation
81.2%	0.0999%	1.56	logarithmic interpolation
81.3%	0.0999%	1.58	logarithmic interpolation
81.4%	0.0999%	1.60	logarithmic interpolation
81.5%	0.0999%	1.62	logarithmic interpolation
81.6%	0.0999%	1.63	logarithmic interpolation
81.7%	0.0999%	1.65	logarithmic interpolation
81.8%	0.0999%	1.67	logarithmic interpolation
81.9%	0.0999%	1.69	logarithmic interpolation
82.0%	0.0999%	1.71	estimate from Buckman et al. (2015) using the NCI method
82.1%	0.0999%	1.73	logarithmic interpolation
82.2%	0.0999%	1.75	logarithmic interpolation
82.3%	0.0999%	1.77	logarithmic interpolation
82.4%	0.0999%	1.79	logarithmic interpolation
82.5%	0.0999%	1.81	logarithmic interpolation
82.6%	0.0999%	1.83	logarithmic interpolation
82.7%	0.0999%	1.85	logarithmic interpolation
82.8%	0.0999%	1.87	logarithmic interpolation
82.9%	0.0999%	1.89	logarithmic interpolation
83.0%	0.0999%	1.91	estimate from Buckman et al. (2015) using the NCI method
83.1%	0.0999%	1.94	logarithmic interpolation
83.2%	0.0999%	1.96	logarithmic interpolation
83.3%	0.0999%	1.98	logarithmic interpolation
83.4%	0.0999%	2.00	logarithmic interpolation
83.5%	0.0999%	2.03	logarithmic interpolation
83.6%	0.0999%	2.05	logarithmic interpolation
83.7%	0.0999%	2.07	logarithmic interpolation
83.8%	0.0999%	2.10	logarithmic interpolation
83.9%	0.0999%	2.12	logarithmic interpolation
84.0%	0.0999%	2.15	estimate from Buckman et al. (2015) using the NCI method
84.1%	0.0999%	2.17	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
84.2%	0.0999%	2.20	logarithmic interpolation
84.3%	0.0999%	2.22	logarithmic interpolation
84.4%	0.0999%	2.25	logarithmic interpolation
84.5%	0.0999%	2.28	logarithmic interpolation
84.6%	0.0999%	2.31	logarithmic interpolation
84.7%	0.0999%	2.33	logarithmic interpolation
84.8%	0.0999%	2.36	logarithmic interpolation
84.9%	0.0999%	2.39	logarithmic interpolation
85.0%	0.0999%	2.42	estimate from Buckman et al. (2015) using the NCI method
85.1%	0.0999%	2.45	logarithmic interpolation
85.2%	0.0999%	2.48	logarithmic interpolation
85.3%	0.0999%	2.51	logarithmic interpolation
85.4%	0.0999%	2.54	logarithmic interpolation
85.5%	0.0999%	2.57	logarithmic interpolation
85.6%	0.0999%	2.60	logarithmic interpolation
85.7%	0.0999%	2.64	logarithmic interpolation
85.8%	0.0999%	2.67	logarithmic interpolation
85.9%	0.0999%	2.70	logarithmic interpolation
86.0%	0.0999%	2.74	estimate from Buckman et al. (2015) using the NCI method
86.1%	0.0999%	2.77	logarithmic interpolation
86.2%	0.0999%	2.80	logarithmic interpolation
86.3%	0.0999%	2.84	logarithmic interpolation
86.4%	0.0999%	2.87	logarithmic interpolation
86.5%	0.0999%	2.91	logarithmic interpolation
86.6%	0.0999%	2.94	logarithmic interpolation
86.7%	0.0999%	2.98	logarithmic interpolation
86.8%	0.0999%	3.02	logarithmic interpolation
86.9%	0.0999%	3.05	logarithmic interpolation
87.0%	0.0999%	3.09	estimate from Buckman et al. (2015) using the NCI method
87.1%	0.0999%	3.13	logarithmic interpolation
87.2%	0.0999%	3.17	logarithmic interpolation
87.3%	0.0999%	3.22	logarithmic interpolation
87.4%	0.0999%	3.26	logarithmic interpolation
87.5%	0.0999%	3.30	logarithmic interpolation
87.6%	0.0999%	3.35	logarithmic interpolation
87.7%	0.0999%	3.39	logarithmic interpolation
87.8%	0.0999%	3.44	logarithmic interpolation
87.9%	0.0999%	3.48	logarithmic interpolation
88.0%	0.0999%	3.53	estimate from Buckman et al. (2015) using the NCI method
88.1%	0.0999%	3.58	logarithmic interpolation
88.2%	0.0999%	3.62	logarithmic interpolation
88.3%	0.0999%	3.67	logarithmic interpolation
88.4%	0.0999%	3.72	logarithmic interpolation
88.5%	0.0999%	3.77	logarithmic interpolation
88.6%	0.0999%	3.82	logarithmic interpolation
88.7%	0.0999%	3.88	logarithmic interpolation
88.8%	0.0999%	3.93	logarithmic interpolation
88.9%	0.0999%	3.98	logarithmic interpolation
89.0%	0.0999%	4.03	estimate from Buckman et al. (2015) using the NCI method
89.1%	0.0999%	4.09	logarithmic interpolation
89.2%	0.0999%	4.15	logarithmic interpolation
89.3%	0.0999%	4.21	logarithmic interpolation
89.4%	0.0999%	4.27	logarithmic interpolation
89.5%	0.0999%	4.33	logarithmic interpolation
89.6%	0.0999%	4.40	logarithmic interpolation
89.7%	0.0999%	4.46	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
89.8%	0.0999%	4.53	logarithmic interpolation
89.9%	0.0999%	4.59	logarithmic interpolation
90.0%	0.0999%	4.66	estimate from Buckman et al. (2015) using the NCI method
90.1%	0.0999%	4.73	logarithmic interpolation
90.2%	0.0999%	4.80	logarithmic interpolation
90.3%	0.0999%	4.87	logarithmic interpolation
90.4%	0.0999%	4.95	logarithmic interpolation
90.5%	0.0999%	5.02	logarithmic interpolation
90.6%	0.0999%	5.10	logarithmic interpolation
90.7%	0.0999%	5.18	logarithmic interpolation
90.8%	0.0999%	5.26	logarithmic interpolation
90.9%	0.0999%	5.34	logarithmic interpolation
91.0%	0.0999%	5.42	estimate from Buckman et al. (2015) using the NCI method
91.1%	0.0999%	5.51	logarithmic interpolation
91.2%	0.0999%	5.59	logarithmic interpolation
91.3%	0.0999%	5.69	logarithmic interpolation
91.4%	0.0999%	5.78	logarithmic interpolation
91.5%	0.0999%	5.87	logarithmic interpolation
91.6%	0.0999%	5.97	logarithmic interpolation
91.7%	0.0999%	6.06	logarithmic interpolation
91.8%	0.0999%	6.16	logarithmic interpolation
91.9%	0.0999%	6.26	logarithmic interpolation
92.0%	0.0999%	6.36	estimate from Buckman et al. (2015) using the NCI method
92.1%	0.0999%	6.47	logarithmic interpolation
92.2%	0.0999%	6.58	logarithmic interpolation
92.3%	0.0999%	6.69	logarithmic interpolation
92.4%	0.0999%	6.80	logarithmic interpolation
92.5%	0.0999%	6.92	logarithmic interpolation
92.6%	0.0999%	7.04	logarithmic interpolation
92.7%	0.0999%	7.16	logarithmic interpolation
92.8%	0.0999%	7.28	logarithmic interpolation
92.9%	0.0999%	7.40	logarithmic interpolation
93.0%	0.0999%	7.53	estimate from Buckman et al. (2015) using the NCI method
93.1%	0.0999%	7.67	logarithmic interpolation
93.2%	0.0999%	7.82	logarithmic interpolation
93.3%	0.0999%	7.98	logarithmic interpolation
93.4%	0.0999%	8.13	logarithmic interpolation
93.5%	0.0999%	8.29	logarithmic interpolation
93.6%	0.0999%	8.45	logarithmic interpolation
93.7%	0.0999%	8.62	logarithmic interpolation
93.8%	0.0999%	8.79	logarithmic interpolation
93.9%	0.0999%	8.96	logarithmic interpolation
94.0%	0.0999%	9.14	estimate from Buckman et al. (2015) using the NCI method
94.1%	0.0999%	9.33	logarithmic interpolation
94.2%	0.0999%	9.52	logarithmic interpolation
94.3%	0.0999%	9.72	logarithmic interpolation
94.4%	0.0999%	9.93	logarithmic interpolation
94.5%	0.0999%	10.1	logarithmic interpolation
94.6%	0.0999%	10.3	logarithmic interpolation
94.7%	0.0999%	10.6	logarithmic interpolation
94.8%	0.0999%	10.8	logarithmic interpolation
94.9%	0.0999%	11.0	logarithmic interpolation
95.0%	0.0999%	11.2	estimate from Buckman et al. (2015) using the NCI method
95.1%	0.0999%	11.5	logarithmic interpolation
95.2%	0.0999%	11.8	logarithmic interpolation
95.3%	0.0999%	12.0	logarithmic interpolation

Table A2. Alternate Interpolated Idaho Fish Consumption Distribution for the General Population

Percentile	Discrete Probability	FCR (g/day)	Basis
95.4%	0.0999%	12.3	logarithmic interpolation
95.5%	0.0999%	12.6	logarithmic interpolation
95.6%	0.0999%	12.9	logarithmic interpolation
95.7%	0.0999%	13.1	logarithmic interpolation
95.8%	0.0999%	13.4	logarithmic interpolation
95.9%	0.0999%	13.7	logarithmic interpolation
96.0%	0.0999%	14.1	estimate from Buckman et al. (2015) using the NCI method
96.1%	0.0999%	14.4	logarithmic interpolation
96.2%	0.0999%	14.8	logarithmic interpolation
96.3%	0.0999%	15.2	logarithmic interpolation
96.4%	0.0999%	15.6	logarithmic interpolation
96.5%	0.0999%	16.0	logarithmic interpolation
96.6%	0.0999%	16.4	logarithmic interpolation
96.7%	0.0999%	16.9	logarithmic interpolation
96.8%	0.0999%	17.3	logarithmic interpolation
96.9%	0.0999%	17.8	logarithmic interpolation
97.0%	0.0999%	18.2	estimate from Buckman et al. (2015) using the NCI method
97.1%	0.0999%	18.8	logarithmic interpolation
97.2%	0.0999%	19.5	logarithmic interpolation
97.3%	0.0999%	20.1	logarithmic interpolation
97.4%	0.0999%	20.8	logarithmic interpolation
97.5%	0.0999%	21.5	logarithmic interpolation
97.6%	0.0999%	22.2	logarithmic interpolation
97.7%	0.0999%	23.0	logarithmic interpolation
97.8%	0.0999%	23.7	logarithmic interpolation
97.9%	0.0999%	24.5	logarithmic interpolation
98.0%	0.0999%	25.3	estimate from Buckman et al. (2015) using the NCI method
98.1%	0.0999%	26.6	logarithmic interpolation
98.2%	0.0999%	27.8	logarithmic interpolation
98.3%	0.0999%	29.2	logarithmic interpolation
98.4%	0.0999%	30.6	logarithmic interpolation
98.5%	0.0999%	32.0	logarithmic interpolation
98.6%	0.0999%	33.6	logarithmic interpolation
98.7%	0.0999%	35.2	logarithmic interpolation
98.8%	0.0999%	36.9	logarithmic interpolation
98.9%	0.0999%	38.7	logarithmic interpolation
99.0%	0.0999%	40.5	estimate from Buckman et al. (2015) using the NCI method
99.1%	0.0999%	57	logarithmic interpolation
99.2%	0.0999%	81	logarithmic interpolation
99.3%	0.0999%	114	logarithmic interpolation
99.4%	0.0999%	160	logarithmic interpolation
99.5%	0.0999%	226	logarithmic interpolation
99.6%	0.0999%	319	logarithmic interpolation
99.7%	0.0999%	450	logarithmic interpolation
99.8%	0.0999%	634	logarithmic interpolation
99.9%	0.0999%	895	logarithmic interpolation
100%	0.0999%	1261	estimate from Buckman et al. (2015) using the NCI method

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
Mean	--	19.2	arithmetic mean of discrete distribution
0%	0.0999%	0.992	set equal to the 5th percentile value
0.1%	0.0999%	0.992	linear interpolation
0.2%	0.0999%	0.992	linear interpolation
0.3%	0.0999%	0.992	linear interpolation
0.4%	0.0999%	0.992	linear interpolation
0.5%	0.0999%	0.992	linear interpolation
0.6%	0.0999%	0.992	linear interpolation
0.7%	0.0999%	0.992	linear interpolation
0.8%	0.0999%	0.992	linear interpolation
0.9%	0.0999%	0.992	linear interpolation
1.0%	0.0999%	0.992	linear interpolation
1.1%	0.0999%	0.992	linear interpolation
1.2%	0.0999%	0.992	linear interpolation
1.3%	0.0999%	0.992	linear interpolation
1.4%	0.0999%	0.992	linear interpolation
1.5%	0.0999%	0.992	linear interpolation
1.6%	0.0999%	0.992	linear interpolation
1.7%	0.0999%	0.992	linear interpolation
1.8%	0.0999%	0.992	linear interpolation
1.9%	0.0999%	0.992	linear interpolation
2.0%	0.0999%	0.992	linear interpolation
2.1%	0.0999%	0.992	linear interpolation
2.2%	0.0999%	0.992	linear interpolation
2.3%	0.0999%	0.992	linear interpolation
2.4%	0.0999%	0.992	linear interpolation
2.5%	0.0999%	0.992	linear interpolation
2.6%	0.0999%	0.992	linear interpolation
2.7%	0.0999%	0.992	linear interpolation
2.8%	0.0999%	0.992	linear interpolation
2.9%	0.0999%	0.992	linear interpolation
3.0%	0.0999%	0.992	linear interpolation
3.1%	0.0999%	0.992	linear interpolation
3.2%	0.0999%	0.992	linear interpolation
3.3%	0.0999%	0.992	linear interpolation
3.4%	0.0999%	0.992	linear interpolation
3.5%	0.0999%	0.992	linear interpolation
3.6%	0.0999%	0.992	linear interpolation
3.7%	0.0999%	0.992	linear interpolation
3.8%	0.0999%	0.992	linear interpolation
3.9%	0.0999%	0.992	linear interpolation
4.0%	0.0999%	0.992	linear interpolation
4.1%	0.0999%	0.992	linear interpolation
4.2%	0.0999%	0.992	linear interpolation
4.3%	0.0999%	0.992	linear interpolation
4.4%	0.0999%	0.992	linear interpolation
4.5%	0.0999%	0.992	linear interpolation
4.6%	0.0999%	0.992	linear interpolation
4.7%	0.0999%	0.992	linear interpolation
4.8%	0.0999%	0.992	linear interpolation
4.9%	0.0999%	0.992	linear interpolation
5.0%	0.0999%	0.992	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
5.1%	0.0999%	1.01	linear interpolation
5.2%	0.0999%	1.02	linear interpolation
5.3%	0.0999%	1.03	linear interpolation
5.4%	0.0999%	1.04	linear interpolation
5.5%	0.0999%	1.06	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
5.6%	0.0999%	1.07	linear interpolation
5.7%	0.0999%	1.08	linear interpolation
5.8%	0.0999%	1.10	linear interpolation
5.9%	0.0999%	1.11	linear interpolation
6.0%	0.0999%	1.12	linear interpolation
6.1%	0.0999%	1.14	linear interpolation
6.2%	0.0999%	1.15	linear interpolation
6.3%	0.0999%	1.16	linear interpolation
6.4%	0.0999%	1.18	linear interpolation
6.5%	0.0999%	1.19	linear interpolation
6.6%	0.0999%	1.20	linear interpolation
6.7%	0.0999%	1.21	linear interpolation
6.8%	0.0999%	1.23	linear interpolation
6.9%	0.0999%	1.24	linear interpolation
7.0%	0.0999%	1.25	linear interpolation
7.1%	0.0999%	1.27	linear interpolation
7.2%	0.0999%	1.28	linear interpolation
7.3%	0.0999%	1.29	linear interpolation
7.4%	0.0999%	1.31	linear interpolation
7.5%	0.0999%	1.32	linear interpolation
7.6%	0.0999%	1.33	linear interpolation
7.7%	0.0999%	1.35	linear interpolation
7.8%	0.0999%	1.36	linear interpolation
7.9%	0.0999%	1.37	linear interpolation
8.0%	0.0999%	1.38	linear interpolation
8.1%	0.0999%	1.40	linear interpolation
8.2%	0.0999%	1.41	linear interpolation
8.3%	0.0999%	1.42	linear interpolation
8.4%	0.0999%	1.44	linear interpolation
8.5%	0.0999%	1.45	linear interpolation
8.6%	0.0999%	1.46	linear interpolation
8.7%	0.0999%	1.48	linear interpolation
8.8%	0.0999%	1.49	linear interpolation
8.9%	0.0999%	1.50	linear interpolation
9.0%	0.0999%	1.51	linear interpolation
9.1%	0.0999%	1.53	linear interpolation
9.2%	0.0999%	1.54	linear interpolation
9.3%	0.0999%	1.55	linear interpolation
9.4%	0.0999%	1.57	linear interpolation
9.5%	0.0999%	1.58	linear interpolation
9.6%	0.0999%	1.59	linear interpolation
9.7%	0.0999%	1.61	linear interpolation
9.8%	0.0999%	1.62	linear interpolation
9.9%	0.0999%	1.63	linear interpolation
10.0%	0.0999%	1.65	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
10.1%	0.0999%	1.66	linear interpolation
10.2%	0.0999%	1.67	linear interpolation
10.3%	0.0999%	1.68	linear interpolation
10.4%	0.0999%	1.70	linear interpolation
10.5%	0.0999%	1.71	linear interpolation
10.6%	0.0999%	1.72	linear interpolation
10.7%	0.0999%	1.73	linear interpolation
10.8%	0.0999%	1.75	linear interpolation
10.9%	0.0999%	1.76	linear interpolation
11.0%	0.0999%	1.77	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
11.1%	0.0999%	1.78	linear interpolation
11.2%	0.0999%	1.80	linear interpolation
11.3%	0.0999%	1.81	linear interpolation
11.4%	0.0999%	1.82	linear interpolation
11.5%	0.0999%	1.83	linear interpolation
11.6%	0.0999%	1.85	linear interpolation
11.7%	0.0999%	1.86	linear interpolation
11.8%	0.0999%	1.87	linear interpolation
11.9%	0.0999%	1.88	linear interpolation
12.0%	0.0999%	1.90	linear interpolation
12.1%	0.0999%	1.91	linear interpolation
12.2%	0.0999%	1.92	linear interpolation
12.3%	0.0999%	1.94	linear interpolation
12.4%	0.0999%	1.95	linear interpolation
12.5%	0.0999%	1.96	linear interpolation
12.6%	0.0999%	1.97	linear interpolation
12.7%	0.0999%	1.99	linear interpolation
12.8%	0.0999%	2.00	linear interpolation
12.9%	0.0999%	2.01	linear interpolation
13.0%	0.0999%	2.02	linear interpolation
13.1%	0.0999%	2.04	linear interpolation
13.2%	0.0999%	2.05	linear interpolation
13.3%	0.0999%	2.06	linear interpolation
13.4%	0.0999%	2.07	linear interpolation
13.5%	0.0999%	2.09	linear interpolation
13.6%	0.0999%	2.10	linear interpolation
13.7%	0.0999%	2.11	linear interpolation
13.8%	0.0999%	2.12	linear interpolation
13.9%	0.0999%	2.14	linear interpolation
14.0%	0.0999%	2.15	linear interpolation
14.1%	0.0999%	2.16	linear interpolation
14.2%	0.0999%	2.17	linear interpolation
14.3%	0.0999%	2.19	linear interpolation
14.4%	0.0999%	2.20	linear interpolation
14.5%	0.0999%	2.21	linear interpolation
14.6%	0.0999%	2.22	linear interpolation
14.7%	0.0999%	2.24	linear interpolation
14.8%	0.0999%	2.25	linear interpolation
14.9%	0.0999%	2.26	linear interpolation
15.0%	0.0999%	2.27	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
15.1%	0.0999%	2.29	linear interpolation
15.2%	0.0999%	2.30	linear interpolation
15.3%	0.0999%	2.32	linear interpolation
15.4%	0.0999%	2.33	linear interpolation
15.5%	0.0999%	2.34	linear interpolation
15.6%	0.0999%	2.36	linear interpolation
15.7%	0.0999%	2.37	linear interpolation
15.8%	0.0999%	2.38	linear interpolation
15.9%	0.0999%	2.40	linear interpolation
16.0%	0.0999%	2.41	linear interpolation
16.1%	0.0999%	2.42	linear interpolation
16.2%	0.0999%	2.44	linear interpolation
16.3%	0.0999%	2.45	linear interpolation
16.4%	0.0999%	2.46	linear interpolation
16.5%	0.0999%	2.48	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
16.6%	0.0999%	2.49	linear interpolation
16.7%	0.0999%	2.51	linear interpolation
16.8%	0.0999%	2.52	linear interpolation
16.9%	0.0999%	2.53	linear interpolation
17.0%	0.0999%	2.55	linear interpolation
17.1%	0.0999%	2.56	linear interpolation
17.2%	0.0999%	2.57	linear interpolation
17.3%	0.0999%	2.59	linear interpolation
17.4%	0.0999%	2.60	linear interpolation
17.5%	0.0999%	2.61	linear interpolation
17.6%	0.0999%	2.63	linear interpolation
17.7%	0.0999%	2.64	linear interpolation
17.8%	0.0999%	2.65	linear interpolation
17.9%	0.0999%	2.67	linear interpolation
18.0%	0.0999%	2.68	linear interpolation
18.1%	0.0999%	2.69	linear interpolation
18.2%	0.0999%	2.71	linear interpolation
18.3%	0.0999%	2.72	linear interpolation
18.4%	0.0999%	2.74	linear interpolation
18.5%	0.0999%	2.75	linear interpolation
18.6%	0.0999%	2.76	linear interpolation
18.7%	0.0999%	2.78	linear interpolation
18.8%	0.0999%	2.79	linear interpolation
18.9%	0.0999%	2.80	linear interpolation
19.0%	0.0999%	2.82	linear interpolation
19.1%	0.0999%	2.83	linear interpolation
19.2%	0.0999%	2.84	linear interpolation
19.3%	0.0999%	2.86	linear interpolation
19.4%	0.0999%	2.87	linear interpolation
19.5%	0.0999%	2.88	linear interpolation
19.6%	0.0999%	2.90	linear interpolation
19.7%	0.0999%	2.91	linear interpolation
19.8%	0.0999%	2.93	linear interpolation
19.9%	0.0999%	2.94	linear interpolation
20.0%	0.0999%	2.95	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
20.1%	0.0999%	2.97	linear interpolation
20.2%	0.0999%	2.98	linear interpolation
20.3%	0.0999%	2.99	linear interpolation
20.4%	0.0999%	3.01	linear interpolation
20.5%	0.0999%	3.02	linear interpolation
20.6%	0.0999%	3.04	linear interpolation
20.7%	0.0999%	3.05	linear interpolation
20.8%	0.0999%	3.06	linear interpolation
20.9%	0.0999%	3.08	linear interpolation
21.0%	0.0999%	3.09	linear interpolation
21.1%	0.0999%	3.11	linear interpolation
21.2%	0.0999%	3.12	linear interpolation
21.3%	0.0999%	3.13	linear interpolation
21.4%	0.0999%	3.15	linear interpolation
21.5%	0.0999%	3.16	linear interpolation
21.6%	0.0999%	3.18	linear interpolation
21.7%	0.0999%	3.19	linear interpolation
21.8%	0.0999%	3.21	linear interpolation
21.9%	0.0999%	3.22	linear interpolation
22.0%	0.0999%	3.23	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
22.1%	0.0999%	3.25	linear interpolation
22.2%	0.0999%	3.26	linear interpolation
22.3%	0.0999%	3.28	linear interpolation
22.4%	0.0999%	3.29	linear interpolation
22.5%	0.0999%	3.30	linear interpolation
22.6%	0.0999%	3.32	linear interpolation
22.7%	0.0999%	3.33	linear interpolation
22.8%	0.0999%	3.35	linear interpolation
22.9%	0.0999%	3.36	linear interpolation
23.0%	0.0999%	3.37	linear interpolation
23.1%	0.0999%	3.39	linear interpolation
23.2%	0.0999%	3.40	linear interpolation
23.3%	0.0999%	3.42	linear interpolation
23.4%	0.0999%	3.43	linear interpolation
23.5%	0.0999%	3.44	linear interpolation
23.6%	0.0999%	3.46	linear interpolation
23.7%	0.0999%	3.47	linear interpolation
23.8%	0.0999%	3.49	linear interpolation
23.9%	0.0999%	3.50	linear interpolation
24.0%	0.0999%	3.51	linear interpolation
24.1%	0.0999%	3.53	linear interpolation
24.2%	0.0999%	3.54	linear interpolation
24.3%	0.0999%	3.56	linear interpolation
24.4%	0.0999%	3.57	linear interpolation
24.5%	0.0999%	3.58	linear interpolation
24.6%	0.0999%	3.60	linear interpolation
24.7%	0.0999%	3.61	linear interpolation
24.8%	0.0999%	3.63	linear interpolation
24.9%	0.0999%	3.64	linear interpolation
25.0%	0.0999%	3.65	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
25.1%	0.0999%	3.67	linear interpolation
25.2%	0.0999%	3.69	linear interpolation
25.3%	0.0999%	3.70	linear interpolation
25.4%	0.0999%	3.72	linear interpolation
25.5%	0.0999%	3.73	linear interpolation
25.6%	0.0999%	3.75	linear interpolation
25.7%	0.0999%	3.76	linear interpolation
25.8%	0.0999%	3.78	linear interpolation
25.9%	0.0999%	3.79	linear interpolation
26.0%	0.0999%	3.81	linear interpolation
26.1%	0.0999%	3.82	linear interpolation
26.2%	0.0999%	3.84	linear interpolation
26.3%	0.0999%	3.86	linear interpolation
26.4%	0.0999%	3.87	linear interpolation
26.5%	0.0999%	3.89	linear interpolation
26.6%	0.0999%	3.90	linear interpolation
26.7%	0.0999%	3.92	linear interpolation
26.8%	0.0999%	3.93	linear interpolation
26.9%	0.0999%	3.95	linear interpolation
27.0%	0.0999%	3.96	linear interpolation
27.1%	0.0999%	3.98	linear interpolation
27.2%	0.0999%	3.99	linear interpolation
27.3%	0.0999%	4.01	linear interpolation
27.4%	0.0999%	4.03	linear interpolation
27.5%	0.0999%	4.04	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
27.6%	0.0999%	4.06	linear interpolation
27.7%	0.0999%	4.07	linear interpolation
27.8%	0.0999%	4.09	linear interpolation
27.9%	0.0999%	4.10	linear interpolation
28.0%	0.0999%	4.12	linear interpolation
28.1%	0.0999%	4.13	linear interpolation
28.2%	0.0999%	4.15	linear interpolation
28.3%	0.0999%	4.17	linear interpolation
28.4%	0.0999%	4.18	linear interpolation
28.5%	0.0999%	4.20	linear interpolation
28.6%	0.0999%	4.21	linear interpolation
28.7%	0.0999%	4.23	linear interpolation
28.8%	0.0999%	4.24	linear interpolation
28.9%	0.0999%	4.26	linear interpolation
29.0%	0.0999%	4.27	linear interpolation
29.1%	0.0999%	4.29	linear interpolation
29.2%	0.0999%	4.30	linear interpolation
29.3%	0.0999%	4.32	linear interpolation
29.4%	0.0999%	4.34	linear interpolation
29.5%	0.0999%	4.35	linear interpolation
29.6%	0.0999%	4.37	linear interpolation
29.7%	0.0999%	4.38	linear interpolation
29.8%	0.0999%	4.40	linear interpolation
29.9%	0.0999%	4.41	linear interpolation
30.0%	0.0999%	4.43	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
30.1%	0.0999%	4.45	linear interpolation
30.2%	0.0999%	4.46	linear interpolation
30.3%	0.0999%	4.48	linear interpolation
30.4%	0.0999%	4.50	linear interpolation
30.5%	0.0999%	4.52	linear interpolation
30.6%	0.0999%	4.53	linear interpolation
30.7%	0.0999%	4.55	linear interpolation
30.8%	0.0999%	4.57	linear interpolation
30.9%	0.0999%	4.59	linear interpolation
31.0%	0.0999%	4.60	linear interpolation
31.1%	0.0999%	4.62	linear interpolation
31.2%	0.0999%	4.64	linear interpolation
31.3%	0.0999%	4.66	linear interpolation
31.4%	0.0999%	4.67	linear interpolation
31.5%	0.0999%	4.69	linear interpolation
31.6%	0.0999%	4.71	linear interpolation
31.7%	0.0999%	4.72	linear interpolation
31.8%	0.0999%	4.74	linear interpolation
31.9%	0.0999%	4.76	linear interpolation
32.0%	0.0999%	4.78	linear interpolation
32.1%	0.0999%	4.79	linear interpolation
32.2%	0.0999%	4.81	linear interpolation
32.3%	0.0999%	4.83	linear interpolation
32.4%	0.0999%	4.85	linear interpolation
32.5%	0.0999%	4.86	linear interpolation
32.6%	0.0999%	4.88	linear interpolation
32.7%	0.0999%	4.90	linear interpolation
32.8%	0.0999%	4.92	linear interpolation
32.9%	0.0999%	4.93	linear interpolation
33.0%	0.0999%	4.95	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
33.1%	0.0999%	4.97	linear interpolation
33.2%	0.0999%	4.99	linear interpolation
33.3%	0.0999%	5.00	linear interpolation
33.4%	0.0999%	5.02	linear interpolation
33.5%	0.0999%	5.04	linear interpolation
33.6%	0.0999%	5.06	linear interpolation
33.7%	0.0999%	5.07	linear interpolation
33.8%	0.0999%	5.09	linear interpolation
33.9%	0.0999%	5.11	linear interpolation
34.0%	0.0999%	5.13	linear interpolation
34.1%	0.0999%	5.14	linear interpolation
34.2%	0.0999%	5.16	linear interpolation
34.3%	0.0999%	5.18	linear interpolation
34.4%	0.0999%	5.20	linear interpolation
34.5%	0.0999%	5.21	linear interpolation
34.6%	0.0999%	5.23	linear interpolation
34.7%	0.0999%	5.25	linear interpolation
34.8%	0.0999%	5.26	linear interpolation
34.9%	0.0999%	5.28	linear interpolation
35.0%	0.0999%	5.30	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
35.1%	0.0999%	5.32	linear interpolation
35.2%	0.0999%	5.34	linear interpolation
35.3%	0.0999%	5.36	linear interpolation
35.4%	0.0999%	5.38	linear interpolation
35.5%	0.0999%	5.40	linear interpolation
35.6%	0.0999%	5.42	linear interpolation
35.7%	0.0999%	5.44	linear interpolation
35.8%	0.0999%	5.46	linear interpolation
35.9%	0.0999%	5.48	linear interpolation
36.0%	0.0999%	5.50	linear interpolation
36.1%	0.0999%	5.52	linear interpolation
36.2%	0.0999%	5.54	linear interpolation
36.3%	0.0999%	5.56	linear interpolation
36.4%	0.0999%	5.58	linear interpolation
36.5%	0.0999%	5.60	linear interpolation
36.6%	0.0999%	5.63	linear interpolation
36.7%	0.0999%	5.65	linear interpolation
36.8%	0.0999%	5.67	linear interpolation
36.9%	0.0999%	5.69	linear interpolation
37.0%	0.0999%	5.71	linear interpolation
37.1%	0.0999%	5.73	linear interpolation
37.2%	0.0999%	5.75	linear interpolation
37.3%	0.0999%	5.77	linear interpolation
37.4%	0.0999%	5.79	linear interpolation
37.5%	0.0999%	5.81	linear interpolation
37.6%	0.0999%	5.83	linear interpolation
37.7%	0.0999%	5.85	linear interpolation
37.8%	0.0999%	5.87	linear interpolation
37.9%	0.0999%	5.89	linear interpolation
38.0%	0.0999%	5.91	linear interpolation
38.1%	0.0999%	5.93	linear interpolation
38.2%	0.0999%	5.95	linear interpolation
38.3%	0.0999%	5.97	linear interpolation
38.4%	0.0999%	5.99	linear interpolation
38.5%	0.0999%	6.01	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
38.6%	0.0999%	6.03	linear interpolation
38.7%	0.0999%	6.05	linear interpolation
38.8%	0.0999%	6.07	linear interpolation
38.9%	0.0999%	6.09	linear interpolation
39.0%	0.0999%	6.11	linear interpolation
39.1%	0.0999%	6.13	linear interpolation
39.2%	0.0999%	6.15	linear interpolation
39.3%	0.0999%	6.17	linear interpolation
39.4%	0.0999%	6.19	linear interpolation
39.5%	0.0999%	6.21	linear interpolation
39.6%	0.0999%	6.23	linear interpolation
39.7%	0.0999%	6.26	linear interpolation
39.8%	0.0999%	6.28	linear interpolation
39.9%	0.0999%	6.30	linear interpolation
40.0%	0.0999%	6.32	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
40.1%	0.0999%	6.34	linear interpolation
40.2%	0.0999%	6.36	linear interpolation
40.3%	0.0999%	6.38	linear interpolation
40.4%	0.0999%	6.41	linear interpolation
40.5%	0.0999%	6.43	linear interpolation
40.6%	0.0999%	6.45	linear interpolation
40.7%	0.0999%	6.48	linear interpolation
40.8%	0.0999%	6.50	linear interpolation
40.9%	0.0999%	6.52	linear interpolation
41.0%	0.0999%	6.54	linear interpolation
41.1%	0.0999%	6.57	linear interpolation
41.2%	0.0999%	6.59	linear interpolation
41.3%	0.0999%	6.61	linear interpolation
41.4%	0.0999%	6.63	linear interpolation
41.5%	0.0999%	6.66	linear interpolation
41.6%	0.0999%	6.68	linear interpolation
41.7%	0.0999%	6.70	linear interpolation
41.8%	0.0999%	6.73	linear interpolation
41.9%	0.0999%	6.75	linear interpolation
42.0%	0.0999%	6.77	linear interpolation
42.1%	0.0999%	6.79	linear interpolation
42.2%	0.0999%	6.82	linear interpolation
42.3%	0.0999%	6.84	linear interpolation
42.4%	0.0999%	6.86	linear interpolation
42.5%	0.0999%	6.88	linear interpolation
42.6%	0.0999%	6.91	linear interpolation
42.7%	0.0999%	6.93	linear interpolation
42.8%	0.0999%	6.95	linear interpolation
42.9%	0.0999%	6.98	linear interpolation
43.0%	0.0999%	7.00	linear interpolation
43.1%	0.0999%	7.02	linear interpolation
43.2%	0.0999%	7.04	linear interpolation
43.3%	0.0999%	7.07	linear interpolation
43.4%	0.0999%	7.09	linear interpolation
43.5%	0.0999%	7.11	linear interpolation
43.6%	0.0999%	7.14	linear interpolation
43.7%	0.0999%	7.16	linear interpolation
43.8%	0.0999%	7.18	linear interpolation
43.9%	0.0999%	7.20	linear interpolation
44.0%	0.0999%	7.23	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
44.1%	0.0999%	7.25	linear interpolation
44.2%	0.0999%	7.27	linear interpolation
44.3%	0.0999%	7.29	linear interpolation
44.4%	0.0999%	7.32	linear interpolation
44.5%	0.0999%	7.34	linear interpolation
44.6%	0.0999%	7.36	linear interpolation
44.7%	0.0999%	7.39	linear interpolation
44.8%	0.0999%	7.41	linear interpolation
44.9%	0.0999%	7.43	linear interpolation
45.0%	0.0999%	7.45	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
45.1%	0.0999%	7.48	linear interpolation
45.2%	0.0999%	7.50	linear interpolation
45.3%	0.0999%	7.53	linear interpolation
45.4%	0.0999%	7.55	linear interpolation
45.5%	0.0999%	7.58	linear interpolation
45.6%	0.0999%	7.60	linear interpolation
45.7%	0.0999%	7.63	linear interpolation
45.8%	0.0999%	7.65	linear interpolation
45.9%	0.0999%	7.68	linear interpolation
46.0%	0.0999%	7.71	linear interpolation
46.1%	0.0999%	7.73	linear interpolation
46.2%	0.0999%	7.76	linear interpolation
46.3%	0.0999%	7.78	linear interpolation
46.4%	0.0999%	7.81	linear interpolation
46.5%	0.0999%	7.83	linear interpolation
46.6%	0.0999%	7.86	linear interpolation
46.7%	0.0999%	7.88	linear interpolation
46.8%	0.0999%	7.91	linear interpolation
46.9%	0.0999%	7.93	linear interpolation
47.0%	0.0999%	7.96	linear interpolation
47.1%	0.0999%	7.98	linear interpolation
47.2%	0.0999%	8.01	linear interpolation
47.3%	0.0999%	8.03	linear interpolation
47.4%	0.0999%	8.06	linear interpolation
47.5%	0.0999%	8.08	linear interpolation
47.6%	0.0999%	8.11	linear interpolation
47.7%	0.0999%	8.13	linear interpolation
47.8%	0.0999%	8.16	linear interpolation
47.9%	0.0999%	8.18	linear interpolation
48.0%	0.0999%	8.21	linear interpolation
48.1%	0.0999%	8.23	linear interpolation
48.2%	0.0999%	8.26	linear interpolation
48.3%	0.0999%	8.28	linear interpolation
48.4%	0.0999%	8.31	linear interpolation
48.5%	0.0999%	8.33	linear interpolation
48.6%	0.0999%	8.36	linear interpolation
48.7%	0.0999%	8.38	linear interpolation
48.8%	0.0999%	8.41	linear interpolation
48.9%	0.0999%	8.44	linear interpolation
49.0%	0.0999%	8.46	linear interpolation
49.1%	0.0999%	8.49	linear interpolation
49.2%	0.0999%	8.51	linear interpolation
49.3%	0.0999%	8.54	linear interpolation
49.4%	0.0999%	8.56	linear interpolation
49.5%	0.0999%	8.59	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
49.6%	0.0999%	8.61	linear interpolation
49.7%	0.0999%	8.64	linear interpolation
49.8%	0.0999%	8.66	linear interpolation
49.9%	0.0999%	8.69	linear interpolation
50.0%	0.0999%	8.71	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
50.1%	0.0999%	8.74	linear interpolation
50.2%	0.0999%	8.77	linear interpolation
50.3%	0.0999%	8.80	linear interpolation
50.4%	0.0999%	8.83	linear interpolation
50.5%	0.0999%	8.86	linear interpolation
50.6%	0.0999%	8.89	linear interpolation
50.7%	0.0999%	8.92	linear interpolation
50.8%	0.0999%	8.95	linear interpolation
50.9%	0.0999%	8.98	linear interpolation
51.0%	0.0999%	9.01	linear interpolation
51.1%	0.0999%	9.04	linear interpolation
51.2%	0.0999%	9.07	linear interpolation
51.3%	0.0999%	9.10	linear interpolation
51.4%	0.0999%	9.13	linear interpolation
51.5%	0.0999%	9.15	linear interpolation
51.6%	0.0999%	9.18	linear interpolation
51.7%	0.0999%	9.21	linear interpolation
51.8%	0.0999%	9.24	linear interpolation
51.9%	0.0999%	9.27	linear interpolation
52.0%	0.0999%	9.30	linear interpolation
52.1%	0.0999%	9.33	linear interpolation
52.2%	0.0999%	9.36	linear interpolation
52.3%	0.0999%	9.39	linear interpolation
52.4%	0.0999%	9.42	linear interpolation
52.5%	0.0999%	9.45	linear interpolation
52.6%	0.0999%	9.48	linear interpolation
52.7%	0.0999%	9.51	linear interpolation
52.8%	0.0999%	9.54	linear interpolation
52.9%	0.0999%	9.57	linear interpolation
53.0%	0.0999%	9.60	linear interpolation
53.1%	0.0999%	9.63	linear interpolation
53.2%	0.0999%	9.66	linear interpolation
53.3%	0.0999%	9.69	linear interpolation
53.4%	0.0999%	9.72	linear interpolation
53.5%	0.0999%	9.75	linear interpolation
53.6%	0.0999%	9.77	linear interpolation
53.7%	0.0999%	9.80	linear interpolation
53.8%	0.0999%	9.83	linear interpolation
53.9%	0.0999%	9.86	linear interpolation
54.0%	0.0999%	9.89	linear interpolation
54.1%	0.0999%	9.92	linear interpolation
54.2%	0.0999%	9.95	linear interpolation
54.3%	0.0999%	9.98	linear interpolation
54.4%	0.0999%	10.0	linear interpolation
54.5%	0.0999%	10.0	linear interpolation
54.6%	0.0999%	10.1	linear interpolation
54.7%	0.0999%	10.1	linear interpolation
54.8%	0.0999%	10.1	linear interpolation
54.9%	0.0999%	10.2	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
55.0%	0.0999%	10.2	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
55.1%	0.0999%	10.2	linear interpolation
55.2%	0.0999%	10.3	linear interpolation
55.3%	0.0999%	10.3	linear interpolation
55.4%	0.0999%	10.3	linear interpolation
55.5%	0.0999%	10.4	linear interpolation
55.6%	0.0999%	10.4	linear interpolation
55.7%	0.0999%	10.4	linear interpolation
55.8%	0.0999%	10.5	linear interpolation
55.9%	0.0999%	10.5	linear interpolation
56.0%	0.0999%	10.5	linear interpolation
56.1%	0.0999%	10.6	linear interpolation
56.2%	0.0999%	10.6	linear interpolation
56.3%	0.0999%	10.7	linear interpolation
56.4%	0.0999%	10.7	linear interpolation
56.5%	0.0999%	10.7	linear interpolation
56.6%	0.0999%	10.8	linear interpolation
56.7%	0.0999%	10.8	linear interpolation
56.8%	0.0999%	10.8	linear interpolation
56.9%	0.0999%	10.9	linear interpolation
57.0%	0.0999%	10.9	linear interpolation
57.1%	0.0999%	10.9	linear interpolation
57.2%	0.0999%	11.0	linear interpolation
57.3%	0.0999%	11.0	linear interpolation
57.4%	0.0999%	11.0	linear interpolation
57.5%	0.0999%	11.1	linear interpolation
57.6%	0.0999%	11.1	linear interpolation
57.7%	0.0999%	11.2	linear interpolation
57.8%	0.0999%	11.2	linear interpolation
57.9%	0.0999%	11.2	linear interpolation
58.0%	0.0999%	11.3	linear interpolation
58.1%	0.0999%	11.3	linear interpolation
58.2%	0.0999%	11.3	linear interpolation
58.3%	0.0999%	11.4	linear interpolation
58.4%	0.0999%	11.4	linear interpolation
58.5%	0.0999%	11.4	linear interpolation
58.6%	0.0999%	11.5	linear interpolation
58.7%	0.0999%	11.5	linear interpolation
58.8%	0.0999%	11.5	linear interpolation
58.9%	0.0999%	11.6	linear interpolation
59.0%	0.0999%	11.6	linear interpolation
59.1%	0.0999%	11.7	linear interpolation
59.2%	0.0999%	11.7	linear interpolation
59.3%	0.0999%	11.7	linear interpolation
59.4%	0.0999%	11.8	linear interpolation
59.5%	0.0999%	11.8	linear interpolation
59.6%	0.0999%	11.8	linear interpolation
59.7%	0.0999%	11.9	linear interpolation
59.8%	0.0999%	11.9	linear interpolation
59.9%	0.0999%	11.9	linear interpolation
60.0%	0.0999%	12.0	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
60.1%	0.0999%	12.0	linear interpolation
60.2%	0.0999%	12.1	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
60.3%	0.0999%	12.1	linear interpolation
60.4%	0.0999%	12.1	linear interpolation
60.5%	0.0999%	12.2	linear interpolation
60.6%	0.0999%	12.2	linear interpolation
60.7%	0.0999%	12.3	linear interpolation
60.8%	0.0999%	12.3	linear interpolation
60.9%	0.0999%	12.3	linear interpolation
61.0%	0.0999%	12.4	linear interpolation
61.1%	0.0999%	12.4	linear interpolation
61.2%	0.0999%	12.5	linear interpolation
61.3%	0.0999%	12.5	linear interpolation
61.4%	0.0999%	12.6	linear interpolation
61.5%	0.0999%	12.6	linear interpolation
61.6%	0.0999%	12.6	linear interpolation
61.7%	0.0999%	12.7	linear interpolation
61.8%	0.0999%	12.7	linear interpolation
61.9%	0.0999%	12.8	linear interpolation
62.0%	0.0999%	12.8	linear interpolation
62.1%	0.0999%	12.8	linear interpolation
62.2%	0.0999%	12.9	linear interpolation
62.3%	0.0999%	12.9	linear interpolation
62.4%	0.0999%	13.0	linear interpolation
62.5%	0.0999%	13.0	linear interpolation
62.6%	0.0999%	13.0	linear interpolation
62.7%	0.0999%	13.1	linear interpolation
62.8%	0.0999%	13.1	linear interpolation
62.9%	0.0999%	13.2	linear interpolation
63.0%	0.0999%	13.2	linear interpolation
63.1%	0.0999%	13.3	linear interpolation
63.2%	0.0999%	13.3	linear interpolation
63.3%	0.0999%	13.3	linear interpolation
63.4%	0.0999%	13.4	linear interpolation
63.5%	0.0999%	13.4	linear interpolation
63.6%	0.0999%	13.5	linear interpolation
63.7%	0.0999%	13.5	linear interpolation
63.8%	0.0999%	13.5	linear interpolation
63.9%	0.0999%	13.6	linear interpolation
64.0%	0.0999%	13.6	linear interpolation
64.1%	0.0999%	13.7	linear interpolation
64.2%	0.0999%	13.7	linear interpolation
64.3%	0.0999%	13.7	linear interpolation
64.4%	0.0999%	13.8	linear interpolation
64.5%	0.0999%	13.8	linear interpolation
64.6%	0.0999%	13.9	linear interpolation
64.7%	0.0999%	13.9	linear interpolation
64.8%	0.0999%	14.0	linear interpolation
64.9%	0.0999%	14.0	linear interpolation
65.0%	0.0999%	14.0	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
65.1%	0.0999%	14.1	linear interpolation
65.2%	0.0999%	14.1	linear interpolation
65.3%	0.0999%	14.2	linear interpolation
65.4%	0.0999%	14.2	linear interpolation
65.5%	0.0999%	14.3	linear interpolation
65.6%	0.0999%	14.3	linear interpolation
65.7%	0.0999%	14.4	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
65.8%	0.0999%	14.5	linear interpolation
65.9%	0.0999%	14.5	linear interpolation
66.0%	0.0999%	14.6	linear interpolation
66.1%	0.0999%	14.6	linear interpolation
66.2%	0.0999%	14.7	linear interpolation
66.3%	0.0999%	14.7	linear interpolation
66.4%	0.0999%	14.8	linear interpolation
66.5%	0.0999%	14.8	linear interpolation
66.6%	0.0999%	14.9	linear interpolation
66.7%	0.0999%	14.9	linear interpolation
66.8%	0.0999%	15.0	linear interpolation
66.9%	0.0999%	15.0	linear interpolation
67.0%	0.0999%	15.1	linear interpolation
67.1%	0.0999%	15.1	linear interpolation
67.2%	0.0999%	15.2	linear interpolation
67.3%	0.0999%	15.2	linear interpolation
67.4%	0.0999%	15.3	linear interpolation
67.5%	0.0999%	15.3	linear interpolation
67.6%	0.0999%	15.4	linear interpolation
67.7%	0.0999%	15.4	linear interpolation
67.8%	0.0999%	15.5	linear interpolation
67.9%	0.0999%	15.5	linear interpolation
68.0%	0.0999%	15.6	linear interpolation
68.1%	0.0999%	15.6	linear interpolation
68.2%	0.0999%	15.7	linear interpolation
68.3%	0.0999%	15.7	linear interpolation
68.4%	0.0999%	15.8	linear interpolation
68.5%	0.0999%	15.8	linear interpolation
68.6%	0.0999%	15.9	linear interpolation
68.7%	0.0999%	16.0	linear interpolation
68.8%	0.0999%	16.0	linear interpolation
68.9%	0.0999%	16.1	linear interpolation
69.0%	0.0999%	16.1	linear interpolation
69.1%	0.0999%	16.2	linear interpolation
69.2%	0.0999%	16.2	linear interpolation
69.3%	0.0999%	16.3	linear interpolation
69.4%	0.0999%	16.3	linear interpolation
69.5%	0.0999%	16.4	linear interpolation
69.6%	0.0999%	16.4	linear interpolation
69.7%	0.0999%	16.5	linear interpolation
69.8%	0.0999%	16.5	linear interpolation
69.9%	0.0999%	16.6	linear interpolation
70.0%	0.0999%	16.6	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
70.1%	0.0999%	16.7	linear interpolation
70.2%	0.0999%	16.8	linear interpolation
70.3%	0.0999%	16.8	linear interpolation
70.4%	0.0999%	16.9	linear interpolation
70.5%	0.0999%	16.9	linear interpolation
70.6%	0.0999%	17.0	linear interpolation
70.7%	0.0999%	17.1	linear interpolation
70.8%	0.0999%	17.1	linear interpolation
70.9%	0.0999%	17.2	linear interpolation
71.0%	0.0999%	17.3	linear interpolation
71.1%	0.0999%	17.3	linear interpolation
71.2%	0.0999%	17.4	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
71.3%	0.0999%	17.4	linear interpolation
71.4%	0.0999%	17.5	linear interpolation
71.5%	0.0999%	17.6	linear interpolation
71.6%	0.0999%	17.6	linear interpolation
71.7%	0.0999%	17.7	linear interpolation
71.8%	0.0999%	17.8	linear interpolation
71.9%	0.0999%	17.8	linear interpolation
72.0%	0.0999%	17.9	linear interpolation
72.1%	0.0999%	17.9	linear interpolation
72.2%	0.0999%	18.0	linear interpolation
72.3%	0.0999%	18.1	linear interpolation
72.4%	0.0999%	18.1	linear interpolation
72.5%	0.0999%	18.2	linear interpolation
72.6%	0.0999%	18.3	linear interpolation
72.7%	0.0999%	18.3	linear interpolation
72.8%	0.0999%	18.4	linear interpolation
72.9%	0.0999%	18.5	linear interpolation
73.0%	0.0999%	18.5	linear interpolation
73.1%	0.0999%	18.6	linear interpolation
73.2%	0.0999%	18.6	linear interpolation
73.3%	0.0999%	18.7	linear interpolation
73.4%	0.0999%	18.8	linear interpolation
73.5%	0.0999%	18.8	linear interpolation
73.6%	0.0999%	18.9	linear interpolation
73.7%	0.0999%	19.0	linear interpolation
73.8%	0.0999%	19.0	linear interpolation
73.9%	0.0999%	19.1	linear interpolation
74.0%	0.0999%	19.1	linear interpolation
74.1%	0.0999%	19.2	linear interpolation
74.2%	0.0999%	19.3	linear interpolation
74.3%	0.0999%	19.3	linear interpolation
74.4%	0.0999%	19.4	linear interpolation
74.5%	0.0999%	19.5	linear interpolation
74.6%	0.0999%	19.5	linear interpolation
74.7%	0.0999%	19.6	linear interpolation
74.8%	0.0999%	19.6	linear interpolation
74.9%	0.0999%	19.7	linear interpolation
75.0%	0.0999%	19.8	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
75.1%	0.0999%	19.9	linear interpolation
75.2%	0.0999%	19.9	linear interpolation
75.3%	0.0999%	20.0	linear interpolation
75.4%	0.0999%	20.1	linear interpolation
75.5%	0.0999%	20.2	linear interpolation
75.6%	0.0999%	20.3	linear interpolation
75.7%	0.0999%	20.3	linear interpolation
75.8%	0.0999%	20.4	linear interpolation
75.9%	0.0999%	20.5	linear interpolation
76.0%	0.0999%	20.6	linear interpolation
76.1%	0.0999%	20.6	linear interpolation
76.2%	0.0999%	20.7	linear interpolation
76.3%	0.0999%	20.8	linear interpolation
76.4%	0.0999%	20.9	linear interpolation
76.5%	0.0999%	21.0	linear interpolation
76.6%	0.0999%	21.0	linear interpolation
76.7%	0.0999%	21.1	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
76.8%	0.0999%	21.2	linear interpolation
76.9%	0.0999%	21.3	linear interpolation
77.0%	0.0999%	21.4	linear interpolation
77.1%	0.0999%	21.4	linear interpolation
77.2%	0.0999%	21.5	linear interpolation
77.3%	0.0999%	21.6	linear interpolation
77.4%	0.0999%	21.7	linear interpolation
77.5%	0.0999%	21.8	linear interpolation
77.6%	0.0999%	21.8	linear interpolation
77.7%	0.0999%	21.9	linear interpolation
77.8%	0.0999%	22.0	linear interpolation
77.9%	0.0999%	22.1	linear interpolation
78.0%	0.0999%	22.2	linear interpolation
78.1%	0.0999%	22.2	linear interpolation
78.2%	0.0999%	22.3	linear interpolation
78.3%	0.0999%	22.4	linear interpolation
78.4%	0.0999%	22.5	linear interpolation
78.5%	0.0999%	22.6	linear interpolation
78.6%	0.0999%	22.6	linear interpolation
78.7%	0.0999%	22.7	linear interpolation
78.8%	0.0999%	22.8	linear interpolation
78.9%	0.0999%	22.9	linear interpolation
79.0%	0.0999%	23.0	linear interpolation
79.1%	0.0999%	23.0	linear interpolation
79.2%	0.0999%	23.1	linear interpolation
79.3%	0.0999%	23.2	linear interpolation
79.4%	0.0999%	23.3	linear interpolation
79.5%	0.0999%	23.4	linear interpolation
79.6%	0.0999%	23.4	linear interpolation
79.7%	0.0999%	23.5	linear interpolation
79.8%	0.0999%	23.6	linear interpolation
79.9%	0.0999%	23.7	linear interpolation
80.0%	0.0999%	23.8	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
80.1%	0.0999%	23.9	linear interpolation
80.2%	0.0999%	24.0	linear interpolation
80.3%	0.0999%	24.1	linear interpolation
80.4%	0.0999%	24.2	linear interpolation
80.5%	0.0999%	24.3	linear interpolation
80.6%	0.0999%	24.4	linear interpolation
80.7%	0.0999%	24.6	linear interpolation
80.8%	0.0999%	24.7	linear interpolation
80.9%	0.0999%	24.8	linear interpolation
81.0%	0.0999%	24.9	linear interpolation
81.1%	0.0999%	25.0	linear interpolation
81.2%	0.0999%	25.1	linear interpolation
81.3%	0.0999%	25.2	linear interpolation
81.4%	0.0999%	25.4	linear interpolation
81.5%	0.0999%	25.5	linear interpolation
81.6%	0.0999%	25.6	linear interpolation
81.7%	0.0999%	25.7	linear interpolation
81.8%	0.0999%	25.8	linear interpolation
81.9%	0.0999%	25.9	linear interpolation
82.0%	0.0999%	26.0	linear interpolation
82.1%	0.0999%	26.2	linear interpolation
82.2%	0.0999%	26.3	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
82.3%	0.0999%	26.4	linear interpolation
82.4%	0.0999%	26.5	linear interpolation
82.5%	0.0999%	26.6	linear interpolation
82.6%	0.0999%	26.7	linear interpolation
82.7%	0.0999%	26.8	linear interpolation
82.8%	0.0999%	27.0	linear interpolation
82.9%	0.0999%	27.1	linear interpolation
83.0%	0.0999%	27.2	linear interpolation
83.1%	0.0999%	27.3	linear interpolation
83.2%	0.0999%	27.4	linear interpolation
83.3%	0.0999%	27.5	linear interpolation
83.4%	0.0999%	27.6	linear interpolation
83.5%	0.0999%	27.8	linear interpolation
83.6%	0.0999%	27.9	linear interpolation
83.7%	0.0999%	28.0	linear interpolation
83.8%	0.0999%	28.1	linear interpolation
83.9%	0.0999%	28.2	linear interpolation
84.0%	0.0999%	28.3	linear interpolation
84.1%	0.0999%	28.4	linear interpolation
84.2%	0.0999%	28.6	linear interpolation
84.3%	0.0999%	28.7	linear interpolation
84.4%	0.0999%	28.8	linear interpolation
84.5%	0.0999%	28.9	linear interpolation
84.6%	0.0999%	29.0	linear interpolation
84.7%	0.0999%	29.1	linear interpolation
84.8%	0.0999%	29.2	linear interpolation
84.9%	0.0999%	29.4	linear interpolation
85.0%	0.0999%	29.5	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
85.1%	0.0999%	29.7	linear interpolation
85.2%	0.0999%	29.8	linear interpolation
85.3%	0.0999%	30.0	linear interpolation
85.4%	0.0999%	30.2	linear interpolation
85.5%	0.0999%	30.4	linear interpolation
85.6%	0.0999%	30.6	linear interpolation
85.7%	0.0999%	30.7	linear interpolation
85.8%	0.0999%	30.9	linear interpolation
85.9%	0.0999%	31.1	linear interpolation
86.0%	0.0999%	31.3	linear interpolation
86.1%	0.0999%	31.5	linear interpolation
86.2%	0.0999%	31.7	linear interpolation
86.3%	0.0999%	31.8	linear interpolation
86.4%	0.0999%	32.0	linear interpolation
86.5%	0.0999%	32.2	linear interpolation
86.6%	0.0999%	32.4	linear interpolation
86.7%	0.0999%	32.6	linear interpolation
86.8%	0.0999%	32.8	linear interpolation
86.9%	0.0999%	32.9	linear interpolation
87.0%	0.0999%	33.1	linear interpolation
87.1%	0.0999%	33.3	linear interpolation
87.2%	0.0999%	33.5	linear interpolation
87.3%	0.0999%	33.7	linear interpolation
87.4%	0.0999%	33.8	linear interpolation
87.5%	0.0999%	34.0	linear interpolation
87.6%	0.0999%	34.2	linear interpolation
87.7%	0.0999%	34.4	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
87.8%	0.0999%	34.6	linear interpolation
87.9%	0.0999%	34.8	linear interpolation
88.0%	0.0999%	34.9	linear interpolation
88.1%	0.0999%	35.1	linear interpolation
88.2%	0.0999%	35.3	linear interpolation
88.3%	0.0999%	35.5	linear interpolation
88.4%	0.0999%	35.7	linear interpolation
88.5%	0.0999%	35.8	linear interpolation
88.6%	0.0999%	36.0	linear interpolation
88.7%	0.0999%	36.2	linear interpolation
88.8%	0.0999%	36.4	linear interpolation
88.9%	0.0999%	36.6	linear interpolation
89.0%	0.0999%	36.8	linear interpolation
89.1%	0.0999%	36.9	linear interpolation
89.2%	0.0999%	37.1	linear interpolation
89.3%	0.0999%	37.3	linear interpolation
89.4%	0.0999%	37.5	linear interpolation
89.5%	0.0999%	37.7	linear interpolation
89.6%	0.0999%	37.8	linear interpolation
89.7%	0.0999%	38.0	linear interpolation
89.8%	0.0999%	38.2	linear interpolation
89.9%	0.0999%	38.4	linear interpolation
90.0%	0.0999%	38.6	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
90.1%	0.0999%	38.9	linear interpolation
90.2%	0.0999%	39.3	linear interpolation
90.3%	0.0999%	39.7	linear interpolation
90.4%	0.0999%	40.0	linear interpolation
90.5%	0.0999%	40.4	linear interpolation
90.6%	0.0999%	40.7	linear interpolation
90.7%	0.0999%	41.1	linear interpolation
90.8%	0.0999%	41.5	linear interpolation
90.9%	0.0999%	41.8	linear interpolation
91.0%	0.0999%	42.2	linear interpolation
91.1%	0.0999%	42.5	linear interpolation
91.2%	0.0999%	42.9	linear interpolation
91.3%	0.0999%	43.3	linear interpolation
91.4%	0.0999%	43.6	linear interpolation
91.5%	0.0999%	44.0	linear interpolation
91.6%	0.0999%	44.3	linear interpolation
91.7%	0.0999%	44.7	linear interpolation
91.8%	0.0999%	45.1	linear interpolation
91.9%	0.0999%	45.4	linear interpolation
92.0%	0.0999%	45.8	linear interpolation
92.1%	0.0999%	46.1	linear interpolation
92.2%	0.0999%	46.5	linear interpolation
92.3%	0.0999%	46.9	linear interpolation
92.4%	0.0999%	47.2	linear interpolation
92.5%	0.0999%	47.6	linear interpolation
92.6%	0.0999%	47.9	linear interpolation
92.7%	0.0999%	48.3	linear interpolation
92.8%	0.0999%	48.7	linear interpolation
92.9%	0.0999%	49.0	linear interpolation
93.0%	0.0999%	49.4	linear interpolation
93.1%	0.0999%	49.8	linear interpolation
93.2%	0.0999%	50.1	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
93.3%	0.0999%	50.5	linear interpolation
93.4%	0.0999%	50.8	linear interpolation
93.5%	0.0999%	51.2	linear interpolation
93.6%	0.0999%	51.6	linear interpolation
93.7%	0.0999%	51.9	linear interpolation
93.8%	0.0999%	52.3	linear interpolation
93.9%	0.0999%	52.6	linear interpolation
94.0%	0.0999%	53.0	linear interpolation
94.1%	0.0999%	53.4	linear interpolation
94.2%	0.0999%	53.7	linear interpolation
94.3%	0.0999%	54.1	linear interpolation
94.4%	0.0999%	54.4	linear interpolation
94.5%	0.0999%	54.8	linear interpolation
94.6%	0.0999%	55.2	linear interpolation
94.7%	0.0999%	55.5	linear interpolation
94.8%	0.0999%	55.9	linear interpolation
94.9%	0.0999%	56.2	linear interpolation
95.0%	0.0999%	58.9	estimate from Ridolfi and Pacific Market Research (2015) using the NCI method; adjusted by Idaho DEQ to account for exclusion of select species
95.1%	0.0999%	60.4	linear interpolation
95.2%	0.0999%	62.0	linear interpolation
95.3%	0.0999%	63.6	linear interpolation
95.4%	0.0999%	65.3	linear interpolation
95.5%	0.0999%	67.1	linear interpolation
95.6%	0.0999%	69.0	linear interpolation
95.7%	0.0999%	71.0	linear interpolation
95.8%	0.0999%	73.1	linear interpolation
95.9%	0.0999%	75.3	linear interpolation
96.0%	0.0999%	77.5	linear interpolation
96.1%	0.0999%	79.9	linear interpolation
96.2%	0.0999%	82.4	linear interpolation
96.3%	0.0999%	85.0	linear interpolation
96.4%	0.0999%	87.8	linear interpolation
96.5%	0.0999%	90.6	linear interpolation
96.6%	0.0999%	93.6	linear interpolation
96.7%	0.0999%	96.7	linear interpolation
96.8%	0.0999%	99.9	linear interpolation
96.9%	0.0999%	103	linear interpolation
97.0%	0.0999%	107	linear interpolation
97.1%	0.0999%	110	linear interpolation
97.2%	0.0999%	114	linear interpolation
97.3%	0.0999%	118	linear interpolation
97.4%	0.0999%	122	linear interpolation
97.5%	0.0999%	127	linear interpolation
97.6%	0.0999%	131	linear interpolation
97.7%	0.0999%	136	linear interpolation
97.8%	0.0999%	141	linear interpolation
97.9%	0.0999%	146	linear interpolation
98.0%	0.0999%	151	linear interpolation
98.1%	0.0999%	156	linear interpolation
98.2%	0.0999%	162	linear interpolation
98.3%	0.0999%	168	linear interpolation
98.4%	0.0999%	174	linear interpolation
98.5%	0.0999%	180	linear interpolation
98.6%	0.0999%	187	linear interpolation
98.7%	0.0999%	193	linear interpolation

