Uncertainty and Sensitivity Analysis of Chronic Exposure Results with the MACCS Reactor Accident Consequence Model

Manuscript Completed: November 1994
Date Published: January 1995

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Prepared for
Division of Systems Technology
Office of Nuclear Regulatory Research
U.S. Nuclear Regulatory Commission
Washington, DC 20555-0001
NRC Job Code L2294

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ABSTRACT

Uncertainty and sensitivity analysis techniques based on Latin hypercube sampling, partial correlation analysis and stepwise regression analysis are used in an investigation with the MACCS model of the chronic exposure pathways associated with a severe accident at a nuclear power station. The primary purpose of this study is to provide guidance on the variables to be considered in future review work to reduce the uncertainty in the important variables used in the calculation of reactor accident consequences. The effects of 75 imprecisely known input variables on the following reactor accident consequences are studied: crop growing season dose, crop long-term dose, water ingestion dose, milk growing season dose, long-term groundshine dose, long-term inhalation dose, total food pathways dose, total ingestion pathways dose, total long-term pathways dose, total latent cancer fatalities, area-dependent cost, crop disposal cost, milk disposal cost, population-dependent cost, total economic cost, condemnation area, condemnation population, crop disposal area and milk disposal area. When the predicted variables are considered collectively, the following input variables were found to be the dominant contributors to uncertainty: dry deposition velocity, transfer of cesium from animal feed to milk, transfer of cesium from animal feed to meat, ground concentration of Cs-134 at which the disposal of milk products will be initiated, transfer of Sr-90 from soil to legumes, maximum allowable ground concentration of Sr-90 for production of crops, fraction of cesium entering surface water that is consumed in drinking water, groundshine shielding factor, scale factor defining resuspension, dose reduction associated with decontamination, and ground concentration of I-131 at which disposal of crops will be initiated due to accidents that occur during the growing season. Reducing the uncertainty in the preceding variables was found to substantially reduce the uncertainty in the predicted variables under consideration. For total number of latent cancer fatalities, the dominant variable was dry deposition velocity, with small effects indicated for a large number of additional variables.

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ACKNOWLEDGEMENTS

Recognition is extended to David Chanin of Technadyne, Inc. for his role in the development of the MACCS program and for many useful discussions involving MACCS and reactor accident consequence analysis. Review of the report was provided by Sarah Higgins and LeAnn Miller of Sandia National Laboratories. The support and encouragement of Jim Glynn and Christiana Lui of the US Nuclear Regulatory Commission is greatly appreciated. Finally, thanks are extended to Fred Harper of Sandia National Laboratories for providing a productive environment in which to perform this analysis and to Judy Jones and Darla Tyree, also of Sandia National Laboratories, for editorial support in the production of documentation for the analysis.

1. INTRODUCTION

In preparation for a joint study¹ with the Commission of European Communities (CEC) on the uncertainties associated with the input variables used in reactor accident consequence models, the U.S. Nuclear Regulatory Commission (NRC) is sponsoring a sequence of uncertainty and sensitivity analyses with the MACCS^{2,4} reactor accident consequence model. The primary purpose of these analyses is to identify the MACCS input variables that have the greatest effect on the uncertainty in MACCS predictions. The uncertainty in these variables will then be assessed as part of an expert-review process in the joint CEC/NRC study. Owing to the large investments of resources (i.e., time, people, money) associated with an expert-review process, the number of variables that can be considered is limited. Thus, it is important to select variables for the review process that contribute substantially to the uncertainty in MACCS predictions.

Prior uncertainty and sensitivity analyses conducted with MACCS as part of this program have considered early exposure⁵ and food pathway⁶ results. The present analysis considers the effects of uncertainty in the MACCS chronic exposure model. All three analyses use the same source term (Ref. 5, Section 4.1) from the NUREG-1150 analysis⁷ for the Surry Nuclear Power Station.^{8,9} Further, as the chronic exposure model in MACCS involves many of the submodels also used in the calculation of early exposure and food pathway results, the two preceding uncertainty/sensitivity studies^{5,6} are used to help identify input variables for inclusion in this analysis.

As previously discussed,^{5,6} there are two basic types of uncertainty associated with the calculation of reactor accident consequences: stochastic uncertainty, which results because the system under study can behave in many different ways (e.g., many different types of weather are possible at the time of a reactor accident), and subjective uncertainty, which results from the existing state of knowledge with respect to the correctness of the assumptions used in an analysis (e.g., what is the appropriate dry deposition velocity to use for a particular combination of release characteristics and weather). Thus, stochastic uncertainty is a property of the system under study, and subjective uncertainty is a property of the analysts performing the study (Ref. 5, Section 2). Stochastic uncertainty is typically displayed with a complementary cumulative distribution function (CCDF), and the presence of subjective uncertainty gives rise to a distribution of CCDFs. The underlying ideas associated with this classification of uncertainty have been discussed by a number of authors.¹⁰⁻¹⁷ The primary focus of this study is subjective uncertainty. In particular, Monte Carlo techniques based on Latin hypercube sampling¹⁸ will be used to investigate the effects of subjective uncertainty in input variables used in the calculation of chronic exposure results with MACCS.

This presentation is organized as follows. The MACCS input and output variables selected for consideration in this study are discussed in Section 2. Uncertainty and sensitivity analysis results are presented and discussed in Section 3. The effects of reducing the uncertainty in the most important variables identified in the sensitivity analysis in Section 3 are investigated in Section 4. Finally, a concluding discussion is given in Section 5.

Additional background on the uncertainties in reactor accident consequence calculations is available elsewhere.^{5,19-29}

Introduction

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2. PROBLEM FOR ANALYSIS

To facilitate comparisons across analyses, this study and its two companion uncertainty/sensitivity studies^{5,6} use the same source term. In particular, the source term SUR-11-3 from the NUREG-1150 probabilistic risk assessment⁷ for the Surry Nuclear Power Station^{8,9} is used. This source term results from a steam generator tube rupture and is listed in Table 2 of Ref. 5. The following release fractions are associated with this source term: Noble gases ~ 1.0, iodine ~ 0.47, cesium ~ 0.45, tellurium ~ 0.25, strontium ~ 0.07, ruthenium ~ 0.002, lanthanum ~ 0.006, cerium ~ 0.008, and barium ~ 0.06. The performance of a MACCS calculation requires a large amount of input. The development of this input for use in the NUREG-1150 analyses is documented in Sprung et al.,²⁶ with the actual MACCS input files used in the NUREG-1150 analyses for Surry appearing in Appendix A of the indicated report. The MACCS input for Surry described in Sprung et al.²⁶ is taken as the base-line description for the analysis problem considered in this study. An overview of the analysis assumptions used in MACCS for the analyses contained in this presentation is given in Table 3 of Ref. 5.

After a review of the results in Sprung et al.²⁶ and the two preceding uncertainty/sensitivity studies with MACCS,^{5,6} the 75 variables listed in Table 1 were selected for consideration in this study. As indicated in the organization of Table 1, the input variables selected for study can be divided into three groups: variables previously identified as important in the uncertainty/sensitivity study of early exposure results (Table 21, Ref. 5), variables previously identified as important in the uncertainty/sensitivity study of food pathway results (Table 14, Ref. 6), and additional variables used as input to the chronic exposure model that had not been investigated in the two preceding studies. The distributions associated with the individual variables characterize subjective uncertainty. As discussed in Section 3 of Ref. 6, most ranges were obtained by applying a scale factor to a "best-estimate" value. All variables listed in Table 1 were assigned uniform or loguniform distributions, which assured the full coverage of the range of each uncertain variable. The intent is for this preliminary assessment of subjective uncertainty to help to identify the most important contributors to the (subjective) uncertainty in MACCS results. Then, efforts can be focused on better characterizing the uncertainty in the inputs that have significant impacts on the uncertainty in predictions made by MACCS.

The correlations indicated in Table 1 are rank correlations, which provide a measure of the extent to which variables tend to move up and down together.^{42,43} Rank correlations also have the desirable property that they are independent of the distributions assigned to the individual variables. The assigned correlations result from the belief that many MACCS input variables are not independent but are rather influenced by common underlying variables.

The chronic exposure results selected for investigation in this study are listed in Table 2.

Descriptions of the models used in MACCS to go from the input variables in Table 1 to the predicted variables in Table 2 are available elsewhere, and will not be given here. In particular, detailed descriptions of the models in MACCS are given in Refs. 2 and 3. Further, a brief overview of MACCS is given in Sect. 3 of Ref. 5 and, with the exception of the models for cancer induction, the chronic exposure models in MACCS are described in Sect. 2 of Ref. 6. Descriptions of the cancer induction models are given in Sect. 2.1.1 of Ref. 39 and also in Ref. 40.

Table 1. Sampled Variables in Uncertainty/Sensitivity Study of Chronic Exposure Results

Important Variables from Early Exposure Study (Table 21, Ref. 5)	
Variable	Description
CWASH1	Linear term in wet deposition model (h/mm s). Range: 3.1×10^{-5} - 3.1×10^{-4} h/mm s. Distribution: Loguniform. Best estimate value: 1.0×10^{-4} h/mm s. Additional background: Sec. 2.6 Ref. 26; Refs. 30, 31.
CWASH2	Exponent in wet deposition model. Range: 0.7 - 0.9. Distribution: Uniform. Best estimate value: 0.8. Additional background: Sec. 2.6, Ref. 26; Refs. 30, 31.
GSHFACN	Groundshine shielding factor for nonevacuees. Range: 0.2 - 0.75. Distribution: Uniform. Best estimate value: 0.33. Additional background: Sec. 3.2, Ref. 26; Ref. 32.
PROTINN	Inhalation protection factor for nonevacuees. Range: 0.2 - 0.8. Distribution: Uniform. Best estimate value: 0.5. Additional background: Sec. 3.2, Ref. 26; Ref. 32.
SCLADP	Plume rise scaling factor for stability classes A through D. Range: 0.5 - 1.5. Distribution: Uniform. Correlation: 0.5 rank correlation with SCLEFP. Best estimate value: 1. Additional background: Sec. 2.2, Ref. 26; Ref. 33.
SCLCRW	Critical wind speed scaling factor. Range: 0.5 - 2. Distribution: Uniform. Best estimate value: 1. Additional background: Sec. 2.2, Ref. 26; Ref. 33.
SCLEFP	Plume rise scaling factor for stability classes E through F. Range: 0.5 - 1.5. Distribution: Uniform. Correlation: 0.5 rank correlation with SCLADP. Best estimate value: 1. Additional background: Sec. 2.2, Ref. 26; Ref. 33.
VDEPOS	Dry deposition velocity (m/s). Range: 0.003 - 0.03 m/s. Distribution: Loguniform. Best estimate value: 0.01 m/s. Additional background: Sec. 2.5, Ref. 26; Ref. 34.
YSCALE	Scaling factor for sigma-y (i.e., horizontal dispersion). Range: 0.33 - 3. Distribution: Loguniform. Correlation: 0.5 rank correlation with ZSCALE. Best estimate value: 1. Correlation reflects belief that environmental "roughness" produces tendency for YSCALE and ZSCALE to increase together. Additional background: Sec. 2.4, Ref. 26; Refs. 35, 36.
ZSCALE	Scaling factor for sigma-z (i.e., vertical dispersion). Range: 0.423 - 3.81. Distribution: Loguniform. Correlation: 0.5 rank correlation with YSCALE. Best estimate value: 1.27. Range a factor of 3 on value to correct for a surface-roughness length of 10 cm. Additional background: Sec. 2.4, Ref. 26; Refs. 35, 36.

Table 1 (continued)

Important Variables From Food Pathways Study (Table 5.1, Ref. 6)	
Variable	Description
C1GCS	Fraction of cesium deposition onto grain fields that is retained on plant surfaces and transferred directly to grain. Defines MACCS variable CTCOE1 for weathering of cesium from grain, which in conjunction with an infinite (i.e., 1×10^6 yr) weathering half-life produces a transfer factor rather than a weathering term. Range: 0.025 - 0.1 (i.e., 0.05×2). Distribution: Loguniform. Best estimate value: 0.05. Additional information: p. A-25, Appendix A, Ref. 26.
GCMSR90	Maximum allowable Sr90 ground concentration (Bq/m ²) for production of crops that assures the lifetime dose criteria will be met (i.e., the Federal Department of Agriculture protective action guide that the long-term doses to the thyroid and the whole body should be less than 0.015 Sv and 0.005 Sv, respectively ³⁷). Defines MACCS variable GCMAXR for Sr90. Range: 3.67×10^3 - 3.67×10^5 Bq/m ² (i.e., 3.67×10^4 Bq/m ² $\times 10$). Distribution: Loguniform. Correlation: 0.5 rank correlation with QRSR90; -0.5 rank correlation with TCLSR90. Best estimate value: 3.67×10^4 Bq/m ² . Additional information: Sec. 4.4, Ref. 26; Appendix C, Ref. 2.
GCMCS137	Same as GCMSR90 but for Cs137. Range: 1.76×10^5 - 1.76×10^7 Bq/m ² (i.e., 1.76×10^6 Bq/m ² $\times 10$). Distribution: Loguniform. Correlation: 0.5 rank correlation with QRCS137; -0.5 rank correlation with TCPCS137. Best estimate value: 1.76×10^6 Bq/m ² .
PSMCS134	Ground concentration of Cs134 (Bq/m ²) at which disposal of milk products will be initiated to assure that emergency dose criteria will be met (i.e., the Federal Department of Agriculture emergency protective action guide that projected dose commitment to the thyroid and the whole body should be less than 0.15 Sv and 0.05 Sv, respectively ³⁷). Defines MACCS variable PSCMLK. Range: 2.18×10^4 - 2.18×10^6 Bq/m ² (i.e., 2.18×10^5 Bq/m ² $\times 10$). Distribution: Loguniform. Correlation: 0.75 rank correlation with PSMCS137; 0.5 rank correlation with PSMI131, PSMSR90. Best estimate value: 2.18×10^5 Bq/m ² . Additional information: Sec. 4.4, Ref. 26; Appendix C, Ref. 2.
PSMCS137	Same as PSMCS134 but for Cs137. Range: 2.66×10^4 - 2.66×10^6 Bq/m ² (i.e., 2.66×10^5 Bq/m ² $\times 10$). Distribution: Loguniform. Correlation: 0.75 rank correlation with PSMCS134; 0.5 rank correlation with PSMI131, PSMSR90. Best estimate value: 2.66×10^5 Bq/m ² .
PSMI131	Same as PSMCS134 but for I131. Range: 1.34×10^5 - 1.34×10^7 Bq/m ² (i.e., 1.34×10^6 Bq/m ² $\times 10$). Distribution: Loguniform. Correlation: 0.5 rank correlation with PSMCS134, PSMCS137, PSMSR90. Best estimate value: 1.34×10^6 Bq/m ² .
PSMSR90	Same as PSMCS134 but for Sr90. Range: 2.41×10^4 - 2.41×10^6 Bq/m ² (i.e., 2.41×10^5 Bq/m ² $\times 10$). Distribution: Loguniform. Correlation: 0.5 rank correlation with PSMCS134, PSMCS137, PSMI131. Best estimate value: 2.41×10^5 Bq/m ² .

