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

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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 early health effects 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 34 imprecisely known input variables on the following reactor accident consequences are studied: number of early fatalities, number of cases of prodromal vomiting, population dose within 10 mi of the reactor, population dose within 1000 mi of the reactor, individual early fatality probability within 1 mi of the reactor, and maximum early fatality distance. When the predicted variables are considered collectively, the following input variables were found to be the dominant contributors to uncertainty: scaling factor for horizontal dispersion, dry deposition velocity, inhalation protection factor for nonevacuees, groundshine shielding factor for nonevacuees, early fatality hazard function alpha value for bone marrow exposure, and scaling factor for vertical dispersion. The following results were obtained in tests to check the robustness of the analysis techniques that produced the preceding set of variables: two independent Latin hypercube samples produced similar uncertainty and sensitivity analysis results; setting important variables to best-estimate values produced substantial reductions in uncertainty, while setting the less important variables to best-estimate values had little effect on uncertainty; similar sensitivity analysis results were obtained when the original uniform and loguniform distributions assigned to the 34 imprecisely known input variables were changed to left-triangular distributions and then to right-triangular distributions; and analyses with rank-transformed and logarithmically transformed data produced similar results and substantially outperformed analyses with raw (i.e., untransformed) data.

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1. INTRODUCTION

The U.S. Nuclear Regulatory Commission (NRC) has recently completed an assessment of the risks from five commercial nuclear power plants (NUREG-1150) in the United States:¹ Surry,²⁻⁵ Peach Bottom,⁶⁻⁹ Sequoyah,¹⁰⁻¹² Grand Gulf,¹³⁻¹⁵ and Zion.^{16,17} In response to a criticism of the Reactor Safety Study,^{18,19} the NUREG-1150 analysis project made an extensive effort to incorporate and present the effects of uncertainty in the analyses performed for these plants. The NUREG-1150 probabilistic risk assessments consisted of four analysis components: systems analysis, accident progression analysis, source term analysis and consequence analysis.²⁰⁻²³ The effect of uncertainties on the first three analysis components was assessed and incorporated into the final risk results. This assessment made extensive use of expert review^{24,25} and is documented in a sequence of reports.²⁶⁻³²

The NUREG-1150 probabilistic risk assessments used the MACCS computer model³³⁻³⁵ to calculate the off-site consequences of reactor accidents. Although a tentative attempt to assess the uncertainties in the input required by MACCS was made,³⁶ these uncertainties were not incorporated into the NUREG-1150 analyses. This has led to questions involving the extent to which the results obtained in NUREG-1150 might be altered by the incorporation of the uncertainty associated with consequence modeling.³⁷⁻³⁹ However, considerable interest in the United States in uncertainty in consequence modeling predates the NUREG-1150 analyses.⁴⁰⁻⁴⁴ There has long been a similar interest in Europe. For example, both England⁴⁵⁻⁴⁷ and Germany⁴⁸⁻⁵⁴ have had active programs in this area. Much of this European effort has centered on the MARC⁵⁵ and UFOMOD^{56,57} models for assessing the consequences of reactor accidents. In turn, MARC and UFOMOD are the precursors of the new European model for reactor accident consequences, COSYMA.^{58,59}

This extensive interest in assessing the uncertainties in predictions made by reactor accident consequence models has led to a joint project involving the Commission of European Communities (CEC) and the NRC which has the following objectives: (1) to formulate a generic, state-of-the-art methodology for uncertainty estimation that will find broad acceptance, (2) to use the methodology to estimate the uncertainties associated with the predictions of reactor accident consequence models, and (3) to better quantify and obtain more valid estimates of the uncertainties associated with reactor accident consequence models, thus enabling more informed and better judgments to be made in the areas of risk comparison and acceptability.⁶⁰

An important part of this project will be the use of an expert review process to assess the uncertainties in variables used as input to reactor accident consequence models. Such reviews involve the participation of many individuals, require extensive organization, and as a result, are expensive.^{24,25,61} For the preceding reasons, the number of variables that can be subjected to a formal expert review process is limited and is certainly substantially less than the several hundred variables that comprise the complete input to a reactor accident consequence model. As a result, the variables selected for a formal review must be carefully chosen so that limited resources (i.e., time, people, money) can be directed at the largest contributions to the uncertainty in the predictions made by a reactor accident consequence model.

In preparation for its participation in this project, the NRC is supporting a sequence of uncertainty/sensitivity studies with the MACCS reactor accident consequence model (Version 1.5.11.1) to identify the input variables that have the greatest impact on uncertainty in predicted consequences. These variables will then be candidates for formal review in the joint CEC/NRC project. This report describes an uncertainty/sensitivity study conducted for early exposure results (i.e., for fatalities, injuries, and doses caused by radiation exposure incurred within 7 days of a reactor accident) performed for the NRC with the MACCS model as part of this preparation.

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2. TREATMENT OF UNCERTAINTY

An uncertainty/sensitivity study for a reactor accident consequence model such as MACCS actually involves two types of uncertainty: stochastic uncertainty and subjective uncertainty. Stochastic uncertainty results when 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). Subjective uncertainty 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. The importance of maintaining a distinction between these two types of uncertainty has been emphasized by several authors.⁶²⁻⁶⁸

The ordered triple representation for risk proposed by Kaplan and Garrick⁶⁸ provides a useful conceptual model for maintaining this distinction. In this representation, risk is expressed as a set **R** of ordered triples of the form

$$\mathbf{R} = \{ (S_i, pS_i, cS_i) \mid i = 1, 2, \dots, nS \}, \quad (1)$$

where

S_i = a set of similar occurrences (i.e., a scenario),
 pS_i = probability (or frequency, as appropriate) for S_i ,
 cS_i = vector of consequences associated with S_i ,
 nS = number of sets selected for consideration,

and the sets S_i have no occurrences in common (i.e., the S_i are disjoint). This representation formally decomposes risk into what can happen (the S_i), how likely things are to happen (the pS_i), and the consequences of what can happen (the cS_i).

Unless nS is small, the set **R** is difficult to examine. As a result, the information contained in the pS_i and cS_i is usually summarized as complementary cumulative distribution functions (CCDFs). With the assumption that a particular consequence result cS in the vector cS has been ordered so $cS_i \leq cS_{i+1}$ for $i = 1, 2, \dots, nS-1$, the associated CCDF is defined as shown in Figure 1 and presents the probability of exceeding individual consequence values. Thus, a CCDF answers the question "How likely is it to be this bad or worse?" Technically, a CCDF of the form shown in Figure 1 displays the probability of exceeding a quantity rather than the probability of equaling or exceeding a quantity. However, in the limit as the vertical and horizontal stepsizes go to zero, a CCDF does indeed answer the indicated question.

The sets S_i and their associated probabilities pS_i in Eq. (1) are summarizing stochastic uncertainty. In a properly constructed analysis, the set $\cup_i S_i$ should contain all possible occurrences of interest. For an analysis with a reactor accident consequence model such as MACCS, $\cup_i S_i$ might contain all possible weather sequences that could be associated with a reactor accident at the particular site under consideration. If the information needed to determine the S_i , pS_i , and cS_i appearing in Eq. (1) were known with complete certainty, there would be no subjective uncertainty and the expression in Eq. (1) would provide a complete representation for the possible states of the system under consideration (subject, of course, to the inevitable aggregation error that results when an infinite number of possible conditions must be divided into a finite number of sets $S_1, S_2, \dots, S_{nS}$).