Table A3. IDEQ Interpolated Idaho Fish Consumption Distribution for the Nez Perce Tribal Population

Percentile	Discrete Probability	FCR (g/day)	Basis
98.8%	0.0999%	200	linear interpolation
98.9%	0.0999%	208	linear interpolation
99.0%	0.0999%	215	linear interpolation
99.1%	0.0999%	223	linear interpolation
99.2%	0.0999%	231	linear interpolation
99.3%	0.0999%	239	linear interpolation
99.4%	0.0999%	248	linear interpolation
99.5%	0.0999%	257	linear interpolation
99.6%	0.0999%	266	linear interpolation
99.7%	0.0999%	275	linear interpolation
99.8%	0.0999%	285	linear interpolation
99.9%	0.0999%	295	linear interpolation
100%	0.0999%	306	estimated maximum value

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Appendix B

Target Excess Lifetime Cancer Risks Commonly Used in Practice

Michele Amaral, Katy Baker and Brian Magee (ARCADIS)

Introduction

The stated goal of environmental management programs is almost uniformly to protect human health and the environment. However, the standard for defining this goal is not as clear. A common misconception is assuming that routine regulatory practice makes risk-based management decisions for carcinogens solely on a total site excess lifetime cancer risk (ELCR) equal to one additional cancer case in an exposed population of one million (1x10^{-6}). In practice, government agencies typically establish a target ELCR exceeding 1x10^{-6} to protect human health and the environment and to take remedial actions, both on a per chemical basis and a total site risk basis. Target ELCRs set by state, national and international agencies have been collated, and the policies of some agencies that are utilizing risk-based approaches that incorporate socio-economic, geographic and political factors to promote cost-effective remediation are discussed.

Review Process

A literature and online review was undertaken, and information was obtained from local risk assessment practitioners in the ARCADIS global network to collate acceptable ELCRs for the United States, the European Union and elsewhere.

United States

The target ELCR risk range in the United States is between 1x10^{-4} to 1x10^{-6} for decision making purposes. Table 1 summarizes state-specific individual and cumulative target ELCRs gathered in the last six months from online sources. ELCR data were available on the internet for 50 states. American Samoa, Northern Marianas Islands, Puerto Rico and the Virgin Islands are also included in the summary.

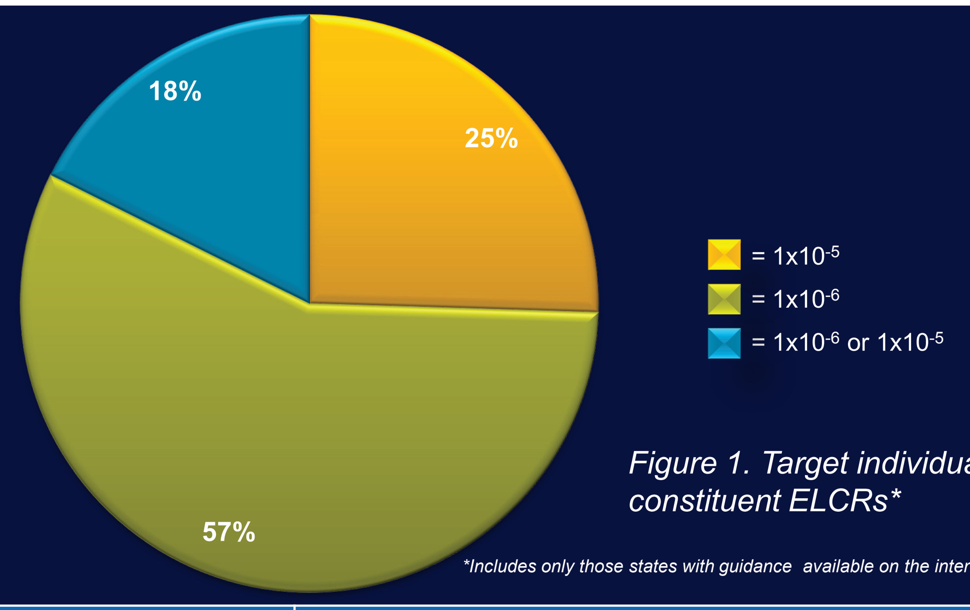

*Figure 1. Target individual constituent ELCRs**

**Includes only those states with guidance available on the internet.*

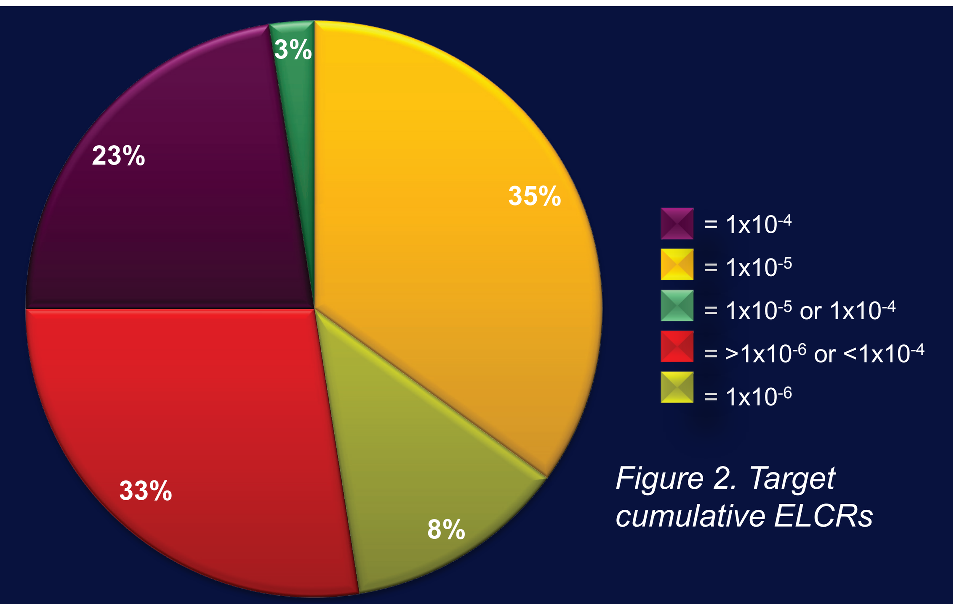

Figure 2. Target cumulative ELCRs

- The general tendency is for states to regulate cumulative ELCRs roughly an order of magnitude or more higher than individual constituent ELCRs (Figures 1 and 2).
- The review shows that most states reviewed (57%) select 1x10^{-6} as an individual constituent target ELCR for a "Tier 1" type of risk-based screen.
- 92% of states reviewed use cumulative target ELCRs exceeding 1x10^{-6} to allow for flexibility in decision making.

Notes:
ELCR = Excess lifetime cancer risk expressed as 1 x 10^{-6} (one-in-one million)
ESL = Environmental screening level
NA = Not available
RECAP = Risk Evaluation Corrective Action Program

Data were obtained from only internet searches.

State	Individual ELCR(s)	Cumulative ELCR(s)	Comments
Alabama	1x10^{-6} or 1x10^{-5}	1x10^{-5}	Preliminary screening levels based on 1x10^{-6}, risk management evaluations based on 1x10^{-5}
Alaska	1x10^{-6}	1x10^{-5}	Alternative cleanup levels based on 1x10^{-5}
American Samoa	NA	NA	
Arizona	1x10^{-6} or 1x10^{-5}	>1x10^{-6} and <1x10^{-4}	May use 1x10^{-5} individual ELCR if constituent is not a human carcinogen or site not used for child care
Arkansas	1x10^{-6}	>1x10^{-6} and <1x10^{-4}	Region 6 human health medium-specific screening levels
California	1x10^{-6}	>1x10^{-6} and <1x10^{-4}	California human health screening levels
Colorado	1x10^{-6}	NA	Soil evaluation values
Connecticut	1x10^{-6}	1x10^{-5}	Water quality standards, remediation standards regulations
Delaware	1x10^{-6}	1x10^{-5}	Remediation standards
District of Columbia	1x10^{-6}	NA	Tier 1 risk-based screening levels, 2A and 2B site-specific target levels are based on 1x10^{-6}
Florida	1x10^{-6}	1x10^{-6}	Contaminant cleanup target levels
Georgia	1x10^{-5}	1x10^{-5}	Environmental Protection Division Risk Reduction Standards
Guam	1x10^{-6} or 1x10^{-5}	>1x10^{-6} and <1x10^{-4}	Pacific Basin ESLs, individual ELCR for soil direct contact select constituents and vapor intrusion risk for TCE is 1x10^{-5}
Hawaii	1x10^{-6} or 1x10^{-5}	>1x10^{-6} and <1x10^{-4}	Pacific Basin ESLs, individual ELCR for soil direct contact select constituents and vapor intrusion risk for TCE is 1x10^{-5}
Idaho	1x10^{-6}	1x10^{-5}	Initial default target levels
Illinois	1x10^{-6}	1x10^{-4}	Risk-based cleanup objectives, cumulative ELCR only discussed for groundwater objectives 742.805(d)
Indiana	1x10^{-5}	NA	Risk Integrated System of Closure (RISC) default soil closure tables, cumulative risk not discussed
Iowa	1x10^{-5}	1x10^{-4}	Targets found in supporting information
Kansas	1x10^{-5}	NA	Tier 2 risk-based standards
Kentucky	1x10^{-6}	>1x10^{-6} and <1x10^{-4}	Follows 2002 preliminary remediation goals
Louisiana	1x10^{-6}	>1x10^{-6} and <1x10^{-4}	RECAP screening standards, management option 3 risk levels higher than 1x10^{-6} may be allowed
Maine	1x10^{-6}	1x10^{-5}	Has guidelines for soil, groundwater, oil and ambient air
Maryland	1x10^{-6} for soil and 1x10^{-5} for groundwater	1x10^{-4}	Hot spot defined as >1x10^{-4}
Massachusetts	1x10^{-6}	1x10^{-5}	Massachusetts Contingency Plan 310 Code of Massachusetts Regulations 40.0902(2)(b)
Michigan	1x10^{-5}	NA	Soil direct contact criteria
Minnesota	1x10^{-5}	1x10^{-5}	Soil reference values
Mississippi	1x10^{-6}	1x10^{-4}	Target remediation goals, Tier 1 to Tier 3 is 1x10^{-6}
Missouri	1x10^{-5}	1x10^{-4}	Risk-based target levels
Montana	1x10^{-6}	1x10^{-5}	Risk-based screening levels for surface, subsurface and groundwater
Nebraska	MCL, 1x10^{-6} or 1x10^{-5}	NA	Risk-based screening levels targets are variable depending on complete exposure pathways
Nevada	1x10^{-6}	1x10^{-6}	Basic comparison levels
New Hampshire	1x10^{-6}	NA	Risk-based soil values, values available for three levels of exposure (S-1 to S-3), including recreator
New Jersey	1x10^{-6}	NA	Soil cleanup criteria
New Mexico	1x10^{-5}	1x10^{-5}	Soil screening levels
New York	1x10^{-6}	1x10^{-6}	Soil cleanup objectives and water standards, cumulative ELCR inferred
North Carolina	1x10^{-6}	>1x10^{-6} and <1x10^{-4}	Soil remediation goals, risk range allowed for soil with a deed restriction and for groundwater if contained on site.
North Dakota	NA	NA	Cleanup action level guidelines
Northern Marianas Islands	1x10^{-6} or 1x10^{-5}	>1x10^{-6} and <1x10^{-4}	Pacific Basin ESLs, individual ELCR for soil direct contact PAHs and PCBs and vapor intrusion risk for TCE is 1x10^{-5}
Ohio	1x10^{-6}	>1x10^{-6} and <1x10^{-4}	U.S. Environmental Protection Agency regional screening levels
Oklahoma	1x10^{-5}	1x10^{-4}	Risk-based screening levels
Oregon	1x10^{-6}	1x10^{-5}	Risk-based concentrations
Pennsylvania	1x10^{-5}	>1x10^{-6} and <1x10^{-4}	Medium specific concentrations, risk range allowed for both USTs and general Act 2 (voluntary) sites
Puerto Rico	NA	NA	
Rhode Island	NA	NA	
South Carolina	1x10^{-6}	>1x10^{-6} and <1x10^{-4}	Risk-based screening level, Tier-3 risk levels higher than 1x10^{-6} may be allowed
South Dakota	1x10^{-5}	NA	Surface soil for benzene, toluene, ethylbenzene, xylenes, methyl tertiary butyl ether and naphthalene only
Tennessee	1x10^{-5}	1x10^{-5} or 1x10^{-4}	Risk-based cleanup levels, site-specific target levels at 1x10^{-5} for residential and 1x10^{-4} for commercial worker
Texas	1x10^{-5}	1x10^{-4}	Protective concentrations levels
Utah	1x10^{-6} or other	NA	Risk-based screening levels (for petroleum sites)
Vermont	1x10^{-6}	NA	Draft soil screening values
Virginia	1x10^{-6}	1x10^{-4}	
Virgin Islands	NA	NA	
Washington	1x10^{-6}	1x10^{-5}	Standard and modified Method B cleanup levels, Method C levels are based on 1x10^{-5}
West Virginia	1x10^{-6} or 1x10^{-5}	1x10^{-4}	For individual ELCR, 1x10^{-6} is used for residential receptors and 1x10^{-5} is used for commercial/industrial receptors
Wisconsin	1x10^{-6}	1x10^{-5}	For direct contact with arsenic and chromium-6 the individual ELCR is 1x10^{-7}
Wyoming	1x10^{-6}	>1x10^{-6} and <1x10^{-4}	Soil cleanup levels

European Union

Concerted Action on Risk Assessment for Contaminated Sites (CARACAS, 1998) and the European Commission Joint Research Centre (2007) reported that the tolerable ELCR typically used in the context of genotoxic carcinogens on contaminated sites in the European Union ranges from 1x10^{-6} (e.g., Denmark) to 1x10^{-4} per substance (Netherlands), with the majority of countries preferring 1x10^{-5}. In the UK, an acceptable risk level has not been defined because margin of safety approaches are used for both carcinogenic and noncarcinogenic criteria instead of calculating ELCR levels as done in other countries.

Policy decisions

Good evidence exists that acceptable ELCRs are influenced by policy decisions and other political elements, such as the receptor at risk (Provoost et al., 2006), along with scientific evidence. For example, the current USEPA National Primary Drinking Water Regulations or primary standards, such as Maximum Contaminant Levels (MCLs) applicable to public water systems are based on policy decisions which incorporate social, economic and best available technology considerations and not target ELCRs. This policy appears to be changing with EPA's recent proposal to set MCLs for groups of related chemicals on a cumulative risk basis. Also, the WHO air constituent concentrations are presented for 1x10^{-4}, 1x10^{-5} and 1x10^{-6} target ELCRs to enable flexibility in decision-making.

International

- The World Health Organization (2011) drinking water quality guidelines are based on a target ELCR of 1x10^{-5}.
- New Zealand (New Zealand Ministry for the Environment, 2010), Mexico, Brazil, China (PRC, 1999), South Africa and Thailand (PCD, 2004) commonly use a target ELCR of 1x10^{-5}.
- Canadian Soil Quality Guidelines (CCME, 2006) are based on the more conservative of either human health or ecological receptors. For human exposures target ELCRs of 1x10^{-6} and 1x10^{-5} are used.
- Australia has no formal policy regarding the level of acceptable risk. However, common practice has been to use an ELCR of 1x10^{-5} (Friebel and Nadebaum, 2010).

Conclusions

- As use of risk-based approaches to make future site environmental management decisions continues, the need for consistency is becoming more apparent (ITRC, 2008).
- Acceptable ELCRs range from 1x10^{-4} to 1x10^{-6} globally, but many countries, including those with newly developing risk-based programs, typically select a cumulative ELCR of 1x10^{-5}.
- Potential benefits of using ELCRs exceeding 1x10^{-6} for decision making purposes include flexibility within risk-based corrective action programs and prioritization of remedial actions where the greatest potential for risk reduction exists allowing for better allocation of technical and financial resources.

Recommendations

Understanding the basis for risk-based cleanup criteria and risk management decisions is imperative to site managers. Ultimately, the goals should be to protect human health and the environment, but in a cost-effective and technically defensible manner.

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References provided on separate handout

DERIVATION OF ALTERNATE RELATIVE SOURCE CONTRIBUTION FACTORS

November 2015

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ACRONYMS AND ABBREVIATIONS

AMA	Ambient Monitoring Archive
BAF	bioaccumulation factor
BBP	butylbenzyl phthalate
EWG	Environmental Working Group
FDEP	Florida Department of Environmental Protection
HHAWQC	human health ambient water quality criteria
IDEQ	Idaho Department of Environmental Quality
IRIS	Integrated Risk Information System
MCL	maximum contaminant level
PAH	polycyclic aromatic hydrocarbons
ppb	parts per billion
RfD	reference dose
RSC	relative source contribution
USEPA	United States Environmental Protection Agency
USGS	United States Geological Survey

1 INTRODUCTION

On October 7, 2015, the Idaho Department of Environmental Quality (IDEQ) released its draft human health ambient water quality criteria (HHAWQC) rule. The draft HHAWQC were calculated using relative source contribution (RSC) factors adopted from the 2015 United States Environmental Protection Agency (USEPA) update of HHAWQC (USEPA 2015). The recent USEPA guidance (2015) and the proposed IDEQ draft HHAWQC recommend using an RSC factor to account for non-ambient exposures when deriving human health water quality criteria (HHWQC) for non-carcinogens. The RSCs can be based on chemical-specific information or on an arbitrary default value of 0.2 when the USEPA determines that data or resources are not available to derive reliable quantitative estimates for all (surface water and non-surface water) relevant exposure pathways. However, if exposure estimates are available for all non-surface water related exposure pathways, the remaining exposure below the allowable daily intake or exposure (typically the reference dose, RfD) can be conservatively allocated to surface water sources.

This report presents the calculation of chemical-specific RSCs for the following 11 compounds: acenaphthalene, anthracene, fluoranthene, fluorene, pyrene, 2-chlorophenol, selenium, diethyl phthalate, chloroform, butylbenzyl phthalate (BBP) and toluene. The recent USEPA updated HHAWQC (USEPA 2015) concluded that insufficient data are available to derive exposure estimates for all 11 of these compounds and have thus incorporated the default RSC of 0.2 in the calculation of each HHAWQC. Contrary to USEPA's conclusions and consistent with the recent information compiled by the Florida Department of Environmental Protection (FDEP 2014), Arcadis determined that sufficient data are available to develop conservative estimates of non-surface water exposures and robust, scientifically defensible and conservative RSCs. As summarized in the table below, the Arcadis derived RSCs are greater than the default RSC of 0.2. Using the chemical-specific RSCs results in HHAWQC that are 2 to 5 times greater than HHAWQC derived using a default RSC. Arcadis recommends that final Idaho HHAWQC for these eleven compounds incorporate the RSCs derived in this report.

Compound	IDEQ Draft RSCs	Arcadis Proposed RSCs	Idaho Draft HHAWQC (ug/L)	Idaho Draft HHAWQC adjusted with Arcadis RSC (ug/L)
Acenaphthene	0.2	0.99	78	386
Anthracene	0.2	1.0	340	1700
Fluoranthene	0.2	1.0	20	100
Fluorene	0.2	0.99	51	252
Pyrene	0.2	1.0	26	130
2-chlorophenol	0.2	0.91	19	86
Selenium	0.2	0.65	20	65
Diethyl phthalate	0.2	0.97	620	3007
Chloroform	0.2	0.64	39	125
Toluene	0.2	0.31	36	56
Butylbenzyl phthalate	0.2	0.99	0.11	0.54

2 NON-CARCINOGENIC PAHS

The recent 2015 USEPA Update of HHAWQC (USEPA 2015) selects an RSC of 0.2 for the following five polycyclic aromatic hydrocarbons (PAHs) that are considered to be non-carcinogenic: acenaphthene, anthracene, fluoranthene, fluorene, and pyrene. USEPA (2015) indicates that information is not available to quantitatively characterize exposure from all potentially significant sources of PAHs. According to the USEPA (2000), relevant sources and pathways for consideration in the RSC include both ingestion and routes other than oral for water-related exposures and non-water sources of exposure, including ingestion exposures (e.g., food), inhalation, and/or dermal. In 2014, the FDEP conducted an extensive review of the information available on exposure to these five non-carcinogenic PAHs. As a result of that review FDEP derived the following RSCs:

PAH	FDEP (2014) RSC
Acenaphthene	0.95
Anthracene	1
Fluoranthene	0.99
Fluorene	0.92
Pyrene	0.99

Arcadis reviewed information relevant to the derivation of an RSC for acenaphthene, anthracene, fluoranthene, fluorene, and pyrene. Specifically, information about concentrations of these PAHs in various environmental media and exposure assessment approaches used by FDEP and USEPA were reviewed and updated as appropriate. Based on the physical properties and available exposure information for acenaphthene, anthracene, fluoranthene, fluorene, and pyrene; air, diet, soil, and drinking water are potential exposure sources. To the contrary of USEPA's conclusions and consistent with the information developed by FDEP in 2014, sufficient data are available to develop conservative estimates of non-surface water exposure to these non-carcinogenic PAHs and to develop a robust, scientifically defensible and conservative RSCs.

Ambient air exposures were estimated in FDEP (2014) using concentration data obtained from a Florida – specific study (Poor et al. 2004). For this assessment, available ambient air data collected by the IDEQ were obtained for acenaphthene, anthracene, fluoranthene, and pyrene from the USEPA Ambient Monitoring Archive[1] (AMA). Idaho-specific ambient air data for fluorene was not reported in the AMA. The following table summarizes the AMA data for individual PAH ambient air concentrations collected from December 2002 through March 2005 for Site ID 160270004 located in Nampa, the second largest city in Idaho, and centrally located in the Treasure Valley[2]. These data are reported as the total of both gas-phase and particle-phase ambient air concentrations for individual PAHs, as PAHs occur in the atmosphere in both the vapor phase and the particle phase.

[1] http://www.epa.gov/ttnamti1/toxdat.html#data

[2] According to the IDEQ (IDEQ 2009), Nampa has a diverse source profile including Title V (major point sources) and minor sources, light industry, and sprawling residential areas feeding heavy commuter traffic. As such, these concentrations likely overestimate the concentrations of these PAHs in many areas of Idaho and can, therefore, be considered conservative estimates of the air concentrations of these PAHs for Idaho.

PAH	Minimum Total Gas and Particle Phase Result (ng/m^3)	Maximum Total Gas and Particle Phase Result (ng/m^3)	Mean Total Gas and Particle Phase Result (ng/m^3)
Acenaphthene	<0.05	4.48	0.68
Anthracene	<0.05	4.65	0.85
Fluoranthene	0.05	5.97	1.52
Pyrene	0.05	5.29	1.42

Note: Data obtained from USEPA Ambient Monitoring Archive.

Mean outdoor air values were combined with a revised upper percentile outdoor breathing rate of 3.6 m^3/day and an updated body weight of 80 kg to derive ambient air exposures to acenaphthene, anthracene, fluoranthene, and pyrene. FDEP uses an assumed bodyweight of 70 kg, whereas Arcadis assumes a bodyweight of 80 kg per USEPA (2011a) and consistent with the bodyweight assumed by USEPA recently updated HHAWQC (USEPA 2015). For the outdoor breathing rate, FDEP (2014) assumes a value of 3.12 m^3/day derived from a mean breathing rate of 16 m^3/day obtained from USEPA (2011a) and an adjustment to account for time spent outdoors (20%) versus indoors (80%) per Table 16-22a of USEPA (2011a). Arcadis uses this same 20% adjustment to determine an outdoor breathing rate of 3.6 m^3/day; however, Arcadis applies this adjustment to the 90th percentile breathing rate of 18 m^3/day (Table 6-4 USEPA 2011a; mean of 90th percentile male and female values) instead of the mean breathing rate. Ambient air exposures for fluorene are consistent with methods presented in FDEP (2014) with the exception of the assumed bodyweight of 80 kg and the revised upper percentile breathing rate of 3.6 m^3/day.

Methods used in this assessment to determine indoor air exposures to individual PAHs are consistent with methods presented in FDEP (2014) with the exception of the assumed bodyweight (80 kg was used in this assessment versus 70 kg) and the use of a revised upper percentile indoor breathing rate. Specifically, mean indoor air PAH concentrations identified in FDEP (2014) were combined with an indoor breathing rate of 14.4 m^3/day and a body weight of 80 kg. FDEP assumes indoor breathing rate of 12.88 m^3/day derived from a mean breathing rate of 16 m^3/day (USEPA 2011a) and an adjustment to account for time spent indoors (80% per Table 16-22a of USEPA 2011a), while Arcadis applies the 80% indoor adjustment to the 90th percentile breathing rate of 18 m^3/day (Table 6-4 USEPA 2011a; mean of 90th percentile male and female values).

Exposure from diet was estimated using methods consistent with methods presented in FDEP (2014). As summarized in FDEP (2014), acenaphthene and fluorene exposures were estimated from Santodonato et al. (1981) and are conservatively based on the total PAH concentrations reported in that study. Dietary exposures for anthracene, fluoranthene, and pyrene were obtained from an occurrence study prepared by the European Commission (EC 2002).

Soil ingestion exposures for individual non-carcinogenic PAHs were presented in FDEP (2014). For anthracene, fluoranthene, fluorene, and pyrene, FDEP (2014) relies on PAH concentrations presented in Chahal et al. (2010), a Florida-specific study on urban residential soil in Pinellas County, Florida. For acenaphthene, the FDEP (2014) soil exposures are based on data presented in Wang et al. (2008). The Wang study reported PAHs from two major United States cities, New Orleans and Detroit, and the sampling sites included house foundations, open spaces, and soils bordering residential (light to moderate traffic) and busy (heavy traffic) streets. For this assessment, one additional background PAH study (Bradley et al. 1994) was reviewed. The Bradley study focuses on background PAH surface soil concentrations in three urban areas of New England: Boston, Massachusetts; Springfield, Massachusetts; and Providence, Rhode Island. A summary of mean soil concentrations reported in these three studies is provided below.

Mean Background Soil Data (ug/kg)			
PAH	**Chahal et al. (2010)**	**Wang et al. (2008)**	**Bradley et al. (1994)**
Acenaphthene	Not Evaluated	16.5	**201**
Anthracene	110	**679**	351
Fluoranthene	133	12.8	**3,047**
Fluorene	33	46.6	**214**
Pyrene	297	573	**2,393**

Note: Maximum values for each non-carcinogenic PAH are bolded

The maximum of the three available mean background concentrations (in bold above) were combined with a soil ingestion rates of 50 mg/day and a bodyweight of 80 kg (USEPA 2011a) to derive soil exposure estimates for acenaphthene, anthracene, fluoranthene, fluorene, and pyrene. The soil exposure estimates are conservative, as data available from Bradley et al. (1994) and Wang et al. (2008) were collected from highly urbanized locations with historic development and have many more sources that expected in most of Idaho. Additionally, data from Bradley et al (1994) represent PAH concentrations from sources present 25 years ago. Present day soils would be expected to be much lower based on emission controls on mobile sources such as cars, trucks, and buses.

Treated drinking water exposures to non-carcinogenic PAHs were presented in FDEP (2014). FDEP relies on concentration data published in Kabziński et al. (2002), which reports individual PAH concentrations in drinking water from several Polish cities. Arcadis researched available drinking water data within the United States, including the National Drinking Water Database created by the Environmental Working Group (EWG). EWG requested water data from public and environmental health agencies from around the country and has compiled nearly 20 million records from 45 states. According to EWG's analysis of water quality data supplied by state water agencies, no water utilities in Idaho reported detecting these five non-carcinogenic PAHs in treated tap water between 2005 and 2009. However, EWG does list the highest of the average reported concentrations in United States drinking water for acenaphthene (3.7 ug/L), anthracene (0.1 ug/L), fluoranthene (1.1 ug/L), fluorene (9.1 ug/L), and pyrene (0.4 ug/L). In this assessment, these average reported United States drinking water concentrations were combined with an assumed bodyweight and a drinking water ingestion rate of 2.4 L/day to derive drinking water exposures.