Problem for Analysis

Table 1 (continued)

Variable	Description
PSOCS134	Ground concentration of Cs134 (Bq/m ²) at which disposal of crops will be initiated to assure that emergency dose criteria are met (see PSMCS134). Defines MACCS variable PSCOTH. Range: 2.16×10^6 - 2.16×10^8 Bq/m ² (i.e., 2.16×10^7 Bq/m ² $\times 10$). Distribution: Loguniform. Correlation: 0.5 rank correlation with PSOI131, PSOSR90. Best estimate value: 2.16×10^7 Bq/m ² . Additional information: Same as PSMCS134.
PSOI131	Same as PSOCS134 but for I131. Range: 7.95×10^5 - 7.95×10^7 Bq/m ² (i.e., 7.95×10^6 Bq/m ² $\times 10$). Distribution: Loguniform. Correlation: 0.5 rank correlation with PSOCS134, PSOSR90. Best estimate value: 7.95×10^6 Bq/m ² .
PSOSR90	Same as PSOCS134, but for Sr90. Range: 2.41×10^4 - 2.41×10^6 Bq/m ² (i.e., 2.41×10^5 Bq/m ² $\times 10$). Distribution: Loguniform. Correlation: 0.5 rank correlation with PSOCS134, PSOI131. Best estimate value: 2.41×10^5 Bq/m ² .
QRCS137	Rate of depletion (yr ⁻¹) of Cs137 from the root zone (includes radioactive decay, percolation into soil below root zone, irreversible binding with soil components). Used in determination of interdiction period for farmland before crops can be grown without violating the Federal Department of Agriculture lifetime dose criteria (see GCMR90). Defines MACCS variable QROOT. Range: 0.028 - 2.8 yr ⁻¹ (i.e., 0.28 yr ⁻¹ $\times 10$). Distribution: Loguniform. Correlation: 0.5 rank correlation with GCMCS137; -0.5 rank correlation TCPCS137. Best estimate value: 0.28 yr ⁻¹ . Additional information: Sec. 4.4.2, Ref. 26; Sec. 3.2.4, Ref. 2.
QRSR90	Same as QRCS137 but for Sr90. Range: 0.0065 - 0.65 yr ⁻¹ (i.e., 0.065 yr ⁻¹ $\times 10$). Distribution: Loguniform. Correlation: 0.5 rank correlation with GCMR90; -0.5 rank correlation with TCLSR90. Best estimate value: 0.065 yr ⁻¹ .
TCLSR90	Ratio of Sr90 transferred to legumes due to root uptake and resuspension and Sr90 deposition to soil surface (units: Bq/Bq). Numerator in ratio (i.e., Sr90 transferred to legumes) is an integrated quantity in the sense that it equals the total transfer to legumes over all years subsequent to the deposition and thus incorporates effects due to radioactive decay, percolation into soil below root zone, irreversible binding with soil, and efficiency of root uptake. Defines MACCS variable TCROOT. Range: 2.8×10^{-3} - 2.8×10^{-1} (i.e., $2.8 \times 10^{-2} \times 10$). Distribution: Loguniform. Correlation: -0.5 rank correlation with GCMR90, QRSR90. Best estimate value: 2.8×10^{-2} . Additional information: Sec. 4.3.8, Ref. 26; Sec. 3.2.4, Ref. 2.
TCPCS137	Same as TCLSR90 but for Cs137 and pasture. Range: 6.9×10^{-4} - 6.9×10^{-2} (i.e., $6.9 \times 10^{-3} \times 10$). Distribution: Loguniform. Correlation: -0.5 rank correlation with GCMCS137, QRCS137. Best estimate value: 6.9×10^{-2} .
TFBCS	Ratio of amount of cesium in edible meat at time of slaughter to amount of cesium consumed by meat producing animals. Defines MACCS variable TFBF for Cs134 and Cs137. Range: 4.8×10^{-3} - 1.2×10^{-1} (i.e., $2.4 \times 10^{-2} \times 5$). Distribution: Loguniform. Best estimate value: 2.4×10^{-2} . Additional information: Sec. 4.3.9, Ref. 26; Sec. 3.2.4, Ref. 2.

Table 1 (continued)

Variable	Description
TFMCS	Ratio of amount of cesium in milk to amount of cesium consumed by milk-producing animals. Defines MACCS variable TFMLK for Cs134 and Cs137. Range: 0.022 - 0.55 (i.e., 0.11×5). Distribution: Loguniform. Best estimate value: 0.11. Additional information: Sec. 4.3.10, Ref. 26; Sec. 3.2.4, Ref. 2.
TFMI131	Same as TFMCS but for I131. Defines MACCS variable TFMLK for I131. Range: 0.026 - 0.65 (i.e., 0.13×5). Distribution: Loguniform. Best estimate value: 0.13.
TFMSR	Same as TFMCS but for strontium. Defines MACCS variable TFMLK for Sr89 and Sr90. Range: 0.0044 - 0.11 (i.e., 0.022×5). Distribution: Loguniform. Best estimate value: 0.022.

Additional Variables	
Variable	Description
CDFRM1	Farmland decontamination cost (\$/ha) to produce a factor of 3 reduction in dose due to groundshine and resuspension. MACCS assumes farmland decontamination reduces direct exposure doses to farmers without reducing crop uptake of radioactivity from the soil. Defines MACCS variable CDFRM. Range: 421 - 658 \$/ha (i.e., $526.5 \text{ $/ha} \times 1.25$). Distribution: Loguniform. Best estimate value: 526.5 \$/ha. Additional information: Appendix A.3, Ref. 26; Ref. 38.
CDFRM2	Same as CDFRM1 but for a factor of 15 reduction in dose. Range: 625 - 2500 \$/ha (i.e., $1250 \text{ $/ha} \times 2$). Distribution: Loguniform. Best estimate value: 1250 \$/ha.
CDNFRM1	Nonfarmland decontamination cost (\$/ha) to produce a factor of 3 reduction in dose due to groundshine and resuspension. Range: 1500 - 6000 \$/ha (i.e., $3000 \text{ $/ha} \times 2$). Distribution: Loguniform. Best estimate value: 3000 \$/ha. Additional information: Appendix A.3, Ref. 26; Ref. 38.
CDNFRM2	Same as CDNFRM1 but for a factor of 15 reduction in dose. Range: 4000 - 16000 \$/ha (i.e., $8000 \text{ $/ha} \times 2$). Distribution: Loguniform. Best estimate value: 8000 \$/ha.
CFRBRE	Risk factor (1/Sv) for latent fatalities resulting from breast cancer. Product of breast exposure (Sv) for an individual and CFRBRE equals probability that the individual will die of breast cancer. Defines MACCS variable CFRISK. Range: 4.3×10^{-3} - 8.4×10^{-3} 1/Sv. Distribution: Uniform. Best estimate value: 6.4×10^{-3} 1/Sv. Additional information: Sect. 2.1.1, Ref. 39; Ref. 40.
CFRGI	Same as CFRBRE but for gastrointestinal exposure. Range: 1.35×10^{-2} - 3.36×10^{-2} 1/Sv. Distribution: Uniform. Best estimate value: 2.36×10^{-2} 1/Sv.
CFRLUN	Same as CFRBRE but for lung exposure. Range: 6.7×10^{-3} - 3.31×10^{-2} 1/Sv. Distribution: Uniform. Best estimate value: 1.99×10^{-2} 1/Sv.
CFROTH	Same as CFRBRE but for "other" cancers. Range: 1.18×10^{-2} - 2.76×10^{-2} 1/Sv. Distribution: Uniform. Best estimate value: 1.97×10^{-2} 1/Sv.

Problem for Analysis

Table 1 (continued)

DDRBON	Dose and dose rate reduction factor for bone cancer. Probability of developing fatal bone cancer is given by $CFRBON \cdot (\text{Bone Dose in Sv})/DDRBON$, where CFRBON is the risk factor (1/Sv) for latent cancer fatalities resulting from bone marrow exposure. Defines MACCS variable DDREFA. Range: 1 - 4. Distribution: Loguniform. Best estimate value: 2. Cancer risk factor CFRBON set to 9×10^{-4} 1/Sv. Additional information: Sect. 2.1.1, Ref. 39; Ref. 40.
DDRBRE	Same as DDRBON but for breast cancer. Range: 1 - 4. Distribution: Loguniform. Best estimate value: 2.
DDRGI	Same as DDRBON but for gastrointestinal cancers. Range: 1 - 4. Distribution: Loguniform. Best estimate value: 2.
DDRLEU	Same as DDRBON but for leukemia. Range: 1 - 4. Distribution: Loguniform. Best estimate value: 2. Cancer risk factor CFRLEU for leukemia set to 9.7×10^{-3} 1/Sv.
DDRLUN	Same as DDRBON but for lung cancer. Range: 1 - 4. Distribution: Loguniform. Best estimate value: 2.
DDROTH	Same as DDRBON but for "other" cancers. Range: 1 - 4. Distribution: Loguniform. Best estimate value: 2.
DDRTHY	Same as DDRBON but for thyroid cancer. Range: 1 - 3. Distribution: Loguniform. Best estimate value: 1. Cancer risk factor CFRTHY set to 7.2×10^{-4} 1/Sv.
DLBCST	Decontamination worker labor cost (\$/yr). Defines MACCS variable DLBCST. Range: 2.8×10^4 - 4.5×10^4 \$/yr. Distribution: Uniform. Best estimate value: 3.5×10^4 \$/yr. Additional information: Appendix A.3, Ref. 26; Ref. 38.
DPRATE	Depreciation rate for buildings and other structures on interdicted land (1/yr). Defines MACCS variable DPRATE. Range: 0.16 - 0.25 1/yr. Distribution: Uniform. Best estimate value: 0.2 1/yr. Additional information: Ch. 5, Ref. 26; Ref. 38.
DSCRLT	Maximum allowable direct exposure dose commitment to the long-term critical organ (i.e., whole body) during the long-term phase action period (Sv). If DSCRLT is exceeded in a spatial element, mitigative actions such as decontamination or decontamination followed by temporary interdiction are employed to limit dose to the critical organ. Defines MACCS variable DSCRLT. Range: 0.02 - 0.08 Sv. Distribution: Uniform. Best estimate value: 0.04 Sv. Additional information: Sect. 5.3.1, Ref. 3; Appendix A, p. A-20, Ref. 26.
DSRATE	Rate of return from investments in land, buildings and equipment (1/yr). Defines MACCS variable DSRATE. Range: 0.1 - 0.15 yr ⁻¹ . Distribution: Uniform. Best estimate value: 0.12 yr ⁻¹ . Additional information: Ch. 5, Ref. 26; Ref. 38.
DSRFCT1	Dose reduction associated with decontamination costs CDFRM1 and CDNFRM1. Defines MACCS variable DSRFCT. Range: 2 - 3. Distribution: Uniform. Best estimate value: 2.5. Additional information: Appendix A.3, Ref. 26; Ref. 38.
DSRFCT2	Same as for DSRFCT1 but for CDFRM2 and CDNFRM2. Range: 7 - 30. Distribution: Uniform. Best estimate value: 15.

Table 1 (continued)

EVACST	Cost to feed and house an individual who undergoes evacuation during the emergency phase of an accident (\$/day). Defines MACCS variable EVACST. Range: 30 - 48 \$/day. Distribution: Uniform. Best estimate value: 38 \$/day. Additional information: Ch. 5, Ref. 26; Ref. 38.
FRFDL1	Fraction of farmland decontamination cost CDFRM1 that is due to labor. Defines MACCS variable FRFDL. Range: 0.24 - 0.4. Distribution: Uniform. Best estimate value: 0.3. Additional information: Appendix A.3, Ref. 26; Ref. 38.
FRFDL2	Same as FRFDL1 but for CDFRM2. Range: 0.28 - 0.45. Distribution: Uniform. Best estimate value: 0.35.
FRNFDL1	Fraction of nonfarmland decontamination cost CDNFRM1 that is due to labor. Defines MACCS variable FRNFDL. Range: 0.56 - 0.9. Distribution: Uniform. Best estimate value: 0.7. Additional information: Appendix A.3, Ref. 26; Ref. 38.
FRNFDL2	Same as FRNFDL1 but for CDNFRM2. Range: 0.4 - 0.65. Distribution: Uniform. Best estimate value: 0.5.
FRNFIM	Fraction of non-farm wealth due to improvements. Includes buildings, infrastructure such as roads and utilities, and nonrecoverable equipment or machinery. Defines MACCS variable FRNFIM. Range: 0.64 - 1. Distribution: Uniform. Best estimate value: 0.80. Additional information: Ch. 5, Ref. 26; Ref. 38.
FRFIM	Fraction of farm wealth due to improvements. Includes farm buildings, non-recoverable machinery, and infrastructure such as silos and irrigation systems. Range: 0.12 - 0.5. Distribution: Uniform. Best estimate value: 0.25. Additional information: Ch. 5, Ref. 26; Ref. 38.
GWCOEF1	Fraction of initial groundshine that decreases with a halflife of TGWHLF1; the remaining fraction $1 - GWCOEF1$ of initial groundshine decreases with a halflife of TGWHLF2. Defines MACCS variable GWCOEF. Range: 0.4 - 0.63. Distribution: Uniform. Best estimate value: 0.5. Additional information: Sect. 2.7, Ref. 26.
POPCST	Per capita cost for temporary or permanent relocation of population and businesses in a region rendered uninhabitable during the long-term phase time period (\$). This cost is incurred if any of the following actions are required: decontamination, decontamination followed by interdiction, or condemnation. Defines MACCS variable POPCST. Range: \$4000 - \$6300. Distribution: Uniform. Best estimate value: \$5000. Additional information: Ch. 5, Ref. 26; Ref. 38.
RELCST	Same as EVACST but for relocation. Defines MACCS variable RELCST.

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Table 1 (continued)

RWCOEF	Scale factor used in definition of resuspension coefficients. MACCS models radionuclide resuspension with scale factors RWCOEF1, RWCOEF2 and RWCOEF3 (units: $(\text{Bq}/\text{m}^3)/(\text{Bq}/\text{m}^2) = \text{m}^{-1}$) for short-term (months), intermediate-term (years) and long-term (tens of years) resuspension, respectively. In this analysis, $\text{RWCOEF1} = \text{RWCOEF} \cdot 10^{-4} \text{ m}^{-1}$, $\text{RWCOEF2} = \text{RWCOEF} \cdot 10^{-6} \text{ m}^{-1}$, $\text{RWCOEF3} = \text{RWCOEF} \cdot 10^{-8} \text{ m}^{-1}$. Distribution: Loguniform. Best estimate value = 0.1. Correlation: -0.75 rank correlation with TRWHLF. Correlation results from belief that high initial resuspension would tend to decrease more rapidly than low initial resuspensions. Additional information: Sect. 2.9, Ref. 26; Ref. 34.
TFWKF1	Fraction of compensated work time that a farmland decontamination worker spends in the contaminated area to produce a dose reduction of 3. Defines MACCS variable TFWKF. Range: 0.08 - 0.15. Distribution: Uniform. Best estimate value: 0.1. Additional information: Appendix A.3, Ref. 26; Ref. 38.
TFWKF2	Same as TFWKF1 but for a dose reduction of 15. Range: 0.25 - 0.45. Distribution: Uniform. Best estimate value: 0.33.
TFWKNF1	Fraction of compensated work time that a nonfarmland decontamination worker spends in the contaminated area to produce a dose reduction of 3. Defines MACCS variable TFWKNF. Range: 0.25 - 0.45. Distribution: Uniform. Best estimate value: 0.33. Additional information: Appendix A.3, Ref. 26; Ref. 38.
TFWKNF2	Same as TFWKNF1 but for a dose reduction of 15.
TGWHLF1	Half-life(s) for rapid groundshine weathering (i.e., for the fraction GWCOEF1 of initial groundshine that undergoes rapid weathering). Defines MACCS variable TGWHLF. Range: 8×10^6 - 3.2×10^7 s. Distribution: Uniform. Best estimate value: 1.6×10^7 s. Additional information: Sect. 2.7, Ref. 26.
TGWHLF2	Same as TGWHLF1 but for slow groundshine weathering (i.e., for the fraction 1 - GWCOEF1 of initial groundshine that undergoes slow weathering). Range: 1.4×10^9 - 5.6×10^9 s. Distribution: Uniform. Best estimate value: 2.8×10^9 s.
TRWHLF	Scale factor used in definition of resuspension half-life. As indicated in conjunction with RWCOEF, MACCS models resuspension for three time periods. The coefficients RWCOEF1, RWCOEF2 and RWCOEF3 define the initial resuspensions which are then assumed to decrease with half-lives TRWHLF1, TRWHLF2 and TRWHLF3, respectively. In this analysis, $\text{TRWHLF1} = \text{TRWHLF} \cdot 10^7 \text{ s}$, $\text{TRWHLF2} = \text{TRWHLF} \cdot 31 \cdot 10^8 \text{ s}$, and $\text{TRWHLF3} = \text{TRWHLF} \cdot 10^9 \text{ s}$, where $1.6 \times 10^7 \text{ s} \approx 6 \text{ mn}$, $1.6 \times 10^8 \text{ s} \approx 5 \text{ yr}$ and $1.6 \times 10^9 \text{ s} \approx 50 \text{ yr}$. Defines MACCS variables TRWHLF. Range: 0.8 - 3.2. Distribution: Loguniform. Correlation: -0.75 rank correlation with RWCOEF. Best estimate value: 1.6. Additional information: Same as RWCOEF.
VALWF	Value of farm wealth (\$/ha). Includes value of publicly and privately owned grazing lands, farmland, farm buildings, farm machinery and infrastructure serving the farm industry. Defines MACCS variable VALWF. Range: 2300 - 3700 \$/ha. Distribution: Uniform. Best estimate value: 2952 \$/ha. Additional information: Ch. 5, Ref. 26; Ref. 38.