Figure 1. Estimated CCDF for Consequence Result cS (Ref. 71, Figure VI-1).

Subjective uncertainty enters when the computational reality of evaluating the risk representation in Eq. (1) must be addressed. In practice, evaluation of the expression in Eq. (1) requires extensive computation and, in turn, this computation requires many inputs. If these inputs are represented by a vector

$$\mathbf{x} = [x_1, x_2, \dots, x_{nV}], \quad (2)$$

where nV is the number of such inputs, the representation in Eq. (1) becomes

$$\mathbf{R}(\mathbf{x}) = \{[S_i(\mathbf{x}), pS_i(\mathbf{x}), cS_i(\mathbf{x})], i = 1, 2, \dots, nS(\mathbf{x})\}. \quad (3)$$

If the vector $\mathbf{x}$ was known with complete certainty, then the expression in Eq. (3) could be evaluated and presented as the unambiguous outcome of the analysis. However, $\mathbf{x}$ is not known with certainty in most analyses.

The uncertainty in $\mathbf{x}$ is characterized by developing a distribution

$$D_j, j = 1, 2, \dots, nV, \quad (4)$$

for each variable x_j in $\mathbf{x}$. These distributions describe a degree of belief as to where the appropriate value for x_j is located given that the analysis has been structured so that only a single value of each variable x_j is required in the determination of the set $\mathbf{R}(\mathbf{x})$. Correlations and other restrictions between the x_j are also possible, which is equivalent to the specification of a joint probability distribution for the variables contained in $\mathbf{x}$. The distributions developed for the x_j are characterizing subjective uncertainty as they indicate the possible locations of fixed, but unknown, quantities.

Uncertainty in $\mathbf{x}$ results in uncertainty in the set $\mathbf{R}(\mathbf{x})$ shown in Eq. (3). Ultimately, this leads to a distribution of CCDFs for each consequence result of interest as illustrated in Figure 2 rather than a single CCDF as shown in Figure 1. In a suitably designed analysis, the individual CCDFs in Figure 2 show the effects of stochastic uncertainty, and the distribution of CCDFs shows the effects of subjective uncertainty.

The analyses contained in this presentation attempt to maintain a separation between stochastic and subjective uncertainty. As discussed in Section 3, stochastic uncertainty enters into the analysis through the different weather conditions that could exist at the time of an accident. The risk representation shown in Eq. (1) is actually implemented within MACCS. There, logic based on a simple event tree is used to divide all possible 5-day weather sequences that could occur over the course of one year into the sets S_i and to determine the probabilities pS_i for these sets. Then, a vector of consequences cS_i is calculated for each set S_i . The analysis results for the individual consequence measures contained in cS can be summarized with CCDFs of the form shown in Figure 1. Conceptually, this is equivalent to the development and implementation of an importance-sampling procedure (i.e., experimental design) to ensure the inclusion of different types of weather in the calculation [Ref. 69, Section 5.4]. In this and other similar analyses, importance sampling is often used to ensure the inclusion of low-probability, high-consequence conditions.

Figure 2. Example of Distribution of CCDFs as a Result of Subjective Uncertainty. Each CCDF shown in this figure results from one of the sets $R(x_i)$ shown in Eq. (3).

Subjective uncertainty enters into the analysis through the uncertainty in the appropriate values for various inputs required by MACCS. As discussed in Section 4, distributions were developed for a number of the input variables required by MACCS. These distributions characterize subjective uncertainty. As already discussed and illustrated in Figure 2, the uncertainty characterized by these distributions will ultimately lead to distributions of CCDFs. The development of distributions of CCDFs of the form shown in Figure 2 will also require a sampling procedure. However, unlike the importance-sampling procedure used for coverage of stochastic uncertainty, a random or Monte Carlo sampling procedure will be used. More specifically, Latin hypercube sampling⁷⁰ will be used because of the efficient manner in which it stratifies across the range of each imprecisely known variable.

The investigation of the effects of subjective uncertainty will proceed with the selection of a Latin hypercube sample

$$x_k = [x_{1k}, x_{2k}, \dots, x_{nV,k}], \quad k = 1, 2, \dots, nLHS, \quad (5)$$

according to the distributions characterizing the subjective uncertainty in the individual elements x_j of x , where $nLHS$ is the sample size. In turn, this will produce the risk results

$$R(x_k) = \{[S_i, pS_i, cS_i(x_k)], \quad i = 1, 2, \dots, nS\}, \quad (6)$$

for $k = 1, 2, \dots, nLHS$, and hence, distributions of CCDFs of the form shown in Figure 2, with a single CCDF resulting for each sample element. Although the general representation for $R(x)$ in Eq. (3) shows S_i , pS_i , cS_i and nS as all being functions of x , in this particular study only cS_i will be a function of x .

The primary purpose of the analyses contained in this presentation is to assess the impact of subjective uncertainty in individual variables on predictions made by the MACCS model. This assessment will be made by using techniques based on regression analysis and partial correlation analysis^{71,72} to determine which variables dominate the uncertainty in the MACCS outcomes $R(x_k)$ shown in Eq. (6) and associated CCDFs of the form shown in Figure 2.

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3. OVERVIEW OF MACCS^a

The MACCS program³³⁻³⁵ estimates the following quantities for a severe reactor accident that releases a plume of radioactive materials to the atmosphere: (1) the downwind transport, dispersion, and deposition of the radioactive materials released to the atmosphere from the failed reactor containment; (2) the short- and long-term radiation doses received by exposed populations via direct (cloudshine, plume inhalation, groundshine and resuspension inhalation) and indirect (ingestion) pathways; (3) the mitigation of those doses by protective actions (evacuation, sheltering, and postaccident relocation of people; disposal of milk, meat, and crops; and decontamination, temporary interdiction or condemnation of land and buildings); (4) the early fatalities and injuries expected to occur within 1 year of the accident (early health effects) and the delayed cancer fatalities and injuries (latent health effects) expected to occur over the lifetime of the exposed individuals; and (5) the off-site costs of short-term emergency response actions (evacuation, sheltering, relocation); crop and milk disposal, and the decontamination, temporary interdiction, or condemnation of land and buildings.

To calculate the preceding quantities, MACCS requires the following information as input: (1) the inventory at accident initiation (e.g., reactor scram) of the radionuclides important for the calculation of ex-plant consequences; (2) the atmospheric source term produced by the accident (number of plume segments, sensible heat content, timing, duration and height of each plume segment, time at which off-site officials are warned that an emergency response should be initiated; and for each important radionuclide, the fraction of that radionuclide's inventory released with each plume segment); (3) meteorological data characteristic of the site region (usually 1 year of hourly wind speed, atmospheric stability and rainfall data recorded at the site or at a nearby National Weather Service station); (4) the population distribution around the reactor site (distributions are constructed from census data on a polar coordinate grid having 16 angular sectors aligned with the 16 compass directions and a number of radial intervals that extend outward to 500 miles or more); (5) emergency response assumptions for evacuation (delay time before evacuation, area evacuated, average evacuation speed and travel distance), sheltering (delay time before sheltering and area in which people take shelter), and postaccident relocation (dose criteria and relocation time), (6) long-term protective measures, such as decontamination, temporary relocation, condemnation of contaminated crops and milk, and prohibition of farming; and (7) land use (habitable land fractions, farmland fractions) and economic data (worth of crops, land, and buildings) for the region around the reactor site.