When the changes described above (i.e., updated drinking water, soil, ambient air concentrations; updated drinking water ingestion rate; updated indoor and outdoor inhalation rates; and updated body weight for drinking water, inhalation, and soil exposures) are incorporated into the exposure estimates, the

RSCs for acenaphthene, anthracene, fluoranthene, fluorene, and pyrene are 0.99, 1, 1, 0.99, and 1, respectively[3]. The environmental media concentration data reviewed to develop the above estimated exposures from non-surface water exposures overestimate, likely greatly in most cases, PAH concentrations in Idaho. When these estimated concentrations are combined with high-end assumptions about intake rates, background exposures are overestimated. As a result, the estimated RSCs are smaller (more conservative) than necessary to prevent the total exposure of Idahoans with high-end exposures from exceeding the reference dose for each of these PAHs. Arcadis recommends that final HHAWQC for these five PAHs incorporate the RSCs derived in this report.

Exposure Route	Acenaphthene	Anthracene	Fluoranthene	Fluorene	Pyrene
	mg/kg-day				
Inhalation of Outdoor Air	3.06E-08	3.81E-08	6.82E-08	2.89E-07	6.41E-08
Inhalation of Indoor Air	6.84E-07	1.75E-06	3.96E-07	8.28E-07	2.16E-07
Diet	2.90E-04	9.00E-06	2.40E-05	2.90E-04	1.6E-05
Soil Ingestion	1.26E-07	4.24E-07	1.90E-06	1.34E-07	1.50E-06
Treated Drinking Water	1.11E-04	3.00E-06	3.30E-05	2.73E-04	1.20E-05
Estimated Total Daily Dose	**4.02E-04**	**1.42E-05**	**6.02E-05**	**5.64E-04**	**3.07E-05**
Reference Dose	0.06	0.3	0.04	0.04	0.03
Relative Source Contribution	**0.99**	**1**	**1**	**0.99**	**1**

3 2-CHLOROPHENOL

The recent 2015 USEPA HHAWQC (USEPA 2015) selects an RSC of 0.2 for 2-chlorophenol and indicates that information is not available to quantitatively characterize exposure from potential significant exposures. According to the USEPA (2000), relevant sources and pathways for consideration in the RSC include both ingestion and routes other than oral for water-related exposures and non-water sources of exposure, including ingestion exposures (e.g., food), inhalation, and/or dermal. In 2014, the FDEP conducted an extensive review of the information available on exposure to 2-chlorophenol. As a result of that review, FDEP derived an RSC of 0.89 for 2-chlorophenol (FDEP 2014). Ultimately, FDEP selected a final RSC of 0.8 for 2-chlorophenol for reasons described below.

> *"…the estimated exposure was calculated based on limited data or surrogate estimates (i.e., drinking water); therefore, it only serves as one line of evidence supporting an RSC. FDEP also considered the fact that 2-chlorophenol, like most chlorophenols, exhibits objectionable taste and odor at very low concentrations. The ATSDR (1999) noted that potential exposure, for the general population, to chlorophenols tends to be limited because of the pronounced odor and taste imparted by the presence of these substances. Taste and odor thresholds for 2-chlorophenol have been noted in the range of 2 to 4 parts per billion (ppb) and have been noted to affect the flavor of fish at concentrations of about 2 to 43*

[3] RSCs of 1.0 arise when the fraction of the RfD taken up by non-surface water sources is less than 0.005 and, therefore, the RSC rounds to 1, meaning that essentially all of the RfD can be allotted to exposures associated with regulated surface water exposures.

> *times lower than the odor thresholds for these compounds in water. Thus, it is highly unlikely that the general population is exposed to significant levels of the compound. An RSC of 0.8 (USEPA ceiling) was selected based on a consideration of both the characteristics of the compound (i.e., objectionable taste and odor) and the estimated low total non-ambient exposure."*

Arcadis reviewed information relevant to the derivation of an RSC for 2-chlorophenol. Specifically, information about concentrations of 2-chlorophenol in various environmental media and exposure assessment approaches used by FDEP and USEPA were reviewed and updated as appropriate. Based on the physical properties and available exposure information for 2-chlorophenol, drinking water, air, and diet are potential exposure sources. To the contrary of USEPA's conclusions and consistent with the information developed by FDEP in 2014, sufficient data are available to develop conservative estimates of non-surface water exposure to 2-chlorophenol and to develop a robust, scientifically defensible and conservative RSC for 2-chlorophenol.

Treated drinking water exposures were calculated consistent with methods presented in FDEP (2014) with the exception of the assumed bodyweight and the drinking water ingestion rate (80 kg was used as the bodyweight in this assessment versus 70 kg used by FDEP; 2.4 L/day was used as the ingestion rate in this assessment versus 2 L/day). As summarized in FDEP (2014), a value of 0.1 ug/L was selected as a 2-chlorophenol drinking water concentration because this is the concentration that USEPA recommends to mitigate chemical-specific taste (ATSDR 1999).

Ambient air inhalation exposures were calculated consistent with methods presented in FDEP (2014) with the exception of the assumed bodyweight. FDEP uses an assumed bodyweight of 70 kg, whereas Arcadis assumes a bodyweight of 80 kg per USEPA (2011a). An assumed air concentration of 2 ug/m^3 was combined with a 90th percentile daily breathing rate of 18 m^3/day (average of men and women) and a mean body weight of 80 kg. The assumed air concentration is based on available ambient air data collected after the accidental derailment and rupture of a train tanker. On the day of the accident, air concentrations ranging from 0.02 to 0.7 mg/m^3 were detected in the immediate vicinity of the spill (Scow et al. 1982). Eighteen days after the spill, 2-chlorophenol was not detected in ambient air (< 2 μg/m^3) and 2-chlorophenol levels in urine of clean-up workers and people living within 40 to 200 feet of the spill had no detectable levels in their urine two to three months after the spill. Similar to FDEP, this assessment assumes that concentrations below the detection limit of 2 μg/m^3 represent typical ambient air conditions. Using the full detection limit in the exposure calculations is conservative since actual concentrations of 2-chlorophenol in air are likely lower than the detection limit.

Data concerning typical concentrations of 2-chlorophenol in soils are limited; however, soil exposures to 2-chlorophenol were presented in FDEP (2014). The same methodology was used in this assessment, with the exception of the assumed bodyweight used in the exposure calculations and the assumed soil concentration (80 kg was used in this assessment versus 70 kg used by FDEP). FDEP assumes a soil concentration of 130 mg/kg based on the FDEP residential direct exposure soil clean-up target level of 130 mg/kg (FDEP 2005). In this assessment, the Idaho Initial Default Target Level of 0.365 mg/kg (based on groundwater protection) developed by the Idaho IDEQ (2004) was combined with a soil ingestion rate of 50 mg/day and a bodyweight of 80 kg (USEPA 2011a) to derive soil exposure estimates for 2-

chlorophenol. The IDTL represents a level above which the state of Idaho would initiate clean-up protocols.

Based on a review of literature data, FDEP (2014) concludes that exposures to 2-chlorophenol in diet is negligible. Few data were found on the levels of chlorophenols in United States Foods and most of the data or estimates are for concentrations in fish or shellfish. Based on Arcadis' additional review of the DeVault (1985) study in which 2-chlorophenol was not detected in 22 composite samples of fish collected from harbors and tributaries of the Great Lakes (DeVault 1985), Arcadis concurs with FDEPs assessment of dietary exposures.

When the changes described above (updated drinking water ingestion rate; updated inhalation rate; updated bodyweight for water, air, and soil exposures; and an updated soil concentration for soil exposures) are incorporated into the exposure estimates, the RSC for 2-chlorophenol becomes 0.91. The RSC is slightly higher than the RSC of 0.89 derived by FDEP (2014) because of the change in assumed soil concentration. The RSC is also higher than the final RSC of 0.8 selected by FDEP, as FDEP further reduced the derived value of 0.89 to account for limited data on background exposures to 2-chlorophenol. The environmental media concentration data reviewed to develop the above estimated exposures from non-surface water exposures overestimate, likely greatly in most cases, 2-chlorophenol concentrations in Idaho. When these estimated concentrations are combined with high-end assumptions about intake rates, background exposures are overestimated. As a result, the estimated RSC is smaller (more conservative) than necessary to prevent the total exposure of Idahoans with high-end exposures from exceeding the reference dose for 2-chlorophenol. Arcadis recommends that final HHAWQC for 2-chlorophenol incorporate the RSC derived in this report.

Exposure Route	**Arcadis Estimated Exposure mg/kg-day**
Treated Drinking Water	3.00E-06
Inhalation of Air	4.50E-04
Soil Ingestion	2.28E-07
Estimated Total Daily Dose	**4.53E-04**
Reference Dose	0.005
Relative Source Contribution	**0.91**

4 SELENIUM

The recent 2015 USEPA HHAWQC (USEPA 2015) did not apply an RSC for ambient water quality criteria development and cited "*outstanding technical issues related to toxicity values and/or bioaccumulation factors*". However, the proposed Idaho HHAWQC selected an RSC of 0.2 for selenium and indicates that information is not available to quantitatively characterize exposure from potential significant exposures. In 2014, the FDEP conducted an extensive review of the information available on exposure to selenium. As a result of that review, FDEP derived an RSC value of 0.58 for selenium (FDEP 2014).

Arcadis reviewed information relevant to the derivation of an RSC for selenium. Specifically, information about concentrations of selenium in various environmental media and exposure assessment approaches used by FDEP and USEPA were reviewed and updated as appropriate. Based on the physical properties and available exposure information for selenium, air, drinking water, soil, and diet are potential exposure sources. To the contrary of USEPA's conclusions and consistent with the information developed by FDEP in 2014, sufficient data are available to develop conservative estimates of non-surface water exposure to selenium and to develop a robust, scientifically defensible and conservative RSC for selenium.

Treated drinking water exposures were calculated consistent with methods presented in FDEP (2014) with the exception of the assumed bodyweight and the drinking water ingestion rate (80 kg was used as the bodyweight in this assessment versus 70 kg used by FDEP; 2.4 L/day was used as the ingestion rate in this assessment versus 2 L/day). As summarized in FDEP (2014), a value of 10 ug/L was selected as a selenium drinking water concentration based on ATSDR (2003), which reported that levels of selenium are less than 10 µg/L/ in 99.5 percent of drinking water sources tested. A recent review of Idaho-specific data between 2004 and 2009 correlates well with the FDEP selected exposure data, as the highest reported average level of selenium in Idaho tap water was 8 ug/L (http://www.ewg.org/tap-water/whatsinyourwater/1045/ID/Idaho/Selenium-total/).

Outdoor air inhalation exposures were calculated consistent with methods presented in FDEP (2014) with the exception of the assumed bodyweight and inhalation rate. FDEP uses an assumed bodyweight of 70 kg, whereas Arcadis assumes a bodyweight of 80 kg per USEPA (2011a). An upper-bound outdoor air breathing rate of 3.6 m^3/d was calculated based on the 90th percentile daily breathing rate of 18 m^3/d for the average of male and female adults (Table 6-4 from USEPA 2011a) and an assumption that 20% of time is spent outdoors (Table 16-22 of USEPA 2011a). An upper-bound outdoor air selenium concentration of 10 ng/m^3 (World Health Organization 2011) was combined with the outdoor air breathing rate of 3.6 m^3/day and a body weight of 80 kg. As part of this assessment, available ambient air data collected by the IDEQ were obtained for selenium from the USEPA AMA (http://www.epa.gov/ttnamti1/toxdat.html#data). A review of the 2013 AMA data indicates maximum detected concentrations of selenium PM 2.5 at three Idaho ambient air sampling sites of 1.5 ng/m^3, 0.56 ng/m^3, and 0.43 ng/m^3. As such, the FDEP ambient air exposures are conservative estimates of Idaho-specific exposures.

In this assessment, diet exposures differ from those by FDEP (2014) in that the assumed bodyweight was updated and selenium intake values were revised. FDEP uses an assumed bodyweight of 70 kg, whereas Arcadis assumes a bodyweight of 80 kg per USEPA (2011). In FDEP (2014), dietary exposure estimates were derived from dietary intake data presented in Bialostosky et al. (2002), which reports a mean selenium intake of 114 ug/day for the total population sampled. This is consistent with dietary intake estimates summarized in ATSDR (2003), which range from 71 to 152 ug/day for the general United States Population. This is also consistent with the more recent NHANES 2011-2012 study that reports a mean selenium intake from food and supplements of 129.7 ug/day for all individuals ages 2 and over (Table 37 of NHANES 2011-2012).

Soil ingestion exposures for selenium were presented in FDEP (2014) and were based on a Florida-specific study (ATSDR (2003). For this assessment, an Idaho-specific soil background study completed for the Ballard, Henry and Enoch Valley phosphate mines was reviewed (MWH Americas, Inc. 2013) and proposed an upland soil background selenium concentration of 1.8 mg/kg. This is consistent with the range of selenium concentrations reported in Western United States soils by Shacklette and Boerngen, (1984) (<0.1 – 4.3 mg/kg). A concentration of 1.8 mg/kg was combined with a soil ingestion rate of 50 mg/day and a bodyweight of 80 kg (USEPA 2011a) to derive soil exposure estimates for selenium. When the changes described above (i.e., updated drinking water ingestion rate; updated body weight for drinking water, inhalation, diet, and soil exposures; and updated soil concentrations) are incorporated into the exposure estimates, the RSC for selenium becomes 0.65. The RSC is higher than that the RSC developed by FDEP (2014) primarily because of an increase in assumed bodyweight and a calculation error by FDEP in their estimate of soil ingestion exposure. The Arcadis derived RSC combines upper bound exposure parameters with scientifically defensible and conservative exposure concentrations. Arcadis recommends that final HHAWQC for selenium incorporate the RSC derived in this report.

Exposure Route	Arcadis Estimated Exposure mg/kg-day
Treated Drinking Water	3.00E-04
Inhalation of Outdoor Air	4.50E-07
Diet	1.43E-03
Soil Ingestion	1.13E-06
Estimated Total Daily Dose	1.73E-03
Reference Dose	5.0E-03
Relative Source Contribution	0.65

5 DIETHYL PHTHALATE

The recent 2015 USEPA Update of HHAWQC (USEPA 2015) selected an RSC of 0.2 for diethyl phthalate and indicates that information is not available to quantitatively characterize exposure from some of those different sources. In 2014, the FDEP conducted an extensive review of the information available on exposure to diethyl phthalate. As a result of that review, FDEP derived an RSC of 0.96 for diethyl phthalate (FDEP 2014).

Arcadis reviewed information relevant to the derivation of an RSC for diethyl phthalate. Specifically, information about concentrations of diethyl phthalate in various environmental media and exposure assessment approaches used by FDEP and USEPA were reviewed and updated as appropriate. Based on the physical properties and available exposure information for diethyl phthalate, drinking water, air, soil, dust, cosmetics/personal care products, and food are potential exposure sources. To the contrary of USEPA's conclusions and consistent with the information developed by FDEP in 2014, sufficient data are available to develop conservative estimates of non-surface water exposure to diethyl phthalate and to develop a robust, scientifically defensible and conservative RSC for diethyl phthalate.

Treated drinking water exposures to diethyl phthalate were presented in FDEP (2014). The same methodology was used in this assessment, with the exception of the assumed bodyweight and drinking water ingestion rates used in the exposure calculations, which were updated to be consistent with USEPA (2011a) exposure assumptions (80 kg was used as the bodyweight in this assessment versus 70 kg used by FDEP; 2.4 L/day was used as the ingestion rate in this assessment versus 2 L/day). FDEP assumes a diethyl phthalate concentration of 2 ug/L in treated water based on the average concentration in treated drinking water reported in a United States Geological Survey (USGS) study conducted in Miami-Dade County Florida (USGS 2008). This assumption is consistent with other available national studies (IPCS 2003, ATSDR 1995, Clark et al. 2011) and was retained for this assessment. In addition, a review of 2012 discharge sampling results from the Brownlee Reservoir in Idaho indicates non-detect levels (< 10 ug/L) of diethyl phthalate (Harrison 2012).

Outdoor and indoor air inhalation diethyl phthalate exposures were calculated consistent with methods presented in FDEP (2014) with the exception of the assumed bodyweight and breathing rate. FDEP uses an assumed bodyweight of 70 kg, whereas Arcadis assumes a bodyweight of 80 kg per USEPA (2011a). FDEP assumes outdoor and indoor breathing rates of 3.12 m^3/day and 12.88 m^3/day, respectively, derived from a mean breathing rate of 16 m^3/day obtained from USEPA 2011a and an adjustment to account for time spent outdoors (20%) versus indoors (80%) per Table 16-22a of USEPA 2011a. Arcadis uses this same 20%/80% adjustment to determine outdoor versus indoor exposures; however, Arcadis applies these adjustments to the 90th percentile breathing rate of 18 m^3/day (Table 6-4 USEPA 2011a; mean of 90th percentile male and female values) instead of the mean breathing rate, resulting in outdoor and indoor breathing rates of 3.6 m^3/day and 14.4 m^3/day, respectively. For the purpose of RSC calculation, a mean outdoor air concentration of 0.47 μg/m^3 and a mean indoor air concentration of 1.81 μg/m^3 were selected as exposure concentrations based on a volatile organic compounds study conducted by Shields and Weschler (1987) in New Jersey. These exposure concentrations are conservative, as exposure estimates from several intake and primary metabolite studies compiled in Clark et al. (2011) indicate lower mean outdoor air concentration of 0.013 μg/m^3 and a lower mean indoor air concentration of 0.91 μg/m^3.

Soil and dust ingestion exposures to diethyl phthalate were presented by FDEP (2014). The same methodology was used in this assessment, with the exception of the assumed bodyweight used in the exposure calculations (80 kg was used in this assessment versus 70 kg used by FDEP (2014) and the soil ingestion rate used for soil exposures (50 mg/day was used in this assessment versus 20 mg/day used by FDEP). Mean soil and dust concentrations of 0.0023 ug/g and 25 ug/g were combined with soil and dust ingestion rates of 50 mg/day and 30 mg/day, respectively, to derive exposure estimates. The mean soil and dust concentrations are based on values reported in Clark et al. (2011). These concentrations were selected because they represent the highest estimates concerning diethyl phthalate soil/dust exposures available for the United States.

As summarized in FDEP (2014), Schecter et al. (2013) conducted an analysis of 72 different foods collected from the Albany, New York area to determine phthalate concentrations in different food groups. Arcadis re-grouped and modified the values presented in Schecter et al. (2013) using upper percentile consumption rates available from USEPA (2008, 2011) for most food types. The dietary exposures include exposure to beverages, dairy, fish, fruits, vegetables, meats, condiments, and infant foods. Arcadis assumed an Idaho-specific marine fish consumption rate of 42.68 g/day based on the 90th percentile value of market fish as presented in Buckman et al. (2015). This is conservative as it assumes that all market fish are marine fish.

Given the presence of diethyl phthalate in cosmetics and personal care products, FDEP (2014) reviewed available data from this exposure source. As presented in FDEP (2014), Koo and Lee (2004) conducted an investigation that analyzed phthalate concentrations in a variety of different commonly used cosmetic products including 42 perfumes, 21 nail polishes, 31 hair products, and 8 deodorants. Koo and Lee (2004) estimated a total exposure to diethyl phthalate from the use of consumer care products of 24.879 µg/kg-day, based on both dermal and inhalation exposure routes. FDEP (2014) used this value in the computation of total estimated non-ambient exposure to diethyl phthalate. The same value was also used in this assessment.

When the changes described above (updated drinking water ingestion rate; updated bodyweight for water, air, soil and dust exposures; and updated soil and dust ingestion rates for soil exposures, revised dietary consumption rates based on upper percentiles and an Idaho specific fish consumption rate) are incorporated into the exposure estimates, the RSC for diethyl phthalate becomes 0.97. The RSC is slightly higher than the RSC derived by FDEP (2014) because of the change in assumed bodyweight.

Exposure Route	Arcadis Estimated Exposure mg/kg-day
Treated Drinking Water	6.00E-05
Inhalation of Indoor Air	3.26E-04
Inhalation of Outdoor Air	2.12E-05
Soil Ingestion	1.44E-09
Dust Ingestion	9.38E-06
Diet	1.46E-04
Personal Care Products	2.49E-02
Estimated Total Daily Dose	**2.54E-02**
Reference Dose	0.8
Relative Source Contribution	**0.97**

It should be noted that phthalates are widely used in laboratory equipment, which can result in higher estimated concentrations in analyzed samples (Guo and Kannan 2012). The dietary exposure estimates above assume 100% bioavailability, which is likely to overestimate intakes as well. For these reasons, the estimated exposures may be biased high and contribute to the derivation of a more conservative RSC. The RSC is further supported by total exposure estimates based on extrapolations from urinary metabolites. Blount et al. (2000) estimates the geometric mean and the 95th percentile of total daily exposures for the general population (based on 289 individuals) to be 1.2E-02 mg/kg-day and 1.1E-01 mg/kg-day, respectively. When Blount et al (2000) exposure estimates are compared with the diethyl phthalate Reference Dose (0.8 mg/kg-day), RSC estimates range from 0.86 (95th percentile of exposure) to 0.99 (geometric mean exposure). The Chronic Hazard Advisory Panel (CHAP 2014) reports more recent exposure data from the 2005-2006 NHANES study in United States women of childbearing age (considered to be a more highly exposed subgroup). Total daily FDEP intakes of 3.3 ug/kg bw-d (median) and 37.6 ug/kg bw-d (95th percentile) were back-calculated from measured urinary metabolites (CHAP 2014), which correspond to RSC values of 0.99 and 0.95, respectively. Additionally, exposure to diethyl phthalate is decreasing; urinary metabolite concentrations have decreased monotonically in the general population since 2005-2006, and were 42% lower in 2009-2010 than in 2001 (Zota et al. 2014).

Therefore, although the RSC calculated herein exceeds the ceiling value of 0.8 (USEPA 2015), diethyl phthalate exposure from non-ambient sources (diet and consumer product) contributes a small fraction of the RfD and exposure from these sources is likely to decline given recent trends diethyl phthalate use, the 0.97 RSC is considered conservative and appropriate for use in water quality criteria derivation. Arcadis recommends that final HHAWQC for diethyl phthalate incorporate the RSC derived in this report.

6 CHLOROFORM

The recent 2015 USEPA Update of HHAWQC (USEPA 2015) selected an RSC of 0.2 for chloroform and indicates that information is not available to quantitatively characterize exposure from some of those different sources. Specifically, USEPA notes that exposures from inland, nearshore, and ocean fish and shellfish could not be quantified due to the lack of data. However, as described below, information to quantitatively characterize exposure from these difference sources, including fish, is available. In 2014, the FDEP conducted an extensive review of the information available on exposure to chloroform. As a result of that review, FDEP derived an RSC of 0.76 for chloroform (FDEP 2014).

Arcadis reviewed information relevant to the derivation of an RSC for chloroform. Specifically, information about concentrations of chloroform in various environmental media and exposure assessment approaches used by FDEP and USEPA were reviewed and updated as appropriate. Based on the physical properties and available exposure information for chloroform, air, drinking water, and food are potentially significant sources. To the contrary of USEPA’s conclusions and consistent with the information developed by FDEP in 2014, sufficient data are available to develop conservative estimates of non-surface water exposure to chloroform and to develop a robust, scientifically defensible and conservative RSC for chloroform.

Outdoor and indoor air inhalation chloroform exposures were calculated consistent with methods presented in FDEP (2014) with the exception of the assumed bodyweight, the outdoor and indoor breathing rates, and the inhalation fraction term. FDEP uses an assumed bodyweight of 70 kg, whereas Arcadis assumes a bodyweight of 80 kg per USEPA (2011a) and consistent with the bodyweight assumed by USEPA recently updated HHAWQC (USEPA 2015). FDEP assumes outdoor and indoor breathing rates of 3.12 m^3/day and 12.88 m^3/day, respectively, derived from a mean breathing rate of 16 m^3/day obtained from USEPA 2011a and an adjustment to account for time spent outdoors (20%) versus indoors (80%) per Table 16-22a of USEPA 2011a. Arcadis uses this same 20%/80% adjustment to determine outdoor versus indoor exposures; however, Arcadis applies these adjustments to the 90th percentile breathing rate of 18 m^3/day (Table 6-4 USEPA 2011a; mean of 90th percentile male and female values) instead of the mean breathing rate, resulting in outdoor and indoor breathing rates of 3.6 m^3/day and 14.4 m^3/day, respectively. The inhalation exposure estimates in this assessment do not include the inhalation fraction term of 0.63 used by FDEP (2014), as the basis of this term was not clear. The mean outdoor air chloroform concentration for locations in the United States presented in USEPA 2001 (1.6 ug/m^3) was combined with a breathing rate of 3.6 m^3/day and a body weight of 80 kg. The mean indoor air chloroform concentration in USEPA (2001) (3 ug/m^3) was combined with a breathing rate of 14.4 m^3/day and a body weight of 80 kg. As part of this assessment, available ambient air data collected in Idaho were obtained for chloroform from the USEPA AMA (http://www.epa.gov/ttnamti1/toxdat.html#data). A review of the ambient air sampling data collected routinely from five sampling sites[4] in Idaho between May 2006 and April 2007 indicates average detected concentrations of chloroform ranging from 0.02 ug/m^3 to 0.065 ug/m^3, while more recent AMA data collected at two sampling sites[5] in Idaho in 2009 and 2011 indicate a maximum detected concentration of chloroform of 0.024 ug/m^3. As such, the FDEP outdoor ambient air exposures are conservative estimates of Idaho-specific exposures.

Inhalation and dermal exposures to chloroform while showering and exposure to treated drinking water were derived in USEPA (2003) and in FDEP (2014). The same methodology was used in this assessment, with the exception of the assumed bodyweight, the use of an upper percentile value instead of a mean value for the shower breathing rate, and revised values for surface area and shower durations per USEPA (2011a). Specifically, Arcadis used a bodyweight of 80 kg versus 70 kg, an upper bound shower breathing rate of 0.75 m^3/hour versus the FDEP value of 0.67 m^3/hour, a whole body surface area 20,900 cm^3 obtained from USEPA (2011a) versus the value of 20,300 cm^3 used by FDEP from an undisclosed source, and an average shower duration time of 17 minutes based on USEPA (2011a, Table 16.1) versus a duration of 7.3 minutes used by FDEP from an undisclosed source. These conservative exposure parameters were combined with the USEPA (2001) recommended mean concentration of chloroform in air during showering (190 ug/m^3) and mean concentration of chloroform in treated water (24 ug/L) to determine inhalation and dermal exposures.

Exposure from diet was estimated in USEPA (2003) and was recently updated by the FDEP (2014) to account for more recent average per capita food ingestion rate data available in USEPA (2011a). In this assessment, Arcadis calculates diet exposures by combining the estimated concentrations in dietary items from USEPA (2003) with upper percentile per capita food consumption rates available from USEPA (2011a) rather than the average consumption rates used by FDEP (2014). The dietary exposures include exposure to fruits, vegetables, meats, grain, dairy, and marine fish. Arcadis assumed an Idaho-specific marine fish consumption rate of 42.68 g/day based on the 90th percentile value of market fish as presented in Buckman et al. 2015. This fish consumption rate is conservative as it assumes that all market fish are marine fish.

Given USEPA’s statement that information is not available to estimate exposures to fish and shellfish (USEPA 2015), Arcadis reviewed fish data available from studies in Florida (Staples et al. 1985) and additional fish data (not reviewed in FDEP (2014)) from Texas (http://fishadvisoryonline.epa.gov/). Median biota concentrations in Staples et al (1985) are reported as 0.032 mg/kg, while no concentrations of chloroform (in 199 samples) were detected above the reporting limits (0.04 and 0.02 mg/kg) in available fish tissue data from Texas. These results are lower than the concentration of 0.052 mg/kg assumed by FDEP to be in marine fish when developing the RSC of 0.76 for chloroform. Additionally, the national-level

[4] Station 160690006 in Nez Perce County (n=113), 160690009 in Nez Perce County (n=54), 160690012 in Nez Perce County (n=51), 160690013 in Nez Perce County (n=57), and 160690222 in Nez Perce County (n=58).

[5] Station 160695501 via School Air Toxics Program (n=13; collected from September 2009 to December 2009), 160695502 via School Air Toxics Program (n=10; collected from June 2011 to August 2011).

bioaccumulation factor (BAF) estimates for chloroform range from 2.8 L/kg (T2) to 3.8 L/kg (TL4), which indicate that chloroform has a low potential for bioaccumulation (USEPA 2011b) supporting the low and non-detectable concentrations described above and the concentrations used by FDEP (2014) when deriving their RSC.

Based on the information summarize above, the exposures estimated by FDEP (2014) for all exposures were updated to account for USEPA's increase of the default body weight from 70 to 80 kilograms and to account for upper percentile exposure parameter values, including an Idaho-specific fish consumption rate. In addition, the inhalation fraction terms was not considered for inhalation exposure estimates. When those changes are made the RSC for chloroform becomes 0.64. The Arcadis derived RSC combines upper bound exposure parameters with scientifically defensible and conservative exposure concentrations that likely overestimate exposures in Idaho. Arcadis recommends that final HHAWQC for chloroform incorporate the RSC derived in this report.

Exposure Route	Arcadis Estimated Exposure mg/kg-day
Inhalation of Indoor Air	5.40E-04
Inhalation of Outdoor Air	7.20E-05
Inhalation while showering	4.99E-04
Dermal during showering	3.75E-04
Treated drinking water ingestion	7.20E-04
Diet	1.40E-03
Estimated Total Daily Dose	**3.61E-03**
Reference Dose	0.01
Relative Source Contribution	**0.64**

7 BUTYLBENZYL PHTHALATE (BBP)

The recent 2015 USEPA Update of HHAWQC (USEPA 2015) selected an RSC of 0.2 for BBP and indicates that information is not available to quantitatively characterize exposure from potentially significant sources. In 2014, the FDEP conducted an extensive review of the information available on exposure to BBP. As a result of that review, FDEP derived an RSC of 0.95 for BBP (FDEP 2014).

Arcadis reviewed information relevant to the derivation of an RSC for BBP. Specifically, information about concentrations of BBP in various environmental media and exposure assessment approaches used by FDEP and USEPA were reviewed and updated as appropriate. Based on the physical properties and available exposure information for BBP, fish and shellfish, non-fish food, inhalation, and consumer products are potential sources. Contrary of USEPA's conclusions and consistent with the information developed by FDEP in 2014, sufficient data are available to develop conservative estimates of non-surface water exposure to BBP and to develop a robust, scientifically defensible and conservative RSC for BBP.

Based on available data, FDEP (2014) concludes that exposures to drinking water and soils are negligible. Arcadis concurs with FDEPs assessment of these exposures.

Ambient air inhalation BBP exposures were calculated consistent with methods presented in FDEP (2014) with the exception of the assumed bodyweight and inhalation rate. FDEP uses an assumed bodyweight of 70 kg, whereas Arcadis assumes a bodyweight of 80 kg per USEPA (2011a) and consistent with the bodyweight assumed by USEPA recently updated HHAWQC (USEPA 2015). A 90th percentile daily breathing rate of 18 m^3/day was selected based on the average for male and female adults (Table 6-4 from USEPA 2011a). A 90th percentile outdoor air BBP concentration of 6.7 ng/m^3 (IPCS 1999) from a survey of 65 California homes was combined with the daily breathing rate of 18 m^3/day and a body weight of 80 kg. It is expected that Idaho homes will have similar air concentrations to those reported in the California study.

In this assessment, dietary exposures are identical to those presented by FDEP (2014) and are based on a 2000-2001 study from the USEPA (2011b) that assessed total exposure to BBP in preschool aged children from Ohio and North Carolina. The daily intake was estimated to be 10 µg/kg-day based on median estimates from individual sources (based on Ohio children; North Carolina exposure was reported as lower). Sources included in the study were indoor and outdoor air, soil, dust, drinking water, food, and dermal absorption. However, the FDEP conservatively assumes that the reported daily intake was solely related to exposure to BBP through food.

Given the presence of BBP in consumer and personal care products, FDEP (2014) reviewed available data from these exposure sources. As summarizes in FDEP (2014), Wormuth et al. (2006) conducted an extensive analysis of exposure to eight phthalate esters, including BBP, in seven consumer groups in Europe. The analysis included exposures from inhalation of indoor air, outdoor air, and while using spray paints; dermal exposure from personal care products, gloves, and textiles; and oral exposure from food, dust, mouthing (young children) and ingestion of personal care products. As such, the results of this study are not representative of consumer products alone. However, mean total daily intakes for these exposure pathways estimated by Wormuth et al. (2006) never exceeded 0.001 mg/kg bw-d, and were due primarily to food intake. As the dietary exposure estimate of 0.010 mg/kg bw-d selected above (USEPA 2011b) already accounts for many of these additional consumer product exposure pathways and is an order of magnitude greater than estimated by Wormuth et al. (2006), no additional exposure due to consumer product use was assumed.

Based on the information summarized above, the inhalation exposures estimated by FDEP (2014) were updated to account for USEPA's increase of the default body weight from 70 to 80 kilograms and use of a daily inhalation rate based on the 90th percentile of adults. When that change is made, the RSC for BBP is 0.95, which is consistent with the selected FDEP RSC.

Exposure Route	Arcadis Estimated Exposure mg/kg-day
Soil Ingestion	Negligible
Treated Drinking Water ingestion	Negligible
Inhalation of Air	1.51E-06
Diet	1.00E-02
Estimated Total Daily Dose	1.00E-02
Reference Dose	1.3
Relative Source Contribution	0.99

This RSC exceeds the 0.8 ceiling value recommended by USEPA (2015). However, the selected RSC of 0.99 is considered to be conservative and appropriate even for highly exposed populations for the following reasons. First, the dietary and consumer product exposure assumption is likely greater than actual exposures in the United States. United States studies of phthalate dietary intake (Schecter et al. 2013, Clark et al. 2011, Clark et al. 2003) generally report lower food concentrations than in Wormuth et al (2006), and exposures are decreasing as BBP has been replaced with substitute products (Clark et al. 2011, Zota et al. 2014). The European estimates from Wormuth et al. (2006) showed much lower levels of total exposure than estimated above in all consumer groups, including infants and toddlers, even when consumer and personal care products were considered (mean estimates for the consumer groups ranged from 0.00004 mg/kg-day to 0.00073 mg/kg-day), which is 13 to more than 200 times lower than the estimate of exposure used to derive this RSC. Median daily intake estimates for highly exposed populations (pregnant women, women of reproductive age, children, and infants) back-calculated from BBP metabolites are also below the exposure estimate used to derive this RSC (Table 2.7 in CHAP 2014), and modelled 95th percentile exposures are also below 0.010 mg/kg bw-d (Table 2.11 in CHAP 2014). Additionally, phthalates are widely used in laboratory equipment, which can result in higher estimated concentrations in analyzed food samples (Guo and Kannan 2012), and the dietary estimates above assume 100% bioavailability, which is likely to overestimate intakes. As BBP exposure from non-ambient sources (diet and consumer product) contributes a small fraction of the RfD and exposure from these sources is likely overestimated given recent trends BBP use, a default RSC ceiling of 0.8 is not warranted.

It should also be noted that the recent 2015 USEPA update of HHAWQC for BBP (USEPA 2015) and the Idaho proposed HHAWQC for BBP selected an RfD of 1.3 mg/kg-day based on a Health Canada assessment (Health Canada 2000) and that the RSC of 0.99 is specific to the RfD of 1.3 mg/kg-day. The FDEP used and RfD of 0.2 mg/kg-day based on the USEPA Integrated Risk Information System (IRIS) assessment (USEPA 1989) when deriving their RSC. If the more stringent (lower) IRIS RfD is considered, the RSC would decrease to 0.95. The use of the current IRIS RfD and lower RSC would result in a decrease in the HHAWQC. If the final HHAWQC is based on the more recent Health Canada RfD, Arcadis recommends the final HHAWQC for BBP incorporate the RSC of 0.99.

8 TOLUENE

The recent 2015 USEPA update of HHAWQC (USEPA 2015) selected an RSC of 0.2 for toluene and indicates that information is not available to quantitatively characterize exposure from potentially significant sources. In 2014, the FDEP conducted an extensive review of the information available on exposure to toluene. As a result of that review, FDEP derived an RSC of 0.55 for toluene (FDEP 2014).

Arcadis reviewed information relevant to the derivation of an RSC for toluene. Specifically, information about concentrations of toluene in various environmental media and exposure assessment approaches used by FDEP and USEPA were reviewed and updated as appropriate. Based on the physical properties and available exposure information for toluene, air, drinking and diet are potentially significant sources. To the contrary of USEPA's conclusions and consistent with the information developed by FDEP in 2014, sufficient data are available to develop conservative estimates of non-surface water exposure to toluene and to develop a robust, scientifically defensible and conservative RSCs.

The FDEP (2014) review of American surface, tap, and drinking waters, indicates that toluene concentrations typically found in treated drinking water are scarce. However, to calculate the RSC for the drinking water ingestion route, FDEP (2014) uses the Maximum Contaminant level (MCL), which defines the threshold above which water is not suitable for drinking, of 1,000 µg/L. Arcadis researched available drinking water data for Idaho, including the National Drinking Water Database created by the EWG. EWG requested water data from public and environmental health agencies from around the country and has compiled nearly 20 million records from 45 states. According to EWG's analysis of water quality data supplied by state water agencies, seven water utilities in Idaho reported detecting toluene in tap water between 2005 and 2009. The average concentrations ranged from 0.01 ug/L to 0.65 ug/L, with a maximum reported value of 2.8 ug/L. In this assessment, the maximum reported concentration was utilized because it represents a conservative estimate of exposure. A standard water intake rate of 2.4 L/day and a standard body weight of 80 kg were also utilized in this drinking water exposure calculation (USEPA 2011a).

Outdoor and indoor air inhalation toluene exposures were calculated consistent with methods presented in FDEP (2014) with the exception of the assumed bodyweight and breathing rates. FDEP uses an assumed bodyweight of 70 kg, whereas Arcadis assumes a bodyweight of 80 kg per USEPA (2011a). FDEP assumes outdoor and indoor breathing rates of 3.12 m^3/day and 12.88 m^3/day, respectively, derived from a mean breathing rate of 16 m^3/day obtained from USEPA (2011a) and an adjustment to account for time spent outdoors (20%) versus indoors (80%) per Table 16-22a of USEPA 2011a. Arcadis uses this same 20%/80% adjustment to determine outdoor versus indoor exposures; however, Arcadis applies these adjustments to the 90th percentile breathing rate of 18 m^3/day (Table 6-4 USEPA, 2011a; mean of 90th percentile male and female values) instead of the mean breathing rate, resulting in outdoor and indoor breathing rates of 3.6 m^3/day and 14.4 m^3/day, respectively. The USEPA reports that average levels of toluene measured in rural, urban, and indoor air are 1.3, 10.8, and 31.5 µg/m^3 respectively (USEPA 2012). For the purposes of RSC calculation, the urban outdoor air average concentration of 10.8 µg/m^3 was selected to represent Idaho and combined with a breathing rate of 3.6 m^3/day and a body weight of 80 kg to determine outdoor inhalation exposures, while the mean indoor air toluene concentration (31.5 ug/m^3) was combined with a breathing rate of 14.4 m3/day and a body weight of 80 kg to determine indoor inhalation exposures. The mean California state-wide concentration of air-borne toluene measured in 1996 was reported as 2.26 μg/m^3. The outdoor exposure concentration selected for this assessment is a conservative estimate for Idaho-specific exposures because it does not account for rural areas with lower reported concentrations. It is expected that Idaho state-wide ambient air concentrations would be similar to those reported for California.

In this assessment, Arcadis calculates diet exposures by combining the estimated concentrations of toluene in dietary items obtained from USFDA (2006) with per capita upper percentile food consumption rates available from USEPA (2011a). This differs from FDEP in that FDEP (2014) relies on average per capita consumption rates from USEPA (2011a) to derive dietary exposures to toluene. The dietary exposures include exposure to fruits, vegetables, meats, grain, dairy, and marine fish. Arcadis assumed an Idaho-specific marine fish consumption rate of 42.68 g/day based on the 90th percentile value of “market fish” as presented in Buckman et al. (2015). This fish consumption rate is conservative as it assumes that all market fish are marine fish. An Idaho-specific value exclusively for marine fish was not presented in Buckman et al. (2015).

The recent 2015 USEPA update of HHAWQC (USEPA 2015) and the IDEQ proposed draft HHAWQC selected an RfD of 0.0097 mg/kg-day for toluene based on a recent Health Canada assessment (Health Canada 2015), while the value used in the FDEP RfD evaluation is 0.08 mg/kg-day based on the USEPA IRIS assessment (USEPA 2005). The RfD used in the IDEQ proposed draft HHAWQC for toluene was used in this assessment.

When the changes described above (i.e., updated drinking water concentrations; updated drinking water ingestion rate; updated body weight for drinking water and inhalation exposures, updated indoor and outdoor inhalation rates, revised food intake values, and a RfD of 0.0097 mg/kg-day) are incorporated into the exposure estimates, the RSC for toluene becomes 0.92. The RSC is lower than that the RSC developed by FDEP (2014) primarily because the RfD is more stringent (lower) than the RfD assumed by FDEP. The Arcadis derived RSC combines upper bound exposure parameters with scientifically defensible and conservative exposure concentrations that likely overestimate toluene exposures in Idaho. Arcadis recommends that final HHAWQC for toluene incorporate the RSC derived in this report.

Exposure Route	Arcadis Estimated Exposure mg/kg-day
Treated Drinking Water	8.4E-05
Inhalation of Indoor Air	5.67E-03
Inhalation of Outdoor Air	4.86E-04
Diet	4.67E-04
Estimated Total Daily Dose	6.71E-03
Reference Dose	0.0097
Relative Source Contribution	0.31

It should be noted that if the current USEPA IRIS RfD of 0.08 mg/kg-day is considered, the resulting toluene RSC would increase to 0.92 and the HHAWQC would also increase, both because of the increase in the RSC and the increase in the RfD.

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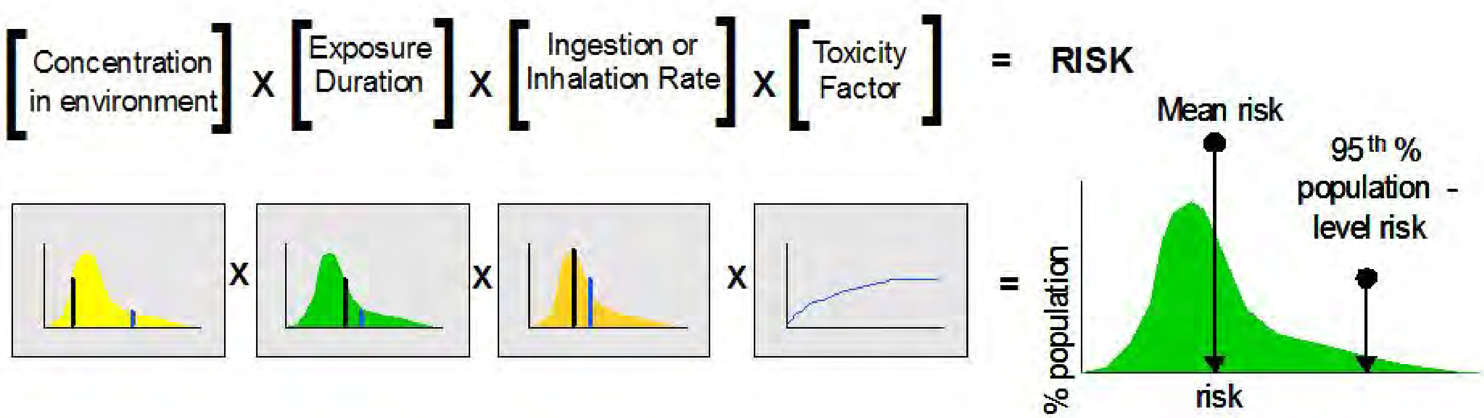
Equation 2. Probabilistic Risk Assessment



Office of the Science Advisor
Risk Assessment Forum

EPA/100/R-14/004

Risk Assessment Forum White Paper:

Probabilistic Risk Assessment Methods and Case Studies

July 25, 2014

U.S. Environmental Protection Agency
Office of the Science Advisor
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Disclaimer

This document has been reviewed in accordance with U.S. Environmental Protection Agency (EPA) policy and approved for publication. Mention of trade names or commercial products does not constitute endorsement or recommendation for use.

This document was produced by a Technical Panel of the EPA Risk Assessment Forum (RAF). The authors drew on their experience in doing probabilistic assessments and interpreting them to improve risk management of environmental and health hazards. Interviews, presentations and dialogues with risk managers conducted by the Technical Panel have contributed to the insights and recommendations in this white paper and the associated document titled *Probabilistic Risk Assessment to Inform Decision Making: Frequently Asked Questions*.

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Foreword

Throughout many of the U.S. Environmental Protection Agency's (EPA) program offices and regions, various forms of probabilistic methods have been used to answer questions about exposure and risk to humans, other organisms and the environment. Risk assessors, risk managers and others, particularly within the scientific and research divisions, have recognized that more sophisticated statistical and mathematical approaches could be utilized to enhance the quality and accuracy of Agency risk assessments. Various stakeholders, inside and outside of the Agency, have called for a more comprehensive characterization of risks, including uncertainties, to improve the protection of sensitive or vulnerable populations and lifestages.

The EPA identified the need to examine the use of probabilistic approaches in Agency risk assessments and decisions. The RAF developed this paper and the companion document, *Probabilistic Risk Assessment to Inform Decision Making: Frequently Asked Questions,* to provide a general overview of the value of probabilistic analyses and similar or related methods, as well as provide examples of current applications across the Agency. Drafts of both documents were released, with slightly different titles, for public comment and external peer review in August 2009. An external peer review was held in Arlington, Virginia in May 2010.

The goal of these publications is not only to describe potential and actual uses of these tools, but also to encourage their further implementation in human, ecological and environmental risk analysis and related decision making. The enhanced use of probabilistic analyses to characterize uncertainty in assessments will not only be responsive to external scientific advice (e.g., recommendations from the National Research Council) on how to further advance risk assessment science, but also will help to address specific challenges faced by managers and increase the confidence in the underlying analysis used to support Agency decisions.