Table 1 (continued)

VALWNF	Value of nonfarm wealth (\$/person). Includes all public and private property not associated with farming that would be unusable if the region was rendered either temporarily or permanently uninhabitable. Defines MACCS variable VALWNF. Range: 6.5×10^4 - 1.1×10^5 \$/person. Distribution: Uniform. Best estimate value: 8.4×10^4 \$/person. Additional information: Ch. 5, Ref. 26; Ref. 38.
WSHFRISR	Fraction of ground-deposited strontium that moves rapidly (i.e., in less than a year) into surface water bodies. Defines MACCS variable WSHFRI. Range: 0.002 - 0.05. Distribution: Loguniform. Best estimate value: 0.01. Additional information: Sect. 2.8, Ref. 26; Ref. 41.
WSHFRICS	Same as WSHFRISR but for cesium. Range: 0.001 - 0.025. Distribution: Loguniform. Best estimate value: 0.005.
WSHRTASR	Rate constant (yr^{-1}) for movement of ground-deposited strontium into surface water bodies. Defines MACCS variable WSHRTA. Range: 8×10^{-4} - $2 \times 10^{-2} \text{ yr}^{-1}$. Distribution: Loguniform. Best estimate value: $4 \times 10^{-3} \text{ yr}^{-1}$. Additional information: Sect. 2.8, Ref. 26; Ref. 41.
WSHRTACS	Same as WSHRTASR but for cesium. Range: 2×10^{-4} - $5 \times 10^{-3} \text{ yr}^{-1}$. Distribution: Loguniform. Best estimate value: $1 \times 10^{-3} \text{ yr}^{-1}$.
WINGSR	Fraction of strontium entering surface water bodies that is consumed in drinking water. Defines MACCS variable WINGF. Range: 1×10^{-6} - 2.5×10^{-5} . Distribution: Loguniform. Best estimate value: 5×10^{-6} . Additional information: Sect. 2.8, Ref. 26.
WINGCS	Same as WINGSR but for cesium.

Table 2. Predicted Variables Associated with the Food Pathways Model in MACCS Selected for Analysis

Population Dose
<u>Crop Growing Season Dose</u> --total population dose (Sv) resulting from consumption of nondairy food products contaminated as a result of deposition onto crops during the growing season.
<u>Crop Long-Term Dose</u> --total population dose (Sv) resulting from consumption of non-dairy food products contaminated by long-term uptake in the period following the accident.
<u>Milk Growing Season Dose</u> --total population dose (Sv) resulting from consumption of dairy products contaminated as a result of deposition onto crops during the growing season.
<u>Long-Term Groundshine Dose</u> --total long-term population dose (Sv) received by resident population from groundshine.
<u>Long-Term Inhalation Dose</u> --total long-term population dose (Sv) received by resident population from inhalation of resuspended radionuclides.
<u>Total Food Pathways Dose</u> --total population dose (Sv) from the consumption of contaminated dairy and nondairy products (excludes dose due to consumption of contaminated water).
<u>Total Ingestion Pathways Dose</u> --total population dose (Sv) from the consumption of contaminated dairy products, nondairy products, and water.
<u>Total Long-Term Pathways Dose</u> --total population dose (Sv) from groundshine, resuspension, consumption of contaminated food, ingestion of contaminated surface water, and decontamination work.
<u>Water Ingestion Dose</u> --total population dose (Sv) from the consumption of contaminated surface water.

Table 2 (concluded)

Impacted Area
<u>Condemnation Area</u> --area (Ha) within which farmland condemnation is required.
<u>Condemnation Population</u> --Population (persons) living on land that is permanently condemned for human habitation.
<u>Crop Disposal Area</u> --affected area (Ha) requiring the loss of nondairy food product sales for one year.
<u>Milk Disposal Area</u> --area (Ha) requiring the loss of dairy product sales for three months.
Economic Costs
<u>Area-Dependent Cost</u> --sum of area-dependent decontamination, interdiction, condemnation, milk disposal, and crop disposal costs (\$). The phrase "area-dependent" derives from the fact that all costs in MACCS related to agricultural production are based on contaminated area.
<u>Crop Disposal Cost</u> --compensation (\$) for lost crops.
<u>Milk Disposal Cost</u> --compensation (\$) for lost dairy product sales.
<u>Population-Dependent Cost</u> --sum of population-dependent decontamination, interdiction, and condemnation costs (\$). The phrase "population-dependent" derives from the fact that all costs in MACCS related to human exposure are based on the size of the affected population.
Latent Cancer Fatalities
<u>Total Latent Cancer Fatalities</u> --Number of latent cancer fatalities due to total long-term pathways dose.

Problem for Analysis

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3. DETERMINATION OF DOMINANT VARIABLES

The purpose of the analyses presented in this section is to determine the effects of uncertainty in the MACCS input variables listed in Table 1 on the chronic exposure results indicated in Table 2. To accomplish this, the LHS program⁴⁴ was used to generate a Latin hypercube sample¹⁸ of size 120 from the 75 variables in Table 1, with the Iman/Conover restricted pairing technique⁴² being used to induce the indicated rank correlations. The resultant sample was then propagated through MACCS to produce a mapping from MACCS input (i.e., the variables in Table 1) to MACCS results (i.e., the variables in Table 2). Once generated and stored, this mapping can be explored with sensitivity analysis techniques based on partial correlation analysis and stepwise regression analysis. Further, the mapping itself provides a representation of the uncertainty in the predicted variables under consideration. This approach to uncertainty and sensitivity is described in several presentations.⁴⁵⁻⁵⁰ The analyses for the individual chronic exposure results follow.

3.1 Population Dose and Total Latent Cancer Fatalities

As described in Table 2, nine predicted variables related to long-term population dose (Sv) are considered in this study: total long-term pathways dose, long-term groundshine dose, long-term inhalation dose, total ingestion pathways dose, milk growing season dose, crop growing season dose, crop long-term dose, water ingestion dose, and total food pathways dose. Of these variables, total long-term pathways dose is the most inclusive as it is the sum of the total ingestion pathways dose, the long-term groundshine dose and the long-term inhalation dose. In turn, the total number of latent cancer fatalities is closely related to the total long-term pathways dose. Summaries for total long-term pathways dose and total number of latent cancer fatalities are given in Figure 1.

The top two frames in Figure 1 contain the 120 CCDFs generated in the analysis (i.e., one CCDF for each sample element). The lower two frames contain summaries based on mean and percentile curves for the distributions of CCDFs in the top two frames. Specifically, at each point on the abscissa in the two upper frames in Figure 1, a vertical line is drawn through the 120 CCDFs above this point. As a reminder, the individual CCDFs do not really end at points in space as shown in Figure 1, but rather drop vertically from their last point to an exceedance probability of zero and then continue along the abscissa to the right. The points at which the indicated vertical line crosses the CCDFs yields 120 exceedance probabilities, from which the mean and various percentiles (e.g., 5%, 50%, 95%) can be determined. The curves in the lower two frames of Figure 1 result from connecting the mean and percentile values obtained for individual consequence values on the abscissa. The mean and percentile curves constructed in this manner provide a convenient summary for a distribution of CCDFs and will be used extensively in this presentation. To the extent that the distributions assigned to the variables in Table 1 can be viewed as representing a degree of belief as where the appropriate input to MACCS is located for the analysis problem under consideration, the percentile curves can also be viewed as providing confidence intervals for the exceedance probabilities associated with individual consequence values.

Determination of Dominant Variables

Figure 1. Distribution of CCDFs for Total Long-Term Dose (Sv) and Total Latent Cancer Fatalities.Top two frames contain the 120 CCDFs generated in the analysis; the lower two frames contain mean and percentile curves constructed from the distributions in the top two frames.

The primary purpose of the analyses presented in this report is to determine the importance of the individual variables in Table 1 in influencing results associated with the chronic exposure model in MACCS. One way to make such a determination is by using partial correlation analysis to determine the influence of the individual variables in Table 1 on the exceedance probabilities associated with the CCDFs summarized in Figure 1. For a distribution of CCDFs of the form shown in Figure 1, there are 120 exceedance probabilities for each consequence value on the abscissa. Partial correlation coefficients can be calculated between these probabilities and the variables in Table 1 and then plotted above the corresponding consequence values on the abscissa. When the partial correlation values for individual variables from Table 1 are connected, plots of the form shown in Figure 2 are obtained. To reduce the effects of nonlinear relationships, the analyses presented in Figure 2 and other similar figures in this report use partial rank correlation coefficients (PRCCs), which are correlation coefficients calculated with rank-transformed data. Further, to reduce clutter, the individual plot frames in Figure 2 only show PRCC plots for the four variables that have the largest PRCCs that exceed 0.6 in absolute value. The remaining variables that have PRCCs that exceed 0.6 in absolute value are listed in order of the absolute value of their PRCCs and are followed by a "+" or "-" to indicate whether the PRCC is positive (+) or negative (-) when it exceeds 0.6 in absolute value. The PRCCs in Figure 2 and other similar figures were calculated with the PCCSRC program.⁵¹

Figure 2 Partial Rank Correlation Coefficients for Exceedance Probabilities Associated with Total Long-Term Dose (Sv) and Total Number of Latent Cancer Fatalities.

Determination of Dominant Variables

The PRCCs for total long-term dose appear in the left frame of Figure 2. The dominant variable with respect to the probability that a given dose value will be exceeded is VDEPOS (dry deposition velocity). The negative PRCCs associated with VDEPOS indicate that the probability of exceeding a given dose level tends to decrease as VDEPOS increases. This negative effect results because increasing VDEPOS leads to higher concentrations of deposited radionuclides, which in turn results in more effective interdiction of contaminated areas. The opposite effect is produced by YSCALE (scaling factor for horizontal dispersion) and ZSCALE (scaling factor for vertical dispersion), which are the two variables ranked second and third in importance on the basis of the absolute value of their PRCCs. The variables YSCALE and ZSCALE have positive correlations with the probability that a given dose value will be exceeded owing to their effects on spreading the plume out. In particular, increasing YSCALE and ZSCALE tends to reduce the concentrations of deposited radionuclides, which in turn results in less effective interdiction of contaminated areas. The fourth variable selected in the analysis is GSHFACN (groundshine shielding factor for nonevacuees), which has a positive PRCC because increasing GSHFACN reduces the effectiveness of radiation shielding and hence increases population exposure to deposited radionuclides. In addition, positive effects are indicated for TFBCS (ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals), WINGCS (fraction of cesium entering surface water bodies that is consumed in drinking water), DSCRLT (maximum allowable direct exposure during long-term action period) and GCMSR90 (maximum allowable SR-90 ground concentration for production of crops), and a negative effect is indicated for CWASH1 (linear term in wet deposition model). The positive effects for TFBCS and WINGCS result from increasing the transfer of cesium through the meat and water food chains, respectively. The effects of DSCRLT, CWASH1 and GCMSR90 result from their influence on land interdiction. The positive effects for DSCRLT and GCMSR90 result from increasing the radionuclide ground concentrations at which human habitation and agricultural production, respectively, will be allowed. The negative effect for CWASH1 results because increasing CWASH1 tends to result in higher concentrations of deposited radionuclides, which in turn are more likely to be interdicted than lower concentrations.

The PRCCs for total number of latent cancer fatalities appear in the right frame of Figure 2. Due to the close relationship between dose and cancer induction, the analyses presented in Figure 2 for long-term dose and number of latent cancer fatalities are similar. In particular, VDEPOS (dry deposition velocity) is the dominant variable in both analyses, with the exceedance probabilities for both dose and number of latent cancer fatalities tending to decrease as VDEPOS increases. The variables YSCALE (scaling factor for horizontal dispersion), TFBCS (ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals), ZSCALE (scaling factor for vertical dispersion), GCMSR90 (maximum allowable Sr-90 ground concentration for production of crops) and CWASH1 (linear term in wet deposition model) appear in both analyses with PRCCs of the same sign. The reasons for the selection of these variables and the signs of their PRCCs have already been discussed. In addition, the analysis for number of latent cancer fatalities also identifies the variables DDRBRE (dose and dose rate reduction factor for breast cancer), DDRGI (dose and dose rate reduction factor for gastrointestinal cancers) and CFRLUN (risk factor for latent fatalities resulting from lung exposure), with the probability of exceeding a given number of latent cancer fatalities tending to decrease as DDRBRE and DDRGI increase and tending to increase as CFRLUN increases. The negative effects for DDRBRE and DDRGI result because increasing each of these variables tends to decrease the probability that a given dose will result in a latent cancer fatality, and the positive effect for CFRLUN results because increasing CFRLUN tends to increase the probability that a given dose will result in a latent cancer fatality.

The individual CCDFs in the two upper frames of Figure 1 display the effects of stochastic uncertainty. Each of these CCDFs can be reduced to a single mean result, where this mean is obtained by weighting the individual consequence values by the probability of the weather conditions for which each value was calculated (Ref. 5, Eqs. 27 and 28). The result of this calculation is shown in Figure 3. The individual means summarized in this figure result from stochastic uncertainty (i.e., the fact that many different types of weather are possible at the time of a reactor accident). However, the distributions of means result from subjective uncertainty (i.e., the fact that the calculation of the mean value requires many imprecisely known quantities).

Stepwise regression analysis⁴⁶⁻⁵⁰ can be used to identify the dominant variables from Table 1 with respect to the uncertainty in the mean results summarized in Figure 3 and other similar figures in this presentation. In such an analysis, the importance of a variable is indicated by the order in which variables enter the regression model, the changes in R^2 values with the entry of successive variables into the regression model, and the standardized regression coefficients in the final regression model. When the independent (i.e., sampled) variables are uncorrelated, all three ranking procedures produce the same ordering of variable importance, and the standardized regression coefficients and differences between successive R^2 values will decrease monotonically as additional variables are added to the regression model.

The regression analyses contained in this presentation were performed with the STEP program.⁵² Alpha values of 0.01 and 0.02 were required for variables to enter and remain in the regression models, respectively. Further, the PRESS criterion⁵³ was used to check for overfitting the data. The mean values for total long-term dose, total number of latent cancer fatalities and the other variables listed in Table 2.2 were analyzed with raw (i.e., untransformed) data, rank-transformed data⁵⁴, and logarithmically transformed data. As illustrated in Table 3, the regression analyses with rank-transformed and logarithmically transformed data produced similar results and tended to outperform the analyses with raw data.

Figure 3. Distributions of Mean Value for Total Long-Term Dose (Sv) and Total Number of Latent Cancer Fatalities.

Determination of Dominant Variables

Table 3. Stepwise Regression Analyses with Raw (i.e., untransformed) Data, Log-Transformed Data and Rank-Transformed Data for Total Long-Term Population Dose (Sv)

Step ^a	Raw Data			Log-Transformed Data			Rank-Transformed Data		
	Variable ^b	SRC ^c	R ^{2d}	Variable	SRC	R ²	Variable	SRC	R ²
1	VDEPOS	-0.64	0.41	VDEPOS	-0.79	0.63	VDEPOS	-0.81	0.67
2	ZSCALE	0.20	0.51	ZSCALE	0.19	0.73	YSCALE	0.20	0.75
3	TFBCS	0.29	0.60	GSHFACN	0.17	0.77	GSHFACN	0.18	0.78
4	GSHFACN	0.25	0.66	YSCALE	0.20	0.80	ZSCALE	0.17	0.81
5	DSCRLT	0.18	0.70	TFBCS	0.17	0.83	TFBCS	0.16	0.83
6	YSCALE	0.20	0.73	CWASH1	-0.15	0.86	DSCRLT	0.15	0.85
7	CWASH1	-0.16	0.75	DSCRLT	0.15	0.88	CWASH1	-0.10	0.86
8	PSOSR90	0.15	0.77	PSOSC134	0.10	0.90	PSOI131	0.09	0.87
9	CIGCS	0.12	0.79	GWCOEF1	-0.11	0.91	GWCOEF1	-0.09	0.88
10				SCLEFP	0.08	0.91	SCLEFP	0.08	0.89
11				SCLCRW	0.07	0.92	GCMSR90	0.08	0.90
12				GCMSR90	0.07	0.93			
13				CIGCS	0.07	0.93			
14				DDRBRE	-0.07	0.94			

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cStandardized regression coefficients in final regression model.

^dCumulative R² value with entry of each variable into regression model.

Specifically, the analyses with rank and logarithmically transformed data tended to identify the effects of more variables and produce regression models with higher R² values than the corresponding analyses with raw data. As the use of logarithmically transformed data is more intuitively appealing than the use of rank-transformed data, the stepwise regression analyses presented in this report use logarithmically transformed data. The logarithmic transformation was not considered as an option in the analyses for distributions of CCDFs owing to the presence of large numbers of zero exceedance probabilities that must be incorporated into the analysis as the size of the consequence under consideration increases.