The models in MACCS are implemented in three modules: ATMOS, EARLY, and CHRONC. The ATMOS module models the atmospheric dispersion and transport of material and its deposition onto the ground. The EARLY module provides direct exposure pathways, dosimetry, mitigative actions, and health effects during the emergency phase of an accident. The CHRONC module models direct and indirect exposure pathways, dosimetry, mitigative actions, and health effects during the period that follows the emergency phase: the intermediate and long-term phases of an accident. The CHRONC module also models the economic costs associated with mitigative actions performed during the emergency, intermediate, and long-term phases. The uncertainty/sensitivity results given in this presentation involve early exposure and thus were calculated with the ATMOS and EARLY modules of MACCS.

^aThe material presented in this section is adapted in part from Sections 1.2 and 1.3 of Ref. 34.

3.1 Treatment of Stochastic Uncertainty

As indicated in Section 2, MACCS explicitly incorporates the stochastic uncertainty present in reactor accident consequences that derives from weather variability. For notational convenience, let S denote the set

$$S = \{x: x \text{ a weather sequence that could occur at the site of the nuclear power plant under consideration}\}, \quad (7)$$

where a weather sequence is a possible sequence of meteorological conditions, including time of occurrence, that contains all the information needed to calculate a reactor accident consequence. The set S is infinite. Thus, S must be broken into a finite collection of subsets to facilitate the actual performance of consequence calculations.

As indicated in Figure 3, the division of S into subsets by MACCS, and also by its precursor CRAC2,⁷³ is based on type of weather (i.e., weather bin), wind direction and time of year (i.e., time interval). In general, nWB weather bins, nWD wind directions and nTI time intervals are possible. Both the NUREG-1150 analyses and the analyses contained in this presentation use the $nWB = 40$ weather bins listed in Table 1. Each weather bin WB_j , $j = 1, 2, \dots, 40$, defined in Table 1 is a subset of S , and the weather bins collectively are all inclusive in the sense that

$$S = \cup_j WB_j. \quad (8)$$

In turn, each weather bin WB_j is further subdivided on the basis of wind direction and time interval. Wind direction and time of year are handled in MACCS by the use of $nWD = 16$ wind directions of equal angular spacing (i.e., 22.5°) and nTI_j time intervals $[t_{j,l-1}, t_{j,l}]$, $l = 1, 2, \dots, nTI_j$, of equal probability for each weather bin WB_j . The time intervals $[t_{j,l-1}, t_{j,l}]$ are defined by the relationship

$$\text{prob}(t_{j,l-1} \leq t_x < t_{j,l} | x \in WB_j) = 1/nTI_j, \quad (9)$$

where

$$t_x = \text{time (measured from beginning of year) at which weather sequence } x \text{ starts.} \quad (10)$$

The number of wind directions (i.e., nWD) is fixed in MACCS at 16. The NUREG-1150 analyses and the analyses contained in this report used $nTI_j = 4$ for most weather bins.

The following subsets of S can now be defined:

$$WD_k = \{x: x \in S \text{ and the wind at the start of the sequence (i.e., at time } t_x) \text{ blows in direction } k\} \quad (11)$$

and

$$TI_l = \{x: x \in S \text{ and the start of the sequence (i.e., at time } t_x) \text{ is contained in the time interval } [t_{j,l-1}, t_{j,l}]\}. \quad (12)$$

Figure 3. Construction of Scenarios for Consequence Calculations.

Table 1. Weather Bin Descriptions

BIN	DESCRIPTION OF WEATHER SEQUENCES IN BIN
1	Rainfall: None. ^a Initial stability class: A or B. Initial windspeed: [0, 3 m/s].
2	Rainfall: None. Initial stability class: A or B. Initial windspeed: (3, ∞ m/s).
3	Rainfall: None. Initial stability class: C or D. Initial windspeed: [0, 1 m/s].
4	Rainfall: None. Initial stability class: C or D. Initial windspeed: (1, 2 m/s].
5	Rainfall: None. Initial stability class: C or D. Initial windspeed: (2, 3 m/s].
6	Rainfall: None. Initial stability class: C or D. Initial windspeed: (3, 5 m/s].
7	Rainfall: None. Initial stability class: C or D. Initial windspeed: (5, 7 m/s].
8	Rainfall: None. Initial stability class: C or D. Initial windspeed: (7, ∞ m/s).
9	Rainfall: None. Initial stability class: E. Initial windspeed: [0, 1 m/s].
10	Rainfall: None. Initial stability class: E. Initial windspeed: (1, 2 m/s].
11	Rainfall: None. Initial stability class: E. Initial windspeed: (2, 3 m/s].
12	Rainfall: None. Initial stability class: E. Initial windspeed: (3, ∞ m/s).
13	Rainfall: None. Initial stability class: F. Initial windspeed: [0, 1 m/s].
14	Rainfall: None. Initial stability class: F. Initial windspeed: (1, 2 m/s].
15	Rainfall: None. Initial stability class: F. Initial windspeed: (2, 3 m/s].
16	Rainfall: None. Initial stability class: F. Initial windspeed: (3, ∞ m/s).
17	Rainfall: [0, 3 km]. ^b Rainfall intensity: (0, 1 mm/h]. ^c
18	Rainfall: (3, 6 km]. Rainfall intensity: (0, 1 mm/h].
19	Rainfall: (6, 11 km]. Rainfall intensity: (0, 1 mm/h].
20	Rainfall: (11, 21 km]. Rainfall intensity: (0, 1 mm/h].
21	Rainfall: [21, 40 km]. Rainfall intensity: (0, 1 mm/h].
22	Rainfall: (40, 80 km]. Rainfall intensity: (0, 1 mm/h].
23	Rainfall: (0, 3 km]. Rainfall intensity: (1, 2 mm/h].
24	Rainfall: (3, 6 km]. Rainfall intensity: (1, 2 mm/h].
25	Rainfall: (6, 11 km]. Rainfall intensity: (1, 2 mm/h].
26	Rainfall: (11, 21 km]. Rainfall intensity: (1, 2 mm/h].
27	Rainfall: (21, 40 km]. Rainfall intensity: (1, 2 mm/h].
28	Rainfall: (40, 80 km]. Rainfall intensity: (1, 2 mm/h].
29	Rainfall: [0, 3 km]. Rainfall intensity: (2, 3 mm/h].
30	Rainfall: (3, 6 km]. Rainfall intensity: (2, 3 mm/h].
31	Rainfall: (6, 11 km]. Rainfall intensity: (2, 3 mm/h].
32	Rainfall: (11, 21 km]. Rainfall intensity: (2, 3 mm/h].
33	Rainfall: (21, 40 km]. Rainfall intensity: (2, 3 mm/h].
34	Rainfall: (40, 80 km]. Rainfall intensity: (2, 3 mm/h].
35	Rainfall: (0, 3 km]. Rainfall intensity: (3, ∞ mm/h).
36	Rainfall: [3, 6 km]. Rainfall intensity: (3, ∞ mm/h).
37	Rainfall: (6, 11 km]. Rainfall intensity: (3, ∞ mm/h).
38	Rainfall: (11, 21 km]. Rainfall intensity: (3, ∞ mm/h).
39	Rainfall: (21, 40 km]. Rainfall intensity: (3, ∞ mm/h).
40	Rainfall: (40, 80 km]. Rainfall intensity: (3, ∞ mm/h).