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List of Acronyms and Abbreviations

1-D MCA	One-Dimensional Monte Carlo Analysis
2-D MCA	Two-Dimensional Monte Carlo Analysis
APEX	Air Pollutants Exposure Model
BBN	Bayesian Belief Network
CAA	Clean Air Act
CASAC	Clean Air Scientific Advisory Committee
CCA	Chromated Copper Arsenate
CPSC	Consumer Product Safety Commission
CRA	Cumulative Risk Assessment
CSFII	Continuing Survey of Food Intake by Individuals
CWA	Clean Water Act
DEEM	Dietary Exposure Evaluation Model
DRA	Deterministic Risk Assessment
DRES	Dietary Risk Evaluation System
ERA	Ecological Risk Assessment
EMAP	Environmental Monitoring and Assessment Program
EPA	U.S. Environmental Protection Agency
FACA	Federal Advisory Committee Act
FAQ	Frequently Asked Questions
FDA	U.S. Food and Drug Administration
FFDCA	Federal Food, Drug, and Cosmetic Act
FIFRA	Federal Insecticide, Fungicide, and Rodenticide Act
FQPA	Food Quality Protection Act
GAO	Government Accountability Office
HHRA	Human Health Risk Assessment
HI	Hazard Index
IPCC	Intergovernmental Panel on Climate Change
IRIS	Integrated Risk Information System
LHS	Latin Hypercube Sampling
LOAEL	Lowest-Observed-Adverse-Effect Level
LT	Long-Term
LT2	Long-Term 2 Enhanced Surface Water Treatment Rule
MCA	Monte Carlo Analysis
MCS	Monte Carlo Simulation
MEE	Microexposure Event Analysis
MOEs	Margins of Exposure
NAAQS	National Ambient Air Quality Standards
NAS	National Academy of Sciences
NERL	National Exposure Research Laboratory
NOAEL	No-Observed-Adverse-Effect Level
NRC	National Research Council
OAQPS	Office of Air Quality Planning and Standards
OAR	Office of Air and Radiation
OCSPP	Office of Chemical Safety and Pollution Prevention
OERR	Office of Emergency and Remedial Response
OGWDW	Office of Groundwater and Drinking Water
OMB	Office of Management and Budget
OP	Organophosphorus Pesticide

OPP	Office of Pesticide Programs
ORD	Office of Research and Development
OSA	Office of the Science Advisor
OSTP	Office of Science and Technology Policy
OSWER	Office of Solid Waste and Emergency Response
OW	Office of Water
PAH	Polycyclic Aromatic Hydrocarbon
PCB	Polychlorinated Biphenyl
PCCRARM	Presidential/Congressional Commission on Risk Assessment and Risk Management
PDP	Pesticide Data Program
PM	Particulate Matter
PRA	Probabilistic Risk Assessment
RAF	Risk Assessment Forum
RfC	Reference Concentration (Inhalation)
RfD	Reference Dose (Oral)
RIA	Regulatory Impact Analysis
RME	Reasonable Maximum Exposure
SAB	Science Advisory Board
SAP	Scientific Advisory Panel
SHEDS	Stochastic Human Exposure and Dose Simulation Model
SHEDS-PM	Stochastic Human Exposure and Dose Simulation Model for Particulate Matter
STPC	Science and Technology Policy Council
TRIM.Expo	Total Risk Integrated Methodology/Exposure Model
UI	Uncertainty Interval
USDA	U.S. Department of Agriculture
USGS	U.S. Geological Survey
WHO	World Health Organization

EXECUTIVE SUMMARY

Probabilistic risk assessment (PRA), in its simplest form, is a group of techniques that incorporate uncertainty and variability into risk assessments. Variability refers to the inherent natural variation, diversity and heterogeneity across time, space or individuals within a population or lifestage, while uncertainty refers to imperfect knowledge or a lack of precise knowledge of the physical world, either for specific values of interest or in the description of the system (USEPA 2011c). Variability and uncertainty have the potential to result in overestimates or underestimates of the predicted risk.

PRA provides estimates of the range and likelihood of a hazard, exposure or risk, rather than a single point estimate. Stakeholders inside and outside of the Agency have recommended a more complete characterization of risks, including uncertainties and variability, in protecting more sensitive or vulnerable populations and lifestages. PRA can be used to support risk management by assessment of impacts of uncertainties on each of the potential decision alternatives.

Numerous advisory bodies, such as the Science Advisory Board (SAB) and the National Research Council (NRC) of the National Academy of Sciences (NAS), have recommended that EPA incorporate probabilistic analyses into the Agency's decision-making process. EPA's Risk Assessment Forum (RAF) formed a Technical Panel, consisting of representatives from the Agency's program and regional offices, to develop this white paper and its companion document, titled *Probabilistic Risk Assessment to Inform Decision Making: Frequently Asked Questions* (FAQ). The RAF is recommending the development of Agency resources, such as a clearinghouse of PRA case studies, best practices, resources and seminars, to raise general knowledge about how these probabilistic tools can be used.

The intended goal of this white paper is to explain how EPA can use probabilistic methods to address data, model and scenario uncertainty and variability by capitalizing on the wide array of tools and methods that comprise PRA. This white paper describes where PRA can facilitate more informed risk management decision making through better understanding of uncertainty and variability related to Agency decisions. The information contained in this document is intended for both risk analysts and managers faced with determining when and how to apply these tools to inform their decisions. This document does not prescribe a specific approach but, rather, describes the various stages and aspects of an assessment or decision process in which probabilistic assessment tools may add value.

Probabilistic Risk Assessment

PRA is an analytical methodology used to incorporate information regarding uncertainty and/or variability into analyses to provide insight regarding the degree of certainty of a risk estimate and how the risk estimate varies among different members of an exposed population, including sensitive populations or lifestages. Traditional approaches, such as deterministic analyses, often report risks as "central tendency," "high end" (e.g., 90th percentile or above) or "maximum anticipated exposure," but PRA can be used to describe more completely the uncertainty surrounding such estimates and identify the key contributors to variability or uncertainty in predicted exposures or risk estimates. This information then can be used by decision makers to achieve a science-based level of safety, to compare the risks related to different management options, or to invest in research with the greatest impact on risk estimate uncertainty.

To support regulatory decision making, PRA can provide information to decision makers on specific questions related to uncertainty and variability. For example, in the context of a decision analysis that has been conducted, PRA can: identify "tipping points" where the decision would be different if the risk estimates were different; estimate the degree of confidence in a particular decision; and help to estimate trade-offs related to different risks or management options. PRA can provide useful (even critical) information about the uncertainties and variability in the data, models, scenario, expert judgments and values incorporated in risk assessments to support decision making across the Agency.

PRA is applicable to both human health risk assessment (HHRA) and ecological risk assessment (ERA); however, there are differences between how PRA is used for the two. Both HHRA and ERA have a similar structure and use the same risk assessment steps, but HHRA focuses on individuals, a single species, morbidity and mortality, but ERA is more concerned with multiple populations of organisms (e.g., individual species of fish in a river) or ecological integrity (e.g., will the types of species living in the river change over time). In ERA, there also is a reliance on indicators of impacts (e.g., sentinel species and other metrics).

Risk Assessment at EPA

PRA began playing an increasingly important role in Agency risk assessments following the 1997 release of EPA's *Policy for Use of Probabilistic Analysis in Risk Assessment at the U.S. Environmental Protection Agency* (USEPA 1997a) and publication of the *Guiding Principles for Monte-Carlo Analysis* (USEPA 1997b). PRA was a major focus in an associated review of EPA risk assessment practices by the SAB (USEPA 2007b). The NRC recommended that EPA adopt a "tiered" approach for selecting the level of detail used in uncertainty and variability assessment (NRC 2009). Furthermore, the NRC recommended that a discussion about the level of detail used for uncertainty analysis and variability assessment should be an explicit part of the planning, scoping and problem formulation step in the risk assessment process. Both this white paper and the companion FAQ document take into account recommendations on risk assessment processes described in the NRC's report *Science and Decisions: Advancing Risk Assessment* (NRC 2009) and *Environmental Decisions in the Face of Uncertainty* (IOM 2013).

EPA's recent risk assessment publications, including the document titled *Framework for Human Health Risk Assessment to Inform Decision Making* (UAEPA 2014b) as well as this white paper, emphasize the importance of communicating the results of a PRA because it provides the range and likelihood estimates for one or more aspects of hazard, exposure or risk, rather than a single point estimate. Risk assessors are responsible for sharing information on probabilistic results so that decision makers have a clear understanding of quantitative assessments of uncertainty and variability, and how this information will affect the decision. Effective communication between the risk assessor and decision maker is key to promote understanding and use of the results from the PRA.

PRA generally requires more resources than standard Agency default-based deterministic approaches. Appropriately trained staff and the availability of adequate tools, methods and guidance are essential for the application of PRA. Proper application of probabilistic methods requires not only software and data, but also guidance and training for analysts using the tools, and for managers and decision makers tasked with interpreting and communicating the results. In most circumstances, probabilistic assessments may take more time and effort to conduct than conventional approaches, primarily because of the comprehensive inclusion of available information on model inputs. The potentially higher resource costs may be offset, however, by a more informed decision than would be provided by a comparable deterministic analysis.

Content of the White Paper and Frequently Asked Questions Companion Documents

These two documents describe how PRA can be applied to enhance the scientific foundation of EPA's decision making across the Agency. This white paper describes the challenges faced by EPA decision makers, defines and explains the basic principles of probabilistic analysis, briefly highlights instances where these techniques have been implemented in EPA decisions, and describes criteria that may be useful in determining whether and how the application of probabilistic methods may be useful and/or applicable to decision making. This white paper also describes commonly employed methods to address uncertainty and variability, including those used in the consideration of uncertainty in scenarios and uncertainty in models. Additionally, it addresses uncertainty and variability in the inputs and outputs of models and the impact of these uncertainties on each of the potential management options. A general description of the range of methods from simple to complex, rapid to more time consuming and least to most resource intensive is provided, as well as uses of these methods.

Both documents address issues such as uncertainty and variability, their relevance to decision making and the PRA goal to provide quantitative characterization of the uncertainty and variability in estimates of hazard, exposure, or risk. The difference between the white paper and the FAQs document is the level of detail provided about PRA concepts and practices, and the intended audience (e.g., risk assessors vs. decision makers). Detailed examples of applications of these methods are provided in the Appendix of this white paper, which is titled "Case Study Examples of the Application of Probabilistic Risk Analysis in U.S. Environmental Protection Agency Decision Making." The white paper Appendix includes 16 case studies—11 HHRA and 5 ERA examples—that illustrate how EPA's program and regional offices have used probabilistic techniques in risk assessment. To aid in describing how these tools were applied, the 16 case studies are subdivided among 3 categories for purposes of this document. Group 1 includes 2 case studies demonstrating point estimate, including sensitivity analysis; Group 2 is comprised of 5 case studies demonstrating probabilistic risk analysis, including one-dimensional Monte Carlo analysis and probabilistic sensitivity analysis; and Group 3 includes 9 case studies demonstrating advanced probabilistic risk analysis, including two-dimensional Monte Carlo analysis with micro exposure (micro environments) modeling, Bayesian statistics, geostatistics and expert elicitation.

The FAQ document provides answers to common questions regarding PRA, including key concepts such as scientific and institutional motivations for the use of PRA, and challenges in the application of probabilistic techniques. The principal reason for including PRA as an option in the risk assessor's toolbox is its ability to support the refinement and improvement of the information leading to decision making by incorporating known uncertainties.

1. INTRODUCTION: RELEVANCE OF UNCERTAINTY TO DECISION MAKING: HOW PROBABILISTIC APPROACHES CAN HELP

1.1. EPA Decision Making

To discuss where probabilistic approaches can aid EPA's decision making, it is important to generally describe the Agency's current decision-making processes and how better understanding and improving elements within these processes can clarify where probabilistic approaches might provide benefits. The enhanced use of PRA and characterization of uncertainty would allow EPA decision makers opportunities to use a more robust and transparent process, which may allow greater responsiveness to outside comments and recommendations. Such an approach would support higher quality EPA assessments and improve confidence in Agency decisions.

There are two major areas in the decision-making process that might be improved with PRA. Scientists currently are generally focused on the first area—the understanding of data, model and scenario uncertainties and variability. The second area is one that has not, until recently and only in a limited fashion, been used by EPA decision makers. This area is formal decision analysis. With decision analytic techniques, decision makers can weigh the relative importance of risk information compared to other information in making the decision, understand how uncertainty affects the relative attractiveness of potential decision alternatives, and assess overall confidence in a decision. In addition to data, model and scenario uncertainty, there is a separate category of uncertainties specifically associated with how the decision criteria relate to the decision alternatives. Although it is quite relevant to risk management decisions, the topic and decision analysis in general are outside of the scope of this report. This white paper focuses on technical information that would allow better understanding of the relationships among alternative decisions in assessing risks.

1.2. The Role of Probabilistic Risk Analysis in Characterizing Uncertainty and Variability

Probabilistic analyses include techniques that can be applied formally to address both uncertainty and variability, typically arising from limitations of data, models or adequately formulating the scenarios used in assessing risks. Probability is used in science, business, economics and other fields to examine existing data and estimate the chance of an event, from health effects to rain to mental fatigue. One can use probability (chance) to quantify the frequency of occurrence or the degree of belief in information. For variability, probability distributions are interpreted as representing the relative frequency of a given state of the system (e.g., that the data are distributed in a certain way); for uncertainty, they represent the degree of belief or confidence that a given state of the system exists (e.g., that we have the appropriate data; Cullen and Frey 1999). PRA often is defined narrowly to indicate a statistical or thought process used to analyze and evaluate the variability of available data or to look at uncertainty across data sets.

For the purposes of this document, PRA is a term used to describe a process that employs probability to incorporate variability in data sets and/or the uncertainty in information (such as data or models) into analyses that support environmental risk-based decision making. PRA is used here broadly to include both quantitative and qualitative methods for dealing with scenario, model and input uncertainty. Probabilistic techniques can be used with other types of analysis, such as benefit-cost analysis, regulatory impact analysis and engineering performance standards; thus, they can be used for a variety of applications and by experts in many disciplines.

1.3. Goals and Intended Audience

The primary goals of this white paper are to introduce PRA, describe how it can be used to better inform and improve the decision-making process, and provide case studies where it has been used in human health and ecological analyses at EPA (see the Appendix for the case studies). A secondary goal of this paper is to bridge communication gaps regarding PRA among analysts of various disciplines, between these analysts and Agency decision makers, and among affected stakeholders. This white paper also is intended to serve as a communication tool to introduce key concepts and background information on approaches to risk analysis that incorporate uncertainty and provide a more comprehensive treatment of variability. Risk analysts, decision makers and affected stakeholders can benefit from understanding the potential uses of PRA. PRA and related approaches can be used to identify additional research that may reduce uncertainty and more thoroughly characterize variability in a risk assessment. This white paper explains how PRA can enhance the decision-making processes faced by managers at EPA by better characterizing data, model, scenario and decision uncertainties.

1.4. Overview of This Document

This white paper provides an overview of EPA's interest and experience in addressing uncertainty and variability using probabilistic methods in risk assessment; identifies key questions asked or faced by Agency decision makers; demonstrates how conventional deterministic approaches to risk analysis may not answer these questions fully; provides examples of applications; and shows how and why "probabilistic risk analysis" (broadly defined) could provide added value, compared to traditional methods, with regard to regulatory decision making by more fully characterizing risk estimates and exploring decision uncertainties. For the purposes of this white paper, PRA and related tools for both human health and ecological assessments include a range of approaches, from statistical tools, such as sensitivity analysis, to multi-dimensional Monte Carlo models, geospatial approaches and expert elicitation. Key points addressed by this document include definitions and key concepts pertaining to PRA, benefits and challenges of PRA, a general conceptual framework for PRA, conclusions regarding products and insights obtained from PRA, and examples where EPA has used PRA in human health and ecological analyses. A Glossary and a Bibliography also are provided.

1.5. What Are Common Challenges Facing EPA Risk Decision Makers?

EPA operates under statutory and regulatory constraints that often limit the types of criteria that can be considered (including whether the use of PRA is appropriate) and impose strict timeframes in which decisions must be made. Typically, the decision begins with understanding (1) who or what will be protected; (2) the relationship between the data and decision alternatives; and (3) the impact of data, model and decision uncertainties related to each decision alternative. These are among the considerations of the planning and scoping and problem formulation phases of risk assessment (US EPA 2014). EPA decision makers need to consider multiple decision criteria, which are informed by varying degrees of confidence in the underlying information. Decision makers need to balance the regulatory/ statutory requirements and timeframes, resources (i.e., expertise, costs of the analysis, review times, etc.) to conduct the assessment, management options, and stakeholders while at the same time keeping risk assessment and decision making separate.

Uncertainty can be introduced into any assessment at any step in the process, even when using highly accurate data with the most sophisticated models. Uncertainty can be reduced or better characterized through knowledge. Variability or natural heterogeneity is inherent in natural systems and therefore cannot be reduced, but can be examined and described. Uncertainty in decisions is unavoidable because real-world situations cannot be perfectly measured, modeled or predicted. As a result, EPA decision makers face scientifically complex problems that are compounded by varying levels of uncertainty and variability. If uncertainty and variability have not been well characterized or acknowledged, potential complications arise in the process of decision making. Increased uncertainty can make it more difficult to determine, with reasonable confidence, the balance point between the costs of regulation and the implications for avoiding damages and producing benefits. Characterization facilitated by probabilistic analyses can provide insight into weighing the relative costs and benefits of varying levels of regulation and also can assist in risk communication activities.

Decision makers often want to know who is at risk and by how much, the tradeoffs between alternative actions and the likely or possible consequences of decisions. To this end, it is particularly useful for decision makers to understand the distribution of risk across potentially impacted populations and ecological systems. It can be important to know the number of individuals experiencing different magnitudes of risk, the differences in risk magnitude experienced by individuals in different lifestages or populations or the probability of an event that may lead to unacceptable levels of risk. Given the limitations of data, traditional methods of risk analyses are not well suited to produce such estimates. Probabilistic analytical methods are capable of addressing these shortcomings and can contribute to a more thorough recognition of the impact of data gaps on the projected risk estimates. Although PRA can be used to characterize the uncertainty and variability in situations with limited data, currently there is not extensive experience using PRA to characterize the range of effects or dose-response relationships for populations, including sensitive populations and lifestages.

Other challenges facing EPA decision makers include the need to consider multiple decision criteria, which are informed by varying degrees of confidence in the underlying information, understanding the relationship between and among those decision criteria (including multi-pollutant and multi-media effects) and the decision alternatives, and the timeliness of the decision making. Furthermore, even when PRA is used, EPA decision makers must be mindful of potential misuses and obfuscations when conducting or presenting PRA results. Decision makers also need to consider the evolving science behind PRA. As the use of PRA increases decision makers will become more familiar with the techniques and their application.

A risk assessment process needs to consider uncertainties, variability and the rationale or factors influencing how they may be addressed by a decision maker. Decision makers need a foundation for estimating the value of collecting additional information to allow for better informed decisions. There are costs associated with ignoring uncertainty (McConnell 1997 and Toll 1999), and a focus by decision makers on the information provided by uncertainty analysis can strengthen their choices.

1.6. What Are Key Uncertainty and Variability Questions Often Asked by Decision Makers?

As described above, determining the decision-making context and specific concerns is a critical first step toward developing a useful and responsive risk assessment that will support the decision. For example, the appropriate focus and level of detail of the analysis should be commensurate with the needs of the decision maker and stakeholders, as well as the appropriate use of science. Analyses often are conducted at a level of detail dictated by the issue being addressed, the breadth and quality of the available information upon which to base an analysis, and the significance surrounding a decision. The analytical process tends to be iterative. Although a guiding set of questions may frame the initial analyses, additional questions can arise that further direct or even reframe the analyses.

Based on a series of discussions with Agency decision makers and risk assessors, some typical questions about uncertainty and variability relevant to risk analyses including:

- ❒ Factors influencing decision uncertainty:
    - Would my decision be different if the data were different, improved or expanded? Would additional data collection and research likely lead to a different decision? How long will it take to collect the information, how much would it cost, and would the resulting decision be significantly altered?
    - What are the liabilities and consequences of making a decision under the current level of knowledge and uncertainty?
    - How do the alternatives and their associated uncertainty and variability affect the target population or lifestage?
- ❒ Considerations for evaluating data or method uncertainty:
    - How representative or conservative is the estimate due to data or method uncertainty (also incorporating variability)?
    - What are the major gaps in knowledge, and what are the major assumptions used in the assessment? How reasonable are the assumptions?
- ❒ Issues arising when addressing variability:
    - Can a probabilistic approach (e.g., to better characterize uncertainties and variability) be accomplished in a timely manner?
    - What is the desired percentile of the population to be protected? By choosing this percentile, who may not be protected?

The questions that arise concerning uncertainty and variability change depending on the stage and nature of the decision-making process and analysis. General phases of the risk assessment process are illustrated in Figure 1. For further information on the process of decision making, we suggest referring to the description provided by EPA Region 3 on the Multi-Criteria Integrated Resource

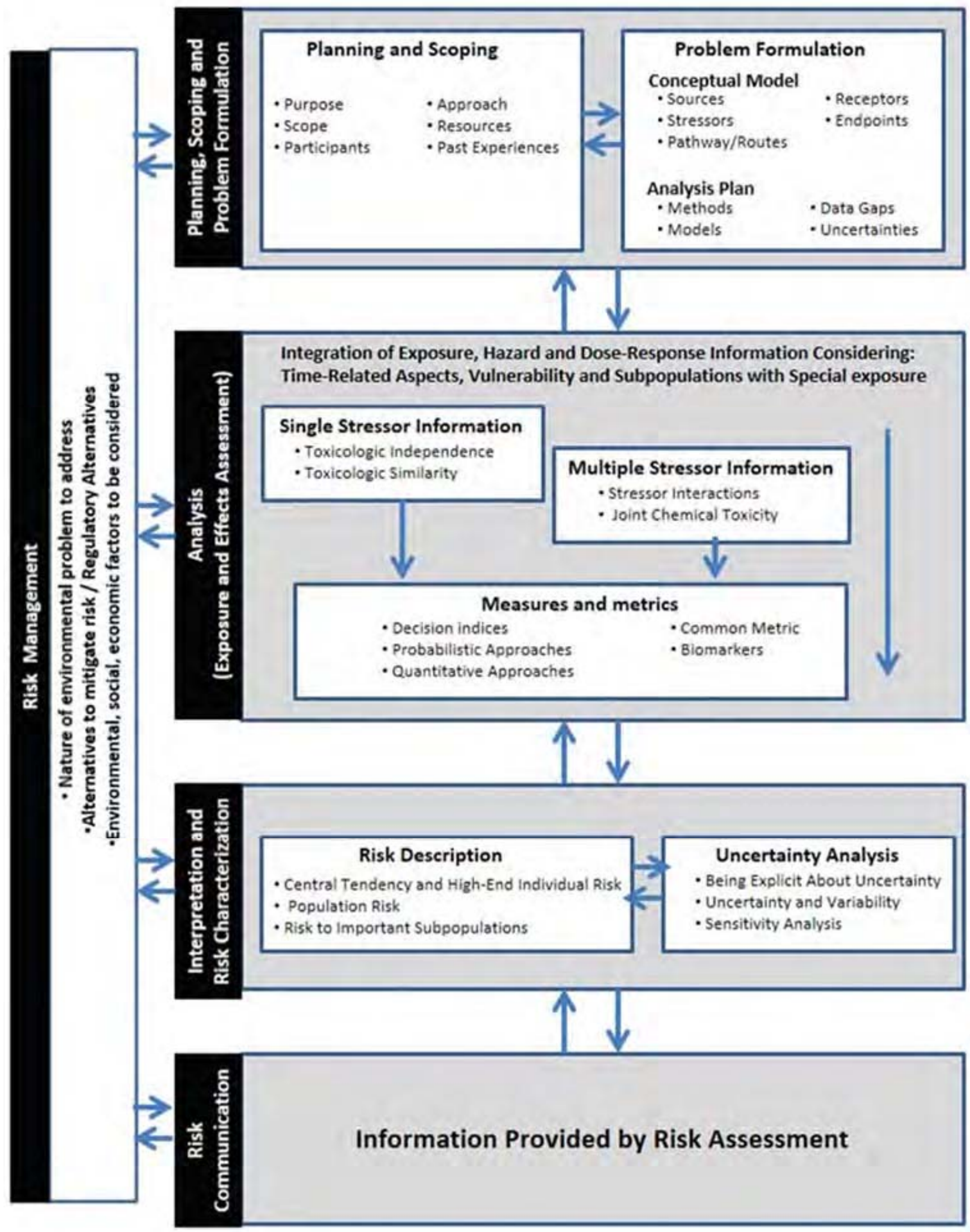

Figure 1. General Phases of the Risk Assessment Process. Risk assessment is an iterative process comprised of planning, scoping and problem formulation; analysis (e.g., hazard identification, dose-response assessment and exposure assessment); interpretation and risk characterization; and risk communication. The highlighted boxes explain how PRA fits into the overall process.

Assessment Internet page at http://www.epa.gov/reg3esd1/data/mira.htm. The utility of various levels of analysis and sophistication in answering these questions is illustrated in the case studies described in Section 1.10 and presented in the Appendix of this white paper. References to examples beyond these EPA case studies can be found in the Bibliography. Additionally, Lester *et al.* (2007) identified more than 20 PRA application case studies (including EPA examples) performed since 2000; these case study examples are categorized as site-specific applications and regional risk assessments.

1.7. Why Is the Implementation of Probabilistic Risk Analysis Important?

The principal reason for the inclusion of PRA as an option in the risk assessor's toolbox is PRA's ability to support refinement and improvement of the information leading to decision making by incorporating known uncertainties. Beginning as early as the 1980s, expert scientific advisory groups, such as the National Research Council (NRC), recommended that risk analyses include a clear discussion of the uncertainties in risk estimation (NRC 1983). The NRC stated the need to describe uncertainty and to capture variability in risk estimates (NRC 1994). The Presidential/ Congressional Commission on Risk Assessment and Risk Management (PCCRARM) recommended against a requirement or need for a "bright line" or single-number level of risk (PCCRARM 1997). See Section 2.4 for more information regarding the scientific community's opinion on the use of PRA.

Regulatory science often requires selection of a limit for a contaminant, yet that limit always contains uncertainty as to how protective it is. PRA and related tools quantitatively describe the very real variations in natural systems and living organisms, how they respond to stressors, and the uncertainty in estimating those responses.

Risk characterization became EPA policy in 1995 (USEPA 1995b), and the principles of transparency, clarity, consistency and reasonableness are explicated in the 2000 *Risk Characterization Handbook* (USEPA 2000a). Transparency, clarity, consistency and reasonableness criteria require decision makers to describe and explain the uncertainties, variability and known data gaps in the risk analysis and how they affect the resulting decision-making processes (USEPA 1992, 1995a, 2000a).

The use of probabilistic methods also has received support from some decision makers within the Agency, and these methods have been incorporated into a number of EPA decisions to date. Program offices, such as the Office of Pesticide Programs (OPP), Office of Solid Waste and Emergency Response (OSWER), Office of Air and Radiation (OAR), and Office of Water (OW), as well as the Office of Research and Development (ORD), have utilized probabilistic approaches in different ways and to varying extents, for both human exposure and ecological risk analyses. In addition, OSWER has provided explicit guidance on the use of probabilistic approaches for exposure analysis (USEPA 2001). Some program offices have held training sessions on Monte Carlo simulation (MCS) software that is used frequently in probabilistic analyses.

The NRC recommended that EPA should adopt a tiered approach for selecting the level of detail used in uncertainty and variability assessment (NRC 2009). Furthermore, NRC recommended that a discussion about the level of detail used for uncertainty analysis and variability assessment should be an explicit part of the planning, scoping and problem formulation step in the risk assessment process. The way that PRA fits into a graduated hierarchical (tiered) approach is more fully described in Section 2.10 and illustrated in Figure 2.

When it is beneficial to refine risk estimates, the use of PRA can help in the characterization and communication of uncertainty, variability and the impact of data gaps in risk analyses for assessors, decision makers and stakeholders (including the target population or lifestage).

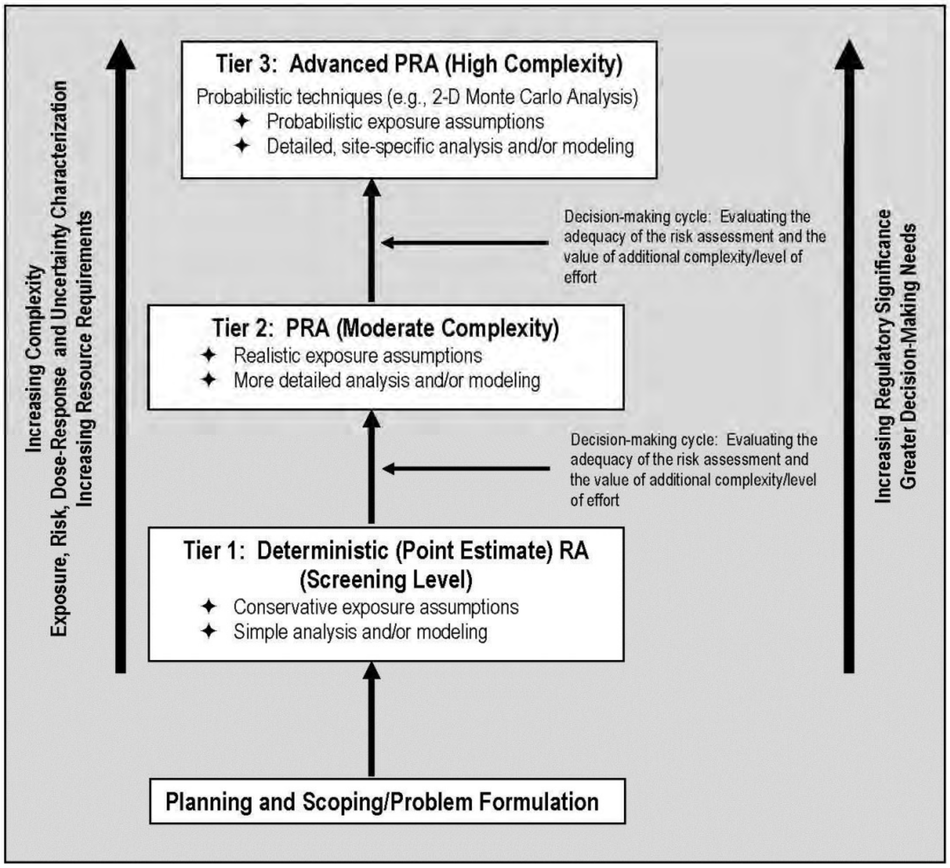

Figure 2. Tiered Approach for Risk Assessment. The applicability of a probabilistic approach depends on the needs of decision makers and stakeholders. Assessments that are high in complexity and regulatory significance benefit from the application of probabilistic techniques.
Source: Adapted from USEPA 2004a and WHO 2008.

1.8. How Does EPA Typically Address Scientific Uncertainty and Variability?

Environmental assessments can be complex, such as covering exposure to multiple chemicals in multiple media for a wide-ranging population. The Agency has developed simplified approaches to characterize risks associated with such complex assessments through the use of point estimates for model variables or parameters. Such an approach typically produces point estimates of risks (e.g., 10^{-5} or a lifetime probability of cancer risk of one individual in 100,000). These often are called "deterministic" assessments. As a result of the use of point estimates for variables in model algorithms, deterministic risk results usually are reported as what are assumed to be either average or worst-case estimates. They do not contain any quantitative estimate of the uncertainty in that estimate, nor report what percentile of the exposed population the estimate applies. The methods typically used in EPA risk assessments rely on a combination of point values with potentially varying levels of conservatism and certainty, yielding a point estimate of exposure at some point in the range of possible risks.

Because uncertainty is inherent in all risk assessments, it is important that the risk assessment process enable handling uncertainties in a logical way that is transparent and scientifically defensible, consistent with the Agency's statutory mission and responsive to the needs of decision makers (NRC 1994). Uncertainty is a factor in both ecological and human health risk assessments.

For human health risk assessments, uncertainties arise for both noncancer and cancer endpoints. Thus, when data are missing, EPA often uses several options to provide boundaries on uncertainty and variability in an attempt to avoid risk underestimation; attempting to give a single quantification of how much confidence there is in the risk estimate may not be informative or feasible.

In exposure assessment, for example, the practice at EPA is to collect new data where they are needed and where time and resources allow. Alternative approaches to address uncertainty include narrowing the scope of the assessment; using screening-level default assumptions that include upper-end values and/or central tendency values that are generally combined to generate risk estimates that fall within the higher end of the population risk range (USEPA 2004b); applying models to estimate missing values; using surrogate data (e.g., data on a parameter that come from a different region of the country than the region being assessed); or applying professional judgment. The use of individual assumptions can range from qualitative (e.g., assuming that one is secured to the residence location and does not move through time or space) to more quantitative (e.g., using the 95th percentile of a sample distribution for an ingestion rate). This approach also can be applied to the practice of hazard identification and dose-response assessment when data are missing. Identifying the sensitivity of exposure or risk estimates to key inputs can help focus efforts to reduce uncertainty by collecting additional data.

Current EPA practices to address uncertainty and variability are focused on the evaluation of data, model, and scenario uncertainty and variability. In addition, decision makers are faced with combining many different decision criteria that may be informed by science and PRA as well as by expert judgment or the weighting of values to choose a decision alternative. Data, model, and scenario uncertainties and variability (including their probability distributions), as well as expert judgment, can be important considerations in the selection of one alternative over another (Costanza *et al*. 1997; Morgan *et al*. 2009; Stahl and Cimorelli 2005; Wright *et al.* 2002).

1.9. What Are the Limitations of Relying on Default-Based Deterministic Approaches?

Default-based deterministic approaches are applied to data, model and scenario uncertainties. Deterministic risk assessment (DRA) often is considered a traditional approach to risk analysis because of the existence of established guidance and procedures regarding its use, the ease with which it can be performed, and its limited data and resource needs. The use of defaults supporting DRA provides a procedural consistency that allows for risk assessments to be feasible and tractable. Decision makers and members of the public tend to be relatively familiar with DRA, and the use of such an approach addresses assessment-related uncertainties primarily through the incorporation of predetermined default values and conservative assumptions. It addresses variability by combining input parameters intended to be representative of typical or higher end exposure (i.e., considered to be conservative assumptions). The intention often is to implicitly provide a margin of safety (i.e., more likely to overestimate risk than underestimate risk) or construct a screening-level estimate of high-end exposure and risk (i.e., an estimate representative of more highly exposed and susceptible individuals).

DRA provides an estimation of the exposures and resulting risks that addresses uncertainties and variabilities in a qualitative manner. The methods typically used in EPA DRA rely on a combination of point values—some conservative and some typical—yielding a point estimate of exposure that is at some unknown point in the range of possible risks. Although this conservative bias aligns with the public health mission of EPA (USEPA 2004b), the degree of conservatism in these risk estimates (and in any concomitant decision) cannot be estimated well or communicated (Hattis and Burmaster 1994). Typically, this results in unquantified uncertainty in risk statements.

Quantitative information regarding the precision or potential systematic error and the distribution of exposures, effects and resulting risks across different members of an exposed population are usually not provided with estimates generated using default approaches. Although DRA may present qualitative information regarding the robustness of the estimates, the impact of data and model limitations on the quality of the results cannot be quantified. Reliance on deterministically derived estimations of risk can result in decision making based solely on point estimates with an unknown degree of conservatism, which can complicate the comparison of risks or management options.

In risk assessments of noncancer endpoints, metrics such as an oral reference dose (RfD) and an inhalation reference concentration (RfC) are typically used. The use of conservative defaults long has been the target of criticism (Finkel 1989) and has led to the presumption by critics that EPA assessments are overly conservative and unrealistic. The use of PRA would be advantageous in eliminating a single value and might be less likely to imply undue precision and lessen the need for conservative assumptions, thereby reducing bias in the estimate. In the probabilistic framework, a probability distribution would be used to express the belief that any particular value represents the dose or exposure concentration that would pose no appreciable risk of adverse effects (NRC 2009). EPA is investigating the use of PRA to derive risk values for RfD and RfC in EPA's Integrated Risk Information System (IRIS) Database (www.epa.gov/IRIS/).

EPA commissioned a white paper (Hattis and Lynch 2010) presented at the Hazardous Air Pollutant Workshop, 2009, illustrating the implementation of probabilistic methods in defining RfDs and assessing the benefits for reducing exposure to toxicants that act in part through traditional individual threshold processes. The use of PRA, among other things, makes provision for interactions with background pathological processes, as recommended by the NRC (2009), and shows how the system can inform assessments for "data-poor" toxicants.

PRA may be more suitable than DRA for complex assessments, including those of aggregate and cumulative exposures and time-dependent individual exposure, dose and effects analyses. Identification and prioritization of contributory sources of uncertainty can be difficult and time consuming when using deterministic methods, leading to difficulties in model evaluation and the subsequent appraisal of risk estimates (Cullen and Frey 1999). Quantitative analyses of model sensitivities are essential for the prioritization of key uncertainties—a critical process in identifying steps for data collection or research to improve exposure or risk estimates.

1.10. What Is EPA's Experience with the Use of Probabilistic Risk Analysis?

EPA's experience with PRA has, to date, primarily been limited to the evaluation of data, model and scenario uncertainties. To assist with the growing number of probabilistic analyses of exposure data in these uncertainty areas, EPA issued *Guiding Principles for Monte Carlo Analysis* (USEPA 1997b). Given adequate supporting data and credible assumptions, probabilistic analysis techniques, such as Monte Carlo analysis, can be viable statistical tools for analyzing uncertainty and variability in risk assessments. EPA's policy for the use of probabilistic analysis in risk assessment, released in 1997, is inclusive of human exposure and ecological risk assessments and does not rule out probabilistic health effects analyses (USEPA 1997a). Subsequently, EPA's SAB and Scientific Advisory Panel (SAP) have reviewed PRA approaches to risks used by EPA offices such as OAR, OPP and others. Several programs have developed specific guidance on the use of PRA, including OPP and OSWER (USEPA 1998a, 2001).

To illustrate the practical application of PRA to problems relevant to the Agency, several example case studies are briefly described here. The Appendix titled Case Study Examples of *Application of*

Probabilistic Risk Analysis in U.S. Environmental Protection Agency Regulatory Decision Making, discusses these and other case studies in greater detail, including the procedures and outcomes. The Appendix includes 16 case studies—11 HHRA and 5 ERA examples—that are intended to illustrate how some of EPA's programs and offices currently utilize PRA. To aid in describing how probabilistic analyses were used, the 16 case studies are subdivided among 3 categories of PRA tools: Group 1—point estimate, including sensitivity analysis; Group 2—probabilistic risk analysis, including one-dimensional Monte Carlo analysis (1-D MCA) and probabilistic sensitivity analysis; and Group 3—advanced probabilistic risk analysis, including two-dimensional Monte Carlo analysis (2-D MCA) with microexposure (microenvironments) modeling, Bayesian statistics, geostatistics and expert elicitation .

It is useful to note that the NRC (2009) recommended a tiered approach to risk assessment using both qualitative and quantitative (deterministic and probabilistic) tools, with the complexity of the analysis increasing as progress is made through the tiers. The use of PRA tools to address issues of uncertainty and variability in a tiered approach is described more completely in Section 2.10 and was illustrated in Figure 2. The three tiers illustrated in that figure approximately correspond to the three groups of EPA case studies described in the Appendix that provide examples of the use of various PRA tools.

Table A-1 in the Appendix offers a summary of the 16 case studies based on the type of risk assessment, the PRA tools used in the assessment, and the EPA program or regional office responsible for the assessment. Some of the approaches that are profiled in these case studies can be used in the planning and scoping phases of risk assessments and risk management. Other, more complex PRA approaches are used to answer more specific questions and provide a richer description of the risks. Most studies show that PRA can improve or expand on information generated by deterministic methods. In some of the case studies, the use of multiple PRA tools is illustrated. For example, Case Study 1 describes the use of a point estimate sensitivity analysis to identify exposure variables critical to the analysis summarized in Case Study 9. Both of these case studies focus on children's exposure to chromated copper arsenate (CCA)-treated wood. In Case Study 9, an MCA was used as an example of a two-dimensional (i.e., addressing both variability and uncertainty) probabilistic exposure assessment.

Overall, the case studies illustrate that the Agency already has applied the science of PRA to ecological risk and human exposure estimation and has begun using PRA to describe health effects. Some of the applications have used existing "off-the-shelf" software, whereas others have required significant effort and resources. Once developed, however, some of the more complex models have been used many times for different assessments. All of the assessments have been validated by internal and external peer review. Table 1 gives some highlights the case studies from deterministic to more complex assessments, which are described in more detail in the Appendix.

Table 1. Selected Examples of EPA Applications of Probabilistic Risk Assessment Techniques

Case Study No.	Description	Group	Type of Risk Assessment	Office/Region
2	**Atmospheric Deposition to Watershed Contamination:** The Office of Research and Development (ORD) developed an analysis of nitrogen, mercury and polycyclic aromatic hydrocarbons (PAHs) depositions toward watershed contamination in the Casco Bay Estuary in southwestern Maine.	Group 1: Point Estimate	Ecological	ORD
5	**Hudson River Polychlorinated Biphenyl (PCB)-Contaminated Sediment Site:** Region 2 evaluated the variability in risks to anglers who consume recreationally caught fish contaminated with PCBs from sediment contamination in the Hudson River.	Group 2: 1-D Monte Carlo Analysis	Human Health	Superfund/ Region 2 (New York)
7	**Environmental Monitoring and Assessment Program (EMAP):** ORD developed and the Office of Water (OW) applied probabilistic sampling techniques to evaluate the Nation's aquatic resources under the Clean Water Act (CWA) Section 305(b).	Group 2: Probabilistic Sensitivity Analysis	Ecological	ORD/OW
9	**Chromated Copper Arsenate (CCA) Risk Assessment:** ORD and the Office of Pesticide Programs (OPP) conducted a probabilistic assessment of children's exposure (addressing both variability and uncertainty) to arsenic and chromium from contact with CCA-treated wood play sets and decks.	Group 3: 2-D Monte Carlo Analysis	Human Health	ORD/OPP
13	**Evaluating Ecological Effects of Pesticide Uses:** OPP developed a probabilistic model, which evaluates acute mortality levels in generic and specific ecological species for user-defined pesticide uses and exposures.	Group 3: Probabilistic Analysis	Ecological	OPP
14	**Fine Particulate Matter Health Impacts:** ORD and the Office of Air and Radiation (OAR) used expert elicitation to more completely characterize, both qualitatively and quantitatively, the uncertainties associated with the relationship between reduction in fine particulate matter ($PM_{2.5}$) and benefits of reduced $PM_{2.5}$-related mortality.	Group 3: Expert Elicitation	Human Health	ORD/OAR

2. PROBABILISTIC RISK ANALYSIS

2.1. What Are Uncertainty and Variability, and How Are They Relevant to Decision Making?

The concepts of uncertainty and variability are introduced here, and the relevance of these concepts to decision making is discussed.

2.1.1. Variability

Variability refers to real differences over time, space or members of a population and is a property of the system being studied (e.g., drinking water consumption rates for each of the many individual adult residents living in a specific location or differences in body lengths or weights for humans or ecological species) (Cullen and Frey 1999; USEPA 2011c). Variability can arise from inherently random processes, such as variations in wind speed over time at a given location or from true variation across members of a population that, in principle, could be explained, but which, in practice, may not be explainable using currently available models or data (e.g., the range of lead levels in the blood of children 6 years old or younger following a specific degree of lead exposure). Of particular interest in both HHRA and ERA is inter-individual variability, which typically refers to differences between members of the same population in either behavior related to exposure (e.g., dietary consumption rates for specific food items), or biokinetics related to chemical uptake (e.g., gastrointestinal uptake rates for lead following intake) or toxic response (e.g., differences among individuals or species in the internal dose needed to produce a specific amount of neurological impairment).

Inter-individual variability is illustrated in Case Study 5 in the Appendix, which assesses a PCB-contaminated sediment site in the Hudson River. In this case study, the quantification of variability is illustrated through the use of a PRA tool—1-D MCA—to describe the variability of exposure as a function of individual exposure factors (i.e., young children's fish ingestion).

2.1.2. Uncertainty

Uncertainty is the lack of knowledge of the true value of a quantity or relationships among quantities (USEPA 2011c). For example, there may be a lack of information regarding the true distribution of variability between individuals for consumption of certain food items. There are a number of types of uncertainties for both risk analysis. The following descriptions of the types of uncertainty (adapted from Cullen and Frey 1999) addresses uncertainties that arise during risk analyses. These uncertainties can be separated broadly into three categories: (1) scenario uncertainty; (2) model uncertainty; and (3) input or parameter uncertainty. Each of these is explained in the paragraphs that follow.

Scenario uncertainty refers to errors, typically of omission, resulting from incorrect or incomplete specification of the risk scenario to be evaluated. The risk scenario refers to a set of assumptions regarding the situation to be evaluated, such as: (1) the specific sources of chemical emissions or exposure to be evaluated (e.g., one industrial facility or a cluster of varied facilities impacting the same study area); (2) the specific receptor populations and associated exposure pathways to be modeled (e.g., indoor inhalation exposure, track-in dust or consumption of home-produced dietary items); and (3) activities by different lifestages to be considered (e.g., exposure only at home, or consideration of workplace or commuting exposure). Mis-specification of the risk scenario can result in underestimation, overestimation or other mischaracterization of risks. Underestimation may occur because of the exclusion of relevant situations or the inclusion of irrelevant situations with respect to a particular analysis. Overestimation may occur because of the inclusion of unrealistic or irrelevant situations (e.g., assuming continuous exposure to an intermittent airborne contaminant source rather than accounting for mobility throughout the day).

Model uncertainty refers to limitations in the mathematical models or techniques that are developed to represent the system of interest and often stems from: (1) simplifying assumptions; (2) exclusion of relevant processes; (3) mis-specification of model boundary conditions (e.g., the range of input parameters); or (4) misapplication of a model developed for other purposes. Model uncertainty typically arises when the risk model relies on missing or improperly formulated processes, structures or equations. Sources of model uncertainty are defined in the Glossary.