A compact summary of the regression analyses for total long-term dose and total number of latent cancer fatalities is given in Table 4. Specifically, each regression analysis is summarized by listing the

variables in the order that they were selected in the stepwise process, the cumulative R^2 value with the entry of each variable into the regression model, and the sign of the regression coefficient for each variable in the final regression model. This summary procedure will be used in the remainder of this report to present the results of stepwise regression analyses.

As shown in Table 4, the mean value for total long-term population dose is dominated by VDEPOS (dry deposition velocity), which has a negative regression coefficient and can account for 63% of the uncertainty in population dose. As discussed in conjunction with the PRCCs in Figure 2, this effect results from increasing the portion of the release that will undergo interdiction. The variable ZSCALE (scale factor vertical dispersion) can account for an additional 10% (i.e., $73\% - 63\% = 10\%$) of the uncertainty in population dose. The variables GSHFACN (groundshine shielding factor for nonevacuees), YSCALE (scale factor for horizontal dispersion), TFBCS (ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals), CWASH1 (linear term in wet deposition model), DSCRLT (maximum allowable direct exposure during long-term action period) and PSOCS134 (ground concentration of Cs-134 at which disposal of crops will be initiated) can each account for an additional 2 - 4% of the uncertainty in population dose. With the exception of PSOCS134, each of these variables was also identified in the analysis with PRCCs presented in Figure 2. The regression coefficients summarized in Table 4 indicate that population dose tends to decrease as VDEPOS and CWASH1 increase and tends to increase as ZSCALE, GSHFACN, YSCALE, TFBCS, DSCRLT and PSOCS134 increase, which is consistent with the results based on PRCCs presented in Figure 2 (i.e., variables appearing in both analyses have regression coefficients and PRCCs of the same sign). The variables VDEPOS, ZSCALE, GSHFACN, YSCALE, TFBCS, CWASH1, DSCRLT and PSOCS134 can account for approximately 90% of the uncertainty in population dose. After these variables, the regression analysis selects several additional variables that have small (i.e., $\leq 1\%$) effects.

As for the analyses with PRCCs in Figure 2, the regression analyses for total long-term population dose and number of latent cancer fatalities in Table 4 are also quite similar. The first two variables selected in both regression analyses are VDEPOS (dry deposition velocity) and ZSCALE (scale factor for vertical dispersion). The variable VDEPOS can account for approximately 64% of the uncertainty in number of latent cancer fatalities, with latent cancer fatalities tending to decrease as VDEPOS increases. The variable ZSCALE can account for an additional 8% of the uncertainty in number of latent cancer fatalities, with latent cancer fatalities tending to increase as ZSCALE increases. As previously discussed, these effects result from the influence of VDEPOS and ZSCALE on the amount of the release that will be interdicted. After VDEPOS and ZSCALE, the regression analysis identifies a number of additional variables that have small effects (i.e., $\leq 4\%$) on the number of latent cancer fatalities. These variables can be divided into two groups: variables that affect exposure to released radionuclides and were already identified in the analysis for population dose (i.e., CWASH1, TFBCS, GSHFACN, DSCRLT, YSCALE, PSOCS134, GWCOEF1, SCLEFP) and variables that relate radiation exposure to cancer induction (i.e., DDRBRE, DDRGI, CFRLUN, DDROTH, DDRLUN). The individual effects of these variables are small, with most variables accounting for approximately 1% of the uncertainty in the number of latent cancer fatalities. The final regression model can account for approximately 92% of the uncertainty in the number latent cancer fatalities but requires 16 variables to do so. As for population dose, VDEPOS is the only variable that can account for a substantial part of the uncertainty in the number of latent cancer fatalities.

Determination of Dominant Variables

Table 4. Stepwise Regression Analyses with Log-Transformed Data for Total Long-Term Population Dose (Sv) and Total Number of Latent Cancer Fatalities

Step ^a	Total Long-Term Population Dose		Total Latent Cancer Fatalities	
	Variable ^b	R ^{2c}	Variable	R ²
1	VDEPOS	0.63(-)	VDEPOS	0.56(-)
2	ZSCALE	0.73(+)	ZSCALE	0.64(+)
3	GSHFACN	0.77(+)	DDRBRE	0.68(-)
4	YSCALE	0.80(+)	CWASH1	0.71(-)
5	TFBCS	0.83(+)	TFBCS	0.74(+)
6	CWASH1	0.86(-)	DDRGI	0.77(-)
7	DSCRLT	0.88(+)	CFRLUN	0.79(+)
8	PSOCS134	0.90(+)	DDROTH	0.81(-)
9	GWCOEF1	0.91(-)	GSHFACN	0.83(+)
10	SCLEFP	0.91(+)	DSCRLT	0.85(+)
11	SCLCRW	0.92(+)	YSCALE	0.87(+)
12	GCMSR90	0.93(+)	PSOCS134	0.88(+)
13	C1GCS	0.93(+)	DDRLUN	0.89(-)
14	DDRBRE	0.94(+)	GWCOEF1	0.90(-)
15			SCLEFP	0.91(+)

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cCumulative R² value with entry of each variable into regression model, with "+" and "-" indicating positive (+) and negative (-) regression coefficients, respectively.

3.2 Ingestion Dose

The ingestion dose consists of four components: milk growing season dose, crop growing season dose, crop long-term dose and water ingestion dose. Further, the total food dose is obtained by combining the first three doses, and the total ingestion pathway dose is obtained by combining all four doses. Due to the sampling procedures in use, the present analysis produced 120 CCDFs for each of these doses. As a reminder, the individual CCDFs represent the effect of stochastic uncertainty, and the distribution of CCDFs represents the effect of subjective uncertainty. Summaries based on mean and percentile curves for the distributions of CCDFs associated with the preceding six ingestion doses are given in Figure 4.

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Figure 4. Mean and Percentile Curves for Milk Growing-Season Dose (Sv), Crop-Growing Season Dose (Sv), Long-Term Crop Dose (Sv), Total Food Dose (Sv), Water Ingestion Dose (Sv), and Total Ingestion Dose (Sv).

Determination of Dominant Variables

As examination of Figure 4 shows, the milk growing dose and crop long-term dose are similar in size, and the largest doses are associated with the crop growing season dose. As a result, the crop growing season dose tends to dominate the total food pathways dose. The water ingestion dose tends to be smaller than the milk growing season dose and the crop long-term dose and also much smaller than the crop growing season dose. As a result, the total ingestion pathway dose is also dominated by the crop growing season dose.

The PRCCs that result from analyzing the distributions of CCDFs summarized in Figure 4 are presented in Figure 5. For milk growing season dose, the top four variables identified in the analysis are TFMCS (ratio of amount of cesium in milk to amount of cesium consumed by milk-producing animals), VDEPOS (dry deposition velocity), YSCALE (scale factor for horizontal dispersion) and PSMI131 (ground concentration of I-131 at which disposal of milk products will be initiated), with the probability of exceeding a given dose tending to increase as TFMCS, YSCALE and PSMI131 increase and tending to decrease as VDEPOS increases. Additional positive effects are indicated for PSMCS134 (ground concentration of Cs-134 at which disposal of milk products will be initiated), TFMI131 (ratio of amount of I-131 in milk to amount of I-131 consumed by milk-producing animals), ZSCALE (scale factor for vertical dispersion) and TFMSR (ratio of amount of strontium in milk to amount of strontium consumed by milk-producing animals), and a negative effect is indicated for CWASH1 (linear term in wet deposition model). The positive effects for TFMCS, TFMI131 and TFMSR result from increasing radionuclide transfer from feed to milk; the negative effects for VDEPOS and CWASH1 result from increasing radionuclide ground concentrations and thus increasing the amount of the radioactive release that will be interdicted; the positive effects for YSCALE and ZSCALE result from reducing radionuclide ground concentrations and thus reducing the amount of the radioactive release that will be interdicted, and the positive effects for PSMI131 and PSMCS134 result from increasing the ground concentration at which interdiction will occur and thus reducing the amount of the radioactive release that will be interdicted.

A similar pattern of effects is shown for crop growing season dose, with a positive effect indicated for TFBCS (ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals), negative effects indicated for VDEPOS (dry deposition velocity) and CWASH1 (linear term in wet deposition model), a positive effect indicated for YSCALE (scale factor for horizontal dispersion), and additional positive effects indicated for PSOI131 and PSOCS134 (ground concentrations of I-131 and Cs-134, respectively, at which disposal of crops will be initiated). Further, small effects are also indicated for GSHFACN (groundshine shielding factor for nonevacuees), DDRBRE (dose and dose rate reduction factor for breast cancer), and C1GCS (fraction of cesium deposition onto grain fields that is retained on plant surfaces and transferred directly to grain). The variables GSHFACN and DDRBRE should not affect crop growing season dose and thus their identification in the analysis is spurious; such identifications are not uncommon in analyses with partial correlation coefficients in which the number of independent variables is large relative to the sample size (e.g., 75 independent variables and a sample size of 120 in this analysis).^{55, 56}

The dominant variables with respect to crop long-term dose are VDEPOS (dry deposition velocity), TCLSR90 (ratio of Sr-90 transferred to legumes due to root uptake and resuspension and Sr-90 deposition to soil surface), GCMSR90 (maximum allowable Sr-90 ground concentration for production of crops) and YSCALE (scale factor for horizontal dispersion), with exceedance probabilities tending to

Figure 5. Partial Rank Correlation Coefficients for Milk Growing-Season Dose (Sv), Crop-Growing Season Dose (Sv), Long-Term Crop Dose (Sv), Total Food Dose (Sv), Water Ingestion Dose (Sv), and Total Ingestion Dose (Sv).

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decrease as VDEPOS increases and tending to increase as TCLSR90, GCMSR90 and YSCALE increase. The effects of VDEPOS and YSCALE have already been discussed. The positive effects associated with TCLSR90 and GCMSR90 result because increasing TCLSR90 increases the transfer of Sr-90 from soil to an edible crop (i.e., legumes) and increasing GCMSR90 increases the amount of contaminated land on which crop production will be allowed. Additional positive effects are indicated for TFBCS (ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals), ZSCALE (scale factor for vertical dispersion) and TCPCS137 (ratio of Cs-137 transferred to pasture due to root uptake and resuspension and Cs-137 deposition to soil surface).

The total food pathways dose results from combining the milk growing dose, the crop growing season dose and the crop long-term dose. Thus, rather unsurprisingly, the dominant variables with respect to the probability that a given total food pathways dose will be exceeded are similar to the variables that have already been identified as important with respect to the three component doses. In particular, VDEPOS (dry deposition velocity) and CWASH1 (linear term in wet deposition model) have negative effects because they increase the fraction of the radionuclide release that will be interdicted; YSCALE and ZSCALE (scale factors for horizontal and vertical dispersion, respectively) have positive effects because they decrease the fraction of the radionuclide release that will be interdicted; GCMSR90 (maximum allowable Sr-90 ground concentration for production of crops) and PSOI131 (ground concentration of I-131 at which disposal of crops will be initiated) have positive effects because they decrease the fraction of the radionuclide release that will be interdicted, and TFBCS (ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals), TCLSR90 (ratio of Sr-90 transferred to legumes due to root uptake and resuspension and Sr-90 deposition to soil surface) and TFMCS (ratio of amount of cesium in milk to amount of cesium consumed by milk-producing animals) have positive effects because they increase the amount of radioactive material transferred within the food chain. As previously discussed for crop growing season dose, the appearance of GSHFACN (groundshine shielding factor for nonevacuees) is probably spurious.

The probability of exceeding a given water ingestion dose is dominated by WINGCS and WINGSR (fraction of cesium and strontium, respectively, entering surface water bodies that is consumed in drinking water), with the probability of exceeding a given dose tending to increase as each of these variables increases. Unlike the other food pathways doses, the water ingestion dose is not affected by the dry deposition velocity (VDEPOS) because the interdiction of land has no effect on the amount of radionuclide being transferred from land to surface water bodies. The MACCS program has no criterion for the interdiction of the drinking water pathway. However, as examination of Figure 4 shows, the water ingestion dose is making a small contribution to the total ingestion pathways dose in this analysis.

The final analysis presented in Figure 5 is for the total ingestion pathways dose. As shown in Figure 4, the water ingestion dose makes a relatively small contribution to the total ingestion pathways dose. As a result, the PRCCs in this analysis are similar to those obtained for the total food pathways dose, although there is some shifting in the order of importance. In particular, every variable identified in the analysis for total food pathways dose also appears in the analysis for total ingestion pathways with the sign of its PRCC unchanged. In addition, WINGCS and WINGSR (fraction of cesium and strontium, respectively, entering surface water bodies that is consumed in drinking water) are also identified in the analysis.

The individual CCDFs summarized with the mean and percentile curves appearing in Figure 4 can be reduced to mean results as previously discussed in conjunction with Figure 3. The distributions of mean results obtained in this manner are summarized in Figure 6. As examination of Figure 6 shows, the smallest doses are associated with water ingestion and the largest doses are associated with the crop growing season. The milk growing season doses and crop long-term doses are of an intermediate size. However, the ranges for all four doses overlap to some extent. As the crop growing season dose tends to be the largest dose, the distributions for total food pathways dose and total ingestion pathways dose resemble the distribution for crop growing season dose.

Stepwise regression analyses for the mean results summarized in Figure 6 are given in Table 5. The indications of variable importance are generally the same as those obtained from the analyses with PRCCs summarized in Figure 5. However, the results should not be expected to be exactly the same as different dependent variables are under consideration (i.e., mean values rather than exceedance probabilities) and a different measure of importance is being used (i.e., stepwise regression analysis rather than PRCCs).

For milk growing season dose, the dominant variables are TFMCS (ratio of amount of cesium in milk to amount of cesium consumed by milk-producing animals), PSMCS134 (ground concentration of Cs-134 at which disposal of milk products will be initiated) and VDEPOS (dry deposition velocity), with these variables able to account for 30%, 26% and 19%, respectively, of the observed uncertainty. The dose tends to increase as TFMCS and PSMCS134 increase and tends to decrease as VDEPOS increases. Smaller effects are indicated for YSCALE (scale factor for horizontal dispersion), PSMI131 (ground concentration of I-131 at which disposal of milk products will be initiated), TFMI131 (ratio of amount of I-131 in milk to amount of I-131 consumed by milk-producing animals), CWASH1 (linear term in wet deposition model) and TFMSR (ratio of amount of strontium in milk to amount of strontium consumed by milk-producing animals), with dose tending to increase as YSCALE, PSMI131, TFMI131 and TFMSR increase and tending to decrease as CWASH1 increases. The regression model with all eight variables can account for approximately 93% of the observed uncertainty. The positive effects for TFMCS, TFMI131 and TFMSR result from increasing the transfer of radionuclides from animal feed to milk; the positive effects for PSMCS134 and PSMI131 result from decreasing the fraction of the radionuclide release that will be interdicted; the negative effects for VDEPOS and CWASH1 result from increasing the fraction of the radionuclide release that will be interdicted, and the positive effect for YSCALE results from decreasing the fraction of the radionuclide release that will be interdicted.

For crop growing season dose, the dominant variables are VDEPOS (dry deposition velocity), TFBCS (ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals) and PSOI131 (ground concentration of I-131 at which disposal of crops will be initiated), with these variables able to account for 46%, 21% and 11%, respectively, of the observed uncertainty. Dose tends to decrease as VDEPOS increases and tends to increase as TFBCS and PSOI131 increase. Smaller effects are indicated for YSCALE (scale factor for horizontal dispersion), CWASH1 (linear term in wet deposition model), C1GCS (fraction of cesium deposition onto grain fields that is retained on plant surfaces and transferred directly to grain), PSOCS134 (ground concentration of Cs-134 at which disposal of crops will be initiated) and ZSCALE (scale factor for vertical dispersion), with dose tending to increase as YSCALE, C1GCS, PSOCS134 and ZSCALE increase and tending to decrease as CWASH1 increases.

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Figure 6. Distributions of Mean Value for Milk Growing-Season Dose (Sv), Crop-Growing Season Dose (Sv), Long-Term Crop Dose (Sv), Total Food Dose (Sv), Water Ingestion Dose (Sv), and Total Ingestion Dose (Sv).

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The regression model with all eight variables can account for approximately 94% of the observed uncertainty. The negative effects for VDEPOS and CWASH1 result from increasing the fraction of the radionuclide release that will be interdicted; the positive effects for TFBCS and C1GCS result from increasing the transfer of cesium within the food chain; the positive effects for PSOI131, PSOCS134, YSCALE and ZSCALE result from decreasing the fraction of the radionuclide release that will be interdicted.