^aWhile leading edge of plume is within 80 km of reactor.^bDistance interval measured from reactor in which leading edge of plume first encounters rainfall.^cIntensity of rainfall first encountered by leading edge of plume.

Memberships in these sets are the basis for the last two questions on the event tree in Figure 3. A single path through the tree in Figure 3 defines a set S_i of the form

$$S_i = \mathbf{WB}_j \cap \mathbf{WD}_k \cap \mathbf{TI}_j. \quad (13)$$

For $nWB = 40$, $nWD = 16$ and $nTI_j = 4$, there are

$$nS = (40)(16)(4) = 2560 \quad (14)$$

such sets. Further, the probabilities for these sets are given by

$$pS_i = \text{prob}(\mathbf{WB}_j) \text{prob}(\mathbf{WD}_k | \mathbf{WB}_j) \text{prob}(\mathbf{TI}_j | \mathbf{WB}_j \cap \mathbf{WD}_k). \quad (15)$$

As noted earlier, the representation of stochastic uncertainty due to weather variability by MACCS is consistent with the ordered triple representation for risk shown in Eq. (1). In particular, the sets S_i and probabilities pS_i in Eqs. (13) and (15) correspond to the S_i and pS_i appearing in Eq. (1).

Estimates for the probabilities pS_i appearing in Eq. (15) are obtained by MACCS from 1 year of hourly weather data obtained at or close to the reactor site under consideration. These data are used to define 8760 5-day weather sequences (i.e., one weather sequence for each hour in a year). The probability $\text{prob}(\mathbf{WB}_j)$ for weather bin $\mathbf{WB}_j$ is approximated by

$$\text{prob}(\mathbf{WB}_j) = nWB_j / \phi nWB_w = nWB_j / 8760,$$

where nWB_w = number of weather sequences (out of the 8760) belonging to weather bin $\mathbf{WB}_w$. (17)

The probability $\text{prob}(\mathbf{WD}_k | \mathbf{WB}_j)$ that wind blows in direction k at the beginning of a weather sequence given the occurrence of weather bin $\mathbf{WB}_j$ is approximated by

$$\text{prob}(\mathbf{WD}_k | \mathbf{WB}_j) = nWD_{jk} / nWB_j, \quad (18)$$

where nWD_{jk} = number of weather sequences (out of the 8760) that belong to both $\mathbf{WB}_j$ and $\mathbf{WD}_k$. (19)

The probability $\text{prob}(\mathbf{TI}_j | \mathbf{WB}_j \cap \mathbf{WD}_k)$ is approximated with the assumption that

$$\text{prob}(\mathbf{TI}_j | \mathbf{WB}_j \cap \mathbf{WD}_k) = \text{prob}(\mathbf{TI}_j | \mathbf{WB}_j), \quad (20)$$

with the result that

$$\text{prob}(\mathbf{TI}_j | \mathbf{WB}_j \cap \mathbf{WD}_k) = 1/nTI_j \quad (21)$$

owing to the original definition of $\mathbf{TI}_j$ given in Eq. (12). The number of time intervals $n\mathbf{TI}_j$ associated with weather bin $\mathbf{WB}_j$ is defined by

$$n\mathbf{TI}_j = \min \{ n\mathbf{TI} = 4, n\mathbf{WB}_j \}. \quad (22)$$

Further, the time intervals $[t_{j,l-1}, t_{j,l}]$, $l = 1, 2, \dots, n\mathbf{TI}_j$, are determined so that the equality in Eq. (21) is satisfied.

The relations in Eqs. (16), (18), and (21) lead to the approximation

$$pS_i = n\mathbf{WD}_{jk} / (8760 n\mathbf{TI}_j) \quad (23)$$

for the set S_i in Eq. (13).

As described in this section, MACCS uses the risk representation in Eq. (1) to represent the stochastic uncertainty associated with weather variability. The sets S_i and probabilities pS_i are formally defined as shown in Eqs. (13) and (15). Further, MACCS calculates an approximation to pS_i with the relationship shown in Eq. (23). The third element of the risk representation in Eq. (1) is the vector $\mathbf{c}S_i$ of consequences (e.g., early fatalities, latent cancer fatalities, population doses, economic costs, ...) associated with each set S_i . As shown in Figure 1, it is the probabilities pS_i and the individual consequence results in $\mathbf{c}S_i$ that are used to produce the CCDFs that are typically used to display the results of a reactor accident consequence analysis. The remainder of Section 3 provides an overview of the procedures used in MACCS to produce the vector $\mathbf{c}S_i$ for each set S_i of weather sequences; more detailed information is available in the program documentation.³³⁻³⁵

3.2 Calculation of Consequences

The MACCS program allows a release of radioactive materials to the atmosphere to be divided into successive plume segments, which can have different compositions, release times, durations, and release heights and energies (amounts of sensible heat). Plume segment lengths are determined by the product of release duration and average wind speed during release. The initial vertical and horizontal dimensions of each plume segment are user specified. If release into a building wake occurs, then wake dimensions can be used to set the initial crosswind dimensions of the plume. If not, a point source can be specified.

A lift-off criterion (a critical wind speed that increases as plume buoyancy increases⁷⁴) determines whether buoyant plumes are subject to plume rise. When the wind speed at release equals or exceeds the critical wind speed, plume rise is prevented. When the wind speed at release is less than the critical wind speed, plume rise is allowed, and the height to which a buoyant plume rises is determined by using equations recommended by Briggs.^{75,76} After release, wind speed determines the rates at which plume segments transport in the downwind direction, and wind direction at the time of release determines the direction of travel. As is done in many consequence codes,^{77,78} MACCS neglects wind trajectories.

During transport, dispersion of the plume in the vertical and horizontal (crosswind) directions is estimated by using an empirical straight-line Gaussian plume model.⁷⁹ Dispersion rates depend on wind

speed and atmospheric stability. Although horizontal dispersion of plume segments is unconstrained, vertical dispersion is bounded by the ground and the top of the mixing layer (as specified by seasonal mixing layer heights⁸⁰), which are modeled as totally reflecting layers using mirror image sources.⁷⁹ Since the number of reflections increases as travel times lengthen, the vertical distribution of each plume segment eventually becomes uniform and is so modeled thereafter.⁸¹

In MACCS, aerosols are removed from the plume by washout, which varies with rainfall rate,⁸² and by diffusion to, impaction on, and gravitational settling onto surfaces. The combined removal rate from diffusion, impaction, and settling is modeled using an empirical dry-deposition velocity.⁸³ If the aerosol size distribution is divided into ranges, a dry deposition velocity can be specified for each range. Radioactive decay during transport is determined for the individual radionuclides but is limited to two-member decay chains. Weathering, resuspension, washoff, and radioactive decay decrease surface concentrations of radioactive materials deposited on the ground. Weathering is modeled using Gale's equation.⁸⁴ Resuspension is modeled using resuspension factors⁸³ that attempt to represent the average effect of resuspension by many processes throughout a large region.