Input or parameter uncertainty typically refers to errors in characterizing the empirical values used as inputs to the model (e.g., engineering, physical, chemical, biological or behavioral variables). Input uncertainty can originate from random or systematic errors involved in measuring a specific phenomenon (e.g., biomarker measurements, such as the concentration of mercury in human hair); statistical sampling errors associated with small sample sizes (e.g., if the data are based on samples selected with a random, representative sampling design); the use of surrogate data instead of directly measured data; the absence of an empirical basis for characterizing an input (e.g., the absence of measurements for fugitive emissions from an industrial facility); or the use of summary measures of central tendency rather than individual observations. Nonlinear random processes can exhibit a behavior that, for small changes in input values, produces a large variation in results.

Input or parameter uncertainty is illustrated in Case Study 3 in the Appendix titled "Probabilistic Assessment of Angling Duration Used in the Assessment of Exposure to Hudson River Sediments via Consumption of Contaminated Fish." In this case study, a probabilistic analysis of one parameter in an exposure assessment—the time an individual spends fishing in a large river system—was assessed using sensitivity analysis. This analysis was conducted because there was uncertainty that the individual exposure duration based on residence duration may underestimate the time spent fishing (i.e., angling duration). The full distribution of the calculated values was used in conducting the 1-D MCA for the fish consumption pathway, which is presented in Case Study 5.

Decision uncertainty refers to a decision analysis that would include not only the impact of scenario, model and input uncertainties on the relative attractiveness of potential decision alternatives, but also would include the degree to which specific choices (such as selecting input data, models, and scenarios, and even how the problem or decision analysis is framed) impact the relative attractiveness of potential decision alternatives. In decision making, analysts use data to represent decision criteria that decision makers and other stakeholders believe will help them to answer their decision question(s). These questions might include which policy alternative best meets Agency goals (that must be articulated) or which risk assessment scenario best describes the observed effects. Data, model and scenario uncertainties will influence the risk assessment results and those, in turn, will influence the risk management options. Decision makers who understand the uncertainty associated with their specific choices can be more confident that the decision will produce the results that they seek. In addition, these decision makers will be able to defend their decisions better and explain how the decision meets Agency and stakeholder goals.

While this is beyond the scope of this document, Stahl and Cimorelli (2005 and 2012) illustrate how uncertainty throughout the decision making process can be assessed. These case studies explored the assessment of ozone monitoring networks and air quality management policies that seek to minimize the adverse impacts from ozone, fine particulate matter and air toxics simultaneously. These case studies demonstrate the importance and feasibility of better understanding the uncertainty introduced by specific choices (e.g., selecting input data, models, and scenarios) when making public policy decisions.

2.2. When Is Probabilistic Risk Analysis Applicable or Useful?

PRA may be particularly useful, for example, in the following (Cooke 1991; Cullen and Frey 1999; NRC 2009; USEPA 2001):

- ❒ When a screening-level DRA indicates that risks are possibly higher than a level of concern and a more refined assessment is needed.
- ❒ When the consequences of using point estimates of risk are unacceptably high.
- ❒ When significant equity or environmental justice issues are raised by inter-individual variability.
- ❒ To estimate the value of collecting additional information to reduce uncertainty.
- ❒ To identify promising critical control points and levels when evaluating management options.
- ❒ To rank exposure pathways, sites, contaminants and so on for the purposes of prioritizing model development or further research.
- ❒ When combining expert judgments on the significance of the data.
- ❒ When exploring the impact of the probability distributions of stakeholder and decision-maker values on the attractiveness of potential decision alternatives (Fischhoff 1995; Illing 1999; Kunreuther and Slovic 1996; USEPA 2000b).
- ❒ When exploring the impact of the probability distributions of the data, model and scenario uncertainties, and variability together to compare potential decision alternatives.

PRA may add minimal value to the assessment in the following types of situations (Cullen and Frey 1999; USEPA 1997a):

- ❒ When a screening-level deterministic risk assessment indicates that risks are negligible, presuming that the assessment is known to be conservative enough to produce overestimates of risk.
- ❒ When the cost of averting the exposure and risk is smaller than the cost of a probabilistic analysis.
- ❒ When there is little uncertainty or variability in the analysis (this is a rare situation).

2.3. How Can Probabilistic Risk Analysis Be Incorporated Into Assessments?

As illustrated in the accompanying case studies in the Appendix, probabilistic approaches can be incorporated into any stage of a risk assessment, from problem formulation or planning and scoping to the analysis of alternative decisions. In some situations, PRA can be used selectively for certain components of an assessment. It is common in assessments that some model inputs are known with high confidence (i.e., based on site-specific measurements), whereas values for other inputs are less certain (i.e., based on surrogate data collected for a different purpose). For example, an exposure modeler may determine that relevant air quality monitoring data exists, but there is a lack of detailed information on human activity patterns in different microenvironments. Thus, an assessment of the variability in exposure to airborne pollutants might be based on direct use of the monitoring data, whereas assessment of uncertainty and variability in the inhalation exposure component might be based on statistical analysis of surrogate data or use of expert judgment. The uncertainties are likely to be larger for the latter than the former component of the assessment;

efforts to characterize uncertainties associated with pollutant exposures would focus on the latter. PRA also deals with dependency issues; a description of these issues is available in Section 3.3.2.

2.4. What Are the Scientific Community's Views on Probabilistic Risk Analysis, and What Is the Institutional Support for Its Use in Performing Assessments?

The NRC and IOM recently emphasized their long-standing advocacy for PRA (NRC 2007a and b; IOM 2013). Dating from its 1983 *Risk Assessment in the Federal Government: Managing the Process* (NRC 1983)—which first formalized the risk assessment paradigm—through reports released from the late 1980s through the early 2000s, various NRC panels have maintained consistently that because risk analysis involves substantial uncertainties, these uncertainties should be evaluated within a risk assessment. These panels noted that:

1. When evaluating the total population risk, EPA should consider the distribution of exposure and sensitivity of response in the population (NRC 1989).

2. When assessing human exposure to air pollutants, EPA should present model results along with estimated uncertainties (NRC 1991).

3. When conducting ERA, EPA should discuss thoroughly uncertainty and variability within the assessment (NRC 1993).

4. "Uncertainty analysis is the only way to combat the 'false sense of certainty,' which is *caused* by a refusal to acknowledge and [attempt to] quantify the uncertainty in risk predictions," as stated in the NRC report, *Science and Judgment in Risk Assessment* (NRC 1994).

5. EPA's estimation of health benefits was not wholly credible because EPA failed to deal formally with uncertainties in its analyses (NRC 2002).

6. EPA should adopt a "tiered" approach for selecting the level of detail used in uncertainty and variability assessment. Furthermore, the NRC recommended that a discussion of the level of detail used for uncertainty analysis and variability assessment should be an explicit part of the planning, scoping and problem formulation phase of the risk assessment process (NRC 2009).

7. EPA should develop methods to systematically describe and account for uncertainties in decision-relevant factors in addition to estimates of health risk in its decision-making process (IOM 2013).

Asked to recommend improvements to the Agency's HHRA practices, EPA's SAB echoed the NRC's sentiments and urged the Agency to characterize uncertainty and variability more fully and systematically and to replace single-point uncertainty factors with a set of distributions using probabilistic methods (Parkin and Morgan 2007). The key principles of risk assessment cited by the Office of Science and Technology Policy (OSTP) and the Office of Management and Budget (OMB) include "explicit" characterization of the uncertainties in risk judgments; they proceed to cite the National Academy of Science's (NAS) 2007 recommendation to address the "variability of effects across potentially affected populations" (OSTP/OMB 2007).

2.5. Additional Advantages of Using Probabilistic Risk Analysis and How It Can Provide More Comprehensive, Rigorous Scientific Information in Support of Regulatory Decisions.

External stakeholders previously have used the Administrative Procedure Act and the Data Quality Act to challenge the Agency for a lack of transparency and consistency or for not fully analyzing and characterizing the uncertainties in risk assessments or decisions (Fisher *et al*. 2006). The more complete implementation of PRA and related approaches to deal with uncertainties in decision making would address stakeholder concerns in regard to characterizing uncertainties.

The results of any assessment, including PRA, are dependent on the underlying methods and assumptions. Accompanied by the appropriate documentation, PRA may communicate a more robust representation of risks and corresponding uncertainties. This characterization may be in the form of a range of possible estimates as opposed to the more traditionally presented single-point values. Depending on the use of the assessment, ranges can be derived for variability and uncertainty (or a combination of the two) in both model inputs and resulting estimations of risk.

PRA quantifies how exposures, effects and risks differ among human populations or lifestages or target ecological organisms. PRA also provides an estimation of the degree of confidence with which these estimates may be made, given the current uncertainty in scientific knowledge and available data. A 2007 NRC panel stated that the objective of PRAs is *not* to decide "how much evidence is sufficient" to adopt an alternative but, rather, to describe the scientific bases of proposed alternatives so that scientific and policy considerations may be more fully evaluated (NRC 2007a). EPA's SAB similarly noted that PRAs provide more "value of information" through a quantitative assessment of uncertainty and clarify the science underlying Agency decisions (USEPA 2007b).

The SAB articulated a number of advantages for EPA decision makers from the utilization of probabilistic methods (Parkin and Morgan 2007):

- ❒ A probabilistic reference dose could help reduce the potentially inaccurate implication of zero risk below the RfD.
- ❒ By understanding and explicitly accounting for uncertainties underlying a decision, EPA can estimate formally the value of gathering more information. By doing so, the Agency can better prioritize its information needs by investing in areas that yield the greatest information value.
- ❒ Strategic use of PRA would allow EPA to send the appropriate signal to the intellectual marketplace, thereby encouraging analysts to gather data and develop methodologies necessary for assessing uncertainties.

2.6. What Are the Challenges to Implementation of Probabilistic Analyses?

Currently, EPA is using PRA in a variety of programs to support decisions, but challenges remain regarding the expanded use of these tools within the Agency. The challenges include:

- ❒ A lack of understanding of the value of PRA for decision making. PRA helps to improve the rigor of the decision-making process by allowing decision makers to explore the impacts of uncertainty and variability on the decision choices.
- ❒ A clear institutional understanding of how to incorporate the results of probabilistic analyses into decision making is lacking.

- PRA typically requires a different skill set than used in current evaluations, and limited resources (staff, time, training or methods) to conduct PRA are available.
- Communicating probabilistic analysis results and the impact of those results on the decision/policy options can be complex.
- Communication with stakeholders is often difficult and results in the appearance of regulatory delays due the necessity of analyzing numerous scenarios using various models.
- PRA complicates decision making and risk communication in instances where a more comprehensive characterization of the uncertainties leads to a decrease in clarity regarding how to estimate risk for the scenario under consideration. These challenges are discussed in more detail in Sections 2.7 through 2.13.

2.7. How Can Probabilistic Risk Analysis Support Specific Regulatory Decision Making?

Decision makers sometimes perceive that the binary nature of regulatory decisions (e.g., Does an exposure exceed a reference dose or not? Do emissions comply with Agency standards or not?) precludes the use of a risk range developed through PRA. Generally, it is necessary to explain the rationale underlying a particular decision. PRA's primary purpose is to provide information to enhance the ability to make transparent decisions based on the best available science. By conducting a sensitivity analysis of the influence of the uncertainty on the decision-making process, it can be determined how or if PRA can help to improve the process.

PRA can provide information to decision makers on specific questions related to uncertainty and variability. For questions of uncertainty and to minimize the likelihood of unintended consequences, PRA can help to provide the following types of information:

- Characterization of the uncertainty in estimates (i.e., What is the degree of confidence in the estimate?). Could the prediction be off by a factor of 2, a factor of 10 or a factor of 1,000?
- Critical parameters and assumptions that most affect or influence a decision and the risk assessment.
- "Tipping points" where the decision would be altered if the risk estimates were different, or if a different assumption was valid.
- Estimate the likelihood that values for critical parameters will occur or test the validity of assumptions.
- Estimate the degree of confidence in a particular decision and/or the likelihood of specific decision errors.
- The possibility of alternative outcomes with additional information, or estimate tradeoffs related to different risks or risk-management decisions.
- The impact of additional information on decision making, considering the cost and time to obtain the information and the resulting change in decision (i.e., the value of the information).

For the consideration of variability, PRA can help to provide the following types of information for exposures:

- Explicitly defined exposures for various populations or lifestages (i.e., Who are we trying to protect?). That is, will the regulatory action keep 50 percent, 90 percent, 99.9 percent or some other fraction of the population below a specified exposure, dose or risk target?

❒ Variability in the exposures, among various populations or lifestages, and information on the percentile of the population that is being evaluated in the risk assessment (e.g., variations in the number of liters of water per kilogram [kg] body weight per day consumed by the population). This information is helpful in addressing comments:

- On the conservatism of EPA's risk assessments;
- Concerns about whether their particular exposures were evaluated in the risk assessment;
- Whom or what is being protected by implementing a decision; and
- Whether and what additional research may be needed to reduce uncertainty.

PRA helps to inform decisions by characterizing the alternatives available to the decision maker and the uncertainty he or she faces, and by providing evaluation measures of outcomes. Uncertainties often are represented as probabilities or probability distributions numerically or in graphs. As part of a decision analysis, stakeholders can more fully examine how uncertainties influence the preference among alternatives.

2.8. Does Probabilistic Risk Analysis Require More Resources Than Default-Based Deterministic Approaches?

PRA generally can be expected to require more resources than standard Agency default-based deterministic approaches. There is extensive experience within EPA in conducting and reviewing DRA. These assessments tend to follow standardized methods that minimize the effort required to conduct them and to communicate the results. Probabilistic assessments often entail a more detailed analysis, and as a result, these assessments require substantially more resources, including time and effort, than do deterministic approaches.

Appropriately trained staff and the availability of adequate tools, methods and guidance are essential for the application of PRA. Proper application of probabilistic methods requires not only software and data, but also guidance and training for analysts using the tools and for managers and decision makers tasked with interpreting and communicating the results.

An upfront increase in resources needed to conduct a probabilistic assessment can be expected, but development of standardized approaches and/or methods can lead to the routine incorporation of PRA in Agency approaches (e.g., OPP's use of the Dietary Exposure Evaluation Model [DEEM; http://www.epa.gov/pesticides/science/deem/], a probabilistic dietary exposure model). The initial and, in some cases, ongoing resource cost (e.g., for development of site-specific models for site assessments) may be offset by a more informed decision than a comparable deterministic analysis. Probabilistic methods are useful for identifying effective management options and prioritizing additional data collection or research aimed at improving risk estimation, ultimately resulting in decisions that enable improved environmental protection while simultaneously conserving more resources.

2.9. Does Probabilistic Risk Analysis Require More Data Than Conventional Approaches?

There are differences of opinion within the technical community as to whether PRA requires more data than other types of analyses. Although some emphatically believe that PRA requires more data, others argue that probabilistic assessments make better use of all of the available data and information. Stahl and Cimorelli (2005) discuss when and how much data are necessary for a decision. PRA can benefit from more data than might be used in a DRA. For example, where DRA might employ selected point estimates (e.g., the mean or 95th percentile values) from available data sets for use in model inputs, PRA facilitates the use of frequency-weighted data distributions, allowing for a more comprehensive consideration of the available data. In many cases, the data that were used to develop the presumptive 95th percentile can be employed in the development of probabilistic distributions.

Restriction of PRA to principally data-rich situations may prevent its broader application where it is most useful. Because PRA incorporates information on data quality, variability and uncertainty into risk models, the influence of these factors on the characterization of risk can become a greater focus of discussion and debate.

A key benefit of using PRA is its ability to reveal the limitations as well as the strengths of data that often are masked by a deterministic approach. In doing so, PRA can help to inform research agendas, as well as support regulatory decision making, based on the state of the best available science. In summary, PRA typically requires more time for developing input assumptions than a DRA, but when incorporated into the relevant steps of the risk assessment process, PRA can demonstrate added benefits. In some cases, PRA can provide additional interpretations that compensate for the extra effort required to conduct a PRA.

2.10. Can Probabilistic Risk Analysis Be Used to Screen Risks or Only in Complex or Refined Assessments?

Probabilistic methods typically are not necessary where traditional default-based deterministic methods are adequate for screening risks. Such methods are relatively low cost, intended to produce conservatively biased estimates, and useful for identifying situations in which risks are so low that no further action is needed. The application of probabilistic methods can be targeted to situations in which a screening approach indicates that a risk may be of concern or when the cost of managing the risk is high, creating a need for information to help inform decision making. PRA fits directly into a graduated hierarchical approach to risk analysis. This tiered approach, depicted in Figure 2, is a process for a systematic informed progression to increasingly more complex risk assessment methods, depending on the decision-making context and need. Higher tiers reflect increasing complexity and often will require more time and resources. An analysis might typically start at a lower tier and only progress to a higher tier if there is a need for a more sophisticated assessment commensurate with the importance of the problem. Higher tiers also reflect increasing characterization of variability and/or uncertainty in the risk estimate, which may be important for risk-management decisions. The case studies described in the Appendix are presented in three groups that generally correspond to the tiers identified in Figure 2. Group 1 case studies are point estimate (sensitivity analysis) examples (Tier 1); Group 2 case studies include most moderate-complexity PRA examples (Tier 2); and Group 3 case studies are advanced (high complexity) PRA examples (Tier 3).

The tiered approach in Figure 2 depicts a continuum from screening level point estimate that is done with little data and conservative assumptions to PRA that requires an extensive data set and more realistic (less conservative) assumptions. In between, there can be a wide variety of tiers of increasing complexity, or there may be only a few reasonable choices between screening methods and highly refined analyses (USEPA 2004a). A similar four-tiered approach for characterizing the variability and/or uncertainty in the estimated exposure or risk analysis (WHO 2008) has been adapted by EPA in the risk and exposure assessments conducted for the National Ambient Air Quality Standards (NAAQS).

PRA also could be used to examine more fully the existing default-based methods based on the current state of information and knowledge to determine if such methods are truly conservative and adequate for screening (e.g., in dose-response analyses dealing with hazard characterization) (Swartout *et al*. 1998; Hattis *et al*. 2002).

The use of a spectrum of data should be employed both in determining screening risks and in more complex assessments. For HHRA, data from human, animal, mechanistic and other studies should be used to develop a probabilistic characterization of cancer and noncancer risks and to identify uncertainties. The NRC recommended that EPA facilitate this approach by redefining RfD and RfC within the probabilistic framework to take into account the probability of harm (NRC 2009). It is likely that both DRA and PRA will be part of this framework.

2.11. Does Probabilistic Risk Analysis Present Unique Challenges to Model Evaluation?

The concept of "validation" of models used for regulatory decision making has been a topic of intense discussion. In a recent report on the use of models in environmental regulatory decision making, the NRC recommended using the notion of model "evaluation" rather than "validation," suggesting that use of a process that encompasses the entire life cycle of the model and incorporates the spectrum of interested parties in the application of the model often extends beyond the model builder and decision maker. Such a process can be designed to ensure that judgment of the model application is based not only on its predictive value determined from comparison with historical data, but also on its comprehensiveness, rigor in development, transparency and interpretability (NRC 2007b).

Model evaluation is important in all risk assessments. In the case of PRA, there is an additional question as to the validity of the assumptions regarding probability and frequency distributions for model inputs and their dependencies. Probabilistic information can be accounted for during evaluation analyses by considering the range of uncertainty in the model prediction and whether such a range overlaps with the "true" value based on independent data. Thus, probabilistic information can aid in characterizing the precision of the model predictions and whether a prediction is significantly different from a benchmark of interest. For example, comparisons of probabilistic model results and monitoring data were performed for multiple models in developing the cumulative pesticide exposure model. Concurrent PRA model evaluations using a Bayesian analysis also have been published (Clyde 2000).

When risk assessors develop models of risk, they rely on two predominant statistical methods. Both methods arise from axioms of probability, but each applies these axioms differently. Under the frequentist approach, one develops and evaluates a model by testing whether the model—as applied to the observations—conforms to idealized distributions. Under the Bayesian approach, one develops and evaluates a model by testing which—among alternative models—best yields the underlying distribution describing the data. The practical differences between these two approaches can perhaps best be appreciated when considering the structural uncertainty in models (Section 3.3.3). Because Bayesians estimate model parameters with the expectation that these parameters—or even model structures—will be updated as new data become available, they have developed formal techniques to provide uncertainty bounds around these parameter estimates, select models that best explain the given data, or combine the results of alternative models.

2.12. How Do You Communicate the Results of Probabilistic Risk Analysis?

Effective communication makes it easier for regulators and stakeholders to understand the decision criteria driving the decision-making process. In other words, communication of PRA results within the decision-making context facilitates understanding. The specific approaches for reporting results from PRA vary depending on the assessment objective and the intended audience. Beyond the basic 1997 principles and the policy from the same year (USEPA 1997a and b), the *Risk Assessment Guidance for Superfund: Volume III—Part A, Process for Conducting Probabilistic Risk Assessment* also provides some guidance on the quality and criteria for acceptance as well as communication basics (USEPA 2001). There have been limited studies of how information from PRA regarding uncertainty and variability can or should be communicated to key audiences, such as decision makers and stakeholders (e.g., Morgan and Henrion 1990; Bloom *et al*. 1993; Krupnick *et al*. 2006). Among the analyst community, there often is an interest in visualization of the structure of a scenario and model using influence diagrams and depiction of the uncertainty and variability in model inputs and outputs using probability distributions in the form of cumulative density functions or probability distribution functions (Figure 3). Sensitivity of the model output to uncertainty and variability in model inputs can be depicted using graphical tools.

In some cases, these graphical methods can be useful for those less familiar with PRA, but in many cases there is a need to translate the quantitative results into a message that extracts the key insights without burdening the decision maker with obscure technical details. In this regard, the use of ranges of values for a particular metric of decision-making relevance (e.g., the range of uncertainty associated with a particular estimate of risk) may be adequate. The presentation of PRA results to a decision maker may be conducted best as an interactive discussion, in which a principal message is conveyed, followed by exploration of issues such as the source, quality and degree of confidence associated with the information. There is a need for the development of recommendations and a communication plan regarding how to communicate the results of PRA to decision makers and stakeholders, building on the experience of various programs and regions.

2.13. Are the Results of Probabilistic Risk Analysis Difficult to Communicate to Decision Makers and Stakeholders?

Research has shown that the ability of decision makers to deal with concepts of probability and uncertainty varies. Bloom *et al*. (1993) surveyed a group of senior managers at EPA and found that many could interpret information about uncertainty if it was communicated in a manner responsive to decision-maker interests, capabilities and needs. In a more recent survey of ex-EPA officials, Krupnick *et al*. (2006) concluded that most had difficulty understanding information on uncertainty with conventional scientific presentation approaches. The findings of these studies highlight the need for practical strategies for the communication of results of PRA and uncertainty information between risk analysts and decision makers, as well as between decision makers and other stakeholders. The Office of Emergency and Remedial Response (OERR) has compiled guidance to assist analysts and managers in understanding and communicating the results of PRA (USEPA 2001).

Risk analysts need to focus on how to use uncertainty analysis to characterize how confident decision makers should be in their choices. As Wilson (2000) explained, "… uncertainty is the bane of any decision maker's existence. Thus, anyone who wants to inform decisions using scientific information needs to assure that their analyses transform uncertainty into confidence in conclusions." Hence, although environmental risk assessments are complicated and it is easy to get lost in the details, presenting and discussing these results within the context of the decision facilitates understanding. The translation of uncertainty into confidence statements forces a "top-down" perspective that promotes accounting for whether and how uncertainties affect choices (Toll *et al*. 1997).

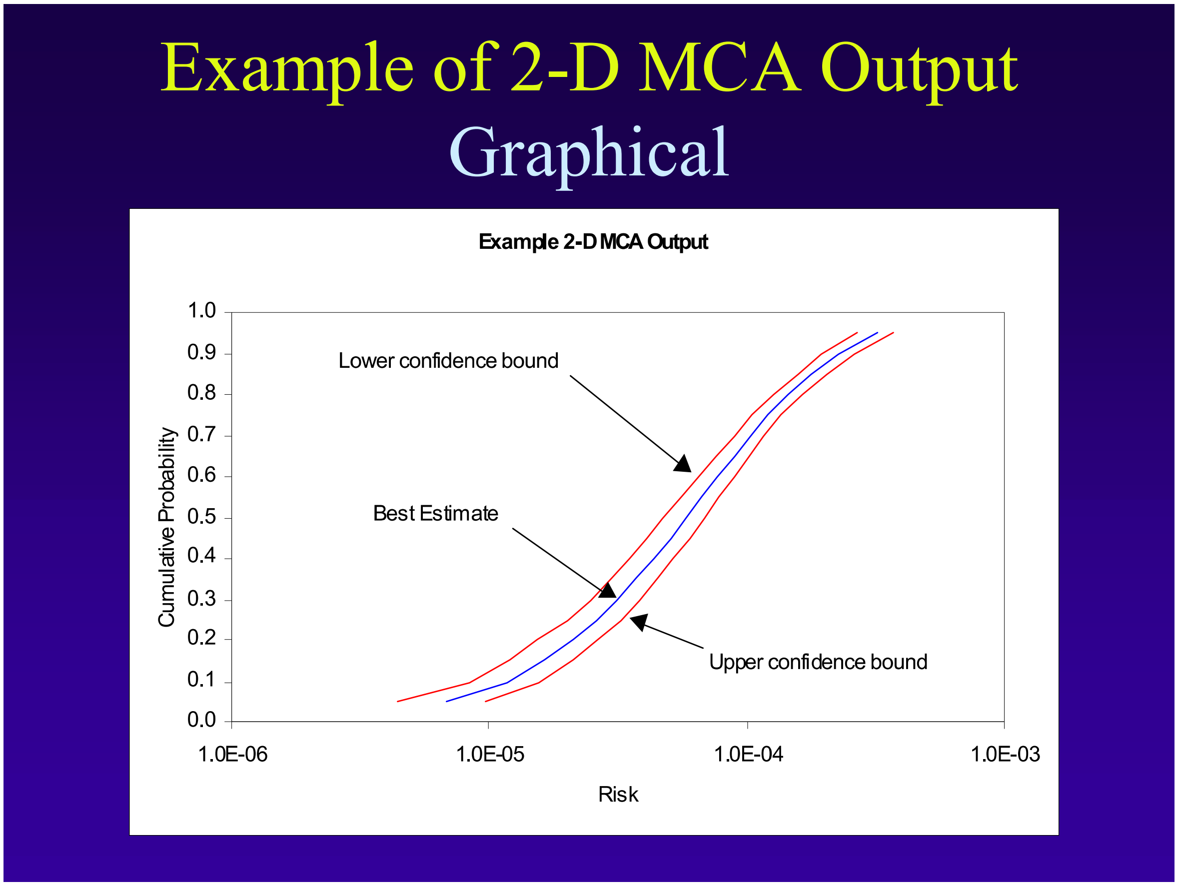

Figure 3. Graphical Description of the Likelihood (Probability) of Risk. Hypothetical fitted data distribution with upper and lower confidence intervals are depicted for the output of a 2-D MCA model.

3. AN OVERVIEW OF SOME OF THE TECHNIQUES USED IN PROBABILISTIC RISK ANALYSIS

3.1. What Is the General Conceptual Approach in Probabilistic Risk Analysis?

PRA includes several major steps, which parallel the accepted environmental health risk assessment process. These include: (1) problem and/or decision criteria identification; (2) gathering information; (3) interpreting the information; (4) selecting and applying models and methods for quantifying variability and/or uncertainty; (5) quantifying inter-individual or population uncertainty and variability in metrics relevant to decision making; (6) sensitivity analysis to identify key sources of variability and uncertainty; and (7) interpreting and reporting results.

Problem formulation entails identifying the assessment endpoints or issues that are relevant to the decision-making process and stakeholders, and that can be addressed in a scientific assessment process. Following problem formulation, information is needed from stakeholders and experts regarding the scenarios to evaluate. Based on the scenarios and assessment endpoints, the analysts select or develop models, which in turn leads to identification of model input data requirements and acquisition of data or other information (e.g., expert judgment encoded as the result of a formal elicitation process) that can be used to quantify inputs to the models. The data or other information for model inputs is interpreted in the process of developing probability distributions to represent variability, uncertainty or both for a particular input. Thus, steps (1) through (4) listed above are highly interactive and iterative in that the data input requirements and how information is to be interpreted depend on the model formulation, which depends on the scenario and that in turn depends on the assessment objective. The assessment objective may have to be refined depending on the availability of information.

Once a scenario, model and inputs are specified, the model output is estimated. A common approach is to use Monte Carlo Analysis (MCA) or other probabilistic methods to generate samples from the probability distributions of each model input, run the model based on one random value from each probabilistic input, and produce one corresponding estimate of the model outputs. This process is repeated typically hundreds or thousands of times to create a synthetic statistical sample of model outputs. These output data are interpreted as a probability distribution of the output of interest. Sensitivity analysis can be performed to determine which model input distributions are most highly associated with the range of variation in the model outputs. The results may be reported in a wide variety of forms depending on the intended audience, ranging from qualitative summaries to tables, graphs and diagrams.

Detailed introductions to PRA methodology are available elsewhere, such as Ang and Tang (1984), Cullen and Frey (1999), EPA (2001), and Morgan and Henrion (1990). A few key aspects of PRA methodology are briefly mentioned here. Readers who seek more detail should consult these references and see the Bibliography for additional references.

3.2. What Levels and Types of Probabilistic Risk Analyses Are There and How Are They Used?

There are multiple levels and types of analysis used to conduct risk assessments (illustrated in Figure 2 and Table 1, respectively). Graduated approaches to analysis are widely recognized (e.g., USEPA 1997a, 2001; WHO 2008). The idea of a graduated approach is to choose a level of detail and refinement for an analysis that is appropriate to the assessment objective, data quality, information available and importance of the decision (e.g., resource implications).

As discussed in section 1.8, there is a variety of approaches to risk assessment that differ in their complexity and the manner in which they address uncertainty and variability. In DRA one does not formally characterize uncertainty or variability but rather typically relies on using default-based assumptions and factors to generate a single estimate of risk. In PRA there is a variety of approaches to explicitly address or characterize uncertainty or variability in risk estimates and these differ in terms of how they accomplish this, the data used, and the overall complexity. Some examples are:

- ❒ Sensitivity analysis
- ❒ Monte Carlo analysis of variability in exposure data
- ❒ Human health or ecological effects data
- ❒ Monte Carlo analysis of uncertainty
- ❒ "Cumulative" PRA—multi-pathway or multi-chemical
- ❒ Two-dimensional PRA of uncertainty and variability
- ❒ Decision uncertainty analysis
- ❒ Geospatial analysis
- ❒ Expert elicitation

The DRA approaches described in Section 1.8 are examples of lower levels in a graduated approach to analysis. Risk at the lower levels of analysis is assessed by conservative, bounding assumptions. If the risk estimate is found to be very low despite the use of conservative assumptions, then there exists a great deal of certainty that the actual risks to the population of interest for the given scenario are below the level of concern and no further intervention is required, assuming that the scenario and model specifications are correct. When a conservative DRA indicates that a risk may be high, it is possible that the risk estimate is biased and the actual risk may be lower. In such a situation, depending on the resource implications of the decision, it may be appropriate to proceed with a more refined or higher level of analysis. The relative costs of intervention versus further analysis should be considered when deciding whether to proceed with a decision based on a lower level analysis or to escalate to a higher level of analysis. In some deterministic assessments (e.g., ecological risks), the assumptions are not well assured of conservatism, and the estimated risks might be biased to appear lower than the unseen actual risk.

A more refined analysis could involve the application of DRA methods, but with alternative sets of assumptions intended to characterize central tendency and reasonable upper bounds of exposure, effects and risk estimates, such that the estimates could be for an actual individual in the population of interest rather than a hypothetical maximally exposed individual. Such analyses are not likely to provide quantification regarding the proportion of the population at or below a particular exposure or risk level of concern, uncertainties for any given percentile of the exposed population, or priorities among input assumptions with respect to their contributions to uncertainty and variability in the estimates.

To more fully answer the questions often asked by decision makers, the analysis can be further refined by incorporating quantitative comparisons of alternative modeling strategies (to represent structural uncertainties associated with scenarios or models), quantifying ranges of uncertainty and variability in model outputs, and providing the corresponding ranges for model outputs of interest. When performing probabilistic analyses, choices are made regarding whether to focus on the quantification of variability only, uncertainty only, both variability and uncertainty together (representing a randomly selected individual), or variability and uncertainty independently (e.g., in a two-dimensional depiction of probability bands for estimates of inter-individual variability; see Figure 4). The simultaneous but distinct propagation of uncertainty and variability in a two-dimensional framework enables quantification of uncertainty in the risk for any percentile of the population. For example, one could estimate the range of uncertainty in the risk faced by the median member of the population or the 95th percentile member of the population. Such information can be used by a decision maker to gauge the confidence that should be placed in any particular estimate of risk, as well as to determine whether additional data collection or information might be useful to reduce the uncertainty in the estimates. The OPP assessment of Chromated Copper Arsenate-treated wood used such an approach. (See Case Study 9 in the Appendix.)

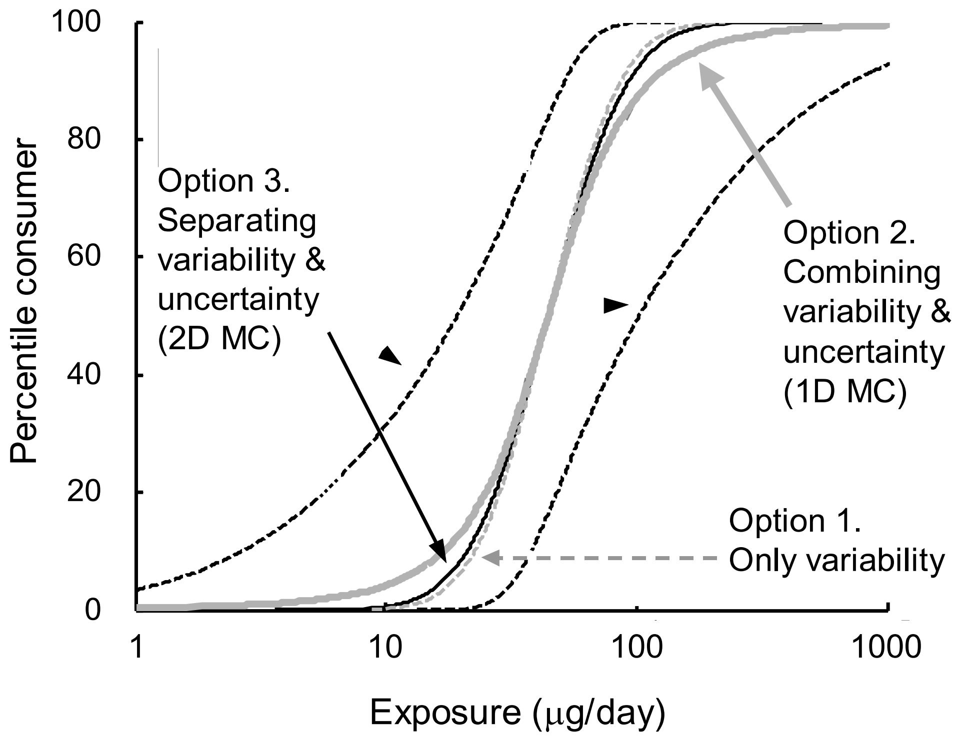

Figure 4. Diagrammatic Comparison of Three Alternative Probabilistic Approaches for the Same Exposure Assessment. In Option 1 (one dimensional Monte Carlo analysis), only variability is quantified. In Option 2 (one dimensional Monte Carlo analysis), both uncertainty and variability are combined. In Option 3 (two dimensional Monte Carlo analysis), variability and uncertainty are analyzed separately. Source: WHO 2008.

When conducting an analysis for the first time, it may not be known or clear, prior to analysis, which components of the model or which model inputs contribute the most to the estimated risk or its uncertainty and variability. As a result of completing an analysis, however, the analyst often gains insight into the strengths and weaknesses of the models and input information. Probabilistic analysis and sensitivity analysis can be used together to identify the key sources of quantified uncertainty in the model outputs to inform decisions regarding priorities for additional data collection. Ideally, time should be allowed for collecting such information and refining the analysis to arrive at a more representative and robust estimate of uncertainty and variability in risk. Thus, the notion of *iteration* in developing and improving an analysis is widely recommended.

The notion of iteration can be applied broadly to the risk assessment framework. For example, a first effort to perform an analysis may lead to insight that the assessment questions might be impossible to address, or that there are additional assessment questions that may be equally or more important. Thus, iteration can include reconsideration of the initial assessment questions and the corresponding implications for definition of scenarios, selection of models and priorities for obtaining data for model inputs. Alternatively, in a time-limited decision environment, probabilistic and sensitivity analyses may offer insight into the effect of management options on risk estimates.

3.3. What Are Some Specific Aspects of and Issues Related to Methodology for Probabilistic Risk Analysis?

This section briefly describes a few key aspects of PRA, model development and associated uncertainties. Detailed introductions to PRA methodology are available elsewhere, such as Ang and Tang (1984), Morgan and Henrion (1990), Cullen and Frey (1999) and EPA (2001). For more detailed information, consult these references and see the Bibliography for additional sources.

3.3.1. Developing a Probabilistic Risk Analysis Model

There are two key issues that should be considered in developing a PRA model; as discussed below.

Structural Uncertainty in Scenarios

A potentially key source of uncertainty in an analysis is the scenario, which includes specification of pollutant sources, transport pathways, exposure routes, timing and locations, geographic extent and related issues. There is no formalized methodology for dealing quantitatively with uncertainty and variability in scenarios. Decisions regarding what to include or exclude from a scenario could be recast as hypotheses regarding which agents, pathways, microenvironments, etc., contribute significantly to the overall exposure and risk of interest. In practice, however, the use of qualitative methods to frame an assessment tends to be more common, given the absence of a formal quantitative methodology.

Coupled Models

For source-to-outcome risk assessments, it often is necessary to work with multiple models, each of which represents a different component of a scenario. For example, there may be separate models for emissions, air quality, exposure, dose and effects. Such models may have different spatial and temporal scales. When conducting an integrated assessment, there may be significant challenges and barriers to coupling such models into one coherent framework. Sometimes, the coupling is done dynamically in a software environment. In other cases, the output of one model might be processed manually to prepare the information for input to the next model. Furthermore, there may be feedback between components of the scenario (e.g., poor air quality might affect human activity, which, in turn, could affect both emissions and exposures) that are incompletely captured or not included. Thus, the coupling of multiple models can be a potentially significant source of structural uncertainty (Özkaynak 2009).

3.3.2. Dealing With Dependencies Among Probabilistic Inputs

When representing two or more inputs to a model as probability distributions, the question arises as to whether it is reasonable to assume that the distributions are statistically independent. If there is a dependence, it could be as simple as a linear correlation between two inputs, or it could be more complicated, such as nonlinear or nonmonotonic relationships. Dependencies typically are not important if the risk estimate or other model output is sensitive to one or none of the probabilistic inputs that might have interdependence. Furthermore, dependencies typically are not of practical importance if they are weak. When dependencies exist and might significantly influence the risk estimate, they can be taken into account using a variety of statistical simulation methods or, perhaps more appropriately, by modeling the dependence analytically where possible. Details on methods for assessing the importance of possible dependencies and of quantifying them when needed are described in Ferson *et al*. (2004 and 2009).

For some types of models, such as air quality models, it is not possible to introduce a probability distribution to one input (e.g., ambient temperature at a particular location) without affecting variables at other locations or times (e.g., temperatures in other locations at the same times or temporal trends in temperature). In such cases, it is better to produce an "ensemble" of alternative temperature fields, each of which is internally consistent. Individual members of an ensemble usually are not interpreted as representing a probability sample; however, comparison of multiple ensembles of meteorological conditions, for example, can provide insight into natural sources of variability in ambient concentrations.

3.3.3. Conducting the Probabilistic Analysis

<u>Quantifying Uncertainty and Variability in Model Inputs and Parameters</u>

After the models are selected or developed to simulate a scenario of interest, attention typically turns to the development of input data for the model. There is a substantial amount of literature regarding the application of statistical methods for quantifying uncertainty and variability in model inputs and parameters based on empirical data (e.g., Ang and Tang 1984; Cullen and Frey 1999; Morgan and Henrion 1990; USEPA 2001). For example, a commonly used method for quantifying variability in a model input is to obtain a sample of data, select a type of parametric probability distribution model to fit to the data (e.g., normal, lognormal or other form), estimate the parameters of the distribution based on the data, critique the goodness-of-fit using graphical (e.g., probability plot) and statistical (e.g., Anderson-Darling, Chi-Square or Kolmogorov-Smirnov tests) methods and choose a preferred fitted distribution. This methodology can be adjusted to accommodate various types of data, such as data that are samples from mixtures of distributions or that contain non-detected (censored) values. Uncertainties can be estimated based on confidence intervals for statistics of interest, such as mean values, or the parameters of frequency distributions for variability. Various texts and guidance documents, both Agency and programmatic, describe these approaches, including the *Guiding Principles for Monte Carlo Analysis* (USEPA 1997b).

The most common method for estimating a probability distribution in the output of a model, based on probability distributions specified for model inputs, is MCS (Cullen and Frey 1999; Morgan and Henrion 1990). MCS is popular because it is very flexible. MCS can be used with a wide variety of probability distributions as well as different types of models. The main challenge for MCS is that it requires repetitive model calculations to construct a set of pseudo-random numbers for model inputs and the corresponding estimates for model outputs of interest. There are alternatives to MCS that are similar but more computationally efficient, such as Latin Hypercube Sampling (LHS). Techniques are available for simulating correlations between inputs in both MCS and LHS. For models with very simple functional forms, it may be possible to use exact or approximate analytical calculations, but such situations are encountered infrequently in practice. There may be situations in which the data do not conform to a well-defined probability distribution. In such cases, algorithms (such as Markov Chain Monte Carlo) can estimate a probability distribution by calculating a mathematical form describing the pattern of observed data. This form, called the likelihood function, is a key component of Bayesian inference and, therefore, serves as the basis for some of the analytical approaches to uncertainty and variability described below.

The use of empirical data presumes that the data comprise a representative, random sample. If known biases or other data quality problems exist, or if there is a scarcity or absence of relevant data, then naïve reliance on available empirical data is likely to result in misleading inferences in the analysis. Alternatively, estimates of uncertainty and variability can be encoded, using formal protocols, based on elicitation of expert judgment (e.g., Morgan and Henrion 1990, USEPA 2011a). Elicitation of expert judgment for subjective probability distributions is used in situations where there are insufficient data to support a statistical analysis of uncertainty, but in which there is sufficient knowledge on the part of experts to make an inference regarding uncertainty. For example, EPA conducted an expert elicitation study on the concentration-response relationship between the annual average ambient less than 2.5 micrometer (μm) diameter particulate matter ($PM_{2.5}$) exposure and annual mortality (IEC 2006; see also Case Studies 6 and 14 in the Appendix). Subjective probability distributions that are based on expert judgment can be "updated" with new data as they become available using Bayesian statistical methods.

Structural Uncertainty in Models

There may be situations in which it proves useful to evaluate not just the uncertainties in inputs and parameter values, but also uncertainties regarding whether a model adequately captures—in a hypothesized, mathematical, structured form—the relationship under investigation. A qualitative approach to evaluating the structural uncertainty in a model includes describing the critical assumptions within a model, the documentation of a model or the model quality, and how the model fits the purpose of the assessment. Quantitative approaches to evaluating structural uncertainty in models are manifold. These include parameterization of a general model that can be reduced to alternative functional forms (e.g., Morgan and Henrion 1990), enumeration of alternative models in a probability tree (e.g., Evans *et al*. 1994), comparing alternative models by evaluating likelihood functions (e.g., Royall 1997; Burnham and Anderson 2002), pooling results of model alternatives using Bayesian model averaging (e.g., Hoeting *et al*. 1999) or testing the causal relationships within alternative models using Bayesian Networks (Pearl 2009).

Sensitivity Analysis: Identifying the Most Important Model Inputs

Probabilistic methods typically focus on how uncertainty or variability in a model input affect [or result in] with respect to uncertainty or variability in a model output. After a probabilistic analysis is completed, sensitivity analysis typically takes the perspective of looking back to evaluate how much of the variation in the model output is attributable to individual model inputs (e.g., Frey and Patil 2002; Mokhtari *et al*. 2006; Saltelli *et al*. 2004).

There are many types of sensitivity analysis methods, including simple techniques that involve changing the value of one input at a time and assessing the effect on an output, and statistical methods that evaluate which of many simultaneously varying inputs contribute the most to the variance of the model output. Sensitivity analysis can answer the following key questions:

- ❒ What is the impact of changes in input values on model output?
- ❒ How can variation in output values be apportioned among model inputs?
- ❒ What are the ranges of inputs associated with best or worst outcomes?
- ❒ What are the key controllable sources of variability?
- ❒ What are the critical limits (e.g., the emission reduction target)?
- ❒ What are the key contributors to the output uncertainty?

Thus, sensitivity analysis can be used to inform decision making.

Iteration

There are two major types of iteration in risk assessment modeling. One is iterative refinement of the type of analysis, perhaps starting with a relatively simple DRA as a screening step in an initial level of analysis and proceeding to more refined types of assessments as needed in subsequent levels of analysis. Examples of more refined levels of assessment include application of sensitivity analysis to DRA; the use of probabilistic methods to quantify variability only, uncertainty only, or combined variability and uncertainty (to represent a randomly selected individual); or the use of two-dimensional probabilistic methods for distinguishing and simultaneously characterizing both uncertainty and variability.

The other type of iteration occurs within a particular level and includes iterative efforts to formulate a model, obtain data and evaluate the model to prioritize data needs. For example, a model may require a large number of input assumptions. To prioritize efforts of specifying distributions for uncertainty and variability for model inputs, it is useful to determine which model inputs are the most influential with respect to the assessment endpoint. Therefore, sensitivity can be used based on preliminary assessments of ranges or distributions for each model input to determine which inputs are the most important to the assessment. Refined efforts to characterize distributions then can be prioritized to the most important inputs.