For crop long-term dose, the dominant variables are VDEPOS (dry deposition velocity), TCLSR90 (ratio of Sr-90 transferred to legumes due to root uptake and resuspension and Sr-90 deposition to soil surface) and GCMSR90 (maximum allowable Sr-90 ground concentration for production of crops), with these variables able to account for 32%, 18% and 17%, respectively, of the observed uncertainty. Dose tends to decrease as VDEPOS increases and tends to increase as TCLSR90 and GCMSR90 increase. Additional positive effects are indicated for TFBCS (ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals), TCPCS137 (ratio of Cs-137 transferred to pasture due to root uptake and resuspension and Cs-137 deposition to soil surface), YSCALE (scale factor for horizontal dispersion), GCMCS137 (maximum allowable Sr-90 ground concentration for production of crops) and ZSCALE (scale factor for vertical dispersion). The regression model with all eight variables can account for approximately 89% of the observed uncertainty. The negative effect for VDEPOS results from increasing the fraction of the radionuclide release that will be interdicted; the positive effects for TCLSR90, TFBCS and TCPCS137 result from increasing the transfer of radionuclides through the food chain; the positive effects for GCMSR90, GCMCS137, YSCALE and ZSCALE result from reducing the fraction of the radionuclide release that will be interdicted.

For total food pathways dose, the dominant variables are VDEPOS (dry deposition velocity) and TFBCS (ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals), with these variables accounting for 55% and 14%, respectively, of the observed uncertainty. Dose tends to decrease as VDEPOS increases and tends to increase as TFBCS increases. Additional effects are indicated for YSCALE (scale factor for horizontal dispersion), PSOI131 (ground concentration of I-131 at which disposal of crops will be initiated), CWASH1 (linear term in wet deposition model), C1GCS (fraction of cesium deposition onto grain fields that is retained on plant surfaces and transferred directly to grain), TFMCS (ratio of amount of cesium in milk to amount of cesium consumed by milk-producing animals), PSOCS134 (ground concentration of Cs-134 at which disposal of crops will be initiated), TCPCS137 (ratio of Cs-137 transferred to pasture due to root uptake and resuspension and Cs-137 deposition to soil surface), GCMSR90 (maximum allowable Sr-90 ground concentration for production of crops), TCLSR90 (ratio of Sr-90 transferred to legumes due to root uptake and resuspension and Sr-90 deposition to soil surface), ZSCALE (scale factor for vertical dispersion) and PSMI131 (ground concentration of I-131 at which disposal of milk products will be initiated), with dose tending to increase as YSCALE, PSOI131, C1GCS, TFMCS, PSOCS134, TCPCS137, GCMSR90, TCLSR90, ZSCALE and PSMI131 increase and tending to decrease as CWASH1 increases. The regression model with all 13 variables can account for approximately 92% of the observed uncertainty. The negative effects for VDEPOS and CWASH1 result from increasing the fraction of the radionuclide release that will be interdicted; the positive effects for TFBCS, C1GCS, TFMCS, TCPCS137, TCLSR90 and PSMI131 result from increasing radionuclide transfer within the food chain; the positive effects for YSCALE, ZSCALE, PSOI131, PSOCS134 and GCMSR90 result from decreasing the fraction of the radionuclide that will be interdicted.

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For water ingestion dose, the dominant variables are WINGCS and WINGSR (fraction of cesium and strontium, respectively, entering surface water bodies that is consumed in drinking water), with these variables accounting for 74% and 14%, respectively, of the observed uncertainty. Dose tends to increase as each of WINGCS and WINGSR increases. Small additional positive effects are indicated for WSHRTASR and WSHRTACS (rate constant for movement of ground-deposited strontium and cesium, respectively, into surface water bodies) and also for WSHFRICS (fraction of ground-deposited cesium that moves rapidly into surface water bodies). The positive effects for WINGCS and WINGSR result from their influence on the consumption of radionuclides that enter surface water bodies, and the positive effects for WSHRTASR, WSHRTACS and WSHFRICS result from their influence on the amount of radionuclides that enter surface water bodies. Collectively, all five variables can account for approximately 92% of the observed uncertainty in the water ingestion dose.

As examination of Figure 6 shows, the water ingestion dose makes a very small contribution to the total ingestion pathway dose, with the result that the summary in Table 5 of the regression analysis for total ingestion pathways dose is identical to the summary for total food pathways dose. Thus, the discussion supplied for the total food pathways dose also applies to the total ingestion pathways dose.

Table 5. Stepwise Regression Analyses with Log-Transformed Data for Milk Growing-Season Dose (Sv), Crop Growing-Season Dose (Sv), Long-Term Crop Dose (Sv), Total Food Dose (Sv), Water Ingestion Dose (Sv), and Total Ingestion Dose (Sv)

Step ^a	Milk Growing-Season Dose		Crop Growing-Season Dose (Sv)	
	Variable ^b	R ^{2c}	Variable	R ²
1	TFMCS	0.30(+)	VDEPOS	0.46(-)
2	PSMCS134	0.56(+)	TFBCS	0.67(+)
3	VDEPOS	0.75(-)	PSOI131	0.78(+)
4	YSCALE	0.83(+)	YSCALE	0.83(+)
5	PSMI131	0.89(+)	CWASH1	0.87(-)
6	TFMI131	0.91(+)	C1GCS	0.90(+)
7	CWASH1	0.92(-)	PSOCS134	0.93(+)
8	TFMSR	0.93(+)	ZSCALE	0.94(+)

Step	Long-Term Crop Dose (Sv)		Total Food Pathways Dose (Sv)	
	Variable	R ²	Variable	R ²
1	VDEPOS	0.32(-)	VDEPOS	0.55(-)
2	TCLSR90	0.50(+)	TFBCS	0.69(+)
3	GCMSR90	0.67(+)	YSCALE	0.76(+)
4	TFBCS	0.76(+)	PSOI131	0.81(+)
5	TCPCS137	0.83(+)	CWASH1	0.84(-)
6	YSCALE	0.86(+)	C1GCS	0.85(+)
7	GCMCS137	0.88(+)	TFMCS	0.86(+)
8	ZSCALE	0.89(+)	PSOCS134	0.87(+)
9			TCPCS137	0.88(+)
10			GCMSR90	0.89(+)
11			TCLSR90	0.91(+)
12			ZSCALE	0.91(+)
13			PSMI131	0.92(+)

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Table 5 (concluded)

Step	Water Ingestion Dose (Sv)		Total Ingestion Pathways Dose (Sv)	
	Variable	R ²	Variable	R ²
1	WINGCS	0.74(+)	VDEPOS	0.55(-)
2	WINGSR	0.88(+)	TFBCS	0.69(+)
3	WSHRTASR	0.90(+)	YSCALE	0.76(+)
4	WSHRTACS	0.91(+)	PSOI131	0.81(+)
5	WSHFRICS	0.92(+)	CWASH1	0.84(-)
6			CIGCS	0.85(+)
7			TFMCS	0.86(+)
8			PSOCS134	0.87(+)
9			TCPCS137	0.88(+)
10			GCMSR90	0.89(+)
11			TCLSR90	0.91(+)
12			ZSCALE	0.91(+)
13			PSMI131	0.92(+)

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cCumulative R² value with entry of each variable into regression model, with "+" and "-" indicating positive (+) and negative (-) regression coefficients, respectively.

3.3 Groundshine and Resuspension Dose

Summaries of the distributions of CCDFs for long-term groundshine and resuspension (i.e., inhalation) doses are given in Figure 7. As examination of this figure shows, the groundshine doses are considerably larger than the resuspension doses.

The PRCCs that result from analyzing the CCDFs summarized in Figure 7 are presented in Figure 8. For long-term groundshine dose, the four variables with the largest PRCCs are VDEPOS (dry deposition velocity), YSCALE (scale factor for horizontal dispersion), GSHFACN (groundshine shielding factor for nonevacuees) and DSCRLT (maximum allowable direct exposure during long-term action period), with dose tending to decrease as VDEPOS increases and tending to increase as YSCALE, GSHFACN and DSCRLT increase. In addition, positive effects are indicated for ZSCALE (scale factor for vertical dispersion) and SCLCRW (critical wind speed scaling factor), and negative effects are indicated for CWASH1 (linear term in wet deposition model) and GWCOEF1 (fraction of initial groundshine undergoing rapid decrease). The negative effects for VDEPOS and CWASH1 result from increasing the fraction of the release that will be interdicted, while the positive effects for YSCALE, DSCRLT, ZSCALE and SCLCRW result from decreasing the fraction of the release that will be interdicted. In particular, increasing VDEPOS and CWASH1 results in higher concentrations of deposited material and hence more interdiction, and increasing YSCALE, ZSCALE and SCLCRW results in lower concentration of deposited material and hence less interdiction. The positive effect for DSCRLT results from raising the dose level at which interdiction will take place. Finally, the negative effect for GWCOEF1 results from increasing the rate at which weathering reduces radiation exposures due to groundshine.

Figure 7. Mean and Percentile Curves for Long-Term Groundshine Dose (Sv) and Long-Term Resuspension Dose (Sv).

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Figure 8. Partial Rank Correlation Coefficients for Exceedance Probabilities Associated with Long-Term Groundshine Dose (Sv) and Long-Term Resuspension Dose (Sv).

For resuspension dose, the dominant variable is RWCOEF (scale factor used in definition of resuspension coefficients), with dose tending to increase as RWCOEF increases. Additional positive effects are indicated for PROTINN (inhalation protection factor for nonevacuees), TRWHLF (scale factor used in definition of resuspension halflife), ZSCALE (scale factor for vertical dispersion), YSCALE (scale factor for horizontal dispersion) and DSCRLT (maximum allowable direct exposure during long-term action period), and a negative effect is indicated for VDEPOS (dry deposition velocity). The positive and negative effects indicated for RWCOEF and TRWHLF result from increasing and decreasing, respectively, the amount of deposited material that will be resuspended. The positive effect for PROTINN results from increasing the fraction of resuspended material that will be inhaled. The indicated effects for VDEPOS, ZSCALE, YSCALE and DSCRLT result from their influence on the amount of released material that will be interdicted, with the fraction of the release interdicted tending to increase as VDEPOS increases and tending to decrease as ZSCALE, YSCALE and DSCRLT increase.

Each of the CCDFs that give rise to the distributions summarized in Figure 7 can be reduced to a single mean result. The result of this reduction is shown in Figure 9. As examination of this figure shows, the mean results for long-term groundshine dose tend to be higher than the mean results for resuspension dose.

As shown in Table 6, stepwise regression analysis can be used to determine the contributors to the uncertainty in the mean doses shown in Figure 9. For groundshine dose, the dominant variables are VDEPOS (dry deposition velocity), GSHFACN (groundshine shielding factor for nonevacuees) and ZSCALE (scale factor for vertical dispersion), with these variables accounting for approximately 50%, 17% and 12% of the observed uncertainty. Further, mean dose tends to decrease as VDEPOS increases and tends to increase as GSHFACN and ZSCALE increase. In addition, small positive effects are indicated for DSCRLT (maximum allowable direct exposure during long-term action period), YSCALE

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(scale factor for horizontal dispersion), SCLCRW (critical wind speed scaling factor) and TGWHLF2 (half-life for slow groundshine weathering), and small negative effects are indicated for GWCOEF1 (fraction of initial groundshine that undergoes rapid weathering) and CWASH1 (linear term in wet deposition model). As seen in several previous analyses, the uncertainty in the mean groundshine dose is dominated by variables related to interdiction. In particular, dose decreases as VDEPOS and CWASH1 increase and dose increases as ZSCALE, DSCRLT, YSCALE and SCLCRW increase due to the influence of these variables on interdiction. The positive effect indicated for GSHFACN results from reducing the shielding to groundshine, and the negative and positive effects indicated for GWCOEF1 and TGWHLF2, respectively, result from increasing the amount of groundshine that will undergo rapid weathering and decreasing the rate at which the slow weathering of groundshine will occur. The regression model with all nine variables can account for approximately 93% of the observed uncertainty.

For resuspension dose, the dominant variable is RWCOEF (scale factor used in definition of resuspension coefficients), as is also the case in the analysis with PRCCs shown in Figure 8. The variable RWCOEF can account for approximately 73% of the uncertainty in mean dose, with dose tending to increase as RWCOEF increases due to increased amounts of material that will be resuspended. In addition, PROTINN (inhalation protection factor for nonevacuees) and VDEPOS (dry deposition velocity) can account for 8 - 9% of the observed uncertainty, with dose tending to increase as PROTINN increases due to increased inhalation of resuspended material and to decrease as VDEPOS increases due to increased interdiction. Additional small positive effects are indicated for TRWHLF (scale factor used in definition of resuspension half-life), ZSCALE (scale factor for vertical dispersion) and DSCRLT (maximum allowable direct exposure during long-term action period). The regression model with all six variables can account for approximately 98% of the observed uncertainty.

Figure 9. Distributions of Mean Value for Long-Term Groundshine Dose (Sv) and Long-Term Resuspension Dose (Sv).

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Table 6. Stepwise Regression Analyses with Log-Transformed Data for Groundshine Dose (Sv) and Resuspension Dose (Sv)

Step ^a	Groundshine Dose (Sv)		Resuspension Dose (Sv)	
	Variable ^b	R ^{2c}	Variable	R ²
1	VDEPOS	0.50(-)	RWCOEF	0.73(+)
2	GSHFACN	0.67(+)	PROTINN	0.82(+)
3	ZSCALE	0.79(+)	VDEPOS	0.90(-)
4	DSCRLT	0.85(+)	TRWHLF	0.94(+)
5	GWCOEF1	0.88(-)	ZSCALE	0.97(+)
6	YSCALE	0.91(+)	DSCRLT	0.98(+)
7	SCLCRW	0.92(+)		
8	CWASH1	0.93(-)		
9	TGWHLF2	0.93(+)		

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cCumulative R² value with entry of each variable into regression model, with "+" and "-" indicating positive (+) and negative (-) regression coefficients, respectively.

3.4 Impacted Area

Summaries of the distributions of CCDFs for impacted area (i.e., condemnation area, crop disposal area and milk disposal area) and population are given in Figure 10. In turn, the distributions of CCDFs underlying these summaries can be analyzed with PRCCs as shown in Figure 11.

For condemnation area (i.e., area within which farmland condemnation is required), the dominant variables are GCMSR90 (maximum allowable Sr-90 ground concentration for crop production), QRSR90 (rate of depletion of Sr-90 from root zone), VDEPOS (dry deposition velocity) and ZSCALE (scale factor for vertical dispersion), with the probability of exceeding a given condemnation area tending to decrease as GCMSR90, QRSR90 and VDEPOS increase and to increase as ZSCALE increases. The negative effects for GCMSR90, QRSR90 and VDEPOS result because increasing GCMSR90 results in less stringent requirements (i.e., higher ground concentrations) for interdiction, increasing QRSR90 increases the rate of Sr-90 depletion from the root zone and thus decreases the time required for ground concentration to reach values below GCMSR90, and increasing VDEPOS decreases the area on which high concentrations of released material will occur. The positive effect indicated for ZSCALE results from the tendency of this variable to spread the released materials over a wider area as its value increases.

Figure 10. Mean and Percentile Curves for Condemnation Area (Ha), Condemnation Population, Crop Disposal Area (Ha) and Milk Disposal Area (Ha).

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Figure 11. Partial Rank Correlation Coefficients for Condemnation Area (Ha), Condemnation Population, Crops Disposal Area (Ha) and Milk Disposal Area (Ha).

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For condemnation population (i.e., population living on land that is permanently condemned for human habitation), the dominant variables are DSRFCT2 (dose reduction associated with aggressive decontamination), DSCRLT (maximum allowable direct exposure dose during long-term action period), VDEPOS (dry deposition velocity) and GSHFACN (groundshine shielding factor for nonevacuees), with the probability of exceeding a given population size tending to decrease as DSRFCT2 and DSCRLT increase and to increase as VDEPOS and GSHFACN increase. In addition, small negative effects are indicated for GWCOEF1 (fraction of initial groundshine undergoing rapid decrease), YSCALE (scale factor for horizontal dispersion) and ZSCALE (scale factor for vertical dispersion) and small positive effects are indicated for CWASH1 (linear term in wet deposition model) and SCLCRW (critical wind speed scaling factor). The negative effects for DSRFCT2 and DSCRLT result because increasing DSRFCT2 increases the effectiveness of decontamination and increasing DSCRLT increases the projected exposure at which condemnation will be required, with both effects tending to reduce the size of the population living on land that is condemned for human habitation. The positive effects for VDEPOS and GSHFACN result because increasing VDEPOS increases the concentration of material deposited close to the reactor and increasing GSHFACN increases exposure to groundshine. The variable VDEPOS shows an interesting pattern, with a positive effect on the probability that a small population will be exceeded but essentially no effect on the probability of exceeding a large population; further, VDEPOS has a negative effect on the probability that a given condemnation area will be exceeded. This pattern of reversed effects can also be seen for YSCALE, ZSCALE and CWASH1, with these variables having the opposite effect on condemnation population that they have on population dose (e.g., see Figures 5 and 8). Thus, as illustrated here, a variable's effect in determining dose to individuals above a specified level may be different from its effect on total population dose. The negative effect for GWCOEF1 results from increasing the rate at which groundshine decreases. Further, like VDEPOS, YSCALE, CWASH1 and ZSCALE, the variable SCLCRW enters the analysis due to an effect on the concentration of deposited material.