Water bodies (rivers, the Great Lakes, oceans) are contaminated by direct deposition of radioactive materials onto their surfaces by dry and wet (washout) deposition, and by washoff of contamination previously deposited on land. Washoff is modeled as a first-order removal process that is integrated over all time after the initial deposition.⁸⁵

The MACCS program divides time after accident initiation into three phases: an emergency phase, an optional intermediate phase, and a long-term phase. During the emergency phase, which can last up to 7 days, doses are reduced by evacuation, sheltering, and temporary relocation of people. During the intermediate phase, doses may be avoided by temporary relocation of people, and ground contamination can be surveyed to prepare for decontamination actions. During the long-term phase, doses are reduced by decontamination of property that is not habitable, by temporary interdiction of property that cannot be restored to habitability by decontamination alone, by condemnation of property that cannot be restored to habitability at a cost that does not exceed the worth of the property, by disposal of contaminated crops, and by banning farming on contaminated farmland.

In MACCS, people are relocated if their projected doses exceed a user-specified dose criterion (e.g., if projected 7 day exposures will exceed 0.25 Sv, people are relocated 1 day after their exposures begin). In contrast to temporary relocation, evacuation and sheltering automatically take place within some specified region without regard to projected exposures. After a delay period that follows warning, evacuation proceeds radially at an average speed chosen to reflect site conditions. At a specified distance outside the evacuation zone, evacuees are assumed to be directed out of the path of the plume, so that further exposures are avoided. The MACCS sheltering model also assumes that there is a delay period between the time when warning is given and the time when shelter is taken. Once shelter is taken, people remain sheltered for a user-specified time, after which no additional exposure is accumulated.

At the beginning of the long-term phase, MACCS projects the doses that people would receive if no recovery actions are taken and compares these doses with the user-specified long-term protective action guides (e.g., the proposed EPA habitability criteria of no more than 0.02 Sv in the first year following an accident and no more than 0.005 Sv in any subsequent year). If the long-term dose criterion is not met, MACCS attempts to meet the criterion, first by decontamination alone and, if that is insufficient, by decontamination followed by a period of temporary interdiction to allow radionuclide

Overview of MACCS

removal by weathering and radioactive decay. However, these actions are taken only if they are cost-effective (i.e., the worth of the recovered property is greater than the sum of the following recovery costs: decontamination costs, earnings from investments that are lost by temporary interdiction of property, and the cost of any repairs necessitated by lack of maintenance of property during the temporary interdiction period).

During the long-term phase, exposure is also avoided by controlling the consumption and production of contaminated foodstuffs. When the accident occurs during the growing season and thus contaminates crops and pasture by direct deposition on plant surfaces, disposal of crops and milk occurs if ground concentrations of food pathway radionuclides exceed user-specified maximum allowable ground concentrations for those nuclides or if the habitability dose criterion is exceeded for the area where the foodstuffs are grown. Farming is prohibited in subsequent years until farmland is habitable (i.e., can be worked without violating habitability criteria), and then crops are grown only if the ground concentrations of food pathway radionuclides do not exceed user-specified maximum allowable concentrations. Because deep ploughing, the most likely decontamination method for farmland, may not remove significant amounts of radioactivity from the root zone, MACCS assumes that decontamination of farmland will reduce doses to farmers from groundshine and from inhalation of resuspended radioactive materials, but will not decrease uptake of radioactivity by root systems. Thus, decontamination of farmland does not affect doses injected through food. Accordingly, root uptake of radioactivity can be decreased only by temporary interdiction of farmland to allow radioactivity to be removed by weathering and decay. Temporary interdiction is assumed to take place provided (1) the value of the interdicted crops is less than the value of the land; (2) the interdiction period does not exceed 8 years, otherwise, the land is assumed to be condemned and permanently removed from agricultural use.

The MACCS program models seven exposure pathways: exposure to the passing plume (cloudshine), exposure to materials deposited on the ground (groundshine), exposure to materials deposited on skin (skin deposition), inhalation of materials directly from the passing plume (cloud inhalation), inhalation of materials resuspended from the ground by natural and mechanical processes (resuspension inhalation), ingestion of contaminated foodstuffs (food ingestion), and ingestion of contaminated water (water ingestion). Ingestion doses do not contribute to the doses calculated for the emergency phase of the accident. Only groundshine and inhalation of resuspended materials produce doses during the optional intermediate phase of the accident. Long-term doses are caused by groundshine, inhalation of resuspended materials, and ingestion of contaminated foodstuffs and water. Ingestion of contaminated food or water exposes to people who reside at unknown locations (i.e., societal doses) both on and off of the computational grid.

Cloudshine doses are calculated by applying a correction factor for finite cloud size to the dose that would be produced by a cloud of infinite extent.⁸⁶ Skin dose is modeled under the assumptions that skin is contaminated only by dry deposition and that skin dose is caused only by β particles.

Ingestion doses result from the consumption of contaminated water or contaminated foods. The drinking water pathway is modeled by assuming that a fixed fraction of all contaminated fresh water is consumed by man. Ingestion doses are also produced by consumption of contaminated milk, meat or crops. Crops are divided into categories (the MACCS default input file uses seven crop categories: pasture, stored forage, grains, green leafy vegetables, legumes and seeds, roots and tubers, and other crops). Transfer of radioactivity through root systems or from plant surfaces to edible portions of plants, losses during harvesting, incorporation into meat and milk, and retention in meat, milk, or edible portions of plants during processing, shelf storage, and cooking are all modeled using transfer factors.

The MACCS program assigns people to three groups: evacuees, people actively taking shelter, and people who continue normal activities indoors, outdoors and riding in vehicles. Doses to evacuees are calculated using vehicle shielding factors. Shielding factors for people who actively take shelter are smaller (i.e., they are better shielded) than the factors for people who continue normal activities indoors and/or outdoors because people who actively take shelter are assumed to close doors and windows, turn off air circulation systems, and move to interior rooms or basements. Shielding factors for people must be calculated outside of the code and specified by the user.

Health effects are calculated from doses to specific organs.⁸⁷ Doses to specific organs are calculated using dose conversion factors.⁸⁸ Early injuries and fatalities (i.e., those that occur within one year of the accident) are estimated using nonlinear dose-response models. As recommended in a recent review of radiation induced health effects,⁸⁹ MACCS uses hazard functions (H_i) for the calculation of early injuries or fatalities due to damage to organ i . Specifically, the probability or risk (r) that an individual will experience a given early health effect is given by

$$r = 1 - \exp \left\{ - \sum_i H_i \right\} , \quad (24)$$

where

$$H_i = (\ln 2) \left[\frac{D_i}{D_{50,i}} \right]^\beta , \quad \text{if } D_i > D_{th,i} , \quad (25)$$

and

$$H_i = 0, \text{ if } D_i \leq D_{th,i} . \quad (26)$$

Here, D_i is the dose received by organ i , $D_{th,i}$ is the damage threshold, $D_{50,i}$ is the dose that induces the specified health effect in half of the exposed population (e.g., the LD_{50} value for deaths), and the exponent β is a parameter that determines the shape of the dose-response curve. Hazards (H_i) are summed (1) over time periods to model any health effect that has D_{50} values that vary significantly with exposure period and (2) over organs to model early fatalities in which fatality may be caused by the impaired functioning of several organs. With regard to early fatalities and injuries, the lessened effectiveness of dose delivered at low dose rates over long time periods (dose protraction) is modeled using "effective" acute dose conversion factors.⁸⁷

As recommended by several reviews,⁹⁰⁻⁹³ MACCS calculates mortality and injuries resulting from radiation-induced cancers using a linear, zero-threshold dose-response model. Accordingly, MACCS cancer fatality predictions are linear with dose. However, the predictions are not always linear with the magnitude of the source term because dose is avoided by crop disposal and by decontamination, temporary interdiction and condemnation of land and buildings.