4. SUMMARY AND RECOMMENDATIONS

4.1. Probabilistic Risk Analysis and Related Analyses Can Improve the Decision-Making Process at EPA

PRA can provide useful (even critical) information about the uncertainties and variability in the data, models, scenario, expert judgments and values incorporated in risk assessments to support decision making across the Agency. As discussed in this paper PRA is an analytical methodology capable of incorporating information regarding uncertainty and/or variability in risk analyses to provide insight on the degree of certainty of a risk estimate and how the risk estimate varies within the exposed population. Traditional approaches such as DRA, often report risks using descriptors such as "central tendency," "high end" (e.g., 90th percentile or above) or "maximum anticipated exposure". By contrast PRA can be used to describe more completely the uncertainty surrounding such estimates, as well as to identify the key contributors to uncertainty and variability in predicted exposures or risk estimates. This information then can be used by decision makers to weigh alternatives, or to make decisions on whether to collect additional data, or to conduct additional research in order to reduce the uncertainty and further characterize variability within the exposed population. Information on uncertainties and variability in exposure and response can ultimately improve the risk estimates.

PRA can be used to obtain insight on whether one management alternative is more likely to reduce risks compared to another. In addition, PRA can facilitate the development of modeling scenarios and the simultaneous consideration of multiple model alternatives. Probabilistic methods offer a number of tools designed to increase confidence in decision making through the incorporation of input uncertainty and variability characterization and prioritization in risk analyses. For example, one PRA tool, sensitivity analyses can be used to identify influential knowledge gaps in the estimation of risk; this improves transparency in the presentation of these uncertainties and improves the ability to communicate the most relevant information more clearly to decision makers and stakeholders. PRA allows one to investigate potential changes in decisions that could result from the collection of additional information. However, the additional resources (e.g., time, costs, or expertise) to undertake need to be weighed against the potential improvements in the decision making process. Ultimately, PRA may enhance the scientific foundation of the EPA's approach to decision making.

The various tools and methods discussed in this white paper can be utilized at all stages of risk analysis and also can aid the decision-making process by, for example, characterizing inter-individual variability and uncertainties.

PRA and related methods are employed in varying degrees across the Agency. Basic guidance exists at EPA on the use and acceptability of PRA for risk estimation, but implementation varies greatly within programs, offices and regions .The use of Monte Carlo or other probability-based techniques to derive a range of possible outputs from uncertain inputs is a fairly well-developed approach within EPA. Although highly sophisticated human exposure assessment and ecological risk applications have been developed, the use of PRA models to assess human health effects and dose-response relationships has been more limited at the Agency.

The evaluation of the application of PRA techniques under specific laws and regulations varies by program, office and region. Moving forward, it is important to broaden discussions between risk assessors and risk managers regarding how PRA tools can be used to support specific decisions and how they can be used within the regulatory framework used by programs, offices, and regions to make decisions. This can be accomplished by expanding the dialogue between assessors and manages at all levels regarding how the PRA tools have been used and how they have enhanced decision making.

Increased use of PRA and consistent application of PRA tools in support of EPA decision making requires enhanced internal capacity for conducting these assessments, as well as improved interpretation and communication of such information in the context of decisions. Improvements of Agency capacity could be accomplished through sharing of experiences, knowledge and training and increased availability of tools and methods.

4.2. Major Challenges to Using Probabilistic Risk Analysis to Support Decisions

The challenges for EPA are two-fold. As an Agency responsible for protecting human health and the environment, EPA makes regulatory and policy decisions, even in the presence of conflicting stakeholder positions and the inevitable uncertainties in the science. The first challenge for EPA is to determine how to conduct its decision-making responsibilities, weighing determinations of what constitutes too much uncertainty to make a decision, against potential adverse consequences of postponing decisions.

The second challenge, is that although current PRA techniques are available that would help to inform EPA decision-making processes, research and guidance are needed to improve these methods for a more complete implementation of PRA in HHRA and ERA. In particular, additional guidance is needed to help analysts and decision makers better understand how to incorporate PRA approaches into the decision-making process. This includes, guidance on which statistical tools to use and when to use them, and how probabilistic information can help to inform the scientific basis of decisions. Both DRA and PRA as well as appropriate statistical methods may be useful at any stage of the risk analysis and decision-making process, from planning and scoping to characterizing and communicating uncertainty.

- As noted in Section 3.3, there are significant challenges in properly accounting for uncertainty and variability when multiple models are coupled together to represent the source-to-outcome continuum. Moreover, the coupling of multiple models might need to involve inputs and corresponding uncertainties that are incorporated into more than one model, potentially resulting in complex dependencies. Integrative research on coupled model uncertainties will be quite valuable.
- There may be mismatches in the temporal and spatial resolution of each model that confound the ability to propagate uncertainty and variability from one model to another. For some models, the key uncertainties may be associated with inputs, whereas for other models, the key uncertainties may be associated with structure or parameterization alternatives. Model integration and harmonization activities will be important to addressing these technical issues.

4.3. Recommendations for Enhanced Utilization of Probabilistic Risk Analysis at EPA

Some examples of areas where new or updated guidance would be helpful are these:

- Identification of different types of information required for the various Agency decision-making processes, such as data analysis, tools, models, and use of experts.
- Use of probabilistic approaches to evaluate health effects data.
- Use of probabilistic approaches for ERA.

- Integrating probabilistic exposure and risk estimates and communicating uncertainty and variability.

In order to support the development of guidance on these or related topics, following studies or research are recommended:

- The use of PRA models to evaluate toxicity data has been very limited. Scientific, technical and policy-based discussions are needed in this area.
- Additional research on formal methods for treating model uncertainties will be valuable.

Some steps to improve implementation include these:

- Informing decision makers about the advantages and disadvantages of using PRA techniques in their decision-making processes through lectures, webinars and communications regarding the techniques and their use in EPA.
- Incorporating a discussion of PRA tools during Planning and Scoping for HHRAs and ERAs.
- Continuing the dialogue between assessors and managers on how to use PRA within the regulatory decision making process.
- Conducting meetings and discussions of PRA techniques and their application with both managers and assessors to aid in providing greater consistency and transparency in EPA's risk assessment and risk management process and in developing EPA's internal capacity.
- Developing a "Community of Practice" for further discussion regarding the application of PRA techniques and the use of these tools in decision making.

Risk assessors and risk managers need information and training so that they can better utilize these tools. Education and experience will generate familiarity with these tools, which will help analysts and decision makers better understand and consider more fully utilizing these techniques within their regulatory programs. Increased training is needed to facilitate understanding on all levels and may include the following:

- Providing introductory as well as advanced training to all EPA offices.
- Training risk assessors and risk managers in the PRA techniques so that they can learn about the various tools available, their applications, software and review considerations, and resources for additional information (e.g., experts and support services within the Agency).
- Providing easily available, flexible, modular training for all levels of experience to familiarize EPA employees with the menu of tools and their capacities.
- Providing live and recorded seminars and webinars for introductory and supplemental education, as well as periodic, centralized hands-on training sessions demonstrating how to utilize software programs.

Training is critical both for an improved understanding but also to build increased capacity in the Agency and explicit steps could include these:

- Demonstrating, through informational opportunities and resource libraries, the various tools and methods that can be used at all stages of risk analysis to aid the decision-making process by characterizing inter-individual variability and uncertainties.
- Promoting the sharing of experience, knowledge, models and best practices via meetings of risk assessors and managers; electronic exchanges, such as the EPA Portal Environmental

Science Connector (https://ssoprod.epa.gov/sso/jsp/obloginESCNew.jsp); and more detailed discussions of the case studies.

As EPA works toward the more integrated evaluation of environmental problems, this will include not just the improved understanding of single pollutants/single media, but multi-pollutant, multi-media and multi-receptor analysis within a decision analytic framework. EPA is beginning to build such integrated capability into analytical tools like PRA (Babendreier and Castleton 2005; Stahl *et al*. 2011).

The RAF will be taking a leadership role through the Uncertainty and Variability Workgroup to more fully evaluate the application and use of PRA tools and broadening the dialogue between assessors and managers. Updates on the progress of this Technical Panel will be provided on the RAF webpage at: www.epa.gov/raf.

GLOSSARY

Analysis. Examination of anything complex to understand its nature or to determine its essential features (WHO 2004).

Assessment. A determination or appraisal of possible consequences resulting from an analysis of data (2011b).

Assessment endpoint. An explicit expression of the environmental value that is to be protected, operationally defined by an ecological entity and its attributes. For example, salmon are valued ecological entities; reproduction and age class structure are some of their important attributes. Together, salmon "reproduction and age class structure" form an assessment endpoint (USEPA 1998b).

Bayesian probability. An approach to probability, representing a personal degree of belief that a value of random variable will be observed. Alternatively, the use of probability measures to characterize the degree of uncertainty (Gelman *et al*. 2004).

Bayesian Analysis. Bayesian analysis is a method of statistical inference in which the knowledge of prior events is used to predict future events (USEPA 2011b).

Correlation. An estimate of the degree to which two sets of variables vary together, with no distinction between dependent and independent variables. Correlation refers to a broad class of statistical relationships involving dependence (USEPA 2012).

Critical control point. A controllable variable that can be adjusted to reduce exposure and risk. For example, a critical control point might be the emission rate from a particular emission source. The concept of critical control point is from the hazard assessment and critical control point concept for risk management that is used in space and food safety applications, among others (USEPA 2006c).

Critical limit. A numerical value of a critical control point at or below which risk is considered to be acceptable. A criterion that separates acceptability from unacceptability (USEPA 2006c).

Deterministic. A methodology relying on point (i.e., exact) values as inputs to estimate risk; this obviates quantitative estimates of uncertainty and variability. Results also are presented as point values. Uncertainty and variability may be discussed qualitatively or semi-quantitatively by multiple deterministic risk estimates (USEPA 2006b).

Deterministic risk assessment (DRA). Risk evaluation involving the calculation and expression of risk as a single numerical value or "single point" estimate of risk, with uncertainty and variability discussed qualitatively (USEPA 2012).

Ecological risk assessment. The process that evaluates the likelihood that adverse ecological effects may occur or are occurring as a result of exposure to one or more stressors (USEPA 1998b).

Ecosystem. The biotic community and abiotic environment within a specified location in space and time (USEPA 1998b).

Ensemble. A method for predictive modeling based on multiple measures of the same event over time (e.g., the amount of carbon dioxide present in the atmosphere at selected time points). The collection of data input is known as an ensemble and can be used to develop a quantification of prediction variability within the model. Ensemble modeling is used most commonly in atmospheric prediction in forecasting, although ensemble modeling has been applied to biological systems to better quantify risks of events or perturbations within biological systems (Fuentes and Foley 2012).

Environment. The sum of all external conditions affecting the life, development and survival of an organism (USEPA 2010a).

Expert elicitation. A systematic process of formalizing and quantifying, typically in probabilistic terms, expert judgments about uncertain quantities (USEPA 2011a).

Frequentist (or frequency) probability. A view of probability that concerns itself with the frequency with which an event occurs given a long sequence of identical and independent trials (USEPA 1997b).

Hazard identification. The risk assessment process of determining whether exposure to a stressor can cause an increase in the incidence or severity of a particular adverse effect, and whether an adverse effect is likely to occur (USEPA 2012).

Human health risk assessment. 1. The process to estimate the nature and probability of adverse health effects in humans who may be exposed to chemicals in contaminated environmental media, now or in the future (USEPA 2010b). 2. The evaluation of scientific information on the hazardous properties of environmental agents (hazard characterization), the dose-response relationship (dose-response assessment), and the extent of human exposure to those agents (exposure assessment). The product of the risk assessment is a statement regarding the probability that populations or individuals so exposed will be harmed and to what degree (risk characterization) (USEPA 2006a).

Inputs. Quantities that are applied to a model (WHO 2008).

Likelihood Function. An approach to modeling exposure in which long-term exposure of an individual is simulated as the sum of separate short-term exposure events (USEPA 2001).

Microenvironment. Well-defined surroundings such as the home, office, automobile, kitchen, store, etc., that can be treated as homogenous (or well characterized) in the concentrations of a chemical or other agent (USEPA 1992).

Microexposure event (MEE) analysis. An approach to modeling exposure in which long-term exposure of an individual is simulated as the sum of separate short-term exposure events (USEPA 2001).

Model. A mathematical representation of a natural system intended to mimic the behavior of the real system, allowing description of empirical data, and predictions about untested states of the system (USEPA 2006b).

Model boundaries. 1. Decisions regarding the time, space, number of chemicals, etc., used in guiding modeling of the system. Risks can be understated or overstated if the model boundary is mis-specified. For example, if a study area is defined to be too large and includes a significant number of low-exposure areas, then a population-level risk distribution can be diluted by including less exposed individuals, which can, in turn, result in a risk-based decision that does not protect sufficiently the most exposed individuals in the study area. 2. Designated areas of competence of the model, including time, space, pathogens, pathways, exposed populations, and acceptable ranges of values for each input and jointly among all inputs for which the model meets data quality objectives (WHO 2008).

Modeling. Development of a mathematical or physical representation of a system or theory that accounts for all or some of its known properties. Models often are used to test the effect of changes of components on the overall performance of the system (USEPA 2010a).

Model uncertainty (sources of):

- ***Model structure.*** *A set of assumptions and inference options upon which a model is based, including underlying theory as well as specific functional relationships (WHO 2008).*

- ❒ ***Model detail.*** *Level of simplicity or detail associated with the functional relationships assumed in the model compared to the actual but unknown relationships in the system being modeled (WHO 2008).*
- ❒ ***Extrapolation.*** *Use of models outside of the parameter space used in their derivation may result in erroneous predictions. For example, a threshold for health effects may exist at exposure levels below those covered by a particular epidemiological study. If that study is used in modeling health effects at those lower levels (and it is assumed that the level of response seen in the study holds for lower levels of exposure), then disease incidence may be overestimated (USEPA 2007a).*

Monte Carlo analysis (MCA) or simulation (MCS). A repeated random sampling from the distribution of values for each of the parameters in a generic exposure or risk equation to derive an estimate of the distribution of exposures or risks in the population (USEPA 2006b).

One-dimensional Monte Carlo analysis (1-D MCA). A numerical method of simulating a distribution for an endpoint of concern as a function of probability distributions that characterize variability or uncertainty. Distributions used to characterize variability are distinguished from distributions used to characterize uncertainty (WHO 2008).

***Parameter*.** A quantity used to calibrate or specify a model, such as 'parameters' of a probability model (e.g., mean and standard deviation for a normal distribution). Parameter values often are selected by fitting a model to a calibration data set (WHO 2008).

***Probability*.** A frequentist approach considers the frequency with which samples are obtained within a specified range or for a specified category (e.g., the probability that an average individual with a particular mean dose will develop an illness) (WHO 2008).

Probabilistic risk analysis (PRA). Calculation and expression of health risks using multiple risk descriptors to provide the likelihood of various risk levels. Probabilistic risk results approximate a full range of possible outcomes and the likelihood of each, which often is presented as a frequency distribution graph, thus allowing uncertainty or variability to be expressed quantitatively (USEPA 2012).

Problem formulation. The initial stage of a risk assessment where the purpose of the assessment is articulated, exposure and risk scenarios are considered, a conceptual model is developed, and a plan for analyzing and characterizing risk is determined (USEPA 2004a).

Reference concentration (RfC). An estimate (with uncertainty spanning approximately an order of magnitude) of a continuous inhalation exposure to the human population (including sensitive subgroups) that is likely to be without an appreciable risk of deleterious effects during a lifetime. It can be derived from a No-Observed-Adverse-Effect Level (NOAEL), Lowest-Observed-Adverse-Effect Level (LOAEL), or benchmark concentration, with uncertainty factors generally applied to reflect limitations of the data used. It is generally used in EPA's noncancer health assessments (USEPA 2007a).

Reference dose (RfD). An estimate (with uncertainty spanning approximately an order of magnitude) of a daily oral exposure to the human population (including sensitive subgroups) that is likely to be without an appreciable risk of deleterious effects during a lifetime. It can be derived from a NOAEL, LOAEL or benchmark dose, with uncertainty factors generally applied to reflect limitations of the data used. It is typically used in EPA's noncancer health assessments (USEPA 2011c).

Risk. 1. Risk includes consideration of exposure to the possibility of an adverse outcome, the frequency with which one or more types of adverse outcomes may occur, and the severity or consequences of the adverse outcomes if such occur. 2. The potential for realization of unwanted, adverse consequences to human life, health, property or the environment. 3. The probability of adverse effects resulting from exposure to an environmental agent or mixture of agents. 4. The combined answers to: What can go wrong? How likely is it? What are the consequences? (USEPA 2011c).

Risk analysis. A process for identifying, characterizing, controlling and communicating risks in situations where an organism, system, subpopulation or population could be exposed to a hazard. Risk analysis is a process that includes risk assessment, risk management and risk communication (WHO 2008).

Risk assessment. 1. A process intended to calculate or estimate the risk to a given target organism, system, subpopulation or population, including the identification of attendant uncertainties following exposure to a particular agent, taking into account the inherent characteristics of the agent of concern, as well as the characteristics of the specific target system (WHO 2008). 2. The evaluation of scientific information on the hazardous properties of environmental agents (hazard characterization), the dose-response relationship (dose-response assessment), and the extent of human exposure to those agents (exposure assessment) (NRC 1983). The product of the risk assessment is a statement regarding the probability that populations or individuals so exposed will be harmed and to what degree (risk characterization; USEPA 2000a). 3. Qualitative and quantitative evaluation of the risk posed to human health or the environment by the actual or potential presence or use of specific pollutants (USEPA 2012).

Risk-based decision making. A process through which decisions are made according to the risk each posed to human health and the environment (USEPA 2012).

Risk management. A decision-making process that takes into account environmental laws; regulations; and political, social, economic, engineering and scientific information, including a risk assessment, to weigh policy alternatives associated with a hazard (USEPA 2011c).

Scenario. A set of facts, assumptions and inferences about how exposure takes place that aids the exposure assessor in evaluating, estimating or quantifying exposures (USEPA 1992). Scenarios might include identification of pollutants, pathways, exposure routes and modes of action, among others.

Sensitivity analysis. The process of changing one variable while leaving the others constant to determine its effect on the output. This procedure fixes each uncertain quantity at its credible lower and upper bounds (holding all others at their nominal values, such as medians) and computes the results of each combination of values. The results help to identify the variables that have the greatest effect on exposure estimates and help focus further information-gathering efforts (USEPA 2011b).

Tiered approach. Refers to various hierarchical tiers (levels) of complexity and refinement for different types of modeling approaches that can be used in risk assessment. A deterministic risk assessment with conservative assumptions is an example of a lower level type of analysis (Tier 0) that can be used to determine whether exposures and risks are below levels of concern. Examples of progressively higher levels include the use of deterministic risk assessment coupled with sensitivity analysis (Tier 1), the use of probabilistic techniques to characterize either variability or uncertainty only (Tier 2), and the use of two-dimensional probabilistic techniques to distinguish between but simultaneously characterize both variability and uncertainty (Tier 3) (USEPA 2004a and WHO 2008).

Two-dimensional Monte Carlo analysis (2-D MCA). An advanced numerical modeling technique that uses two stages of random sampling, also called nested loops, to distinguish between variability and uncertainty in exposure and toxicity variables. The first stage, often called the inner loop, involves a complete 1-D MCA simulation of variability in risk. In the second stage, often called the outer loop, parameters of the probability distributions are redefined to reflect uncertainty. These loops are repeated many times resulting in multiple risk distributions, from which confidence intervals are calculated to represent uncertainty in the population distribution of risk (WHO 2008).

***Uncertainty*.** Uncertainty occurs because of a lack of knowledge. It is not the same as variability. For example, a risk assessor may be very certain that different people drink different amounts of water but may be uncertain about how much variability there is in water intakes within the population. Uncertainty often can be reduced by collecting more and better data, whereas variability is an inherent property of the population being evaluated. Variability can be better characterized with more data but it cannot be reduced or eliminated. Efforts to clearly distinguish between variability and uncertainty are important for both risk assessment and risk characterization, although they both may be incorporated into an assessment (USEPA 2011c).

***Uncertainty analysis*.** A detailed examination of the systematic and random errors of a measurement or estimate; an analytical process to provide information regarding uncertainty (USEPA 2006b).

***Value of information*.** An analysis that involves estimating the value that new information can have to a risk manager before the information is actually obtained. It is a measure of the importance of uncertainty in terms of the expected improvement in a risk management decision that might come from better information (USEPA 2001).

***Variability*.** Refers to true heterogeneity or diversity, as exemplified in natural variation. For example, among a population that drinks water from the same source and with the same contaminant concentration, the risks from consuming the water may vary. This may result from differences in exposure (e.g., different people drinking different amounts of water and having different body weights, exposure frequencies and exposure durations), as well as differences in response (e.g., genetic differences in resistance to a chemical dose). Those inherent differences are referred to as variability. Differences among individuals in a population are referred to as inter-individual variability, and differences for one individual over time are referred to as intra-individual variability (USEPA 2011c).

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APPENDIX: CASE STUDY EXAMPLES OF THE APPLICATION OF PROBABILISTIC RISK ANALYSIS IN U.S. ENVIRONMENTAL PROTECTION AGENCY REGULATORY DECISION MAKING

A. OVERVIEW

This Appendix focuses on examples of how probabilistic risk analysis (PRA) approaches have been used at EPA to inform regulatory decisions. The Appendix was prepared by representatives from various EPA program offices and regions currently involved in the development and application of PRA techniques. The Technical Panel selected the case study examples based on the members' knowledge of the specific PRA procedures, the types of techniques demonstrated, the availability to the reader through the Internet and the condition of having been peer reviewed; they also were selected to be illustrative of a spectrum of PRA used at EPA. The case studies are not designed to provide an exhaustive discussion of the wide variety of applications of PRA used within the Agency, but to highlight specific examples reflecting the range of approaches currently applied within EPA.

This Appendix is intended to serve as a resource for managers faced with decisions regarding when to apply PRA techniques to inform environmental decisions, and for exposure and risk assessors who may not be familiar with the wide variety of available PRA approaches. The document outlines categories of PRAs classified by the complexity of analysis to aid the decision-making process. This approach identifies various PRA tools, which include techniques ranging from a simple sensitivity analysis (e.g., identification of key exposure parameters or data visualization) requiring limited time, resources and expertise to develop (Group 1); to probabilistic approaches, including Monte Carlo analysis, that provide tools for evaluating variability and uncertainty separately and that require more resources and specialized expertise (Group 2); to sophisticated techniques of expert elicitation that generally require significant investment of employee time, additional expertise and external peer review (Group 3).

The case studies in this Appendix used PRA techniques within this ranked framework to provide additional information for managers. The case study summaries are provided in a format designed to highlight how the results of the PRAs were considered in decision making. These summaries include specific information on the conduct of the analyses as an aid in determining what tools might be appropriate to develop specific exposure or risk assessments for other sites.

The case studies range from examples of less resource-intensive analyses, which might assist in identifying key exposure parameters or the need for more data, to more detailed and resource-intensive approaches. Examples of applications in human health and ecological risk assessment include the exposure of children to chromated copper arsenate (CCA)-treated wood, the relation between particulates in air and health, dietary exposures to pesticides, modeling sea level change, sampling watersheds, and modeling bird and animal exposures.

B. INTRODUCTION

Historically, EPA has used deterministic risk assessments, or point estimates of risk, to evaluate cancer risks and noncancer health hazards to high-end exposed individuals (90th percentile or higher) and the average exposed individual (50th percentile) and, where appropriate, risks and hazards to populations, as required by specific environmental laws (USEPA 1992a). The use of default values for exposure parameters in risk assessments provides a procedural consistency that allows risk assessments to be feasible and tractable (USEPA 2004). The methods typically used in EPA deterministic risk assessments (DRA) rely on a combination of point values—some conservative and some typical—yielding a point estimate of exposure that is at some unknown point in the range of possible risks (USEPA 2004).

This Appendix presents case studies of PRA conducted by EPA over the past 10 to 15 years. Table A-1 summarizes the case studies by title, technique demonstrated, classification as a human health risk assessment (HHRA) or ecological risk assessment (ERA), and the program or regional office responsible for developing the case studies. This Appendix, provides a "snapshot" of the utilization of PRA across various programs in EPA.

C. OVERALL APPROACH TO PROBABILISTIC RISK ANALYSIS AT THE U.S. ENVIRONMENTAL PROTECTION AGENCY

C.1. U.S. Environmental Protection Agency Guidance and Policies on Probabilistic Risk Analysis

The case studies presented here build on the principles of PRA outlined in EPA's 1997 *Policy for Use of Probabilistic Analysis in Risk Assessment at the U.S. Environmental Protection Agency* (USEPA 1997a) and *Guiding Principles for Monte Carlo Analysis* (USEPA 1997b), as well as subsequent guidance documents on developing and using PRA. Guidance has been developed for the Agency and individual programs. Specific documents that refer to the use of PRA include the *Risk Assessment Guidance for Superfund: Volume III* (USEPA 2001); Risk Assessment Forum (RAF) *Framework for Ecological Risk Assessment* (USEPA 1992b); *Guidelines for Ecological Risk Assessment* (USEPA 1998); *Guidance for Risk Characterization* (USEPA 1995a); *Policy on Evaluating Health Risks to Children* (USEPA 1995b); *Policy for Use of Probabilistic Analysis in Risk Assessment* (USEPA 1997a); *Guidance on Cumulative Risk Assessment, Part 1: Planning and Scoping* (USEPA 1997c); and *Risk Characterization Handbook* (USEPA 2000a); and *Framework for Human Health Risk Assessment to Inform Decision Making* (USEPA 2014).

As shown in the individual case studies, the range and scope of the PRA will depend on the overall objectives of the decision that the analysis will inform. The *Guiding Principles for Monte Carlo Analysis* (USEPA 1997b) lay out the general approach that should be taken in all cases, beginning with defining the problem and scope of the assessment to selecting the best tools and approach. The *Guiding Principles* also describe the process of estimating and characterizing variability and uncertainty around risk estimates. Stahl and Cimorelli (2005) and the *Risk Assessment Guidance for Superfund: Volume III* (USEPA 2001) highlight the importance of communication between the risk assessor and manager. Stahl and Cimorelli (2005) and Jamieson (1996) indicate that it is important to determine whether a particular level of uncertainty is acceptable or not. The authors also suggest that this decision depends on context, values and regulatory policy. The *Risk Assessment Guidance for Superfund: Volume III* (Chapter 2 and Appendix F in USEPA 2001) describes a process for determining the appropriate level of PRA using a ranked approach from the less resource- and time-intensive approaches to more sophisticated analyses. Furthermore, the *Risk Assessment Guidance for Superfund: Volume III* outlines a process for developing a PRA work plan and a checklist for PRA reviewers (Chapter 2 and Appendix F in USEPA 2001). This guidance also provides information regarding how to communicate PRA results to decision makers and stakeholders (Chapter 6 in USEPA 2001).

C.2. Categorizing Case Studies

The ranked approach used for categorization is a process for a systematic, informed progression to increasingly complex risk assessment methods of PRA, which is outlined in the *Risk Assessment Guidance for Superfund* (USEPA 2001). The use of categories provides a framework for evaluating the various techniques of PRA. Higher categories reflect increasing complexity and often will require more time and resources. Higher categories also reflect increasing characterization of variability and uncertainty in the risk estimate, which may be important for making specific risk management decisions. Central to the approach is a systematic, informed progression using an iterative process of evaluation, deliberation, data collection, planning and scoping, development, and updates to the work plan and communication. All of these steps focus on deciding:

1. Whether or not the risk assessment, in its current state (e.g., DRA) is sufficient to support decisions (i.e., a clear path to exiting the process is available at each step).

2. If the assessment is determined to be insufficient, whether or not progression to a higher level of complexity (or refinement of the current analyses) would provide a sufficient benefit to warrant the additional effort of performing a PRA.

This Appendix groups case studies according to level of effort and complexity of the analysis and the increasing sophistication of the methods used (Table A-1). Although each group generally represents increasing effort and cost, this may not always be true. The groups also are intended to reflect the progression from simple to complex analysis that is determined by the interactive planning and scoping efforts of the risk assessors and managers. The use of particular terms to describe the groups, including "tiers," was avoided due to specific programmatic and regulatory connotations.

Group 1 Case Studies

Assessments within this group typically involve a sensitivity analysis and serve as an initial screening step in the risk assessment. Sensitivity analyses identify important parameters in the assessment where additional investigation may be helpful (Kurowicka and Cooke 2006). Sensitivity analysis can be simple or involve more complex mathematical and statistical techniques, such as correlation and regression analysis, to determine which factors in a risk model contribute most to the variance in the risk estimate.

Within the sensitivity analyses, a range of techniques is available: simple, "back-of-the-envelope" calculations, where the risk parameters are evaluated using a range of exposure parameters to determine the parameter that contributes most significantly to the risk (Case Study 1); analyses to rank the relative contributions of variables to the overall risk (Case Study 2); and data visualization using graphical techniques to array the data or Monte Carlo simulations (e.g., scatter plots).

More sophisticated analyses may include sensitivity ratios (e.g., elasticity); sensitivity scores (e.g., weighted sensitivity ratios); correlation coefficient or coefficient of determination; r^2 (e.g., Pearson product moment, Spearman rank); normalized multiple regression coefficients; and goodness-of-fit tests for subsets of the risk distribution (USEPA 2001).

The sensitivity analyses typically require minimal resources and time. Results of the sensitivity analyses are useful in identifying key parameters where additional Group 2 or Group 3 analyses may be appropriate. Sensitivity analyses also are helpful in identifying key parameters where additional research will have the highest impact on the risk assessment.

Group 2 Case Studies

Case studies within this group include a more sophisticated application of probabilistic tools, including PRA of specific exposure parameters (Case Studies 3 and 4), one-dimensional analyses (Case Study 5) and probabilistic sensitivity analysis (Case Studies 6 and 7).

The Group 2 case studies require larger time commitments for development, specialized expertise and additional analysis of exposure parameter data sources. Depending on the nature of the analysis, peer involvement or peer review may be appropriate to evaluate the products of the analysis.

Group 3 Case Studies

Assessments within this group are the most resource- and time-intensive analyses of the three categories. Risk analyses include two-dimensional Monte Carlo analysis (2-D MCA) that evaluates model variability and uncertainty (Case Studies 8, 9 and 10); microexposure event analysis (MEE), in which long-term exposure of an individual is simulated as the sum of separate short-term exposure events (Case Study 11); and probabilistic analysis (Case Studies 12 and 13).

Other types of analyses within this group include the expert elicitation method that is a systematic process of formalizing and quantifying, in terms of probabilities, experts' judgments about uncertain quantities (Case Studies 14 and 15); Bayesian statistics, which is a specialized branch of statistics that views the probability of an event occurring as the degree of belief or confidence in that occurrence (Case Study 16); and geostatistical analysis, which is another specialized branch of statistics that explicitly takes into account the geo-referenced context of the data and the information (e.g., attributes) attached to the data.

The Group 3 analyses require additional time and expertise in the planning and analysis of the assessment. Within this group, the level of expertise and resource commitments may vary with the techniques. Expert elicitation, for example, requires significantly more time for planning, identification of experts and meetings, when compared with the other techniques.

Table A-1. Case Study Examples of EPA Applications of Deterministic and Probabilistic Risk Assessment Techniques

Case Study Number	Title and Case Study Description	Type of Risk Assessment	Office/Region
Group 1: Point Estimate—Sensitivity Analysis			
1	**Sensitivity Analysis of Key Variables in Probabilistic Assessment of Children's Exposure to Arsenic in Chromated Copper Arsenate (CCA) Pressure-Treated Wood.** This case study demonstrates use of a point estimate sensitivity analysis to identify exposure variables critical to the analysis summarized in Case Study 9. The sensitivity analysis identified critical areas for future research and data collection and better characterized the amount of dislodgeable residue that exists on the wood surface.	**Human Health**	**Office of Research and Development (ORD) and Office of Pesticide Programs (OPP)**
2	**Assessment of the Relative Contribution of Atmospheric Deposition to Watershed Contamination.** An example of a workbook that demonstrates how "back-of-the-envelope" analysis of potential exposure rates can be used to target resources to identify other inputs before further analysis of air inputs in watershed contamination. Identification of key variables aided in identifying uncertainties and data gaps to target resource expenditures for further analysis. A case study example of the application of this technique also is identified.	**Ecological**	**ORD**
Group 2: Probabilistic Risk Analysis, One-Dimensional Monte Carlo Analysis (1-D MCA) and Probabilistic Sensitivity Analysis			
Group 2: Probabilistic Risk Analysis			
3	**Probabilistic Assessment of Angling Duration Used in the Assessment of Exposure to Hudson River Sediments via Consumption of Contaminated Fish.** A probabilistic analysis of one parameter in an exposure assessment—the time an individual fishes in a large river system. Development of site-specific information regarding exposure, with an existing data set for this geographic area, was needed to represent this exposed population. This information was used in the one-dimensional PRA described in Case Study 5.	**Human Health**	**Superfund/ Region 2 (New York)**
4	**Probabilistic Analysis of Dietary Exposure to Pesticides for Use in Setting Tolerance Levels.** The probabilistic Dietary Exposure Evaluation Model (DEEM) provides more accurate information on the range and probability of possible exposures.	**Human Health**	**OPP**

Table A-1. Case Study Examples of EPA Applications of Deterministic and Probabilistic Risk Assessment Techniques

Case Study Number	Title and Case Study Description	Type of Risk Assessment	Office/Region
Group 2: One-Dimensional Monte Carlo Analysis (1-D MCA)			
5	**One-Dimensional Probabilistic Risk Analysis of Exposures to Polychlorinated Biphenyls (PCBs) via Consumption of Fish From a Contaminated Sediment Site.** An example of a one-dimensional PRA (1-D MCA) of the *variability* of exposure as a function of the variability of individual exposure factors to evaluate the risks to anglers who consume recreationally caught fish from a PCB-contaminated river.	**Human Health**	**Superfund/ Region 2 (New York)**
Group 2: Probabilistic Sensitivity Analysis			
6	**Probabilistic Sensitivity Analysis of Knowledge Elicitation of the Concentration-Response Relationship Between $PM_{2.5}$ Exposure and Mortality.** An example of how the probabilistic analysis tools can be used to conduct a probabilistic sensitivity analysis following an expert elicitation (Group 3) presented in Case Study 14.	**Human Health**	**Office of Air and Radiation (OAR)**
7	**Environmental Monitoring and Assessment Program (EMAP): Using Probabilistic Sampling Techniques to Evaluate the Nation's Ecological Resources.** A probability-based sampling program designed to provide unbiased estimates of the condition of an aquatic resource over a large geographic area based on a small number of samples.	**Ecological**	**ORD**
Group 3: Advanced Probabilistic Risk Analysis—Two-Dimensional Monte Carlo Analysis (2-D MCA) Including Microexposure Modeling, Bayesian Statistics, Geostatistics and Expert Elicitation			
Group 3: Two-Dimensional Probabilistic Risk Analysis			
8	**Two-Dimensional Probabilistic Risk Analysis of *Cryptosporidium* in Public Water Supplies, With Bayesian Approaches to Uncertainty Analysis.** An analysis of the variability in the occurrence of *Cryptosporidium* in raw water supplies and in the treatment efficiency, as well as the uncertainty in these inputs. This case study includes an analysis of the dose-response relationship for *Cryptosporidium* infection.	**Human Health**	**Office of Water (OW)**
9	**Two-Dimensional Probabilistic Model of Children's Exposure to Arsenic in Chromated Copper Arsenate (CCA) Pressure-Treated Wood.** A two-dimensional model that addresses both variability and uncertainty in the exposures of children to CCA pressure-treated wood. The analysis was built on the sensitivity analysis described in Case Study 2.	**Human Health**	**OPP/ORD**

Table A-1. Case Study Examples of EPA Applications of Deterministic and Probabilistic Risk Assessment Techniques

Case Study Number	Title and Case Study Description	Type of Risk Assessment	Office/Region
10	**Two-Dimensional Probabilistic Exposure Assessment of Ozone.** A probabilistic exposure assessment that addresses short-term exposures to ozone. Population exposure to ambient ozone levels was evaluated using EPA's Air Pollutants Exposure (APEX) model, also referred to as the Total Risk Integrated Methodology/Exposure (TRIM.Expo) model.	**Human Health**	**OAR**
Group 3: Microexposure Event Analysis			
11	**Analysis of Microenvironmental Exposures to Fine Particulate Matter ($PM_{2.5}$) for a Population Living in Philadelphia, Pennsylvania.** A microexposure event analysis to simulate individual exposures to $PM_{2.5}$ in specific microenvironments, including the outdoors, indoor residences, offices, schools, stores and a vehicle.	**Human Health**	**Region 3 (Philadelphia) and ORD**
Group 3: Probabilistic Analysis			
12	**Probabilistic Analysis in Cumulative Risk Assessment of Organophosphorus Pesticides.** A probabilistic computer software program used to integrate various pathways, while simultaneously incorporating the time dimensions of the input data to calculate margins of exposure.	**Human Health**	**OPP**
13	**Probabilistic Ecological Effects Risk Assessment Models for Evaluating Pesticide Uses.** A multimedia exposure/ effects model that evaluates acute mortality levels in generic or specific avian species over a user-defined exposure window.	**Ecological**	**OPP**
Group 3: Expert Elicitation and Bayesian Belief Network			
14	**Expert Elicitation of Concentration-Response Relationship Between Fine Particulate Matter ($PM_{2.5}$) Exposure and Mortality.** A knowledge elicitation used to derive probabilistic estimates of the uncertainty in one element of a cost-benefit analysis used to support the $PM_{2.5}$ regulations.	**Human Health**	**ORD/ OAR**
15	**Expert Elicitation of Sea-Level Change Resulting From Global Climate Change.** An example of a PRA that describes the probability of sea level rise and parameters that predict sea level change.	**Ecological**	**Office of Policy, Planning, and Evaluation**

Table A-1. Case Study Examples of EPA Applications of Deterministic and Probabilistic Risk Assessment Techniques

Case Study Number	Title and Case Study Description	Type of Risk Assessment	Office/Region
16	**Knowledge Elicitation for Bayesian Belief Network Model of Stream Ecology.** An example of a Bayesian belief network model of the effect of increased fine-sediment load in a stream on macroinvertebrate populations.	**Ecological**	**ORD**

D. CASE STUDY SUMMARIES

D.1. Group 1 Case Studies

Case Study 1: Sensitivity Analysis of Key Variables in Probabilistic Assessment of Children's Exposure to Arsenic in Chromated Copper Arsenate Pressure-Treated Wood

This case study provides an example of the application of sensitivity analysis to identify important variables for population exposure variability for a Group 2 assessment (Case Study 9) and to indicate areas for further research. Specifically, EPA's Office of Research and Development (ORD), in collaboration with the Office of Pesticide Programs (OPP), used sensitivity analyses to identify the key variables in children's exposure to CCA-treated wood.

Approach. The sensitivity analyses used two approaches. The first approach estimated baseline exposure by running the exposure model with each input variable set to its median (50th percentile) value. Next, alternative exposure estimates were made by setting each input to its 25th or 75th percentile value while holding all other inputs at their median values. The ratio of the exposure estimate calculated when an input was estimated at its 25th or 75th percentile to the exposure estimate calculated when the input was at its median value provided a measure of that input's importance to the overall exposure assessment. The second approach applied a multiple stepwise regression analysis to the data points generated from the first approach. The correlation between the input variables and the exposure estimates provided an alternative measure of the input variable's relative importance in the exposure assessment. These two approaches were used in tandem to identify the critical inputs to the exposure assessment model.

Results of Analysis. The two sensitivity analyses together identified six critical input variables that most influenced the exposure assessment. The critical input variables were: wood surface residue-to-skin transfer efficiency, wood surface residue levels, fraction of hand surface area mouthed per mouthing event, average fraction of nonresidential outdoor time spent playing on a CCA-treated playset, frequency of hand washing and frequency of hand-to-mouth activity.

Management Considerations. The results of the sensitivity analyses were used to identify the most important input parameters in the treated wood risk assessments. The process also identified critical areas for future research. In particular, the assessment pointed to a need to collect data on the amount of dislodgeable residue that is transferred from the wood surface to a child's hand upon contact, and to better characterize the amount of dislodgeable residue that exists on the wood surface.

Selected References. The final report on the probabilistic exposure assessment of CCA-treated wood:

Zartarian, V. G., J. Xue, H. A. Özkaynak, W. Dang, G. Glen, L. Smith, and C. Stallings. *A Probabilistic Exposure Assessment for Children Who Contact CCA-Treated Playsets and Decks Using the Stochastic Human Exposure and Dose Simulation Model for the Wood Preservative Scenario (SHEDS-WOOD), Final Report.* EPA/600/X-05/009. Washington, D.C.: USEPA.

See also: Xue, J., V. G. Zartarian, H. Özkaynak, W. Dang, G. Glen, L. Smith, and C. Stallings. 2006. "A Probabilistic Exposure Assessment for Children Who Contact Chromated Copper Arsenate (CCA)-Treated Playsets and Decks, Part 2: Sensitivity and Uncertainty Analyses." *Risk Analysis* 26:533–41.

Case Study 2: Assessment of the Relative Contribution of Atmospheric Deposition to Watershed Contamination

Watershed contamination can result from several different sources, including the direct release of pollution into a water body, input from upstream water bodies and deposition from airborne sources. Efforts to control water body contamination begin with an analysis of the environmental sources to identify the parameters that provide the greatest contribution and determine where mitigation and/or analysis resources should be directed.

Approach. This case study provides an example of a "back-of-the-envelope" deterministic analysis of the contribution of air deposition to overall watershed nitrogen? Nutrient? contamination to identify uncertainties and/or data gaps, as well as to target resource expenditures. Nitrogen inputs have been studied in several east and Gulf Coast estuaries due to concerns about eutrophication. Nitrogen from atmospheric deposition is estimated to be as high as 10 to 40 percent of the total input of nitrogen to many of these estuaries, and perhaps higher in a few cases. For a watershed that has not been studied yet, a back-of-the-envelope calculation could be prepared based on information about the nitrogen deposition rates measured in a similar area. To estimate the deposition load directly to the water body, one would multiply the nitrogen deposition rate by the area of the water body. The analyst then could estimate the nitrogen load from other sources (e.g., point source discharges and runoff) to estimate a total nitrogen load for the water body. The estimate of loading due to atmospheric deposition then could be divided by the total nitrogen load for the water body to estimate the percent of contribution directly to the water body from atmospheric deposition.

The May 2003 report by the Casco Bay Air Deposition Study Team titled *Estimating Pollutant Loading From Atmospheric Deposition Using Casco Bay, Maine as a Case Study* is an analysis using the methodology described above. The Casco Bay Estuary, located in southwestern Maine, is used as a case study. The paper also includes the results of a field air deposition monitoring program conducted in Casco Bay from 1998 to 2000 and favorably compares the estimates developed for the rate of deposition of nitrogen, mercury and polycyclic aromatic hydrocarbons (PAHs) to the field monitoring results. The estimation approach is a useful starting point for understanding the sources of pollutants entering water bodies that cannot be accounted for through runoff or point source discharges.

Results of Analysis. The approach outlined above was applied to the Casco Bay Estuary in Maine. Resources, tools and strategies for pollution abatement can be effectively targeted at priority sources if estuaries are to be protected. Understanding the sources and annual loading of contaminants to an estuary facilitates good water quality management by defining the range of controls of both air and water pollution needed to achieve a desired result. The cost of conducting monitoring to determine atmospheric loading to a water body can be prohibitively high. Also, collection of monitoring data is a long-term undertaking because a minimum of 3 years of data is advisable to "smooth out" inter-annual variability. The estimation techniques described in this paper can serve as a useful and inexpensive "first-cut" at understanding the importance of the atmosphere as a pollution source and can help to identify areas where field measurements are needed to guide future management decisions.

Management Considerations. If a review of information on air deposition available for the analysis indicates a wide range of potential deposition rates, further study of this input would lead to better characterization of the air contribution to overall contamination. If the back-of-the envelope analysis suggests that air deposition is very small relative to other inputs, then resources should be targeted at studying or reducing other inputs before proceeding with further analysis of the air inputs.

Selected References. The back-of-the-envelope calculation is outlined in *Frequently Asked Questions about Atmospheric Deposition: A Handbook for Watershed Managers.* http://www.epa.gov/air/oaqps/gr8water/handbook/airdep_sept.pdf.

Further analysis is available in *Deposition of Air Pollutants to the Great Waters—Third Report to Congress.* http://www.epa.gov/air/oaqps/gr8water/3rdrpt/index.html.

The Casco Bay Estuary example is available at http://epa.gov/owow/airdeposition/cascobay.pdf.

D.2. Group 2 Case Studies

Case Study 3: Probabilistic Assessment of Angling Duration Used in the Assessment of Exposure to Hudson River Sediments via Consumption of Contaminated Fish

In assessing the health impact of contaminated Superfund sites, exposure duration typically is assumed to be the same as the length of time that an individual lives in a specific area (i.e., residence duration). In conducting the HHRA for the Hudson River Polychlorinated Biphenyl (PCB) Superfund Site, however, there was concern that exposure duration based on residence duration may underestimate the time spent fishing (i.e., angling duration).

Risk Analysis. An individual may move from one residence to another and continue to fish in the same location, or an individual may choose to stop fishing irrespective of the location of his or her home. EPA Region 2 developed a site-specific distribution of angling duration using the fishing patterns reported in a New York State-wide angling survey (Connelly *et al*. 1990) and migration data for the five counties surrounding more than 40 miles of the Upper Hudson River collected as part of the U.S. Census.

Results of Analysis. The 50th and 95th percentile values from the distribution of angling durations were higher than the default values based on residence duration using standard default exposure assumptions for residential scenarios. These values were used as a base for the central tendency and reasonable maximum exposure point estimates, respectively, in the deterministic assessment.

Management Considerations. The information provided in this analysis was used in the point estimate analysis. The full distribution was used in conducting a Group 2 PRA for the fish consumption pathway, which is presented as Case Study 5.

Selected References. The final risk assessment was released in November 2000 and is available at http://www.epa.gov/hudson/reports.htm.

Further information, including EPA's January 2002 response to comments on the risk assessment, is available at http://www.epa.gov/hudson/ResponsivenessSummary.pdf.