The analyses in Figure 11 for crop disposal area and milk disposal area are similar. In both analyses, the probability of exceeding a given area tends to decrease as VDEPOS (dry deposition velocity) increases and tends to increase as YSCALE and ZSCALE (scale factors for vertical and horizontal dispersion, respectively) increase. These effects result from influence of these variables on the concentrations of deposited radionuclides. In addition, the radionuclide concentrations at which interdiction occurs also have a positive effect on the probability of exceeding a given disposal area, with PSOI131, PSOSR90 and PSOCS134 (ground concentration of I-131, Sr-90 and Cs-134, respectively, at which disposal of crops will be initiated) affecting crop disposal area and PSMI131 and PSMCS134 (ground concentration of I-131 and Cs-134, respectively, at which disposal of milk products will be initiated) affecting milk disposal area.

Determination of Dominant Variables

Each CCDF in the distributions summarized in Figure 10 can be reduced to a single mean value. The distributions of mean values that result from this calculation are presented in Figure 12. Further, as shown in Table 7, stepwise regression analysis can be used to identify the variables that give rise to the distributions in Figure 12.

For mean condemnation area, the dominant variables are GCMSR90 (maximum allowable Sr-90 ground concentration for crop production) and QRSR90 (rate of depletion of Sr-90 from root zone), with GCMSR90 and QRSR90 accounting for approximately 68% and 14%, respectively, of the observed uncertainty and the mean area tending to decrease as each of these variables increases. In addition, small negative effects are indicated for GCMCS137 (maximum allowable Cs-137 ground concentration for crop production), VDEPOS (dry deposition velocity) and VALWF (value of farm wealth), and a small positive effect is indicated for ZSCALE (scale factor for vertical dispersion). The negative effects for GCMSR90 and GCMCS137 result from increasing the ground concentration at which interdiction will occur, which in turn leads to less land requiring condemnation. The negative effect for QRSR90 results from increasing the rate at which Sr-90 is removed from the root zone, which leads to shortened periods of interdiction and thus less land condemnation. The positive and negative effects for ZSCALE and VDEPOS result from influences on the proportions of the released material being deposited in different concentrations. Finally, the negative effect for VALWF results from farmland being less likely to be condemned as its value increases. The regression model with all six variables can account for approximately 90% of the observed uncertainty.

For mean condemnation population, the dominant variables are DSCRLT (maximum allowable direct exposure dose during long-term action period), DSRFCT2 (dose reduction associated with aggressive decontamination) and GSHFACN (groundshine shielding factor for non-evacuees), with these variables accounting for approximately 31%, 27% and 22% of the observed uncertainty. The mean dose tends to decrease as DSCRLT and DSRFCT2 increase and tends to increase as GSHFACN increases. In addition, small negative effects are indicated for ZSCALE (scale factor for vertical dispersion), GWCOEF1 (fraction of initial groundshine undergoing rapid decrease) and YSCALE (scale factor for horizontal dispersion), and small positive effects are indicated for VDEPOS (dry deposition velocity), SCLEFP (plume rise scaling factor for stability classes A through D), SCLCRW (critical wind speed scaling factor) and FRNFIM (fraction of nonfarm wealth due to improvements). The negative effects of DSCRLT and DSRFCT2 result from reduced requirements for interdiction and increased effectiveness of decontamination, respectively. The positive effect for GSHFACN results from reduced shielding to groundshine, while the negative effect for GWCOEF1 results from an increased rate of reduction in groundshine. The effects of ZSCALE, VDEPOS, YSCALE, SCLEFP and SCLCRW result from influences on the proportion of the released material being deposited in different concentrations. As also seen in the analyses based on PRCCs in Figure 11, the effects of these variables tend to reverse depending on whether dose or condemnation population is under consideration. The positive effect for FRNFIM results because increasing FRNFIM increases the amount of nonfarm wealth that is subject to depreciation and thus increases the likelihood that projected financial losses will be large enough to cause condemnation of land. The regression model with all 10 variables can account for approximately 96% of the observed uncertainty.

The regression analyses for mean crop disposal area and mean milk disposal area are similar, as is also the case for the analyses based on PRCCs in Figure 11. The analyses tend to be dominated by the variables that define interdiction levels, with PSOI131 (ground concentration of I-131 at which

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disposal of crops will be initiated) accounting for approximately 62% of the uncertainty in mean crop disposal area and PSMCS134 (ground concentration of Cs-134 at which disposal of milk products will be initiated) accounting for approximately 50% of the uncertainty in mean milk disposal area. The corresponding mean area tends to decrease as each of these variables increases due to reduced requirements for interdiction. Similarly, mean crop disposal area decreases as PSOSR90 and PSOCS134 (ground concentrations of Sr-90 and Cs-134, respectively, at which disposal of crops will be initiated) increase, and mean milk disposal area decreases as PSMI131 and PSMCS137 (ground concentrations of I-131 and Cs-137, respectively, at which disposal of milk products will be initiated) increase. Both analyses also indicate a negative effect for VDEPOS (dry deposition velocity) and a positive effect for ZSCALE (scale factor for vertical dispersion). In addition, the analysis for mean milk disposal area also indicates a small positive effect for YSCALE (scale factor for horizontal dispersion). As previously discussed, VDEPOS, ZSCALE and YSCALE enter the analysis due to their effect on the proportions of the released material being deposited at different concentrations. The final regression models for mean crop disposal area and mean milk disposal area can account for approximately 82% and 90%, respectively, of the observed uncertainty.

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Figure 12. Distributions of Mean Value for Condemnation Area (Ha), Condemnation Population, Crop Disposal Area (Ha) and Milk Disposal Area (Ha).

Table 7. Stepwise Regression Analyses with Log-Transformed Data for Condemnation Area (Ha), Condemnation Population, Crop Disposal Area (Ha), and Milk Disposal Area (Ha)

Step ^a	Condemnation Area (Ha)		Condemnation Population	
	Variable ^b	R ^{2c}	Variable	R ²
1	GCMR90	0.68(-)	DSCRLT	0.31(-)
2	QRSR90	0.82(-)	DSRFCT2	0.58(-)
3	GCMCS137	0.86(-)	GSHFACN	0.80(+)
4	ZSCALE	0.87(+)	ZSCALE	0.85(-)
5	VDEPOS	0.89(-)	GWCOEF1	0.89(-)
6	VALWF	0.90(-)	VDEPOS	0.92(+)
7			YSCALE	0.94(-)
8			SCLEFP	0.94(+)
9			SCLCRW	0.95(+)
10			FRNFIM	0.96(+)

Step	Crop Disposal Area (Ha)		Milk Disposal Area (Ha)	
	Variable	R ²	Variable	R ²
1	PSOI131	0.62(-)	PSMCS134	0.50(-)
2	PSOSR90	0.74(-)	VDEPOS	0.75(-)
3	VDEPOS	0.77(-)	PSMI131	0.84(-)
4	ZSCALE	0.80(+)	ZSCALE	0.88(+)
5	PSOCS134	0.82(-)	YSCALE	0.89(+)
6			PSMCS137	0.90(-)

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cCumulative R² value with entry of each variable into regression model, with "+" and "-" indicating positive (+) and negative (-) regression coefficients, respectively.

3.5 Cost

Summaries of the distributions of CCDFs for cost are given in Figure 13. Further, as shown in Figure 14, the distributions of CCDFs underlying these summaries can be analyzed with PRCCs.

For area-dependent cost (i.e., the cost associated with agricultural land owing to decontamination, interdiction, condemnation, milk disposal and crop disposal), the dominant variables are GCMSR90 (maximum allowable Sr-90 ground concentration for crop production), VDEPOS (dry deposition velocity), YSCALE (scale factor for horizontal velocity), and ZSCALE (scale factor for vertical dispersion), with the probability of exceeding a given cost tending to decrease as GCMSR90 and VDEPOS increase and tending to increase as YSCALE and ZSCALE increase. Additional negative and positive effects are indicated for QRSR90 (rate of depletion of Sr-90 from root zone) and SCLEFP (plume rise scaling factor for stability classes A through D), respectively. The negative effects for GCMSR90 and QRSR90 result from increasing the ground concentration of Sr-90 at which interdiction is required and increasing the rate at which ground concentrations of Sr-90 above GCMSR90 decrease to concentrations below GCMSR90 respectively. The negative effect for VDEPOS and the positive effects for YSCALE, ZSCALE and SCLEFP result from the influence that these variables have on the proportions of the released material deposited in different concentrations.

For population cost (i.e., the cost associated with areas of human habitation as a result of decontamination, interdiction and condemnation), the dominant variables are DSCRLT (maximum allowable direct exposure dose during long-term action period), GSHFACN (groundshine shielding factor for nonevacuees), VDEPOS (dry deposition velocity) and VALWNF (value of nonfarm wealth), with the probability of exceeding a given cost tending to decrease as DSCRLT and VDEPOS increase and tending to increase as GSHFACN and VALWNF increase. In addition, a positive effect is indicated for ZSCALE (scale factor for vertical dispersion), and negative effects are indicated for YSCALE (scale factor for horizontal dispersion) and DSRFCT2 (dose reduction associated with aggressive decontamination). The negative effect for DSCRLT results from increasing the dose level at which interdiction is required. The positive effect for GSHFACN and the negative effect of DSRFCT2 result from increasing and decreasing, respectively, individual radiation exposure, which in turn influences whether or not radiation exposures will exceed DSCRLT. As comparison with the analysis in Figure 11 for condemnation population shows, DSRFCT2 has a much stronger effect on the population living on land that is condemned than it does on the total costs associated with areas of human habitation. The effects associated with VDEPOS, ZSCALE and YSCALE result from the influence that these variables have on the proportions of the released material deposited in different concentrations. Finally, the positive effect for VALWNF results from increasing the cost of condemning property.

The analyses in Figure 14 for crop disposal cost and milk disposal cost are similar. In both analyses, the ground concentrations at which the disposal of agricultural products will be initiated have a significant effect (i.e., PSOI131 and PSOSR90 in the analysis for crop disposal cost, and PSMI131 and PSMCS134 in the analysis for milk disposal cost). In addition, VDEPOS (dry deposition velocity), YSCALE (scale factor for horizontal dispersion) and ZSCALE (scale factor for vertical dispersion) also have similar effects in both analyses due to their influence on the proportions of the released material deposited in different concentrations.

Figure 13. Mean and Percentile Curves for Area Dependent Cost (\$), Population Cost (\$), Crop Disposal Cost (\$), Total Economic Cost (\$) and Milk Disposal Cost (\$).

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Figure 14. Partial Rank Correlation Coefficients for Area Dependent Cost (\$), Population Cost (\$), Crop Disposal Cost (\$), Total Economic Cost (\$) and Milk Disposal Cost (\$).

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As examination of Figure 13 shows, the total economic cost is dominated by the population cost, with the result that the analyses in Figure 14 for these two variables are similar.

The distributions of mean costs that result from the CCDFs summarized in Figure 13 are presented in Figure 15. These mean results can be analyzed with stepwise regression analysis as shown in Table 8.

For mean area-dependent cost, the dominant variables are GCMR90 (maximum allowable Sr-90 ground concentration for crop production) and VDEPOS (dry deposition velocity), with these variables accounting for approximately 64% and 12%, respectively, of the observed uncertainty. The mean cost tends to decrease as each of these variables increases. In addition, a small positive effect is indicated for ZSCALE (scale factor for vertical dispersion), and small negative effects are indicated for QRSR90 (rate of depletion of Sr-90 from root zone), PSOSR90 (ground concentration of Sr-90 at which disposal of crops will be initiated), GCMCS137 (maximum allowable Cs-137 ground concentration for crop production), DSCRLT (maximum allowable direct exposure dose during long-term action period) and CWASH1 (linear term in wet deposition model). The negative effects associated with GCMR90, QRSR90, PSOSR90, GCMCS137 and DSCRLT result from increasing radionuclide concentrations at which some type of mitigative action will be initiated. The effects associated with VDEPOS, ZSCALE and CWASH1 result from the influence of these variables on the proportion of the released material deposited in different concentrations, which in turn affects the areas undergoing interdiction. The regression model with all eight variables can account for approximately 91% of the observed uncertainty.

For mean population cost, the dominant variables are DSCRLT (maximum allowable direct exposure dose during long-term action period) and GSHFACN (groundshine shielding factor for nonevacuees), with these variables accounting for approximately 44% and 36%, respectively, of the observed uncertainty. The mean cost tends to decrease as DSCRLT increases and tends to increase as GSHFACN increases. In addition, small negative effects are indicated for VDEPOS (dry deposition velocity), GWCOEF1 (fraction of initial groundshine undergoing rapid decrease) and DSRFCT2 (dose reduction associated with aggressive decontamination), and small positive effects are indicated for ZSCALE (scale factor for vertical dispersion), RWCOEF (scale factor used in definition of resuspension coefficients), SCLCRW (critical wind speed scaling factor), VALWNF (value of nonfarm wealth), POPCST (per capita cost for relocation) and TGWHLF1 (half-life for rapid groundshine weathering). The negative effect associated with DSCRLT results from increasing the dose level at which interdiction will be initiated. The effects associated with GSHFACN, GWCOEF1 and TGWHLF1 result from their influence on groundshine exposure. The effects associated with VDEPOS, ZSCALE and SCLCRW result from their influence on the proportion of the released material deposited in different concentrations. The positive effect of RWCOEF results from its role in increasing radionuclide resuspension, while the negative effect of DSRFCT2 results from increasing the effectiveness of decontamination. Finally, the positive effects for VALWNF and POPCST result from the direct role that these variables play in determining cost. The regression model with all eleven variables can account for approximately 94% of the observed uncertainty.

As is the case for the analyses with PRCCs in Figure 14, the analyses for mean crop disposal cost and mean milk disposal cost with stepwise regression analysis are also similar. The dominant variables in both regression analyses are the radionuclide ground concentrations at which crop disposal will take place (i.e., PSOI131, PSOSR90 and PSOC134 for crop disposal cost, and PSMCS134, PSMI131 and

Determination of Dominant Variables

Figure 15. Distributions of Mean Value for Area Dependent Cost (\$), Population Cost (\$), Crop Disposal Cost (\$), Total Economic Cost (\$), and Milk Disposal Cost (\$).

Determination of Dominant Variables

Table 8. Stepwise Regression Analyses with Log-Transformed Data for Area Dependent Cost (\$), Population Cost (\$), Crop Disposal Cost (\$), Total Economic Cost (\$), and Milk Disposal Cost (\$)

		Area Dependent Cost (\$)		Population Cost (\$)		Crop Disposal Cost	
Step ^a	Variable ^b	R ^{2c}	Variable	R ²	Variable	R ²	
1	GCMSR90	0.64(-)	DSCRLT	0.44(-)	PSOI131	0.62(-)	
2	VDEPOS	0.76(-)	GSHFACN	0.80(+)	PSOSR90	0.73(-)	
3	ZSCALE	0.84(+)	VDEPOS	0.83(-)	VDEPOS	0.77(-)	
4	QRSR90	0.86(-)	ZSCALE	0.85(+)	ZSCALE	0.80(+)	
5	PSOSR90	0.87(-)	RWCOEF	0.87(+)	PSOCS134	0.82(-)	
6	GCMCS137	0.89(-)	SCLCRW	0.89(+)			
7	DSCRLT	0.90(-)	GWCOEF1	0.90(-)			
8	CWASH1	0.91(-)	VALWNF	0.91(+)			
9			DSRFCT2	0.92(-)			
10			POPCST	0.93(+)			
11			TGWHLF1	0.94(+)			

		Milk Disposal Cost (\$)		Total Economic Cost	
Step	Variable	R ²	Variable	R ²	
1	PSMCS134	0.50(-)	DSCRLT	0.40(-)	
2	VDEPOS	0.77(-)	GSHFACN	0.66(+)	
3	PSMI131	0.86(-)	VDEPOS	0.74(-)	
4	ZSCALE	0.89(+)	ZSCALE	0.81(+)	
5	PSMCS137	0.90(-)	GCMSR90	0.86(-)	
6	CWASH1	0.91(-)	SCLCRW	0.87(+)	
7			RWCOEF	0.89(+)	
8			VALWNF	0.90(+)	
9			SCLEFP	0.91(+)	
10			TGWHLF1	0.91(+)	

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cCumulative R² value with entry of each variable into regression model, with "+" and "-" indicating positive (+) and negative (-) regression coefficients, respectively.