Overview of MACCS

Economic consequences⁹⁴ are estimated by summing the following costs: evacuation costs, temporary relocation costs (food, lodging, lost income); costs of decontaminating land and buildings; lost return on investment from properties that are temporarily interdicted to allow contamination to be decreased by weathering and radioactive decay; costs of repairing temporarily interdicted property; value of crops destroyed or not grown because they were contaminated by direct deposition or would be contaminated by root uptake; and value of farmland and of individual, public, and nonfarm commercial property that is condemned. Costs associated with damage to the reactor, the purchase of replacement power, medical care, life-shortening, and litigation are not calculated by MACCS.

4. PROBLEM FOR ANALYSIS

4.1 Source Term

The structure of the NUREG-1150 risk assessments produced a large number of individual source terms. As a result, it was not possible to perform a consequence calculation for each source term. To control the overall computational cost of the NUREG-1150 risk assessments, source terms were partitioned into source term groups at the interface between the source term analysis and the consequence analysis. Representative source terms were calculated for the individual source term groups and then consequence calculations were performed for these representative source terms.^{95,96} The consequence results obtained for these representative source terms were then used in the calculation of the consequence risks presented in NUREG-1150. The uncertainty/sensitivity analysis results in this presentation are based on one of the source terms developed in the partitioning process for internally initiated accidents at Surry.^{6,7}

The partitioning process was based on the definition of an early health effect weight and a chronic health effect weight for each source term, where the early health effect weight provides a measure of the potential of a source term to cause early fatalities in the absence of any mitigative actions, and the chronic health effect weight provides a similar measure for latent cancer fatalities. The analysis for internally initiated accidents at Surry produced a total of 18,591 source terms, of which 6820 had early and chronic health effect weights that were both nonzero. The distribution of nonzero early and chronic health effects weights for internally initiated accidents at Surry is shown in Figure 4.

The partitioning process begins by placing a user-defined grid on the plot of early and chronic health effect weights shown in Figure 4. Then, in an interactive mode, lightly populated grid cells can be combined with other cells. For illustration, Figure 5 shows the number of source terms and percent of total frequency in each cell before partitioning for the source terms in Figure 4, and Figure 6 shows the same information after partitioning. The populated cells in Figure 6 correspond to the source term groups used in the NUREG-1150 analyses. Once the source term groups are defined, the source terms are further divided into three subgroups on the basis of evacuation timing:

- Subgroup 1: Evacuation starts at least 30 minutes before the radioactive release begins,
- Subgroup 2: Evacuation starts between 30 minutes before and 1 hour after the release begins,
- Subgroup 3: Evacuation starts more than 1 hour after the release begins.

A frequency-weighted mean source term is calculated for each subgroup in the final step of the partitioning process. The resultant mean source terms are the source terms that are actually used as input to the consequence analysis.

The partitioning process is performed in a similar manner for the source terms in which the early health effect weight is zero and the chronic health effect weight is nonzero except that the cells are one-dimensional.

As already indicated, this presentation uses a source term associated with internally initiated accidents at Surry. A NUREG-1150 source term was selected due to the wide interest in the NUREG-

Figure 4. Distribution of Nonzero Early and Chronic Health Effect Weights for Internally Initiated Accidents at Surry (Figure 3.4-1, Ref. 6).

CELL COUNTS WITHIN THE GRID FOR A TOTAL COUNT OF 6820:

	1	2	3	4	5	6	7	8
1								86
2							50	456
3							224	531
4						12	440	386
5					28	222	1068	242
6	10	25	58	72	106	682	756	
7		1	3	51	262	964	85	

PERCENT OF FREQUENCY CONTAINED IN EACH CELL:

	1	2	3	4	5	6	7	8
1								1.64
2							3.18	6.17
3							2.48	4.34
4						0.07	9.28	4.04
5					0.86	24.49	7.37	3.53
6	0.18	4.89	1.19	1.80	7.06	2.74	5.74	
7		0.00	0.00	0.03	0.21	7.03	1.67	

Figure 5. Distribution of Source Terms with Nonzero Early Health Effect and Chronic Health Effect Weights for Internally Initiated Accidents at Surry (adapted from Table 3.4-2 of Ref. 6).

Problem for Analysis

CELL COUNTS WITHIN THE GRID FOR A TOTAL COUNT OF 6820:

	1	2	3	4	5	6	7	8
1								86
2							50	456
3							224	531
4							446	386
5						303	1068	242
6		94			316		1246	
7						1372		

PERCENT OF FREQUENCY CONTAINED IN EACH CELL:

	1	2	3	4	5	6	7	8
1								1.64
2							3.18	6.17
3							2.48	4.34
4							9.32	4.04
5						25.22	7.37	3.53
6		6.16			9.24		7.82	
7						9.50		

LABELING AFTER PARTITIONING:

	1	2	3	4	5	6	7	8
1								SUR-10
2							SUR-05 SUR-11	
3							SUR-06 SUR-12	
4							SUR-07 SUR-13	
5						SUR-03 SUR-08 SUR-14		
6		SUR-01			SUR-02		SUR-09	
7						SUR-04		

Figure 6. Distribution of Source Terms with Nonzero Early Health Effect and Chronic Health Weights for Internally Initiated Accidents at Surry after Partitioning (adapted from Table 3.4-2 of Ref. 6).

1150 analyses, a desire to use a source term from a published probabilistic risk assessment rather than one "invented" specifically for this uncertainty/sensitivity study, and recognition of the fact that this study is part of a process intended to lead ultimately to an assessment of the impact of consequence modeling uncertainty on NUREG-1150 results. A source term for internally initiated accidents at Surry was selected because that probabilistic risk assessment is often used to illustrate properties of the NUREG-1150 analyses.^{22,23,95,97,98} As this study addresses early health effects (e.g., fatalities occurring within a year of an accident), a relatively large release must be considered; otherwise, there will be no early health effects. For this reason, a source term associated with Surry source term group 11 (i.e., SUR-11) as shown in Figure 6 was selected. The mean source terms associated with this source term group are summarized in Table 2. The source term actually used in the analysis is labeled SUR-11-3 in Table 2 (i.e., the mean source term for Subgroup 3 of Source Term Group 11, which is the subgroup for which evacuation starts more than 1 hour after the release begins). A late evacuating source term was chosen so that the effects of uncertain variables on the doses and early health effects experienced by evacuees could be observed. Although evacuation preceding a release is the typical situation in the NUREG-1150 analyses, this is not very interesting in a sensitivity analysis because the evacuees avoid exposure, and as a result, the effects of the uncertain variables cannot be observed.

4.2 Modeling Assumptions

As indicated in Section 3, performance of a MACCS calculation for the source term SUR-11-3 shown in Table 2 requires a large amount of input. The development of this input for use in the NUREG-1150 analyses is documented in Sprung et al.,³⁶ 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.³⁶ is taken as the base line description for the analysis problem considered in this study. Taken collectively, this input corresponds to the vector x shown in Eqs. (2) and (3). An overview of the analysis assumptions used in MACCS for the analyses contained in this presentation is given in Table 3.