Case Study 4: Probabilistic Analysis of Dietary Exposure to Pesticides for Use in Setting Tolerance Levels

Under the Federal Food, Drug, and Cosmetic Act (FFDCA), EPA may authorize a tolerance or exemption from the requirement of a tolerance to allow a pesticide residue in food, only if the Agency determines that such residues would be "safe." This determination is made by estimating exposure to the pesticide and comparing the estimated exposure to a toxicological benchmark dose. Until 1998, the OPP used a software program called the Dietary Risk Evaluation System (DRES) to conduct its acute dietary risk assessments for pesticide residues in foods. Acute assessments conducted with DRES assumed that 100 percent of a given crop with registered use of a pesticide was treated with that pesticide and all such treated crop items contained pesticide residues at the maximum legal (tolerance) level, matching this to a reasonably high consumption value (around the 95th percentile). The resulting DRES acute risk estimates were considered "high-end" or "bounding" estimates. It was not possible, however, to know where the pesticide exposure estimates from the DRES software fit in the overall distribution of exposures due to the limits of the tools being used.

To address these deficiencies, OPP developed an acute probabilistic dietary exposure guidance to use a model that would estimate the exposure to pesticides in the food supply. Rather than the crude "high-end," single-point estimates provided by deterministic assessments, the probabilistic Dietary Exposure Evaluation Model (DEEM) provides specific information about the range and probability of possible exposures. Depending on the characterization of the input, this could include the 95th percentile regulation—generally for lower tiers that do not include the percent of crop treated—to the 99.9th percentile for the more refined assessments, which would include the percent of crop treated information.

Probabilistic Analysis. This case study provides an example of a one-dimensional PRA of dietary exposure to pesticides (Group 2). The DEEM generates acute, probabilistic dietary exposure assessments using data on: (1) the distribution of daily consumption of specific commodities (e.g., wheat, corn and apples) by specific individuals; and (2) the distribution of concentrations of a specific pesticide in those food commodities. Data on commodity consumption are collected by the U.S. Department of Agriculture (USDA) in its Continuing Survey of Food Intake by Individuals (CSFII). Pesticide residue concentrations on food commodities are generally obtained from crop field trials, USDA's Pesticide Data Program (PDP), U.S. Food and Drug Administration (FDA) monitoring data, or market basket surveys. Using these data, DEEM is able to calculate an estimate of the risk to the general U.S. population, in addition to 26 population subgroups, including 5 subgroups for infants and children (infants less than 1, children 1 to 2, children 3 to 5, youths 6 to 12 and teens 13 to 19 years of age).

Results of Analysis. DEEM has been used in risk assessments to support tolerance levels for several pesticides (e.g., phosalone) and as part of cumulative risk assessments for organophosphorus compounds (see Case Study 12) and other pesticides.

Management Considerations. Using the DRES, decisions were being made without a complete representation of the distribution of risk among the population and without full knowledge of where in the distribution of risk the DRES risk estimate lay. This was of concern not only for regulators interested in public health protection, but also for the pesticide registrants who could argue that the Agency was arbitrarily selecting the level at which to regulate. For most cases reviewed by OPP to date, estimated exposure at the 99.9th percentile calculated by DEEM probabilistic techniques is significantly lower than exposure calculated using DRES-type deterministic assumptions at the unknown percentile.

Selected References. A link to the DEEM model is available at http://www.epa.gov/pesticides/science/deem/index.html.

Case Study 5: One-Dimensional Probabilistic Risk Analysis of Exposure to Polychlorinated Biphenyls via Consumption of Fish From a Contaminated Sediment Site

EPA Region 2 conducted a preliminary deterministic HHRA at the Hudson River PCBs Superfund site. The DRA demonstrated that consumption of recreationally caught fish provided the highest exposure among relevant exposure pathways, which resulted in cancer risks and noncancer health hazards that exceeded regulatory benchmarks.

Probabilistic Analysis. Because of the size, complexity and high level of public interest in this site, EPA Region 2 implemented a Group 2 probabilistic assessment to characterize the variability in risks associated with the fish consumption exposure pathway. The analysis was a one-dimensional Monte Carlo analysis (1-D MCA) of the *variability* of exposure as a function of the variability of individual exposure factors. Uncertainty was assessed using sensitivity analysis of the input variables. Data to characterize the distributions of exposure parameters were drawn from the published literature (e.g., fish consumption rate) or from existing databases, such as the U.S. Census data (e.g., angling duration, see Case Study 3). Mathematical models of the environmental fate, transport and bioaccumulation of PCBs in the Hudson River previously developed were used to forecast changes in PCB concentration over time.

Results of Analysis. The results of the PRA were consistent with the deterministic results. For the central tendency individual, point estimates were near the median (50th percentile). For the reasonable maximum exposure (RME) individual, point estimate values were at or above the 95th percentile of the probabilistic analysis. The DRA and PRA were the subject of a formal peer review by a panel of independent experts.

The Monte Carlo-based case scenario is the one from which point estimate exposure factors for fish ingestion were drawn; thus, the point estimate RMEs and the Monte Carlo-based case estimates can be compared. Similarly, the point estimate central tendency (average) and the Monte Carlo-based case midpoint (50th percentile) are comparable. For cancer risk, the point estimate RME for fish ingestion (1×10^{-3}) falls approximately at the 95th percentile from the Monte Carlo-based case analysis. The point estimate central tendency value (3×10^{-5}) and the Monte Carlo-based case 50th percentile value (6×10^{-5}) are similar. For noncancer health hazards, the point estimate RME for fish ingestion (104 for a young child 1 to 6 years of age) falls between the 95th and 99th percentiles of the Monte Carlo-based case. The point estimate central tendency hazard index (HI; 12 for a young child) is approximately equal to the 50th percentile of the Monte Carlo-based case HI of 11.

Figures A-1 and A-2 provide a comparison of results from the probabilistic analysis with that of the DRA for cancer risks and noncancer health hazards. Figures A-1 and A-2 plot percentiles for 72 combinations of exposure variables (e.g., distributions from creel angler surveys' residence duration, fishing locations and cooking losses) of the noncancer HI values and the cancer risks, respectively. In each of these figures, the variability of cancer risk or noncancer HIs for anglers within the exposed population is plotted on the y-axis for particular percentiles within the population. This variability is a function of the variations in fish consumption rates, fishing duration, differences in fish species ingested and so forth. The uncertainty in the estimates is indicated by the range of either cancer risk or noncancer HI values plotted on the x-axis. This uncertainty is a function of the 72 combinations of the exposure factor inputs examined in the sensitivity analysis. This analysis provides a semi-quantitative confidence interval for the cancer risks and HI values at any particulate percentile. As these figures show, the intervals span somewhat less than two orders of magnitude (e.g., < 100-fold). The vertical lines indicate the deterministic endpoints.

Management Considerations. Early and continued involvement of the community improved public acceptance of the results. In addition, careful consideration of the methods used to present the probabilistic results to the public lead to greater understanding of the findings.

Selected References. The final risk assessment was released in November 2000 and is available at http://www.epa.gov/hudson/reports.htm.

Further information, including EPA's January 2002 response to comments on the risk assessment, is available at http://www.epa.gov/hudson/ResponsivenessSummary.pdf.

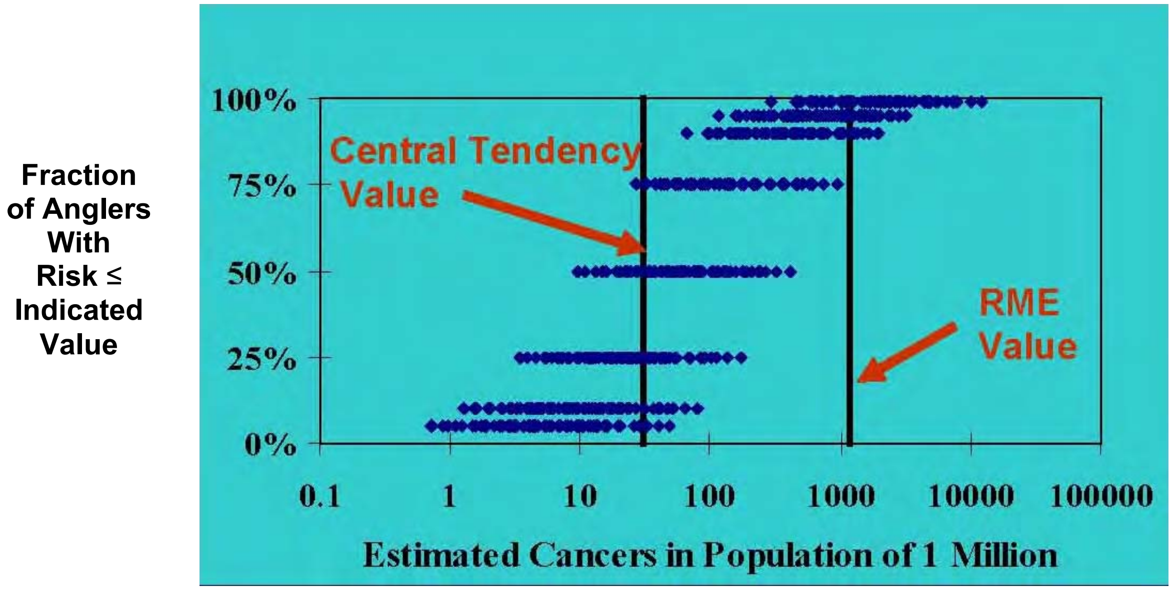

Figure A-1. Monte Carlo Cancer Summary Based on a One-Dimensional Probabilistic Risk Analysis of Exposure to Polychlorinated Biphenyls. The estimated cancer rate was calculated based on the consumption of fish from a contaminated sediment site. Source: USEPA 2000b.

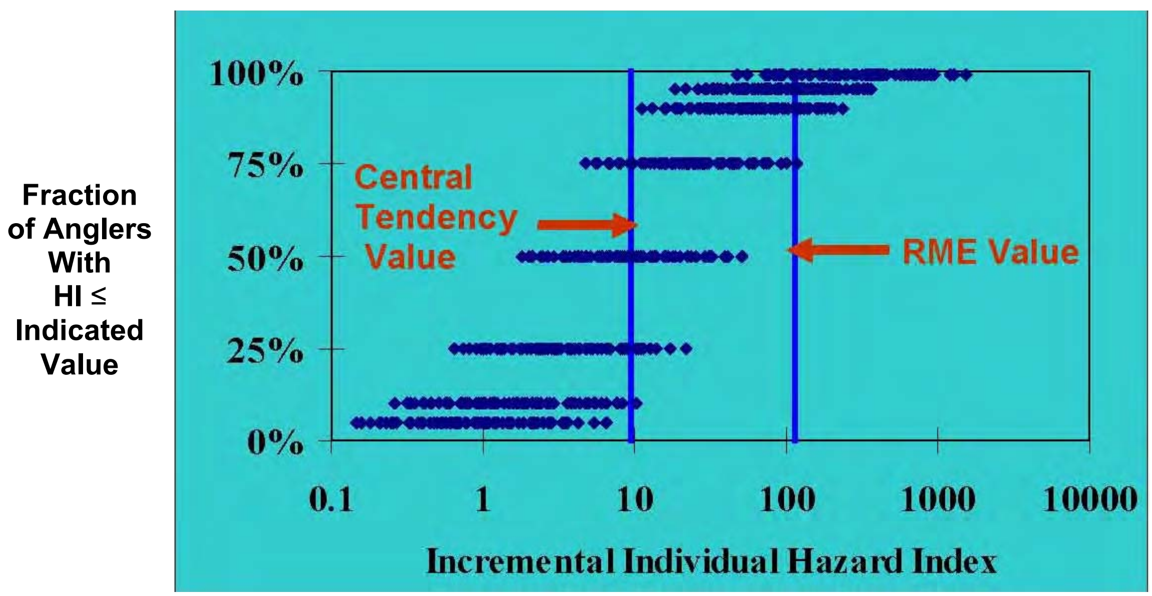

Figure A-2. Monte Carlo Noncancer Hazard Index Summary Based on a One-Dimensional Probabilistic Risk Analysis of Exposure to Polychlorinated Biphenyls. The incremental individual hazard index (HI) was calculated based on the consumption of fish from a contaminated sediment site. Source: USEPA 2000b.

Case Study 6: Probabilistic Sensitivity Analysis of Expert Elicitation of Concentration-Response Relationship Between Fine Particulate Matter Exposure and Mortality

In 2002, the National Research Council (NRC) recommended that EPA improve its characterization of uncertainty in the benefits assessment for proposed regulations of air pollutants. NRC recommended that probability distributions for key sources of uncertainty be developed using available empirical data or through formal elicitation of expert judgments. In response to this recommendation, EPA conducted an expert elicitation evaluation of the concentration-response relationship between fine particulate matter ($PM_{2.5}$) exposure and mortality, a key component of the benefits assessment of the $PM_{2.5}$ regulation. Further information on the expert elicitation procedure and results is provided in Case Study 14. To evaluate the degree to which the results of the assessment depended on the judgments of individual experts or on the methods of expert elicitation, a probabilistic sensitivity analysis was performed on the results.

Probabilistic Analysis. The expert elicitation procedure used carefully constructed interviews to elicit from each of 12 experts an estimate of the probabilistic distribution for the average expected decrease in U.S. annual, adult, all-cause mortality associated with a 1 microgram per cubic meter ($\mu g/m^3$) decrease in annual average $PM_{2.5}$ levels. This case study provides an example of the use of probabilistic sensitivity analysis (Group 2) as one element of the overall assessment. For the sensitivity analysis, a simplified health benefits analysis was conducted to assess the sensitivity of the results to the responses of individual experts and to three factors in the study design: (1) the use of parametric or nonparametric approaches by experts to characterize their uncertainty in the $PM_{2.5}$ mortality coefficient; (2) participation in the Pre-Elicitation Workshop; and (3) allowing experts to change their judgments after the Post-Elicitation Workshop. The individual quantitative expert judgments were used to estimate a distribution of benefits, in the form of the number of deaths avoided, associated with a reduction in ambient, annual average $PM_{2.5}$ concentrations from 12 to 11 $\mu g/m^3$. The 12 individual distributions of estimated avoided deaths were pooled using equal weights to create a single overall distribution reflecting input from each expert. This distribution served as the baseline for the sensitivity analysis, which compared the means and standard deviations of the baseline distribution with several variants.

Results of Analysis. The first analysis examined the sensitivity of the mean and standard deviation of the overall mortality distribution to the removal of individual experts' distributions. In general, the results suggested a fairly equal division between those experts whose removal shifted the distribution mean up and those who shifted it down. There were relatively modest impacts of individual experts. The standard deviation of the combined distribution also was not affected strongly by the removal of individual experts. The second analysis evaluated whether the use of parametric or nonparametric approaches affected the overall results. The results suggested that the use of parametric distributions led to distributions with similar or slightly increased uncertainty compared with distributions provided by experts who offered percentiles of a nonparametric distribution. The last analysis evaluated whether participation in the Pre- or Post-Elicitation Workshops affected the results. Participation in either workshop did not appear to have a significant effect on experts' judgments based on measures of change in the baseline distribution. Overall, the sensitivity analyses demonstrated that the assessment was robust, with little dependence on individual experts' judgments or on the specific elicitation methods evaluated.

Management Considerations. The sensitivity analysis demonstrated the robustness of the $PM_{2.5}$ expert elicitation-based assessment by showing that the panel of experts was generally well balanced and that alternative elicitation methods would not have markedly altered the overall results.

Selected References. The details of this analysis are provided in the Industrial Economics, Inc., document titled: *Expanded Expert Judgment Assessment of the Concentration-Response Relationship Between $PM_{2.5}$ Exposure and Mortality,* Final Report, September 21, 2006. This document is available at http://www.epa.gov/ttn/ecas/regdata/Uncertainty/pm_ee_report.pdf.

The expert elicitation assessment, along with the Regulatory Impact Analysis (RIA) of the $PM_{2.5}$ standard, is available at http://www.epa.gov/ttn/ecas/ria.html.

Case Study 7: Environmental Monitoring and Assessment Program: Using Probabilistic Sampling to Evaluate the Condition of the Nation's Aquatic Resources

Monitoring is a key tool used to identify the locations where the environment is in a healthy biological condition and requires protection, and where environmental problems are occurring and need remediation. Most monitoring, however, is not performed in a way that allows for statistically valid assessments of water quality conditions in unmonitored waters (USGAO 2000). States thus cannot adequately measure the status and trends in water quality as required by the Clean Water Act (CWA) Section 305(b).

The Environmental Monitoring and Assessment Program's (EMAP) focus has been to develop unbiased statistical survey design frameworks and sensitive indicators that allow the condition of aquatic ecosystems to be assessed at state, regional and national scales. A cornerstone of EMAP has been the use of probabilistic sampling to allow representative, unbiased, cost-effective condition assessments for aquatic resources covering large areas. EMAP's statistical survey methods are very efficient, requiring relatively few sample locations to make valid scientific statements about the condition of aquatic resources over large areas (e.g., the condition of all of the wadeable streams in the western United States).

Probabilistic Analysis. This research program provides multiple case studies using probabilistic sampling designs for different aquatic resources (estuaries, streams and rivers). An EMAP probability-based sampling program delivers an unbiased estimate of the condition of an aquatic resource over a large geographic area from a small number of samples. The principal characteristics of a probabilistic sampling design are: the population being sampled is unambiguously described; every element in the population has the opportunity to be sampled with a known probability; and sample selection is conducted by a random process. This approach allows statistical confidence levels to be placed on the estimates and provides the potential to detect statistically significant changes and trends in condition with repeated sampling. In addition, this approach permits the aggregation of data collected from smaller areas to predict the condition of a large geographic area.

The EMAP design framework allows the selection of unbiased, representative sampling sites and specifies the information to be collected at these sites. The validity of the overall inference rests on the design and subsequent analysis to produce regionally representative information. The EMAP uses the approach outlined in the EPA's G*eneralized Random Tessellation Stratified Spatially-Balanced Survey Designs for Aquatic Resources* (Olsen 2012). The spatially balanced aspect spreads out the sampling locations geographically, but still ensures that each element has an equal chance of being selected.

Results of Analysis. Data collected using the EMAP approach has allowed the Agency to make scientifically defensible assessments of the ecological condition of large geographic areas for reporting to Congress under CWA 305(b). The EMAP approach has been used to provide the first reports on the condition of the nation's estuaries, streams, rivers and lakes, and it is scheduled to be used for wetlands. EMAP findings have been included in EPA's Report on the Environment and the Heinz Center's The State of the Nation's Ecosystems. Data collected through an EMAP approach improve the ability to assess ecological progress in environmental protection and restoration, and provide valuable information for decision makers and the public. The use of probabilistic analysis methods allows meaningful assessment and regional comparisons of aquatic ecosystem conditions across the United States. Finally, the probabilistic approach provides scientific credibility for the monitoring network and aids in identifying data gaps.

Management Considerations. Use of an EMAP approach addresses criticisms from the Government Accountability Office (GAO), the National Academy of Sciences (NAS), the Heinz Center (a nonprofit environmental policy institution), and others that noted the nation lacked the data to make scientifically valid characterizations of water quality regionally and across the United States. The program provides cost-effective, scientifically defensible and representative data, to permit the evaluation of quantifiable trends in ecosystem condition, to support performance-based management and facilitate better public decisions regarding ecosystem management. EMAP's approach now has been adopted by EPA's Office of Water (OW) to collect data on the condition of all the nation's aquatic resources. OW, Office of Air and Radiation (OAR) and Office of Chemical Safety and Pollution Prevention (OCSPP; formerly the Office of Prevention, Pesticides, and Toxic Substances) now have environmental accountability endpoints using EMAP approaches in their Agency performance goals.

Selected References. General information concerning EMAP is available at http://www.epa.gov/emap/index.html.

Information on EMAP monitoring designs is available at http://www.epa.gov/nheerl/arm/designpages/monitdesign/monitoring_design_info.htm.

EPA's *Generalized Random Tessellation Stratified Spatially-Balanced Survey Designs for Aquatic Resources* document is available at http://www.epa.gov/nheerl/arm/documents/presents/grts_ss.pdf.

USGAO (U.S. Government Accountability Office). 2000. *Water Quality: Key EPA and State Decisions Limited by Inconsistent and Incomplete Data.* GAO/RCED-00-54. Washington, D.C.: USGAO. http://www.environmental-auditing.org/Portals/0/AuditFiles/useng00ar_ft_key_epa.pdf.

USEPA (U.S. Environmental Protection Agency). 2002. *EMAP Research Strategy.* Research Triangle Park, NC: Environmental Monitoring and Assessment Program, National Health and Environmental Effects Research Laboratory (NHEERL), USEPA. http://www.epa.gov/nheerl/emap/files/emap_research_strategy.pdf.

D.3. Group 3 Case Studies

Case Study 8: Two-Dimensional Probabilistic Risk Analysis of Cryptosporidium in Public Water Supplies, With Bayesian Approaches to Uncertainty Analysis

Probabilistic assessment of the occurrence and health effects associated with *Cryptosporidium* bacteria in public drinking water supplies was used to support the economic analysis of the final Long-Term 2 Enhanced Surface Water Treatment Rule (LT2). EPA's Office of Ground Water and Drinking Water (OGWDW) conducted this analysis and established a baseline disease burden attributable to *Cryptosporidium* in public water supplies that use surface water sources. Next, it modeled source water monitoring and finished water improvements that will be realized as a result of the LT2. Post-Rule risk is estimated and the LT2's health benefit is the result of subtracting this from the baseline disease burden.

Probabilistic Analysis. Probabilistic assessment was used for this analysis as a means of addressing the variability in the occurrence of *Cryptosporidium* in raw water supplies, the variability in the treatment efficiency, and the uncertainty in these inputs and in the dose-response relationship for *Cryptosporidium* infection. This case study provides an example of a PRA that evaluates both variability and uncertainty at the same time and is referred to as a two-dimensional PRA. The analysis also included probabilistic treatments of uncertain dose-response and occurrence parameters. Markov Chain Monte Carlo samples of parameter sets filled this function. This Bayesian approach (treating the unknown parameters as random variables) differs from classical treatments, which would regard the parameters as unknown, but fixed (Group 3: Advanced PRA). The risk analysis used existing datasets (e.g., the occurrence of *Cryptosporidium* and treatment efficacy) to inform the variability of these inputs. Uncertainty distributions were characterized based on professional judgment or by analyzing data using Bayesian statistical techniques.

Results of Analysis. The risk analysis identified the *Cryptosporidium* dose-response relationship as the most critical model parameters in the assessment, followed by the occurrence of the pathogen and treatment efficiency. By simulating implementation of the Rule using imprecise, biased measurement methods, the assessment provided estimates of the number of public water supply systems that would require corrective action and the nature of the actions likely to be implemented. This information afforded a realistic measure of the benefits (in reduced disease burden) expected with the LT2. In response to Science Advisory Board (SAB) comments, additional *Cryptosporidium* dose-response models were added to more fully reflect uncertainty in this element of the assessment.

Management Considerations. The LT2 underwent external peer review, review by EPA's SAB and intense review by the Office of Management and Budget (OMB). Occurrence and dose-response components of the risk analysis model were communicated to stakeholders during the Rule's Federal Advisory Committee Act (FACA) process. Due to the rigor of the analysis and the signed FACA "Agreement in Principle," the OMB review was straightforward.

Selected References. The final assessment of occurrence and exposure to *Cryptosporidium* was released in December 2005 and is available at http://www.epa.gov/safewater/disinfection/lt2/regulations.html.

Case Study 9: Two-Dimensional Probabilistic Model of Children's Exposure to Arsenic in Chromated Copper Arsenate Pressure-Treated Wood

Probabilistic models were developed in response to EPA's October 2001 Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA) Scientific Advisory Panel (SAP) recommendations to use probabilistic modeling to estimate children's exposures to arsenic in CCA-treated playsets and home decks.

Probabilistic Analysis. EPA's ORD, in collaboration with the Office of Pesticide Programs (OPP), developed and applied a probabilistic exposure assessment of children's exposure to arsenic and chromium from contact with CCA-treated wood playsets and decks. This case study provides an example of the use of two-dimensional (i.e., addressing both variability and uncertainty) probabilistic exposure assessment (Group 3: Advanced PRA). The two-dimensional assessment employed a modification of ORD's Stochastic Human Exposure and Dose Simulation (SHEDS) model to simulate children's exposure to arsenic and chromium from CCA-treated wood playsets and decks, as well as the surrounding soil. Staff from both ORD and OPP collaborated in the development of the SHEDS-Wood model.

Results of Analysis. A draft of the probabilistic exposure assessment received SAP review in December 2003; the final report was released in 2005. The results of the probabilistic exposure assessment were consistent with or in the range of the results of deterministic exposure assessments conducted by several other organizations. The model results were used to compare exposures under a variety of scenarios, including cold versus warm weather activity patterns, use of wood sealants to reduce the availability of contaminants on the surface of the wood, and different hand-washing frequencies. The modeling of alternative mitigation scenarios indicated that the use of sealants could result in the greatest exposure reduction, while increased frequency of hand washing also could reduce exposure.

OPP used the SHEDS-Wood model exposure results in its probabilistic children's risk assessment for CCA (USEPA 2008). This included recommendations for risk reduction (use of sealants and careful attention to children's hand washing) to homeowners with existing CCA wood structures. In addition, the exposure assessment was used to identify areas for further research, including: the efficacy of wood sealants in reducing dislodgeable contaminant residues, the frequency with which children play on or around CCA wood, and transfer efficiency and residue concentrations. To better characterize the efficacy of sealants in reducing exposure, EPA and the Consumer Product Safety Commission (CPSC) conducted a 2-year study of how dislodgeable contaminant residue levels changed with the use of various types of commercially available wood sealants.

Management Considerations. The OPP used SHEDS results directly in its final risk assessment for children playing on CCA-treated playground equipment and decks. The model enhanced risk assessment and management decisions and prioritized data needs related to wood preservatives. The modeling product was pivotal in the risk management and re-registration eligibility decisions for CCA, and in advising the public how to minimize health risks from existing treated wood structures. Industry also is using SHEDS to estimate exposures to CCA and other wood preservatives. Some states are using the risk assessment as guidance in setting their regulations for CCA-related playground equipment.

Selected References. The final probabilistic risk assessment based on the SHEDS-Wood exposure assessment is available at
http://www.epa.gov/oppad001/reregistration/cca/final_cca_factsheet.htm.

The model results were included in the final report on the probabilistic exposure assessment of CCA-treated wood surfaces: Zartarian, V.G., J. Xue, H. A. Özkaynak, W. Dang, G. Glen, L. Smith, and C. Stallings. 2006. *A Probabilistic Exposure Assessment for Children Who Contact CCA-Treated Playsets and Decks Using the Stochastic Human Exposure and Dose Simulation Model for the Wood Preservative Scenario (SHEDS-Wood), Final Report.* EPA/600/X-05/009. Washington, D.C.: USEPA.

Results of the sealant studies were released in January 2007 and are available at http://www.epa.gov/oppad001/reregistration/cca/index.htm#reviews.

The results of the analysis were published as: Zartarian, V.G., J. Xue, H. Özkaynak, W. Dang, G. Glen, L. Smith, and C. Stallings. 2006. "A Probabilistic Arsenic Exposure Assessment for Children who Contact CAA-Treated Playsets and Decks, Part 1: Model Methodology, Variability Results, and Model Evaluation." *Risk Analysis* 26: 515–31.

More information on the analysis can be found by consulting the following resource:

USEPA (U.S. Environmental Protection Agency). 2008. *Case Study Examples of the Application of Probabilistic Risk Analysis in U.S. Environmental Protection Agency Regulatory Decision-Making (In Review).* Washington, D.C.: Risk Assessment Forum, USEPA

Case Study 10: Two-Dimensional Probabilistic Exposure Assessment of Ozone

As part of EPA's recent review of the ozone National Ambient Air Quality Standards (NAAQS), the Office of Air Quality Planning and Standards (OAQPS) conducted detailed probabilistic exposure and risk assessments to evaluate potential alternative standards for ozone. At different stages of this review, the Clean Air Scientific Advisory Committee (CASAC) Ozone Panel (an independent scientific review committee of EPA's SAB) and the public reviewed and provided comments on analyses and documents prepared by EPA. A scope and methods plan for the exposure and risk assessments was developed in 2005 (USEPA 2005). This plan was intended to facilitate consultation with the CASAC, as well as public review, and to obtain advice on the overall scope, approaches and key issues in advance of the completion of the analyses. This case study describes the probabilistic exposure assessment, which addresses short-term exposures to ozone. The exposure estimates were used as an input to the HHRA for lung function decrements in all children and asthmatic school-aged children based on exposure-response relationships derived from controlled human exposure studies.

Probabilistic Analysis. Population exposure to ambient ozone levels was evaluated using EPA's Air Pollutants Exposure (APEX) model, also referred to as the Total Risk Integrated Methodology/Exposure (TRIM.Expo) model. Exposure estimates were developed for recent ozone levels, based on 2002 to 2004 air quality data, and for ozone levels simulated to just meet the existing 0.08 ppm, 8-hour ozone NAAQS and several alternative ozone standards, based on adjusting the 2002 to 2004 air quality data. Exposure estimates were modeled for 12 urban areas located throughout the United States for the general population, all school-age children and asthmatic school-age children. This exposure assessment is described in a technical report (USEPA 2007b). The exposure model APEX is documented in a user's guide and technical document (USEPA 2006). A Monte Carlo approach was used to produce quantitative estimates of the uncertainty in the APEX model results, based on estimates of the uncertainties for the most important model inputs. The quantification of model input uncertainties, a discussion of model structure uncertainties, and the results of the uncertainty analysis are documented in Langstaff (2007).

Results of Analysis. Uncertainty in the APEX model predictions results from uncertainties in the spatial interpolation of measured concentrations, the microenvironment models and parameters, people's activity patterns, and to a lesser extent, model structure. The predominant sources of uncertainty appear to be the human activity pattern information and the spatial interpolation of ambient concentrations from monitoring sites to other locations. The primary policy-relevant finding was that the uncertainty in the exposure assessment is small enough to lend confidence to the use of the model results for the purpose of informing the Administrator's decision on the ozone standard.

Figure A-3 illustrates the uncertainty distribution for one model result, the percent of children with exposures above 0.08 ppm, 8-hour while at moderate exertion. The point estimate of 20 percent is the result from the APEX simulation using the best estimates of the model inputs. The corresponding result from the Monte Carlo simulations ranges from 17 to 26 percent, with a 95 percent uncertainty interval (UI) of 19 to 24 percent. Note that the UIs are not symmetric because the distributions are skewed.

Management Considerations. The exposure analysis also provided information on the frequency with which population exposures exceeded several potential health effect benchmark levels that were identified based on the evaluation of health effects in clinical studies.

The exposure and risk assessments are summarized in Chapters 4 and 5, respectively, of the *Ozone Staff Paper* (USEPA 2007a). The exposure estimates over these potential health effect benchmarks were part of the basis for the Administrator's March 27, 2008, decision to revise the ozone NAAQS from 0.08 to 0.075 ppm, 8-hour average (see the final rule for the ozone NAAQS[1]).

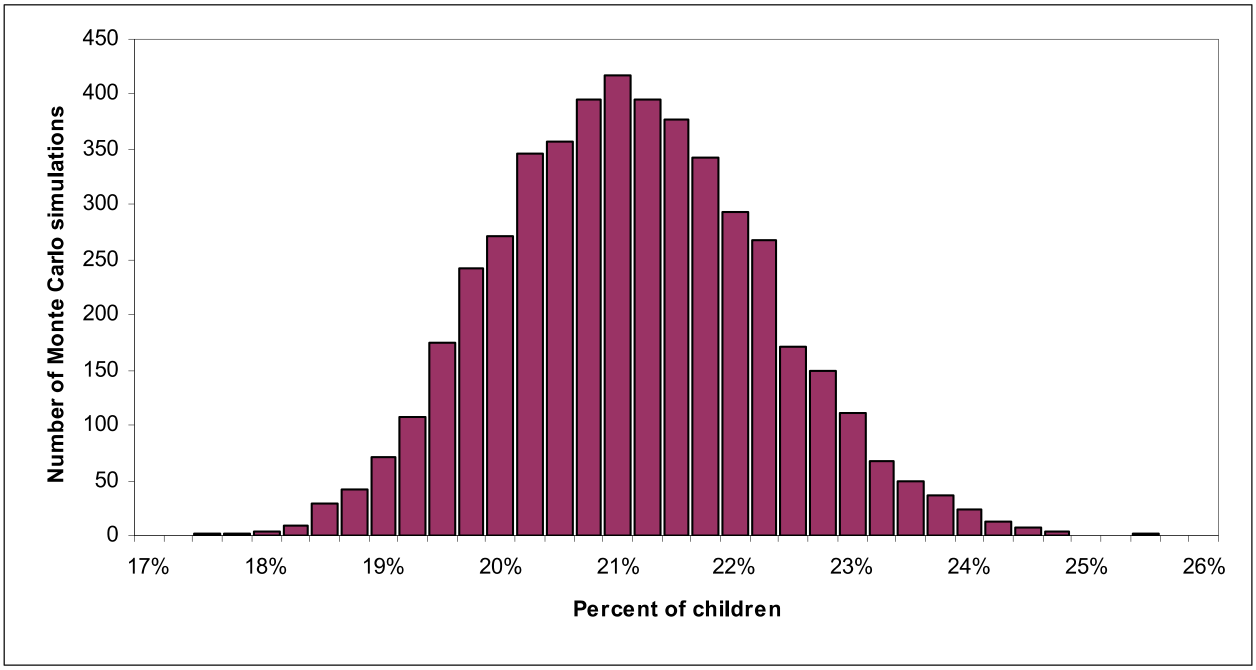

Figure A-3. Uncertainty Distribution Model Results. The estimated percentage of children with 8-hour exposures above 0.08 ppm at moderate exertion (the point estimate is 20%).

Selected References. More information on the analysis can be found by consulting the following resources:

Langstaff, J. E. 2007*. Analysis of Uncertainty in Ozone Population Exposure Modeling.* Office of Air Quality Planning and Standards Staff Memorandum to Ozone NAAQS Review Docket. OAR-2005-0172. http://www.epa.gov/ttn/naaqs/standards/ozone/s_ozone_cr_td.html

USEPA (U.S. Environmental Protection Agency). 2005. *Ozone Health Assessment Plan: Scope and Methods for Exposure Analysis and Risk Assessment.* Research Triangle Park, NC: Office of Air Quality Planning and Standards, USEPA. http://www.epa.gov/ttn/naaqs/standards/ozone/s_o3_cr_pd.html

USEPA. 2006. *Total Risk Integrated Methodology (TRIM)—Air Pollutants Exposure Model Documentation (TRIM.Expo/APEX, Version 4) Volume I: User's Guide; Volume II: Technical Support Document.* Research Triangle Park, NC: Office of Air Quality Planning and Standards, USEPA. June 2006. http://www.epa.gov/ttn/fera/human_apex.html

USEPA. 2007a. *Review of National Ambient Air Quality Standards for Ozone: Policy Assessment of Scientific and Technical Information—OAQPS Staff Paper.* Research Triangle Park, NC: Office of Air Quality Planning and Standards, USEPA. http://www.epa.gov/ttn/naaqs/standards/ozone/s_ozone_cr_sp.html

[1] National Ambient Air Quality Standards for Ozone, Final Rule. 73 Fed. Reg. 16436 (Mar. 27, 2008).

USEPA. 2007b. *Ozone Population Exposure Analysis for Selected Urban Areas.* Research Triangle Park, NC: Office of Air Quality Planning and Standards, USEPA. http://www.epa.gov/ttn/naaqs/standards/ozone/s_ozone_cr_td.html

Case Study 11: Analysis of Microenvironmental Exposures to Fine Particulate Matter for a Population Living in Philadelphia, Pennsylvania

This case study used the Stochastic Human Exposure and Dose Simulation model for Particulate Matter (SHEDS-PM) developed by EPA's National Exposure Research Laboratory (NERL) to prepare a probabilistic assessment of population exposure to $PM_{2.5}$ in Philadelphia, Pennsylvania. This case study simulation was prepared to accomplish three goals: (1) estimate the contribution of $PM_{2.5}$ of ambient (outdoor) origin to total $PM_{2.5}$ exposure; (2) determine the major factors that influence personal exposure to $PM_{2.5}$; and (3) identify factors that contribute the greatest uncertainty to model predictions.

Probabilistic Analysis. The two-dimensional probabilistic assessment used a microexposure event technique to simulate individual exposures to $PM_{2.5}$ in specific microenvironments (outdoors, indoor residence, office, school, store, restaurant or bar, and in a vehicle). The population for the simulation was generated using demographic data at the census-tract level from the U.S. Census. Characteristics of the simulated individuals were selected randomly to match the demographic proportions within the census tract for gender, age, employment status and housing type. The assessment used spatially and temporally interpolated ambient $PM_{2.5}$ measurements from 1992 to 1993 and 1990 U.S. Census data for each census tract in Philadelphia. This case study provides an example of both two-dimensional (variability and uncertainty) probabilistic assessment and microexposure event assessment (Group 3: Advanced PRA).

Results of Analysis. Results of the analysis showed that human activity patterns did not have as strong an influence on ambient $PM_{2.5}$ exposures as was observed for exposure to indoor $PM_{2.5}$ sources. Exposure to $PM_{2.5}$ of ambient origin contributed a significant percent of the daily total $PM_{2.5}$ exposures, especially for the segment of the population without exposure to environmental tobacco smoke in the residence. Development of the SHEDS-PM model using the Philadelphia $PM_{2.5}$ case study also provided useful insights into data needs for improving inputs into the SHEDS-PM model, reducing uncertainty and further refinement of the model structure. Some of the important data needs identified from the application of the model include: daily $PM_{2.5}$ measurements over multiple seasons and across multiple sites within an urban area, improved capability of dispersion models to predict ambient $PM_{2.5}$ concentrations at greater spatial resolution and over a 1-year time period, measurement studies to better characterize the physical factors governing infiltration of ambient $PM_{2.5}$ into residential microenvironments, further information on particle-generating sources within the residence, and data for the other indoor microenvironments not specified in the model.

Management Considerations. The application of the SHEDS-PM model to the Philadelphia population gave insights into data needs and areas for model refinement. The continued development and evaluation of the SHEDS-PM population exposure model are being conducted as part of ORD's effort to develop a source-to-dose modeling system for PM and air toxics. This type of exposure and dose modeling system is considered to be important for the scientific and policy evaluation of the critical pathways, as well as the exposure factors and source types influencing human exposures to a variety of environmental pollutants, including PM.

Selected References. The results of the analysis were published in:

Burke, J., M. Zufall, and H. Özkaynak. 2001. "A Population Exposure Model for Particulate Matter: Case Study Results for $PM_{2.5}$ in Philadelphia, PA." *Journal of Exposure Analysis and Environmental Epidemiology* 11 (6): 470–89.

Georgepoulos, P. G., S. W. Wang, V. M. Vyas, Q. Sun, J. Burke, R. Vedantham, T. McCurdy, and H. Özkaynak. 2005. "A Source-to-Dose Assessment of Population Exposure to Fine PM and Ozone in Philadelphia, PA, During a Summer 1999 Episode." *Journal of Exposure Analysis and Environmental Epidemiology* 15 (5): 439–57.

Case Study 12: Probabilistic Analysis in Cumulative Risk Assessment of Organophosphorus Pesticides

In 1996, Congress enacted the Food Quality Protection Act (FQPA), which requires EPA to consider "available evidence concerning the cumulative effects on infants and children of such residues and other substances that have a common mechanism of toxicity" when setting pesticide tolerances (i.e., the maximum amount of pesticide residue legally allowed to remain on food products). FQPA also mandated that EPA completely reassess the safety of all existing pesticide tolerances (those in effect since August 1996) to ensure that they are supported by current scientific data and meet current safety standards. Because organophosphorus pesticides (OPs) were assigned priority for tolerance reassessment, these pesticides were the first "common mechanism" group identified by EPA's OPP. The ultimate goal associated with this cumulative risk assessment (CRA) was to provide a basis for the decision maker to establish safe tolerance levels for this group of pesticides, while meeting the FQPA standard for protecting infants and children.

Probabilistic Analysis. This case study provides an example of an advanced probabilistic assessment (Group 3). In 2006, EPA analyzed exposures to 30 OPs through food consumption, drinking water intake, and exposure via pesticide application. Distributions of human exposure factors, such as breathing rates, body weight and surface areas used in the assessment, came from the Agency's *Exposure Factors Handbook* (USEPA 1997d). EPA used Calendex, a probabilistic computer software program (available at http://www.epa.gov/pesticides/science/deem/) to integrate various pathways, while simultaneously incorporating the time dimensions of the input data. Based on the results of the exposure assessment, EPA calculated margins of exposure (MOEs) for the total cumulative risk from all pathways for each age group (infant less than 1; children 1–2, 3–5, 6–12; youth 13–19; and adults 20–49 and 50+ years of age).

The food component of the OPs CRA was highly refined, as it was based on residue monitoring data from the USDA's PDP and supplemented with information from the FDA's Surveillance Monitoring Programs and Total Diet Study. The residue data were combined with actual consumption data from USDA's Continuing Survey of Food Intakes by Individuals (CSFII) using probabilistic techniques. The CRA evaluated drinking water exposures on a regional basis. The assessment focused on areas where combined OP exposure is likely to be highest within each region. Primarily, the analysis used probabilistic modeling to estimate the co-occurrence of OP residues in water. Monitoring data were not available with enough consistency to be the sole basis for the assessment; however, they were used to corroborate the modeling results. Data sources for the water component of the assessment included USDA Agricultural Usage Reports for Field Crops, Fruits and Vegetables; USDA Typical Planting and Harvesting Dates for Field Crops and Fresh Market and Processing Vegetables; local sources for refinements; and monitoring studies from the U.S. Geological Survey (USGS) and other sources. Finally, exposure via the oral, dermal and inhalation routes resulting from applications of OPs in and around homes, schools, offices and other public areas were assessed probabilistically for each of the seven regions. The data sources for this part of the assessment included information from surveys and task forces, special studies and reports from published scientific literature, EPA's *Exposure Factors Handbook* (USEPA 1997d), and other sources.

Results of Analysis. The OPs CRA presented potential risk from single-day (acute) exposures across 1 year and from a series of 21-day rolling averages across the year. MOEs at the 99.9th percentile were approximately 100 or greater for all populations for the 21-day average results. The only exception is a brief period (roughly 2 weeks) in which drinking water exposures (identified from the *Exposure Factors Handbook*, USEPA 1997d) attributed to phorate use on sugarcane resulted in MOEs near 80 for children ages 1 to 2 years. Generally, exposures through the food pathway dominated total MOEs, and exposures through drinking water were substantially lower throughout most of the year. Residential exposures were substantially smaller than exposures through both food and drinking water.

The OPs CRA was very resource intensive. Work began in 1997 with the preparation of guidance documents and the development of a CRA methodology. Over 2 to 3 years, more than 25 people spent 50 to 100 percent of their time working on the assessment, with up to 50 people working on the CRA at critical periods. EPA has spent approximately $1 million on this assessment (e.g., for computers, models and contractor support).

Management Considerations. The OPs CRA was a landmark demonstration of the feasibility of a regulatory-level assessment of the risk from multiple chemicals. Upon completion, EPA presented the CRA at numerous public technical briefings and FIFRA SAP meetings, and made all of the data inputs available to the public. The OPP's substantial effort to communicate methodologies, approaches and results to the stakeholders aided in the success of the OPs CRA. The stakeholders expressed appreciation for the transparent nature of the OPs CRA and recognized the innovation and hard work that went into developing the assessments.

Selected References. The 2006 assessment and related documents are available at http://www.epa.gov/pesticides/cumulative/common_mech_groups.htm#op.

USEPA (U.S. Environmental Protection Agency). 1997d. *Exposure Factors Handbook.* Washington, D.C.: National Center for Environmental Assessment, USEPA. http://cfpub.epa.gov/ncea/cfm/recordisplay.cfm?deid=12464.

Case Study 13: Probabilistic Ecological Effects Risk Assessment Models for Evaluating Pesticide Use

As part of the process of developing and implementing a probabilistic approach for ERA, an illustrative case was completed in 1996. This case involved both DRA and PRA for the effects of a hypothetical chemical X (ChemX) on birds and aquatic species. Following the recommendations of the SAP and in response to issues raised by OPP risk managers, the Agency began an initiative to refine the ERA process for evaluating the effects of pesticides to terrestrial and aquatic species within the context of FIFRA, the main statutory authority for regulating pesticides at the federal level. The key goals and objectives of EPA's initiative were to:

- Incorporate probabilistic tools and methods to provide an estimate on the magnitude and probability of effects.
- Build on existing data requirements for registration.
- Utilize, wherever possible, existing databases and create new ones from existing data sources to minimize the need to generate additional data.
- Focus additional data requirements on reducing uncertainty in key areas.

After proposing a four-level risk assessment scheme, with higher levels reflecting more refined risk assessment techniques, the Agency developed pilot models for both terrestrial and aquatic species. Refined risk assessment models (Level II) then were developed and used in a generic chemical case study that was presented to the SAP in 2001.

Probabilistic Analysis. This case study describes an advanced probabilistic model for the ecological effects of pesticides (Group 3). The terrestrial Level II model (version 2.0) is a multimedia exposure/effects model that evaluates acute mortality levels in generic or specific avian species over a user-defined exposure window. The spatial scale is at the field level, which includes the field and surrounding area. Both areas are assumed to meet the habitat requirements for each species, and contamination of edge or adjacent habitat from drift is assumed to be zero. For each individual bird considered in a run of the Level II model, a random selection of values is made for the major exposure input parameters to estimate an external oral dose equivalent for that individual. The estimated dose equivalent is compared to a randomly assigned tolerance for the individual preselected from the dose-response distribution. If the dose is greater than the tolerance, the individual is scored “dead,” if not, the individual is scored “not dead.” After multiple iterations of individuals, a probability density function of percent mortality is generated.