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PSMCS137 for milk disposal cost), with cost tending to decrease as these concentrations increase. The remaining variables selected in the regression analyses (i.e., VDEPOS, ZSCALE, CWASH1) affect the deposition pattern associated with the plume.

As shown in Figure 15, total economic cost is dominated by population cost, with the result that the regression analysis in Table 8 for total economic analysis is similar to the regression analysis for population cost. In particular, the first four variables selected in both analyses are the same. The fifth variable selected in the analysis for total economic cost is GCMSR90 (maximum allowable Sr-90 ground concentration for crop production), the dominant variable in the analysis for area-dependent cost. As examination of Figure 15 shows, area-dependent cost is the largest contributor to total economic cost after population cost. After GCMSR90, the regression analysis for total economic cost selects five additional variables, of which four also appear in the analysis for population cost. The final regression model with ten variables can account for approximately 91 % of the observed uncertainty.

4. EFFECT OF REDUCING UNCERTAINTY IN DOMINANT VARIABLES

After the analyses presented in Section 3 were completed, an additional analysis was performed to determine the effect of reducing the uncertainty in the dominant variables. As summarized in Table 9, all variables that could account for at least 15% of the uncertainty in one of the regression analyses in Section 3 were identified. The MACCS calculations were then repeated with these variables fixed at their best-estimate values in the original Latin hypercube sample.^{57,58}

As comparison of the percentile curves for total long-term dose and total latent cancers in Figures 1 and 16 shows, reduction of the uncertainty in the dominant variables causes a considerable reduction in the uncertainty in the exceedance probabilities for individual consequence values. The CCDFs summarized in Figure 16 can be analyzed with PRCCs as in the analysis presented in Figure 2 for the case in which all variables in Table 1 are treated as being uncertain. The results of this analysis with the variables in Table 9 fixed at their best-estimate values are presented in Figure 17.

As examination of Figure 17 shows, YSCALE and ZSCALE (scale factors for horizontal and vertical dispersion, respectively) are now the dominant variables for both total long-term dose and total latent cancer fatalities. This is not surprising as both YSCALE and ZSCALE were identified as important variables in the original analyses presented in Figure 2. Indeed, YSCALE and ZSCALE were identified in most of the analyses presented in Section 3; however, they never had a sufficiently large effect to account for at least 15% of the uncertainty in the mean value for an individual variable, which means they did not meet the criterion to be held fixed in the analyses presented in this section. For total long-term dose, most variables selected after YSCALE and ZSCALE relate to the spreading and deposition of the plume (CWASH1, SCLCRW, SCLEFP) and the movement of radionuclides into and through the food chain (C1GCS, PSOCS134, WINGSR, PSOSR90). The only exception to this is GWCOEF1, which affects exposure due to groundshine. For total latent cancer fatalities, the most important group of variables selected after YSCALE and ZSCALE relate to cancer induction (DDRGI, DDRLUN, DDROTH, DDRBRE CFRLUN). The remaining variables relate to the spreading and deposition of the plume (CWASH1, SCLEFP, SCLCRW) and the movement of radionuclides into and through the food chain (PSOCS134, C1GCS). In the original analyses presented in Figure 2, VDEPOS (dry deposition velocity) was the dominant variable with respect to both total long-term dose and total latent cancer fatalities.

The individual CCDFs underlying the distributions summarized in Figure 16 can be reduced to mean results. The outcome of this calculation is presented in Figure 18. As comparison of Figures 3 and 18 shows, fixing the variables in Table 9 at their best-estimate values leads to reductions in the uncertainty in the mean values for total long-term dose and total number of latent cancer fatalities, although there is still approximately an order of magnitude uncertainty in these quantities.

Effect of Reducing Uncertainty in Dominant Variables

Table 9. Variables that Account for at Least 15% of the Uncertainty in One or More of the Stepwise Regression Analyses Presented in Section 3^a

Variable	Description	Best-Estimate Value
DSCRLT	Maximum allowable direct exposure dose during long-term action period	0.04 Sv
DSRFCT2	Dose reduction factor associated with aggressive decontamination	15
GCMSR90	Maximum allowable Sr-90 ground concentration for crop production	1.79×10^8 Bq/m ²
GSHFACN	Groundshine shielding factor for nonevacuees	0.33
PSMCS134	Ground concentration of Cs-134 at which disposal of milk products will be initiated	2.18×10^5 Bq/m ²
PSOI131	Ground concentration of I-131 at which disposal of crops will be initiated	7.95×10^6 Bq/m ²
RWCOEF	Scale factor used in definition of resuspension coefficients	0.1
TCLSR90	Ratio of Sr-90 transferred to legumes due to root uptake and resuspension and Sr-90 deposition to soil surface	2.8×10^{-2}
TFBCS	Ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals	2.4×10^{-2}
TFMCS	Ratio of amount of cesium in milk to amount of cesium consumed by milk-producing animals	0.11
VDEPOS	Dry deposition velocity	0.01 m/s
WINGCS	Fraction of cesium entering surface water bodies that is consumed in drinking water	5×10^{-6}

^aAdditional information on these variables is given in Table 1.

Effect of Reducing Uncertainty in Dominant Variables

Figure 16. Mean and Percentile Curves for Total Long-Term Dose (Sv) and Total Latent Cancer Fatalities with Variables in Table 9 Fixed at Best-Estimate Values.

Figure 17. Partial Rank Correlation Coefficients for Exceedance Probabilities Associated with Total Long-Term Dose (Sv) and Total Number of Latent Cancer Fatalities With Variables in Table 9 Fixed at Best-Estimate Values.

Figure 18. Distributions of Mean Value for Total Long-Term Dose (Sv) and Total Number of Latent Cancer Fatalities with Variables in Table 9 Fixed at Best-Estimate Values.

A regression analysis for the mean results summarized in Figure 18 is presented in Table 10. The mean value for both total long-term dose and total latent cancer fatalities is dominated by ZSCALE (scale factor for vertical dispersion). After ZSCALE, both regression analyses select a large number of variables and ultimately produce regression models that can account for most of the observed uncertainty. However, no one variable can account for a very large fraction of this uncertainty. This analysis suggests that after the variables in Table 9 and possibly ZSCALE, the reduction of uncertainty in individual variables will not have a large effect on reducing the total uncertainty associated with estimates for total long-term dose and total latent cancer fatalities.

The analyses presented in Section 3 considered nine variables related to dose. A compact summary of the distributions for mean dose with and without fixed values for the variables in Table 9 is provided by the box plots in Figure 19. As a reminder, the endpoints of the boxes in Figure 19 are formed by the lower and upper quartiles of the data, that is $x_{.25}$ and $x_{.75}$. The vertical line within the box represents the median, $x_{.50}$. The sample mean is identified by the large dot. The bar on the right of the box extends to the minimum of $x_{.75} + 1.5(x_{.75} - x_{.25})$ and the maximum observation. In a similar manner, the bar on the left of the box extends to the maximum of $x_{.25} - 1.5(x_{.75} - x_{.25})$ and the minimum observation. Observations falling outside of these bars are shown with x's. As examination of Figure 19 shows, the use of fixed values for the variables in Table 9 produces substantial reductions in the mean values for the individual doses under consideration, although considerable uncertainty still remains.

Table 10. Stepwise Regression Analyses with Log-Transformed Data for Total Long-Term Population Dose (Sv) and Total Number of Latent Cancer Fatalities with Variables in Table 9 Fixed at Best-Estimate Values

Step ^a	Total Long-Term Population Dose		Total Latent Cancer Fatalities	
	Variable ^b	R ^{2c}	Variable	R ²
1	ZSCALE	0.53(+)	ZSCALE	0.34(+)
2	CWASH1	0.66(-)	DDRGI	0.43(-)
3	YSCALE	0.76(+)	CWASH1	0.52(-)
4	PSOCS134	0.81(+)	CFRLUN	0.58(+)
5	SCLCRW	0.85(+)	DDRBRE	0.64(-)
6	GWCOEF1	0.87(-)	YSCALE	0.69(+)
7	SCLEFP	0.90(+)	DDROTH	0.74(-)
8	C1GCS	0.92(+)	DDRLUN	0.78(-)
9	TCPCS137	0.94(+)	PSOCS134	0.81(+)
10	TGWHLF2	0.94(+)	SCLEFP	0.83(+)
11			DDRLEU	0.86(-)
12			CFRGI	0.87(+)
13			SCLCRW	0.89(+)
14			GWCOEF1	0.91(-)
15			CFROTH	0.93(+)
16			C1GCS	0.94(+)
17			TCPCS137	0.95(+)
18			CFRBRE	0.95(+)

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cCumulative R² value with entry of each variable into regression model, with "+" and "-" indicating positive (+) and negative (-) regression coefficients, respectively.

Effect of Reducing Uncertainty in Dominant Variables

Figure 19. Box Plots for Mean Dose (Sv) Obtained With and Without Variables in Table 9 Fixed at Best-Estimate Values.

Effect of Reducing Uncertainty in Dominant Variables

Of the variables in Figure 19, the regression analyses for total long-term population dose have already been presented and discussed in conjunction with Tables 4 and 10. For the six variables related to ingestion dose, the regression analyses involving all variables are given in Table 5, and the regression analyses with the variables in Table 9 fixed at their best-estimate values are given in Table 11. The top several variables in each of the regression analyses in Table 5 are typically contained in Table 9. As a result, the individual regression analyses in Table 11 tend to start with a variable that made a relatively small contribution to the corresponding regression analysis in Table 5. For all the variables in Table 11, the first two variables selected in the associated regression analysis can account for over 50% of the observed uncertainty, with the amount of the uncertainty that can be accounted for by additional individual variables decreasing rapidly. An interesting pattern occurs in the analyses for milk growing season dose, crop growing-season dose, long-term crop dose and total food pathways dose, with YSCALE (scale factor for horizontal dispersion) being picked as the second variable in the analyses for milk growing-season dose, crop growing-season dose and long-term crop dose and as the first variable in the analysis for total food pathways dose. The total food pathways dose is the sum of the three preceding doses. Thus, although YSCALE is not selected first in the individual analyses for these doses, it is selected first in the analysis for total food pathways because it affects all three doses while the variables selected first (i.e., PSMI131, PSOC134, TCP137) affect only one of the component doses. Due to the small size of the water ingestion doses, the regression analyses for total food pathways dose and total ingestion pathways dose are essentially identical.

For groundshine and resuspension dose, the regression analyses involving all variables are given in Table 6, and the regression analyses with the variables in Table 9 fixed at their best-estimate values are given in Table 12. For groundshine dose, the variable ZSCALE (scale factor for vertical dispersion), which was selected third in the analysis presented in Table 6 and could account for 12% of the observed uncertainty, is now selected first in the analysis presented in Table 12 and can account for 61% of the observed uncertainty. After ZSCALE, the analysis identifies a number of additional variables that make relatively small contributions to the total uncertainty. For resuspension dose, the two dominant variables in Table 12 are PROTINN (inhalation protection factor for nonevacuees) and TRWHLF (scale factor used in definition of resuspension half-life), which can account for 45% and 38%, respectively, of the observed uncertainty. The addition of ZSCALE results in a regression model that can account for 98% of the observed uncertainty in resuspension dose. In the original analysis presented in Table 6, PROTINN, TRWHLF and ZSCALE were the second, fourth and fifth variables selected and could account for 9%, 4%, and 3% respectively, of the observed uncertainty.

Effect of Reducing Uncertainty in Dominant Variables

Table 11. Stepwise Regression Analyses with Log-Transformed Data for Milk Growing-Season Dose (Sv), Crop Growing-Season Dose (Sv), Long-Term Crop Dose (Sv), Total Food Dose (Sv), Water Ingestion Dose (Sv), and Total Ingestion Dose (Sv) with Variables in Table 9 Fixed at Best-Estimate Values

Step ^a	Milk Growing-Season Dose (Sv)		Crop Growing-Season Dose (Sv)	
	Variable ^b	R ^{2c}	Variable	R ²
1	PSMI131	0.45(+)	PSOCS134	0.36(+)
2	YSCALE	0.62(+)	YSCALE	0.59(+)
3	PSMCS137	0.71(+)	CWASH1	0.73(-)
4	CWASH1	0.80(-)	C1GCS	0.83(+)
5	ZSCALE	0.83(+)	ZSCALE	0.90(+)
6	TFMSR	0.85(+)	PSOSR90	0.92(+)
7	TFMI131	0.87(+)	SCLEFP	0.93(+)
8	CWASH2	0.88(-)		

Step	Long-Term Crop Dose (Sv)		Total Food Pathways Dose (Sv)	
	Variable	R ²	Variable	R ²
1	TCPCS137	0.37(+)	YSCALE	0.34(+)
2	YSCALE	0.71(+)	PSOCS134	0.55(+)
3	ZSCALE	0.80(+)	CWASH1	0.69(-)
4	QSR90	0.84(+)	ZSCALE	0.78(+)
5	GCMCS137	0.88(+)	C1GCS	0.85(+)
6	CWASH1	0.91(-)	TCPCS137	0.90(+)
7	SCLCRW	0.93(+)	SCLEFP	0.91(+)
8	FRNFDL2	0.94(+)	SCLCRW	0.92(+)
9	TFWKFI	0.95(-)	PSOSR90	0.92(+)
10	SCLEFP	0.95(+)	CWASH2	0.93(-)
11			FRNFDL20	0.94(+)
12			PSMI131	0.94(+)
13			SCLADP	0.95(+)

Effect of Reducing Uncertainty in Dominant Variables

Table 11 (Concluded)

Step	Water Ingestion Dose (Sv)		Total Ingestion Pathways Dose (Sv)	
	Variable	R ²	Variable	R ²
1	WINGSR	0.65(+)	YSCALE	0.34(+)
2	WSHRTACS	0.77(+)	PSOCS134	0.55(+)
3	WSHRTASR	0.87(+)	CWASH1	0.69(-)
4	WASHFRICS	0.88(+)	ZSCALE	0.78(+)
5	ZSCALE	0.89(-)	C1GCS	0.85(+)
6			TCPSC137	0.90(+)
7			SCLEFP	0.91(+)
8			SCLCRW	0.92(+)
9			PSOSR90	0.92(+)
10			CWASH2	0.93(-)
11			PSMI131	0.94(+)
12			SCLADP	0.94(+)
13			FRNFDL2	0.95(+)

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cCumulative R² value with entry of each variable into regression model, with "+" and "-" indicating positive (+) and negative (-) regression coefficients, respectively.

Effect of Reducing Uncertainty in Dominant Variables

Table 12. Stepwise Regression Analyses with Log-Transformed Data for Groundshine Dose (Sv) and Resuspension Dose (Sv) with Variables in Table 9 Fixed at Best-Estimate Values

Step ^a	Groundshine Dose (Sv)		Resuspension Dose (Sv)	
	Variable ^b	R ^{2c}	Variable	R ²
1	ZSCALE	0.61(+)	PROTINN	0.45(+)
2	GWCOEF1	0.71(-)	TRWHLF	0.83(+)
3	YSCALE	0.78(+)	ZSCALE	0.98(+)
4	SCLCRW	0.84(+)	YSCALE	0.99(+)
5	CWASH1	0.89(-)	CWASH1	0.99(-)
6	TGWHLF2	0.93(+)	SCLCRW	0.99(+)
7	SCLEFP	0.96(+)	SCLEFP	1.00(+)

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cCumulative R² value with entry of each variable into regression model, with "+" and "-" indicating positive (+) and negative (-) regression coefficients, respectively.

The analyses in Section 3 also considered three variables related to area (milk disposal area, crop disposal area and condemnation area) and two variables related to population effects (condemnation population, total number of latent cancer fatalities). A compact summary of the distributions of the mean values for these variables with and without the variables in Table 9 fixed at their best-estimate values is provided by the box plots in Figure 20. As examination of Figure 20 shows, fixing the variables in Table 9 results in a reduction in the uncertainty in the five variables under consideration, although the reductions for milk disposal area and crop disposal are not large.