4.3 Uncertain Variables

If there was no uncertainty in the input supplied to MACCS, then there would also be no uncertainty in the predictions made by MACCS [i.e., in the analysis outcome indicated in Eq. (1)]. Here, uncertainty refers to subjective uncertainty. As a reminder, stochastic uncertainty is already incorporated into MACCS results by the probabilities pS_i shown in Eq. (1) and approximated in Eq. (23). As discussed in both Sprung et al.³⁶ and Helton et al.,³⁷ there is significant subjective uncertainty in the input that must be used with MACCS. This uncertainty is conditional on (1) the level of detail associated with the subdivision of the set S indicated in Eq. (7) into the sets S_i appearing in Eq. (1); (2) the manner in which the individual variables are used by MACCS; and (3) the available experimental, observational, and theoretical results that pertain to the possible values for the individual input variables and the relationships that may exist between them.

After a review of the results in Sprung et al.³⁶ and Helton et al.,³⁷ the 34 variables listed in Table 4 were selected for consideration in this study. The distributions associated with the individual variables characterize subjective uncertainty and thus correspond to the distributions shown in Eq. (4). When done carefully, the development of such distributions is a very demanding task and requires detailed knowledge of the operation of the model under consideration, extensive literature review, and interaction with many individual investigators who are knowledgeable about the individual variables. The distributions in Table

Table 2. Mean Source Terms Associated with Source Term Group SUR-11
for Internally Initiated Accidents at Surry (Ref. 6, Table 3.4-4)

Source Term	Freq ^a (1/yr)	Cond ^b Prob.	Warn ^c (s)	dEvac ^d (s)	Elev ^e (m)	Energy ^f (W)	Start ^g (s)	Dur ^h (s)	Release Fractions ⁱ								
									NG	I	Cs	Te	Sr	Ru	La	Ce	Ba
SUR-11	1.8E-07		8.8E+03	-2.3E+03	3.	3.4E+07	1.4E+04	1.9E+03	9.7E-01	5.0E-01	4.9E-01	1.9E-01	6.8E-02	1.4E-02	5.1E-03	2.5E-02	7.2E-02
						1.6E+05	1.1E+05	1.1E+05	8.6E-03	2.8E-02	5.3E-03	1.3E-01	4.8E-02	2.8E-04	4.2E-03	4.9E-03	3.7E-02
SUR-11-1	0.147	0.147	3.6E+04	7.8E+03	10.	1.0E+06	5.1E+04	2.4E+03	9.8E-01	6.1E-01	5.9E-01	4.2E-01	3.3E-01	6.1E-02	2.7E-02	1.4E-01	3.4E-01
						0.0E+00	5.5E+04	1.0E+04	2.4E-02	2.9E-02	2.1E-02	5.3E-02	2.8E-02	1.5E-03	3.1E-03	6.0E-03	2.5E-02
SUR-11-2	0.164	0.164	1.6E+04	-5.3E+02	10.	2.0E+08	2.3E+04	2.1E+03	8.6E-01	6.7E-01	6.3E-01	4.8E-01	7.8E-02	2.3E-02	4.6E-03	1.5E-02	8.8E-02
						2.6E+05	5.6E+05	5.5E+05	1.1E-02	7.5E-03	6.1E-03	1.4E-02	1.7E-03	3.1E-04	8.8E-05	2.8E-04	1.9E-03 ⁱ
SUR-11-3	0.689	0.689	1.3E+03	-4.8E+3	0.	2.7E+06	3.7E+03	1.8E+03	1.0E+00	4.4E-01	4.3E-01	7.8E-02	9.2E-03	2.3E-03	5.4E-04	2.3E-03	1.1E-02
						1.7E+05	1.0E+04	2.2E+04	4.7E-03	3.2E-02	1.8E-03	1.7E-01	6.4E-02	2.2E-05	5.4E-03	5.7E-03	4.8E-02

^a Frequency (yr⁻¹) of source term group.

^b Conditional probability of source term subgroup given source term group.

^c Time (s) at which warning is given.

^d Difference between time evacuation starts and time release starts for an assumed evacuation delay time of 7200 s.

^e Elevation (m) of release.

^f Energy (W) in release, with one value for each release segment.

^g Time (s) at which release starts, with one value for each release segment.

^h Duration (s) of release, with one value for each release segment.

ⁱ Release fractions (dimensionless) for individual radionuclide release classes, with one value for each release segment.

Table 3. Overview of Modeling Assumptions

Variable	Data
Population Distribution	Based on 1980 census data, corrected for estimated average daily transient populations, for the region surrounding Surry; updated 0-10 mi population data supplied by the NRC. Population distribution described on a polar coordinate grid with 16 angular 22.5° sectors and 26 radial intervals with outer radii of 0.1, 0.32, 0.75, 1, 1.5, 2, 2.5, 3, 3.5, 5, 7, 10, 13, 16, 20, 25, 30, 40, 50, 70, 100, 150, 200, 350, 500 and 1000 miles.
Weather data	Used weather data measured at the Surry reactor site. The data consisted of 1 year of hourly observations of wind speed, atmospheric stability, and precipitation. The 8760 (365 days × 24 hours) weather sequences in this data set were sorted into 40 weather bins. Inspection of the bins showed that (1) stable atmospheric conditions (i.e. stability classes E and F) occurred for 41% of the sequences; (2) precipitation occurred within 21 miles of the reactor site for 9.2% of the sequences; and (3) all weather bins indicated in Table 1 contained at least one sequence. For the reported analyses, four sequences were selected from each weather bin; when a bin contained fewer than four sequences, all sequences were used.
Core inventory	Used an end-of-cycle 3412-MW Westinghouse pressurized water reactor core inventory calculated with the SANDIA-ORIGEN code ⁹⁹ and scaled to 2441 MW, which is the power of the Surry reactor. Sixty radionuclides were used in the consequence calculations. ³³
Emergency response assumptions	Evacuation occurs radially, and evacuees receive no additional dose beyond 20 miles from the reactor. Inhalation shielding factor for evacuees is 1. Nonevacuees continue normal activities. Most emergency response parameters are variables in the sensitivity study.
Source term release form	All radionuclides released from the reactor except for the noble gases were assumed to be incorporated into aerosols with a mass median aerodynamic diameter of about 10 ⁻⁶ m.