From May 29 to 31, 1996, the Agency presented two ERA case studies to the SAP for review and comment. Although recognizing and generally reaffirming the utility of EPA’s current deterministic assessment process, the SAP offered a number of suggestions for improvement. Foremost among their suggestions was a recommendation to move beyond the existing deterministic assessment approach by developing the tools and methodologies necessary to conduct a probabilistic assessment of effects. Such an assessment would estimate the magnitude and probability of the expected impact and define the level of certainty and variation involved in the estimate; risk managers within EPA’s OPP also had requested this information in the past.

The aquatic Level II model is a two-dimensional Monte Carlo risk model consisting of three main components: (1) exposure, (2) effects and (3) risk. The exposure scenarios used at Level II are intended to provide estimates for vulnerable aquatic habitats across a wide range of geographical conditions under which a pesticide product is used. The Level II risk evaluation process yields estimates of likelihood and magnitude of effects for acute exposures. For the estimate of acute risks, a distribution of estimated exposure and a distribution of lethal effects are combined through a 2-D MCA to obtain a distribution of joint probability functions. For the estimate of chronic risks, a distribution of exposure concentrations is compared to a chronic measurement endpoint. The risk analysis for chronic effects provides information only on the probability that the chronic endpoint assessed will be exceeded, not on the magnitude of the chronic effect expected.

Results of Analysis. As part of the process of developing and implementing a probabilistic approach for ERA, a case study was completed. The case study involved both DRAs and PRAs for effects of ChemX on birds and aquatic species. The deterministic screen conducted on ChemX concluded qualitatively that it could pose a high risk to both freshwater fish and invertebrates and showed that PRA was warranted. Based on the probabilistic analysis, it was concluded that the use of ChemX was expected to infrequently result in significant freshwater fish mortalities but routinely result in reduced growth and other chronic effects in exposed fish. Substantial mortalities and chronic effects to sensitive aquatic invertebrates were predicted to occur routinely after peak exposures.

Management Considerations. In its review of the case study, the FIFRA SAP congratulated the Agency on the effort made to conduct PRA of pesticide effects in ecosystems. The panel commented that the approach had progressed greatly from earlier efforts, and that the intricacy of the models was surprisingly good, given the time interval in which the Agency had to complete the task.

Following the case study, EPA refined the models based on the SAP comments. In addition, the terrestrial Level II model was refined to include dermal and inhalation exposure.

Selected References. An overview of the models is available at http://www.epa.gov/oppefed1/ecorisk/fifrasap/rra_exec_sum.htm#Terrestrial.

Case Study 14: Expert Elicitation of Concentration-Response Relationship Between Fine Particulate Matter Exposure and Mortality

In 2002, the NRC recommended that EPA improve its characterization of uncertainty in the benefits assessment for proposed regulations of air pollutants. NRC recommended that probability distributions for key sources of uncertainty be developed using available empirical data or through formal elicitation of expert judgments. A key component of EPA's approach for assessing potential health benefits associated with air quality regulations targeting emissions of $PM_{2.5}$ and its precursors is the effect of changes in ambient $PM_{2.5}$ levels on mortality. Avoided premature deaths constitute, on a monetary basis, between 85 and 95 percent of the monetized benefits reported in EPA's retrospective and prospective Section 812A benefit-cost analyses of the Clean Air Act (CAA; USEPA 1997e and 1999) and in Regulatory Impact Analysis (RIA) for rules such as the Heavy Duty Diesel Engine/Fuel Rule (USEPA 2000c) and the Non-Road Diesel Engine Rule (USEPA 2004). In response to the NRC recommendation, EPA conducted an expert elicitation evaluation of the concentration-response relationship between $PM_{2.5}$ exposure and mortality.

Probabilistic Analysis. This case study provides an example of the use of expert elicitation (Group 3) to derive probabilistic estimates of the uncertainty in one element of a cost-benefit analysis. Expert elicitation uses carefully structured interviews to elicit from each expert a best estimate of the true value for an outcome or variable of interest, as well as their uncertainty about the true value. This uncertainty is expressed as a subjective probabilistic distribution of values and reflects each expert's interpretation of theory and empirical evidence from relevant disciplines, as well as their beliefs about what is known and not known about the subject of the study. For the $PM_{2.5}$ expert elicitation, the process consisted of development of an elicitation protocol, selection of experts, development of a briefing book, conduct of elicitation interviews, the use of expert input prior to and following individual elicitation of judgments and the expert judgments themselves. The elicitation involved personal interviews with 12 health experts who had conducted research on the relationship between $PM_{2.5}$ exposures and mortality.

The main quantitative question asked each expert to provide a probabilistic distribution for the average expected decrease in U.S. annual, adult and all-cause mortality associated with a 1 $\mu g/m^3$ decrease in annual average $PM_{2.5}$ levels. When answering the main quantitative question, each expert was instructed to consider that the total mortality effect of a 1 $\mu g/m^3$ decrease in ambient annual average $PM_{2.5}$ may reflect reductions in both short-term peak and long-term average exposures to $PM_{2.5}$. Each expert was asked to aggregate the effects of both types of changes in their answers. The experts were given the option to integrate their judgments about the likelihood of a causal relationship or threshold in the concentration-response function into their own distributions or to provide a distribution "conditional on" one or both of these factors.

Results of Analysis. The project team developed the interview protocol between October 2004 and January 2006. Development of the protocol was informed by an April 2005 symposium held by the project team, where numerous health scientists and analysts provided feedback; detailed pretesting with independent EPA scientists in November 2005; and discussion with the participating experts at a pre-elicitation workshop in January 2006. The elicitation interviews were conducted between January and April 2006. Following the interviews, the experts reconvened for a post-elicitation workshop in June 2006, in which the project team anonymously shared the results of all experts with the group.

The median estimates for the $PM_{2.5}$ mortality relationship were generally similar to estimates derived from the two epidemiological studies most often used in benefits assessment. However, in almost all cases, the spread of the uncertainty distributions elicited from the experts exceeded the statistical uncertainty bounds reported by the most influential epidemiologic studies, suggesting that the expert elicitation process was successful in developing more comprehensive estimates of uncertainty for the $PM_{2.5}$ mortality relationship. The uncertainty distributions for $PM_{2.5}$ concentration-response resulting from the expert elicitation process were used in the RIA for the revised NAAQS standard for $PM_{2.5}$ (promulgated on September 21, 2006). Because the NAAQS are exclusively health-based standards, this RIA played no part in EPA's determination to revise the $PM_{2.5}$ NAAQS. Benefits estimates in the RIA were presented as ranges and included additional information on the quantified uncertainty distributions surrounding the points on the ranges, derived from both epidemiological studies and the expert elicitation results. OMB's review of the RIA was completed in March 2007.

Management Considerations. The NAAQS are exclusively health-based standards, so these analyses were not used in any manner by EPA in determining whether to revise the NAAQS for $PM_{2.5}$. Moreover, the request to engage in the expert elicitation did not come from the CASAC, the official peer review body for the NAAQS; a decision to conduct the analyses does not reflect CASAC advice that such analyses inform NAAQS determinations. The analyses addressed comments from the NRC that recommended that probability distributions for key sources of uncertainty be addressed. The analyses were used in EPA's retrospective and prospective Section 812A benefit-cost analyses of the CAA (USEPA 1997e and 1999) and in RIAs for rules such as the Heavy Duty Diesel Engine/Fuel Rule (USEPA 2000c) and the Non-Road Diesel Engine Rule (USEPA 2004). In response to the NRC recommendation, EPA conducted an expert elicitation evaluation of the concentration-response relationship between $PM_{2.5}$ exposure and mortality.

Selected Reference. The assessment is available at http://www.epa.gov/ttn/ecas/ria.html.

Case Study 15: Expert Elicitation of Sea-Level Rise Resulting From Global Climate Change

The United Nations Framework Convention on Climate Change requires nations to implement measures for adapting to rising sea level and other effects of changing climate. To decide on an appropriate response, coastal planners and engineers weigh the cost of these measures against the likely cost of failing to prepare, which depends on the probability of the sea rising a particular amount. The U.S. National Academy of Engineering recommended that assessments of sea level rise should provide probability estimates. Coastal engineers regularly employ probability information when designing structures for floods, and courts use probabilities to determine the value of land expropriated by regulations. This 1995 case study describes the development of a probability distribution for sea level rise, using models employed by previous assessments, as well as the expert opinions of 20 climate and glaciology reviewers about the probability distributions for particular model coefficients.

Probabilistic Analysis. This case study provides an example both of an analysis describing the probability of sea level rise, as well as an expert elicitation of the likelihood of particular models and probability distributions of the coefficients used by those models to predict future sea level rise (Group 3). The assessment of the probability of sea level rise used existing models describing the change in five components of sea level rise associated with greenhouse gas-related climate change (thermal expansion, small glaciers, polar precipitation, melting and ice discharge from Greenland

and ice discharge from Antarctica). To provide a starting point for the expert elicitation, initial probability distributions were assigned to each model coefficient based on the published literature.

After the initial probabilistic assessment was completed, the draft report was circulated to expert reviewers considered most qualified to render judgments on particular processes for revised estimates of the likelihood of particular models and the model coefficients' probability distributions. Experts representing both extremes of climate change science (those who predicted trivial consequences and those who predicted catastrophic effects; individuals whose thoughts had been excluded from previous assessments) were included. The experts were asked to provide subjective assessments of the probabilities of various models and model coefficients. These subjective probability estimates were used in place of the initial probabilities in the final model simulations. Different reviewer opinions were not combined to produce a single probability distribution for each parameter; instead, each reviewer's opinions were used in independent iterations of the simulation. The group of simulations resulted in the probability distribution of sea level rise.

Results of Analysis. The analysis, completed with a budget of $100,000, provided a probabilistic estimate of sea level rise for use by coastal engineers and regulators. The results suggested that there is a 65 percent chance that the sea level will rise 1 millimeter (mm) per year more rapidly in the next 30 years than it has been rising in the last century. Under the assumption that nonclimatic factors do not change, the projections suggested that there is a 50 percent chance that the global sea level will rise 45 centimeters (cm), and a 1 percent chance of a 112 cm rise by the year 2100. The median prediction of sea level rise was similar to the midpoint estimate of 48 cm published by the Intergovernmental Panel on Climate Change (IPCC) shortly thereafter (IPCC 1996). The report also found a 1 percent chance of a 4 to 5 meter rise over the next 2 centuries.

Management Considerations. There are two reports (USEPA 1995c; Titus and Narayanan 1996) that discuss several uses of the results of this study. By providing a probabilistic representation of sea level rise, the assessment allows coastal residents to make decisions with recognition of the uncertainty associated with predicted change. Rolling easements that vest when the sea rises to a particular level can be properly valued in both "arms-length" transaction sales or when calculating the allowable deduction for a charitable contribution of the easement to a conservancy. Cost-benefit assessments of alternative infrastructure designs—which already consider flood probabilities—also can consider sea level rise uncertainty. Assessments of the benefits of preventing an acceleration of sea level rise can include more readily low-probability outcomes, which can provide a better assessment of the true risk when the damage function is nonlinear, which often is the case.

Selected References.

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IPCC (Intergovernmental Panel on Climate Change). 1996. *Climate Change 1995: The Science of Climate Change. Contribution of Working Group I to the Second Assessment of the Intergovernmental Panel on Climate Change.* Cambridge: Cambridge University Press.

Titus, J. G., and V. Narayanan. 1996. "The Risk of Sea Level Rise." *Climatic Change* 33(2): 151–212.

Case Study 16: Knowledge Elicitation for a Bayesian Belief Network Model of Stream Ecology

The identification of the causal pathways leading to stream impairment is a central challenge to understanding ecological relationships. Bayesian belief networks (BBNs) are a promising tool for modeling presumed causal relationships, providing a modeling structure within which different factors describing the ecosystem can be causally linked and calculating uncertainties expressed for each linkage.

BBNs can be used to model complex systems that involve several interdependent or interrelated variables. In general, a BBN is a model that evaluates situations where some information already is known, and incoming data are uncertain or partially unavailable. The information is depicted with influence diagrams that present a simple visual representation of a decision problem, for which quantitative estimates of effect probabilities are assigned. As such, BBNs have the potential for representing ecological knowledge and uncertainty in a format that is useful for predicting outcomes from management actions or for diagnosing the causes of observed conditions. Generally, specification of a BBN can be performed using available experimental data, literature review information (secondary data) and expert elicitation. Attempts to specify a BBN for the linkage between fine sediment load and macroinvertebrate populations using data from literature reviews have failed because of the absence of consistent conceptual models and the lack of quantitative data or summary statistics needed for the model. In light of these deficiencies, an effort was made to use expert elicitation to specify a BBN for the relationship between fine sediment load resulting from human activity and populations of macroinvertebrates. The goals of this effort were to examine whether BBNs might be useful for modeling stream impairment and to assess whether expert opinion could be elicited to make the BBN approach useful as a management tool.

Probabilistic Analysis. This case study provides an example of expert elicitation in the development of a BBN model of the effect of increased fine sediment load in a stream on macroinvertebrate populations (Group 3). For the purpose of this study, a stream setting (a Midwestern, low-gradient stream) and a scenario of impairment (introduction of excess fine sediment) were used. Five stream ecologists with experience in the specified geographic setting were invited to participate in an elicitation workshop. An initial model was depicted using influence diagrams, with the goals of structuring and specifying the model using expert elicitation. The ecologists were guided through a knowledge elicitation session in which they defined factors that described relevant chemical, physical and biological aspects of the ecosystem. The ecologists then described how these factors were connected and were asked to provide subjective, quantitative estimates of how different attributes of the macroinvertebrate assemblage would change in response to increased levels of fine sediment. Elicited input was used to restructure the model diagram and to develop probabilistic estimates of the relationships among the variables.

Results of Analysis. The elicited input was compiled and presented in terms of the model as structured by the stream ecologists and their model specifications. The results were presented both as revised influence diagrams and with Bayesian probabilistic terms representing the elicited input. The study yielded several important lessons. Among these were that the elicitation process takes time (including an initial session by teleconference as well as a 3-day workshop), defining a scenario with an appropriate degree of detail is critical and elicitation of complex ecological relationships is feasible.

Management Considerations. The study was considered successful for several reasons. First, the feasibility of the elicitation approach to building stream ecosystem models was demonstrated. The study also resulted in the development of new graphical techniques to perform the elicitation. The elicited input was interpreted in terms of predictive distributions to support fitting a complete Bayesian model. Furthermore, the study was successful in bringing together a group of experts in a particular subject area for the purpose of sharing information and learning about expert elicitation in support of model building. The exercise provided insights into how best to adapt knowledge elicitation methods to ecological questions and informed the assembled stream ecologists on the elicitation process and on the potential benefits of this modeling approach. The explicit quantification of uncertainty in the model not only enhances the utility of the model predictions, but also can help guide future research.

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COST, PERMITTING, AND TREATMENT IMPLICATIONS OF THE DRAFT POLYCHLORINATED BIPHENYLS WATER QUALITY CRITERION

November 4, 2015

COST, PERMITTING, AND TREATMENT IMPLICATIONS OF THE DRAFT POLYCHLORINATED BIPHENYL WATER QUALITY CRITERION

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ACRONYMS AND ABBREVIATIONS

GPM	gallons per minute
GAC	granulated activated carbon
IDEQ	Idaho Department of Environmental Quality
MGD	million gallons per day
NPDES	National Pollutant Discharge Elimination System
PCB	polychlorinated biphenyls
pg/L	picograms per liter
TMDL	total maximum daily load
µg/L	micrograms per liter
USEPA	United States Environmental Protection Agency

1 INTRODUCTION

On October 7, 2015, the Idaho Department of Environmental Quality (IDEQ) released draft changes to the Idaho water quality criteria, which included a reduction of the human health criterion for polychlorinated biphenyls (PCBs) for the consumption of water and fish from 64 picograms per liter (pg/L) to 61 pg/L. Due to the ubiquity of PCBs in ambient surface waters as a result of historic use, high treatment costs to achieve low PCB concentrations in effluents, and limited resources for monitoring and enforcement, the proposed change of the water quality criterion for PCBs would impose significant treatment and monitoring costs on the regulated community and a significant burden on the regulatory community.

2 REGULATORY BURDEN

2.1 PCB Monitoring and Enforcement in Idaho

Idaho Department of Environmental Quality's (IDEQ's) surface water quality monitoring program, consisting of the Beneficial Use Reconnaissance Program, National Aquatic Resource Surveys, Trend Monitoring Network, and special studies, does not currently monitor for PCBs in ambient surface waters. The data collected from these monitoring programs are used to develop Integrated Reports, which are submitted to the U.S. Environmental Protection Agency (USEPA) every 2 years, in accordance with sections 303(d), 305(b), and 314 of the Clean Water Act, and provide an assessment of whether Idaho's water bodies meet state water quality criteria and support beneficial uses. Part of the Integrated Report provides a list of water bodies that do not meet the state's water quality criteria for one or more beneficial uses by one or more pollutant and require the development of a total maximum daily load (TMDL (i.e., "303(d) list of impaired waters"). Given that IDEQ's monitoring program does not actively monitor for PCBs, PCB concentration data are not available for Idaho surface waters and PCBs are not currently listed as a cause of impairment for Idaho's water bodies (IDEQ 2012 Integrated Report).

Although PCB concentration data are not available for ambient surface waters in Idaho, it is expected that PCBs are ubiquitous in surface waters of developed areas, at concentrations that exceed IDEQ's draft water quality criterion for PCBs. The ubiquity of PCBs in surface waters of developed areas is supported by PCB concentration data collected by other states. According to data collected by 26 states between 1975 and 2014 and available in USEPA's Storage and Retrieval Data Warehouse (STORET) and U.S. Geological Survey's National Water Quality Assessment (NAWQA) Program, PCB concentrations in surface waters range from 3.8 pg/L to 124 micrograms per liter (ug/L). Most of these concentrations and/or detection limits are above IDEQ's draft PCB criterion of 61 pg/L. This national presence in waters supports the expectation that PCBs also exist in Idaho waters despite not being used in any industrial or other application as a result of the PCB ban in place since 1979.

2.2 Implications of the Proposed PCB Standard

Enforcement of the draft water quality criterion for PCBs will require IDEQ to include PCBs in its surface water monitoring program, thereby increasing routine monitoring costs. Given the low draft PCB criterion and the ubiquity of PCBs in the environment, the number of water quality impairments caused by PCBs is anticipated to increase if the draft PCB criterion is enforced. Once a water body is listed as impaired, IDEQ is required to develop, implement, and enforce a TMDL, and apply PCB National Pollutant Discharge Elimination System (NPDES) requirements on all dischargers on those waters. These all add significant additional regulatory burden and costs and divert resources that could be better used for other monitoring, enforcement, and clean-up efforts.

3 COSTS TO THE REGULATED COMMUNITY

3.1 PCB Permitting and Treatment

Because PCBs are not currently monitored in Idaho surface waters, industrial and municipal facilities have not been required to monitor and/or treat their effluent for PCBs before discharging to surface waters. Of the 23 industrial and 136 municipal NPDES permits issued to facilities in Idaho, none include monitoring requirements for PCBs or specify treatment technologies to remove PCBs from effluents. Therefore, there are currently no costs to industrial and municipal facilities associated with monitoring and removal of PCBs.

3.2 Implications of the Proposed PCB Criterion

Enforcement of the draft water quality criterion for PCBs will require industrial and municipal facilities to monitor and treat their effluent for PCBs because PCB concentrations in effluents are likely above the criterion given their ubiquitous presence in the environment. These monitoring and treatment efforts will impose significant costs on the regulated community across the state. The Treatment Technology Review and Assessment report by HDR Engineering Inc. “Treatment Technology Review and Assessment. Association of Washington Business, Association of Washington Cities, Washington State Association of Counties” was used as the basis for estimating the cost implications for industrial and municipal permit holders in Idaho. The cost presented by HDR assumed treatment of PCBs, arsenic, mercury and benzo(a)pyrene to the revised Washington State effluent limits as discussed in the report. The tables below present the estimated capital and annual operational costs for all industrial and municipal permit holders based on 2015 dollars and projected out to 2041. Despite these high treatment costs, the draft PCB criterion may not be achievable due to limitations of available technology.

Idaho-Wide Costs for Industrial and Municipal Permit Holders

Idaho-Wide Cost for Industrial Permit Holders		
	Present Day Value (2015)	Net Present Value 25 Years (2015 dollars)
Capital Expenses	$1,950 M	$2,570 M
Annual Operational Expenses	$78.4 M	

Idaho-Wide Cost for Municipal Permit Holders		
	Present Day Value (2015)	Net Present Value 25 Years (2015 dollars)
Capital Expenses	$8,980 M	$13,800 M
Annual Operational Expenses	$366 M	

The cost estimates are planning level and present a cost range for each applicable option. The estimates were developed based on wastewater industry cost references, technical studies, actual project cost histories and professional experience have an expected accuracy range of -30 to +50 percent and typical end usage of budget authorization and cost control.

HDR presented capital cost, operational cost, and net present value for conventional secondary treatment (baseline) and two enhanced secondary treatment options: (1) membrane filtration and reverse osmosis (FM/RO) and (2) membrane filtration and granulated activated carbon (MF/GAC). A median incremental cost was taken from the HDR report for capital and operational expenditures and scaled accordingly to estimate the capital and operational cost for permit holders of varying capacity treatment systems in the state of Idaho and for permit holders as a whole in Idaho.

Incremental cost estimates to upgrade existing Idaho treatment systems for enhanced treatment of PCBs were developed for systems with treatment capacities ranging from 100 gallons per minute (gpm) to 15 million gallons per day (MGD). The tables below show the estimated costs for systems with treatment capacities of 100 gpm, 5 MGD, and 15 MGD based on HRD's cost estimates. These treatment costs were then applied to the 23 industrial and 136 municipal facilities with NPDES permits in Idaho using the design flow rate and average daily flow for each facility, as shown in **Tables 1** and **2**.

Estimated Costs for Treatment Systems

0.15 MGD/100 gpm System	
Capital Expenses	$15.2 M
Annual Operational Expenses	$0.62 M

5 MGD System	
Capital Expenses	$185 M
Annual Operational Expenses	$7.5 M

15 MGD System	
Capital Expenses	$360 M
Annual Operational Expenses	$14.6 M

4 CONCLUSION

The proposed change to the PCB water quality criterion would create a significant regulatory burden and impose significant costs on the regulated community. IDEQ does not currently monitor for PCBs in ambient surface waters, nor are industrial and municipal facilities required to monitor for and/or treat PCBs in their discharges to surface water. However, due to the ubiquitous nature of PCBs in the environment and the very low draft PCB criterion, enforcement of the draft PCB criterion would increase the number of Idaho waterbodies listed as impaired due to PCBs, triggering the development of TMDLs and additional monitoring by IDEQ. Additionally, industrial and municipal dischargers would be held accountable for monitoring and treating PCBs in their effluent, forcing facilities to upgrade their wastewater treatment processes facing capital and operational costs of $15 billion. The increased number of waterbody impairments and upgrades to wastewater treatment systems would result in significant costs both to IDEQ and the regulated community, would not result in any measurable improvement in public health (Arcadis 2015; comments being prepared simultaneously), as well as provide little certainty that ambient PCB concentrations would, in fact, be reduced.

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TABLES

Table 1:
Estimated Costs for Treatment Systems Based on Industrial Facility

Industrial Facility Name	Permit Effective End Date	Average Flow Permit Limit (million gallons per day)	Average Daily Flow (million gallons per day)	Average Maximum Daily Flow (million gallons per day)	Design Flow Rate (million gallons per day)	Monitoring for PCBs?	CapEx (2015)	Annual OpEx (2015)	25-Year Net Present Value (in 2015 dollars)
Armour Fresh Meats	2/2/2004	0.416 (Outfall 010) 0.10 (Outfall 004)	0.44 (Outfall 010) 0.056 (Outfall 004)	--	--	No	$ 46,700,000	$ 1,900,000	$ 61,709,100
Bennett Timber Products Inc.	8/31/2011	0.0645 (Outfall 001)	--	0.018 to 0.0432	--	No	$ 15,200,000	$ 620,000	$ 20,100,900
City of Burley Industrial Wastewater Treatment Plant	5/31/2014	--	--	--	2.4	No	$ 122,500,000	$ 5,000,000	$ 162,030,200
Cabinet Gorge Power Station	1/2/2007	--	0.000224	0.000336	0.0012	No	$ 15,200,000	$ 620,000	$ 20,100,900
Chiquita Processed Foods	1/2/2007	--	0.3	--	--	No	$ 27,400,000	$ 1,120,000	$ 36,258,100
Clearwater Paper Lewiston Mill	4/30/2010	--	41.2	62.5	--	No	$ 360,000,000	$ 14,600,000	$ 475,238,200
Darigold Inc.	11/2/2004	1.7	--	--	--	No	$ 108,000,000	$ 4,400,000	$ 142,770,000
Gem Meat Packing	11/2/2004	0.01	--	--	--	No	$ 15,200,000	$ 620,000	$ 20,100,900
Glanbia Foods, Inc.	2/29/2009	--	--	0.6	--	No	$ 46,700,000	$ 1,900,000	$ 61,709,100
Hecla Mining Co - Grouse Creek Mine	2/12/2007	--	0.648	--	--	No	$ 54,000,000	$ 2,190,000	$ 71,285,700
Hecla Mining Co - Lucky Friday Mine	9/14/2008	--	--	1.7 (Outfall 001) 2.275 (Outfall 003)	--	No	$ 160,000,000	$ 6,500,000	$ 211,327,300
Idaho Cobalt Project	3/31/2014	--	0.16128	--	0.216	No	$ 27,400,000	$ 620,000	$ 31,293,600
Jerome Cheese Co.	10/2/2006	--	0.497	--	--	No	$ 46,700,000	$ 1,900,000	$ 61,709,000
Magic Valley Produce	11/6/2008	--	0.0288	--	--	No	$ 15,200,000	$ 620,000	$ 20,100,900
McCain Foods USA	10/31/2019	--	3.12 (Outfall 001) 0.295 (Outfall 002) 0.216 (Outfall 004)	4.16 (Outfall 001) 0.452 (Outfall 002) 0.974 (Outfall 004)	--	No	$ 204,000,000	$ 8,300,000	$ 269,566,400
Meridian Beartrack Mine	10/31/2008	--	--	0.30 to 1.05	--	No	$ 66,600,000	$ 2,700,000	$ 87,909,100
Minidoka Power Plant	1/8/2007	--	--	0.001	0.05	No	$ 15,200,000	$ 620,000	$ 20,100,900
Pacificorp Idaho Falls Pole Yard	10/31/2001	--	--	--	0.288	No	$ 27,400,000	$ 1,120,000	$ 36,258,100
Potlatch Corp St. Maries Mill	10/31/2001	--	0.403 (log yard runoff) 0.078 (cooling water)	--	--	No	$ 46,700,000	$ 1,510,000	$ 57,836,800
Sorrento Lactailis, Inc.	10/31/2010	--	0.5	0.775	--	No	$ 46,700,000	$ 1,900,000	$ 61,709,100
Thompson Creek Mining Company	1/29/2007	--	--	5.42 (Outfall 001) 7.76 (Outfall 002) 6.27 (Outfall 003) 0.84 (Outfall 004) 1.75 (Outfall 005)	--	No	$ 360,000,000	$ 14,600,000	$ 475,238,200
US Silver Coeur and Galena Mines and Mills	6/30/2012	--	--	1.66 (Outfall 001) 0.895 (Outfall 002)	--	No	$ 122,500,000	$ 5,000,000	$ 162,030,200
							$ 1,949,300,000	$ 78,360,000	$ 2,566,382,700

Notes:
-- = not available
Annual OpEx = annual operational expenses
CapEx = capital expenses
PCB = polychlorinated biphenyl
1. Source: USEPA. Current NPDES Permits in Idaho. Region 10: The Pacific Northwest. Available online at: http://yosemite.epa.gov/r10/water.nsf/NPDES+Permits/Current+ID1319#permits
2. Search Date: 10/15/2015
3. Capital and annual operational expenses are based off of the design flow rate and average daily flow rate, respectively. If the design and/or average daily flow rates are not available, expenses are based off of the available flow rate.
4. Facilities with a design and/or average daily flow rate of less than 100 gallons per minute (gpm) are assumed to have capital and annual operational expenses associated with a 100 gpm facility.
5. Facilities with a design and/or average daily flow rate greater than 15 million gallons per day (mgd) are assumed to have capital and annual operational expenses associated with a 15 mgd facility.
6. For the net present value analysis, a 9% discount rate was applied over an assumed 25 year equipment life.

Table 2:
Estimated Costs for Treatment Systems Based on Municipal Facility

Municipal Facility Name	Permit Effective End Date	Average Daily Flow (million gallons per day)	Average Maximum Daily Flow (million gallons per day)	Design Flow Rate (million gallons per day)	Monitoring for PCBs?	CapEx (2015)	Annual OpEx (2015)	25-Year Net Present Value (in 2015 dollars)
Country Home Mobile Park WWTP		0.001	--	0.001	No	$ 15,200,000	$ 620,000	$ 23,388,800
Albeni Falls Dam WWTP	1/2/2007	0.0002	--	0.0018	No	$ 15,200,000	$ 620,000	$ 23,388,800
Red River Ranger Station USDA Forest Service WWTP	3/31/2017	0.0061	0.00625	0.00625	No	$ 15,200,000	$ 620,000	$ 23,388,800
Elk Valley Subdivision WWTP	5/31/2010	--	--	0.0093	No	$ 15,200,000	$ 620,000	$ 23,388,800
Slate Creek Ranger Station USDA Forest Service WWTP	9/31/2017	--	--	0.012	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Clarkia WWTP	1/2/2007	0.016	--	0.018	No	$ 15,200,000	$ 620,000	$ 23,388,800
USFS Forest Service Fenn Ranger Station WWTP	10/31/2017	--	--	0.02	No	$ 15,200,000	$ 620,000	$ 23,388,800
Wilderness Ranch Water Treatment Plant	10/31/2011	--	--	0.02	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Harrison WWTP	8/31/2010	0.0006	--	0.03	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Fruitland, Payette River WWTP	10/31/2016	--	--	0.035	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Winchester WWTP	2/28/2018	0.025	--	0.035	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Pierce Water Treatment Plant	10/31/2011	--	--	0.036	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Orofino Water Treatment Plant	10/31/2011	--	--	0.039	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Laclede Water Treatment Plant	10/31/2011	--	--	0.04	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Bovill WWTP	3/31/2010	0.053	--	0.05	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Culdesac WWTP	10/31/2007	--	--	0.055	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Dover WWTP	1/2/2007	0.029	--	0.06	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Richfield WWTP	3/31/2010	0.02	--	0.06	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Franklin WWTP	5/31/2009	0.02	--	0.0625	No	$ 15,200,000	$ 620,000	$ 23,388,800
Viola Water and Sewer District WWTP	2/28/2009	--	--	0.063	No	$ 15,200,000	$ 620,000	$ 23,388,800
Riverside Independent Water District Water Treatment Plant WWTP	10/31/2011	--	--	0.068	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Stites WWTP	9/30/2007	0.061	--	0.07	No	$ 15,200,000	$ 620,000	$ 23,388,800
Jug Mountain Ranch (planned unit development)	7/31/2009	--	--	0.07	gfeh	$ 15,200,000	$ 620,000	$ 23,388,800
City of Sandpoint Sand Creek Water Treatment Plant	10/31/2011	--	--	0.07795	gfs	$ 15,200,000	$ 620,000	$ 23,388,800
City of Elk River WWTP	4/30/2009	0.02	--	0.08	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Juliaetta WWTP	4/30/2009	0.036	--	0.08	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Kendrick WWTP	3/31/2010	0.03	--	0.08	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Nezperce WWTP	3/31/2009	--	--	0.09	No	$ 15,200,000	$ 620,000	$ 23,388,800
Carey Water and Sewer District WWTP		0.03	--	0.1	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Ririe WWTP	1/1/2009	Currently not discharging	--	0.1	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Roberts WWTP	4/30/2009	0.03	--	0.1	No	$ 15,200,000	$ 620,000	$ 23,388,800
The Meadows LLC WWTP	7/31/2017	0.029	--	0.1	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Inkom WWTP	5/31/2010	0.076	--	0.105	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Riggins WWTP	8/31/2017	0.04	--	0.105	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Notus WWTP	9/30/2018	--	--	0.11	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Craigmont WWTP		0.15	--	0.12	No	$ 15,200,000	$ 620,000	$ 23,388,800
Elk City Water and Sewer Association WWTP	4/30/2020	--	--	0.12	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Hansen WWTP	10/31/2012	0.084	--	0.125	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Genesee WWTP	3/31/2010	0.1	--	0.15	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Hagerman WWTP	10/31/2012	--	--	0.15	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Fairfield WWTP	8/21/2020	--	--	0.165	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
Southside Water and Sewer District WWTP		0.054	--	0.165	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Mackay WWTP	5/31/2009	0.065	--	0.18	No	$ 27,400,000	$ 1,120,000	$ 42,195,400

Table 2:
Estimated Costs for Treatment Systems Based on Municipal Facility

Municipal Facility Name	Permit Effective End Date	Average Daily Flow (million gallons per day)	Average Maximum Daily Flow (million gallons per day)	Design Flow Rate (million gallons per day)	Monitoring for PCBs?	CapEx (2015)	Annual OpEx (2015)	25-Year Net Present Value (in 2015 dollars)
City of Weiser Water Treatment Plant	10/31/2011	--	--	0.185	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Troy WWTP	4/30/2009	0.11	--	0.19	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Kooskia WWTP	9/30/2007	0.11	--	0.198	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
Cities of Santa and Fernwood WWTP	5/31/2009	0.14	--	0.2	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Horseshoe Bend WWTP	11/24/2008	0.07	--	0.2	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Shoshone WWTP	3/31/2010	0.09	--	0.2	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
Caldwell Housing Authority WWTP	2/2/2004	0.206	--	0.206	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Deary WWTP	4/30/2009	0.2	--	0.23	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Greenleaf WWTP	12/31/2017	--	--	0.24	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Cambridge WWTP	3/31/2010	0.088	--	0.25	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Smelterville WWTP	9/30/2018	--	--	0.25	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Wilder WWTP	5/31/2010	0.17	--	0.25	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Cottonwood WWTP	9/20/2007	0.48	--	0.275	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Filer WWTP	10/31/2012	0.059	--	0.28	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
Cities of Pierce and Judgetown WWTP	4/30/2009	0.19	--	0.3	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Marsing WWTP	10/31/2020	0.01	--	0.3	No	$ 27,400,000	$ 1,120,000	$ 42,195,400
City of Plummer WWTP	6/30/2017	--	--	0.32	No	$ 37,200,000	$ 1,510,000	$ 57,135,100
Lapwai Valley WWTP	7/31/2016	--	--	0.32	No	$ 37,200,000	$ 1,510,000	$ 57,135,100
City of Lava Hot Springs WWTP	5/31/2010	0.13	--	0.343	No	$ 37,200,000	$ 1,510,000	$ 57,135,100
Ahsahka Water and Sewer District WWTP	10/31/2016	--	--	0.35	No	$ 37,200,000	$ 1,510,000	$ 57,135,100
City of New Meadows WWTP	7/31/2018	0.1	--	0.36	No	$ 37,200,000	$ 1,510,000	$ 57,135,100
City of Ashton WWTP	3/31/2019	0.18	--	0.365	No	$ 37,200,000	$ 1,510,000	$ 57,135,100
Cities of Potlatch and Onaway WWTP	3/31/2010	0.12	--	0.4	No	$ 37,200,000	$ 1,510,000	$ 57,135,100
City of Council WWTP	4/30/2009	0.34	--	0.4	No	$ 37,200,000	$ 1,510,000	$ 57,135,100
City of Grace WWTP	10/31/2019	0.06 to 0.07	0.05	0.435	No	$ 37,200,000	$ 1,510,000	$ 57,135,100
City of Bonners Ferry WWTP	10/31/2016	0.39	--	0.45	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Homedale WWTP	9/30/2018	0.25	--	0.45	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Shelley WWTP		0.34	--	0.46	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Fruitland, Snake River WWTP	10/31/2016	--	--	0.48	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Glenns Ferry WWTP	12/31/2016	0.35	--	0.5	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Montpelier WWTP	5/31/2010	0.36	--	0.5	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Priest River WWTP	11/30/2016	--	--	0.5	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Rigby WWTP	7/31/2010	0.6	--	0.53	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Weippe WWTP	10/31/2019	0.370 to 0.424	--	0.536	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Lewistown Water Treatment Plant	10/31/2011	--	--	0.55	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
Mullan WWTP South Fork Coeur d'Alene River Sewer District	9/30/2018	--	--	0.55	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Worley WWTP	4/30/2020	0.047	--	0.57	No	$ 46,700,000	$ 1,900,000	$ 71,789,000
City of Aberdeen WWTP	9/26/2006	0.43	--	0.6	No	$ 54,000,000	$ 2,190,000	$ 82,910,200
City of Driggs WWTP	12/31/2015	0.31	--	0.6	No	$ 54,000,000	$ 2,190,000	$ 82,910,200
City of New Plymouth WWTP	1/2/2007	0.31 to 0.4	--	0.6	No	$ 54,000,000	$ 2,190,000	$ 82,910,200
City of Kamiah WWTP	7/31/2016	0.124 to 0.144	--	0.613	No	$ 54,000,000	$ 2,190,000	$ 82,910,200
City of Heyburn WWTP	1/8/2007	0.32	--	0.66	No	$ 54,000,000	$ 2,190,000	$ 82,910,200
City of Parma WWTP	4/30/2009	0.32	--	0.68	No	$ 54,000,000	$ 2,190,000	$ 82,910,200

Table 2:
Estimated Costs for Treatment Systems Based on Municipal Facility

Municipal Facility Name	Permit Effective End Date	Average Daily Flow (million gallons per day)	Average Maximum Daily Flow (million gallons per day)	Design Flow Rate (million gallons per day)	Monitoring for PCBs?	CapEx (2015)	Annual OpEx (2015)	25-Year Net Present Value (in 2015 dollars)
City of Cascade WWTP		0.119	--	0.72	No	$ 54,000,000	$ 2,190,000	$ 82,910,200
City of Firth WWTP	3/31/2018	0.109 to 0.4	--	0.8	No	$ 61,400,000	$ 2,490,000	$ 94,270,400
City of St. Anthony WWTP	11/30/2014	0.43	--	0.8	No	$ 61,400,000	$ 2,490,000	$ 94,270,400
Kootenaj-Ponderay Sewer District WWTP	1/2/2007	0.319	--	0.8	No	$ 61,400,000	$ 2,490,000	$ 94,270,400
Mountain Home Air Force Base WWTP	11/30/2014	Facility has not discharged to surface	--	0.85	No	$ 61,400,000	$ 2,490,000	$ 94,270,400
City of Grangeville WWTP	9/30/2010	0.7	--	0.88	No	$ 66,600,000	$ 2,700,000	$ 102,241,600
City of Orofino and Orofino/Whiskey Creek District WWTP	7/31/2016	0.5	--	0.88	No	$ 66,600,000	$ 2,700,000	$ 102,241,600
City of Riverside WWTP	10/30/2016	0.13	--	0.88	No	$ 66,600,000	$ 2,700,000	$ 102,241,600
City of American Falls WWTP	7/31/2019	--	--	0.9	No	$ 66,600,000	$ 2,700,000	$ 102,241,600
City of Gooding WWTP	5/1/2005	0.18 to 0.32	--	1	No	$ 66,600,000	$ 2,700,000	$ 102,241,600
City of Preston WWTP	7/31/2010	0.73	--	1.2	No	$ 88,500,000	$ 3,600,000	$ 136,036,400
City of Hailey WWTP	7/31/2017	--	1.26	1.6	No	$ 108,000,000	$ 4,400,000	$ 166,108,000
City of Soda Springs WWTP	12/6/2006	--	--	1.7	No	$ 108,000,000	$ 4,400,000	$ 166,108,000
City of Buhl WWTP	10/31/2012	0.54	--	1.8	No	$ 108,000,000	$ 4,400,000	$ 166,108,000
City of Middleton WWTP	11/2/2004	0.3	--	1.83	No	$ 108,000,000	$ 4,400,000	$ 166,108,000
Star Water and Sewer District WWTP	4/30/2020	--	--	1.85	No	$ 108,000,000	$ 4,400,000	$ 166,108,000
Eastern Idaho Regional Wastewater Authority's Oxbow WWTP	5/31/2019	--	--	2	No	$ 108,000,000	$ 4,400,000	$ 166,108,000
City of Burley WWTP	1/8/2007	1.3	--	2.25	No	$ 122,500,000	$ 5,000,000	$ 188,542,600
Hayden Area Regional Sewer Board WWTP	11/30/2019	--	--	2.4	No	$ 122,500,000	$ 5,000,000	$ 188,542,600
City of Weiser WWTP	12/31/2016	1.2	--	2.43	No	$ 122,500,000	$ 5,000,000	$ 188,542,600
City of Salmon WWTP	9/30/2012	1.57	--	2.5	No	$ 122,500,000	$ 5,000,000	$ 188,542,600
City of McCall WWTP	4/30/2008	0.664 to 0.734	--	2.65	No	$ 138,000,000	$ 5,600,000	$ 211,929,600
City of Payette WWTP	10/31/2019	--	--	2.88	No	$ 138,000,000	$ 5,600,000	$ 211,929,600
City of Jerome WWTP	6/30/2015	2.25	--	3	No	$ 138,000,000	$ 5,600,000	$ 211,929,600
City of Sandpoint WWTP	1/5/2007	1.8	--	3	No	$ 138,000,000	$ 5,600,000	$ 211,929,600
City of Blackfoot WWTP	8/31/2018	--	--	3.2	No	$ 150,500,000	$ 6,200,000	$ 232,459,500
City of Kuna WWTP	5/31/2014	--	--	3.5	No	$ 150,500,000	$ 6,200,000	$ 232,459,500
City of Moscow WWTP	4/14/2004	--	--	3.6	No	$ 160,000,000	$ 6,500,000	$ 245,819,700
City of Rexburg WWTP	9/11/2006	1.65	--	3.6	No	$ 160,000,000	$ 6,500,000	$ 245,819,700
City of Ketchum WWTP	7/31/2017	--	--	4	No	$ 160,000,000	$ 6,500,000	$ 245,819,700
City of Meridian WWTP	11/2/2004	--	--	4	No	$ 160,000,000	$ 6,500,000	$ 245,819,700
Page WWTP South Fork Coeur d'Alene River Sewer District	9/30/2018	--	--	4.3	No	$ 171,000,000	$ 7,000,000	$ 263,483,400
City of Post Falls WWTP	11/30/2019	--	--	5	No	$ 185,000,000	$ 7,500,000	$ 284,004,400
City of Emmett WWTP	1/2/2007	--	--	5.7	No	$ 204,000,000	$ 8,300,000	$ 313,599,800
City of Lewistown WWTP	1/2/2007	4.42	--	5.71	No	$ 204,000,000	$ 8,300,000	$ 313,599,800
City of Coeur d'Alene WWTP		3.2	--	6	No	$ 204,000,000	$ 8,300,000	$ 313,599,800
City of Caldwell WWTP	2/2/2004	5.75	--	7.78	No	$ 244,000,000	$ 9,900,000	$ 374,695,300
City of Twin Falls WWTP	10/31/2014	7.13	--	8.56	No	$ 261,000,000	$ 10,600,000	$ 400,948,400
City of Nampa WWTP	2/2/2004	6.6	--	11.76	No	$ 312,000,000	$ 12,700,000	$ 479,707,700
City of Pocatello WWTP	8/31/2017	--	--	12	No	$ 312,000,000	$ 12,700,000	$ 479,707,700
City of Bosie WWTP - Lander Street	4/30/2017	--	--	15	No	$ 360,000,000	$ 14,600,000	$ 552,734,800
City of Idaho Falls WWTP	10/31/2017	--	--	17	No	$ 360,000,000	$ 14,600,000	$ 552,734,800
City of Boise WWTP - West Boise	4/30/2017	--	--	24	No	$ 360,000,000	$ 14,600,000	$ 552,734,800

Table 2:
Estimated Costs for Treatment Systems Based on Municipal Facility

Municipal Facility Name	Permit Effective End Date	Average Daily Flow (million gallons per day)	Average Maximum Daily Flow (million gallons per day)	Design Flow Rate (million gallons per day)	Monitoring for PCBs?	CapEx (2015)	Annual OpEx (2015)	25-Year Net Present Value (in 2015 dollars)
City of St. Maries WWTP	9/30/2012	--	--	--	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Tensed WWTP	3/31/2009	0.03	--	--	No	$ 15,200,000	$ 620,000	$ 23,388,800
Santa-Fernwood Sewer District WWTP	5/31/2009	--	--	--	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Kamiah Water Treatment Plant	12/31/2017	--	0.0489	--	No	$ 15,200,000	$ 620,000	$ 23,388,800
North Idaho Correctional Facility WWTP		0.03	--	--	No	$ 15,200,000	$ 620,000	$ 23,388,800
Joint School District #171 (Timberline High School) WWTP	9/30/2007	0.0000646 to 0.00323	--	--	No	$ 15,200,000	$ 620,000	$ 23,388,800
City of Rockland WWTP	1/8/2007	0.13	--	0.041 to 0.062	No	$ 15,200,000	$ 620,000	$ 23,388,800
						$ 8,983,300,000	$ 365,500,000	$ 13,809,652,800

Notes:

-- = not available
WWTP = wastewater treatment plant
Annual OpEx = annual operational expenses
CapEx = capital expenses
PCB = polychlorinated biphenyl
1. Source: USEPA. Current NPDES Permits in Idaho. Region 10: The Pacific Northwest. Available online at: http://yosemite.epa.gov/r10/water.nsf/NPDES+Permits/Current+ID1319#permits
2. Search Date: 10/15/2015
3. Capital and annual operational expenses are based off of the design flow rate. If the design flow rate is not available, expenses are based off of the available flow rate.
4. Facilities with a design flow rate of less than 100 gallons per minute (gpm) are assumed to have capital and annual operational expenses associated with a 100 gpm facility.
5. Facilities with a design flow rate greater than 15 million gallons per day (mgd) are assumed to have capital and annual operational expenses associated with a 15 mgd facility.
6. For the net present value analysis, a 5% discount rate was applied over an assumed 25 year equipment life.