With the exception of number of latent cancer fatalities, the regression analyses for the variables in Figure 20 are presented in Tables 7 and 13 for the sample from all variables in Table 1 and the sample with the variables in Table 9 fixed, respectively. The regression analyses for number of latent cancer fatalities have already been presented and discussed in conjunction with Tables 4 and 10. The dominant variables in each of the regression analyses in Table 13 were also identified in the corresponding analyses in Table 7, although they were relatively small contributors to the total uncertainty due to the larger effects of the variables in Table 9. For crop disposal area, the dominant variables are PSOCS134 and PSOSR90 (ground concentration of Cs-137 and Sr-90, respectively, at which disposal of crops will be initiated). In the original analysis in Table 7, the dominant variable was PSOI131 (ground concentration of I-131 at which disposal of crops will be initiated), which could account for 62% of the uncertainty; the next variable selected was PSOSR90, which could account for an additional 12% of the uncertainty. The relatively small reduction in the uncertainty in crop disposal area shown in Figure 20 probably results from the assumed correlations between PSOI131, PSOCS134 and PSOSR90 (see Table 1) and the fact that, even if interdiction does not occur due to I-131, it may still occur over a similar area due to Cs-134 or Sr-90. A similar pattern also holds for milk disposal area.

Effect of Reducing Uncertainty in Dominant Variables

Figure 20. Box Plots of Mean Value for Milk Disposal Area (Ha), Crop Disposal Area (Ha), Condemnation Area (Ha), Condemnation Population (Ind) and Total Number of Latent Cancer Fatalities (Ind) Obtained With and Without the Variables in Table 9 Fixed at Their Best-Estimate Values.

Effect of Reducing Uncertainty in Dominant Variables

Table 13. Stepwise Regression Analyses with Log-Transformed Data for Condemnation Area (Ha), Condemnation Population, Crop Disposal Area (Ha), and Milk Disposal Area (Ha) with Variables in Table 9 Fixed at Best-Estimate Values.

Step ^a	Condemnation Area (Ha)		Condemnation Population	
	Variable ^b	R ^{2c}	Variable	R ²
1	QRSR90	0.71(-)	ZSCALE	0.32(-)
2	ZSCALE	0.78(+)	GWCOEF1	0.60(-)
3	GCMCS137	0.82 (-)	SCLEFP	0.66(+)
4			SCLCRW	0.72(+)
5			CWASH1	0.76(+)
6			YSCALE	0.80(-)
7			FRNFIM	0.83(+)
8			DSRATE	0.86(+)
9			VALWNF	0.88(-)
10			CDNFRM2	0.90(+)
11			TGWHLF2	0.92(+)

Step	Crop Disposal Area (Ha)		Milk Disposal Area (Ha)	
	Variable	R ²	Variable	R ²
1	PSOCS134	0.67(-)	PSMI131	0.63(-)
2	PSOSR90	0.82(-)	PSMCS137	0.77(-)
3	ZSCALE	0.91(+)	YSCALE	0.86(+)
4	SCLCRW	0.92(+)	ZSCALE	0.89(+)
5	SCLEFP	0.93(+)	CWASH1	0.92(-)
6	YSCALE	0.94(+)	SCLEFP	0.92(+)

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cCumulative R² value with entry of each variable into regression model, with "+" and "-" indicating positive (+) and negative (-) regression coefficients, respectively.

Effect of Reducing Uncertainty in Dominant Variables

Finally, the analyses in Section 3 considered five variables related to cost. Box plots for the mean values of these costs with and without the variables in Table 9 fixed at their best estimate values are given in Figure 21. As examination of Figure 21 shows, fixing the values for the variables in Table 9 results in substantial reductions in the uncertainty associated with population cost, area dependent cost and total economic cost, and relatively small reductions in crop disposal cost and milk disposal cost. As comparison of Tables 7 and 8 and also Tables 13 and 14 shows, economic cost is driven to a great extent by the same variables that affect the corresponding areas and population. Thus, the relatively small reductions in crop and milk disposal costs shown in Figure 21 are consistent with the corresponding patterns shown in Figure 20 for crop and milk disposal areas. The dominant variables in each of the regression analyses in Table 14 were also identified in the corresponding analyses in Table 8, although their effects tended to be small.

Figure 21. Box Plots for Mean Economic Cost (\$) Obtained with and without the Variables in Table 9 Fixed at Their Best-Estimate Values.

Effect of Reducing Uncertainty in Dominant Variables

Table 14. Stepwise Regression Analyses with Log-Transformed Data for Area Dependent Cost (\$), Population Cost (\$), Crop Disposal Cost (\$), Milk Disposal Cost (\$), and Total Economic Cost (\$) with Variables in Table 9 Fixed at Best-Estimate Values

	Area Dependent Cost (\$)		Population Cost (\$)		Total Economic Cost (\$)	
Step ^a	Variable ^b	R ^{2c}	Variable	R ²	Variable	R ²
1	ZSCALE	0.48(+)	ZSCALE	0.21(+)	ZSCALE	0.30(+)
2	QRSR90	0.67(-)	GWCOEF1	0.37(-)	GWCOEF1	0.43(-)
3	GCMCS137	0.82(-)	SCLCRW	0.50(+)	SCLCRW	0.55(+)
4	PSOSR90	0.85(-)	TGWHLF1	0.61(+)	TGWHLF1	0.65(+)
5	SCLCRW	0.87(+)	VALWNF	0.71(+)	VALWNF	0.72(+)
6	CWASH1	0.89(-)	SCLEFP	0.76(+)	SCLEFP	0.77(+)
7	VALWF	0.91(+)	POPCST	0.81(+)	POPCST	0.81(+)
8	YSCALE	0.92(+)	FRNFIM	0.83(+)	FRNFIM	0.83(+)
9	PSOCS134	0.93(-)	DPRATE	0.85(+)	DSRATE	0.85(+)
10	SCLCRW	0.94(+)	DSRATE	0.86(+)	DPRATE	0.86(+)
11	DSRATE	0.95(+)	TRWHLF	0.87(+)	QRSR90	0.87(-)
12			CDNFRM2	0.88(+)	TRWHLF	0.88(+)
13					PSOCS134	0.89(-)
14					CDNFRM2	0.90(+)

	Crop Disposal Cost (\$)		Milk Disposal Cost (\$)		
Step	Variable	R ²	Variable	R ²	
1	PSOCS134	0.66(-)	PSMI131	0.65(-)	
2	PSOSR90	0.81(-)	PSMCS137	0.78(-)	
3	ZSCALE	0.91(+)	ZSCALE	0.87(+)	
4	SCLCRW	0.93(+)	CWASH1	0.90(-)	
5	SCLEFP	0.94(+)	YSCALE	0.91(+)	
6			SCLEFP	0.92(+)	

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in regression analysis.

^cCumulative R² value with entry of each variable into regression model, with "+" and "-" indicating positive (+) and negative (-) regression coefficients, respectively.

5. SUMMARY

The analysis described in this report is the third in a sequence of uncertainty/sensitivity studies performed with the MACCS reactor accident consequence model²⁻⁴ to provide guidance to a joint CEC/NRC study¹ to assess the uncertainty in the dominant input variables used in models to estimate the off-site consequences that could result from severe accidents at nuclear power stations. The two preceding analyses considered results associated with early exposure⁵ and food ingestion.⁶ The present analysis considers results associated with chronic exposure.

A total of 75 imprecisely known variables used in MACCS in the estimation of chronic exposure results are considered in this study. As many of the submodels used in MACCS to estimate chronic exposure results are also used in the estimation of early exposure and food pathway results, the sensitivity analyses in the first two studies^{5,6} helped provide guidance on the input variables selected for consideration in the present uncertainty/sensitivity study for chronic exposure. In particular, 28 relevant variables that were identified as being important in the first two analyses are included in the present study; in addition, a further 47 variables that affect chronic exposure results but were not considered in the first two analyses are also included.

Four groups of predicted variables were selected for study: population dose (crop growing season dose, crop long-term dose, milk growing season dose, long-term groundshine dose, long-term inhalation dose, total food pathways dose, total ingestion pathways dose, total long-term pathways dose, water ingestion dose), impacted area (condemnation area, condemnation population, crop disposal area, milk disposal area), economic cost (area-dependent cost, crop disposal cost, milk disposal cost, population dependent cost, total economic cost), and total latent cancer fatalities. Most of the preceding variables were also considered in the food pathways analysis;⁶ however, that analysis only considered variables used within the food pathways model, with all other variables being held fixed at best-estimate values.²⁶

Uncertainty/sensitivity analysis techniques based on Latin hypercube sampling, partial correlation analysis and stepwise regression analysis were used to determine the effect of the imprecisely known variables on MACCS predictions. In performing this analysis, care was taken to maintain a distinction between stochastic uncertainty, which enters the analysis through the probability for different types of weather at the time of occurrence of a reactor accident, and subjective uncertainty, which enters the analysis because of a lack of knowledge about variables supplied as input to MACCS. In particular, the distributions assigned to the variables under consideration characterize subjective uncertainty.

Six ingestion doses were considered in this analysis: milk growing season dose, crop growing season dose, crop long-term dose, total food dose, water ingestion dose, and total ingestion pathway dose. The following ordering of dose magnitude appears in the analysis: water ingestion dose < milk growing season dose < crop long-term dose < crop growing season. Owing to the small size of the water ingestion dose, the total food pathways dose and total ingestion pathways dose are approximately equal. The uncertainty in each dose is dominated by 2 or 3 variables, with a large number of additional variables making small contributions to the uncertainty; this pattern is repeated for all 19 predicted variables considered in this study. The dominant variables for milk growing season dose and crop growing season dose are transferred from animal feed to animal product (i.e., TFMCS for milk growing season dose and TFBCS for crop growing season dose), dry deposition velocity (VDEPOS), and radionuclide ground concentration at which the disposal of agricultural products will be initiated (i.e., PSMCS134 for milk growing season dose and PSOI131 for crop growing season dose). For crop long-term dose, the

Summary

dominant variables are dry deposition velocity (VDEPOS), the ratio of Sr-90 transferred to legumes through root uptake and resuspension and Sr-90 deposition to soil surface (TCLSR90) and maximum allowable Sr-90 ground concentration for production of crops (GCMSR90). The dominant variables for total food pathways dose, which is the sum of the milk growing season, crop growing season and crop long-term doses, are dry deposition velocity (VDEPOS) and ratio of amount of cesium in meat at time of slaughter to amount of cesium consumed by meat-producing animals (TFBCS). Owing to the small size of the water ingestion dose, the total ingestion pathways dose is also dominated by VDEPOS and TFBCS. The water ingestion dose itself is dominated by the fractions of cesium and strontium entering surface water bodies that are consumed in drinking water (WINGCS, WINGSR).

Two noningestion doses were considered: long-term groundshine dose and long-term resuspension dose. The groundshine dose is the larger of these two doses and is approximately equal to the total food pathways dose. The dominant variables for groundshine dose are dry deposition velocity (VDEPOS), groundshine shielding factor for nonevacuees (GSHFACN) and scale factor for horizontal dispersion (ZSCALE). For the resuspension dose, the dominant variables are scale factor used in definition of resuspension coefficients (RWCOEF), inhalation protection factor for nonevacuees (PROTINN) and dry deposition velocity (VDEPOS). The variable TWCOEF is used in the definition of short-, intermediate- and long-term resuspension concentrations (see Table 1).

Total long-term population dose, which is the sum of the eight previously discussed doses, is dominated by dry deposition velocity (VDEPOS). Further, many additional variables make small contributions to the uncertainty in total dose. As previously indicated, long-term groundshine dose and total food pathways dose make approximately equal contributions to the total dose. Total latent cancer fatalities is closely related to total long-term population dose and is dominated by dry deposition velocity (VDEPOS). In addition to variables also identified in the sensitivity analysis for total dose, the sensitivity analysis for total latent cancer fatalities also identifies a number of variables related to the cancer induction model. However, none of these variables makes a large contribution to the total uncertainty in number of latent cancer fatalities.

Of the four variables associated with impacted area, three are areas and one is a population. Condemnation area, which is the area within which farmland condemnation is required, is dominated by maximum allowable Sr-90 ground concentration for crop production (GCMSR90) and rate of depletion of Sr-90 from root zone (QRSR90). Further, crop disposal area and milk disposal area are dominated by variables that define interdiction levels (i.e., PSOI131, PSOSR90 for crop disposal and PSMCS134, PSMI131 for milk disposal) and dry deposition velocity (VDEPOS). Finally, condemnation population, which is the number of individuals living on land that is permanently condemned for human habitation, is dominated by maximum allowable direct exposure dose during long-term action period (DSCRLT), dose reduction associated with aggressive decontamination (DSRFCT2) and groundshine shielding factor for nonevacuees (GSHFACN).

Five variables related to cost were considered. The analyses for crop disposal cost and milk disposal cost were similar, with these costs dominated by variables that define interdiction levels (i.e., PSOI131, PSOSR90 for crop disposal cost and PSMCS134, PSMI131 for milk disposal cost) and dry deposition velocity (VDEPOS). Crop disposal cost tended to be slightly larger than milk disposal cost. Area dependent cost is the sum of all costs related to agricultural production and is thus the sum of costs due crop disposal, milk disposal, decontamination, interdiction and condemnation. The dominant

variables with respect to area-dependent cost are maximum allowable Sr-90 ground concentration for crop production (GCMSR90) and dry deposition velocity (VDEPOS). Population cost is the sum of all costs related to avoiding direct exposure to humans and, in particular, is the sum of costs incurred by decontamination, interdiction, and condemnation. The dominant variables with respect to population cost are maximum allowable direct exposure dose during a long-term action period (DSCRLT) and groundshine shielding factor for nonevacuees (GSHFACN). Population cost tended to be somewhat larger than area-dependent cost. Finally, total economic cost is the sum of the area-dependent and population costs and is dominated by DSCRLT and GSHFACN, with a smaller effect caused by VDEPOS.

After the dominant variables were determined, a second uncertainty/sensitivity analysis was performed to determine if reducing the uncertainty in these dominant variables would also reduce the uncertainty in the predicted variables under consideration. In particular, the dominant variables from the first analysis were set to their best-estimate values, and then the uncertainty-sensitivity analysis was repeated with the remaining variables assigned the same distributions as used in the first analysis. The result was a substantial reduction in the uncertainty in the predicted variables. Further, the associated sensitivity analysis identified a new set of dominant variables conditional on the original set of dominant variables taking on their best-estimate values.

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NUREG/CR-6134
SAND93-2370

2. TITLE AND SUBTITLE

Uncertainty and Sensitivity Analysis of Chronic Exposure
Results with the MACCS Reactor Accident Consequence
Model

3. DATE REPORT PUBLISHED

MONTH

YEAR

January

1995

4. FIN OR GRANT NUMBER

L2294

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6. TYPE OF REPORT

Technical

7. PERIOD COVERED (Inclusive Dates)

8. PERFORMING ORGANIZATION - NAME AND ADDRESS (If NRC, provide Division, Office or Region, U.S. Nuclear Regulatory Commission, and mailing address; if contractor, provide name and mailing address.)

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10. SUPPLEMENTARY NOTES

11. ABSTRACT (200 words or less)

Uncertainty and sensitivity analysis techniques based on Latin hypercube sampling, partial correlation analysis and stepwise regression analysis are used in an investigation with the MACCS model of the chronic exposure pathways associated with a severe accident at a nuclear power station. The primary purpose of this study is to provide guidance on the variables to be considered in future review work to reduce the uncertainty in the important variables used in the calculation of reactor accident consequences. The effects of 75 imprecisely known input variables on the following reactor accident consequences are studied: crop growing season dose, crop long-term dose, water ingestion dose, milk growing season dose, long-term groundshine dose, long-term inhalation dose, total food pathways dose, total ingestion pathways dose, total long-term pathways dose, total latent cancer fatalities, area-dependent cost, crop disposal cost, milk disposal cost, population-dependent cost, total economic cost, condemnation area, condemnation population, crop disposal area and milk disposal area.

12. KEY WORDS/DESCRIPTORS (List words or phrases that will assist researchers in locating the report.)

Latent cancer fatalities, Environmental radionuclide movement,
Latin hypercube sampling, MACCS, Monte Carlo analysis, Radiation
exposure, Reactor accident consequence analysis, Sensitivity
analysis, Uncertainty analysis

13. AVAILABILITY STATEMENT

Unlimited

14. SECURITY CLASSIFICATION

(This Page)

Unclassified

(This Report)

Unclassified

15. NUMBER OF PAGES

16. PRICE