**Table 4. Imprecisely Known Variables Selected for
Inclusion in Uncertainty/Sensitivity Study for MACCS**

Variable	Description
BUILDH	Reactor building height (m). Defines initial vertical height of plume. Range: 15 - 35 m. Distribution: uniform. Correlation: 0.9 rank correlation with BUILDW. Best estimate value: 25 m. Correlation results from belief that weather and accident conditions that increase initial vertical plume extent will also increase initial horizontal plume extent.
BUILDW	Reactor building width (m). Defines initial horizontal width of plume. Range: 15 - 100 m. Distribution: uniform. Correlation: 0.9 rank correlation with BUILDH. Best estimate value: 60 m.
CSFACTE	Cloudshine shielding factor for evacuees. Defines element of MACCS input array CSFACT. Range: 0.9 - 1. Distribution: uniform. Correlation: 0.5 rank correlation with GSHFACE. Best estimate value: 0.95. Correlation results from belief that increasing surface "roughness" will increase both CSFACTE and GSHFACE.
CSFACTN	Cloudshine shielding factor for nonevacuees. Defines element of MACCS input array CSFACT. Range: 0.6 - 0.95. Distribution: uniform. Correlation: 0.5 rank correlation with GSHFACN. Best estimate value: 0.75. Correlation results from belief that increasing surface "roughness" will increase both CSFACTN and GSHFACN. Additional background: Ref. 36.
CSFACTS	Cloudshine shielding factor for individuals who shelter. Defines element of MACCS input array CSFACT. Range: 0.5 - 0.7. Distribution: uniform. Correlation: 0.5 rank correlation with GSHFACS. Best estimate value: 0.6. Correlation results from belief that increasing surface "roughness" will increase both CSFACTS and GSHFACS. Additional background: Ref. 36.
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: Refs. 36, 82, 102.
CWASH2	Exponent in wet deposition model. Range: 0.7 - 0.9. Distribution: uniform. Best estimate value: 0.8. Additional background: Refs. 36, 82, 102.
DOSHOT	Projected dose used to initiate hot-spot relocation (Sv). At time TIMHOT individuals are relocated if their projected dose for the entire emergency phase of the accident (i.e., 0-7 days) exceeds DOSHOT. Range: 0.25 - 1.0 Sv. Distribution: uniform. Correlation: 0.75 rank correlation with P2DOS1. Best estimate value: 0.5 Sv. Correlation reflects belief that the dose criteria used for hot-spot (i.e., DOSHOT) and normal (i.e., P2DOS1) relocation tend to increase and decrease together.

Table 4 (continued)

Variable	Description
EFFACA1	Early fatality hazard function alpha value for bone marrow exposure (Gy). Corresponds to exposure level at which 50% of exposed individuals die (i.e., the LD ₅₀ value). Defines element of MACCS input array EFFACA. Range: 2.5 - 5.5 Gy. Distribution: uniform. Correlation: 0.75 rank correlation with EFFACB1 and EFFTHR1. Correlation with EFFACB1 results from belief that the probability of becoming an early fatality would tend to increase more rapidly above large LD ₅₀ values, and correlation with EFFTHR1 results from belief that threshold doses will tend to increase as the LD ₅₀ increases. Best estimate value: 4 Gy. Additional background: Ref. 89.
EFFACA2	Early fatality hazard function alpha value for lung exposure (Gy). Defines element of MACCS input array EFFACA. Range: 8 - 12 Gy. Distribution: uniform. Correlation: 0.75 rank correlations with EFFACB2 and EFFTHR2. Best estimate value: 10 Gy. See EFFACA1 for rationale for assumed correlations. Additional background: Ref. 89.
EFFACA3	Early fatality hazard function alpha value for gastrointestinal exposure (Gy). Defines element of MACCS input array EFFACA. Range: 10 - 20 Gy. Distribution: uniform. Correlation: 0.75 rank correlation with EFFACB3. Best estimate value: 15 Gy. See EFFACA1 for rationale for assumed correlations. Additional background: Ref. 89.
EFFACB1	Early fatality hazard function beta value for bone marrow exposure. Defines element of MACCS input array EFFACB. Range: 4 - 8. Distribution: uniform. Correlation: 0.75 rank correlation with EFFACA1 and EFFTHR1. Best estimate value: 6. Additional background: Ref. 89.
EFFACB2	Early fatality hazard function beta value for lung exposure (Gy). Defines element of MACCS input array EFFACB. Range: 9 - 14. Distribution: uniform. Correlation: 0.75 rank correlation with EFFACA2 and EFFTHR2. Best estimate value: 11.5. Additional background: Ref. 89.
EFFTHR1	Early fatality threshold dose for bone marrow exposure (Gy). Defines element of MACCS input array EFFTHR. Range: 1 - 2 Gy. Distribution: uniform. Correlation: 0.75 rank correlation with EFFACA1 and EFFACB1. Best estimate value: 1.5 Gy. Additional background: Ref. 89.
EFFTHR2	Early fatality threshold dose for lung exposure (Gy). Defines element of MACCS input array EFFTHR. Range: 4 - 6 Gy. Distribution: uniform. Correlation: 0.75 rank correlation with EFFACA2 and EFFACB2. Best estimate value: 5 Gy. Additional background: Ref. 89.
EIFACA1	Early injury hazard function alpha value for prodromal vomiting (Gy). Corresponds to exposure level at which 50% of exposed individuals will experience prodromal vomiting. Defines element of MACCS input array EIFACA. Range: 1.5 - 2.5 Gy. Distribution: uniform. Best estimate value: 2 Gy. Additional background: Ref. 89.

Table 4 (continued)

Variable	Description
ESPEED	Evacuation speed (m/s). Range: 0.9 - 3.6 m/s. Distribution: uniform. Best estimate value: 2.2 m/s. Additional background: Ref. 36.
EVFRAC	Fraction of population in emergency response zone (i.e., within 10 miles of reactor) that does not evacuate. MACCS input variable WTRAC equals 1 - EVFRAC. Range: 0.005 - 0.05. Distribution: uniform. Best estimate value: 0.027. Additional background: Ref. 36.
GSHFACE	Groundshine shielding factor for evacuees. Defines element of MACCS input array GSHFAC. Range: 0.3 - 0.7. Distribution: uniform. Correlation: 0.5 rank correlation with CSFACTE. Best estimate value: 0.5. Additional background: Refs. 36, 86.
GSHFACN	Groundshine shielding factor for nonevacuees. Defines element of MACCS input array GSHFAC. Range: 0.2 - 0.75. Distribution: uniform. Correlation: 0.5 rank correlation with CSFACTN. Best estimate value: 0.33. Additional background: Refs. 36, 86.
GSHFACS	Groundshine shielding factor for individuals who shelter. Defines element of MACCS input array GSHFAC. Range: 0.1 - 0.3. Distribution: uniform. Correlation: 0.5 rank correlation with CSFACTS. Best estimate value: 0.2. Additional background: Refs. 36, 86.
PHS2T2	Time after plume arrival at which individuals are relocated if their projected dose exceeds P2DOS1 (days). Defines MACCS input variable TIMNRM. Range: 0.5 - 2 days. Distribution: uniform. Correlation: 0.75 rank correlation with TIMHOT. Best estimate value: 1.2 days. Correlation reflects belief that the times used for hotspot (i.e., TIMHOT) and normal (i.e., PHS2T2) relocation tend to increase and decrease together.
P2DOS1	Projected dose used to initiate normal relocation (Sv). At time PHS2T2, individuals are relocated if their projected dose for the entire emergency phase of the accident (i.e., 0-7 days) exceeds P2DOS1. Defines MACCS input variable DOSNRM. Range: 0.05 - 0.5 Sv. Distribution: uniform. Correlation: 0.75 rank correlation with DOSHOT. Best estimate value: 0.28.
TIMHOT	Time after plume arrival at which individuals are relocated if their projected dose exceeds DOSHOT (days). Range: 0.25 - 1 day. Distribution: uniform. Correlation: 0.75 rank correlation with PHS2T2. Best estimate value: 0.5 day.
PROTINN	Inhalation protection factor for nonevacuees. Defines element of MACCS input array PROTIN. Range: 0.2 - 0.8. Distribution: uniform. Best estimate value: 0.5. Additional background: Refs. 36, 86.

Table 4 (concluded)

Variable	Description
PROTINS	Inhalation protection factor for individuals who shelter. Defines element of MACCS input array PROTIN. Range: 0.1 - 0.4. Distribution: uniform. Best estimate value: 0.25. Additional background: Refs. 36, 86.
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: Ref. 103.
SCLCRW	Critical wind speed scaling factor. Range: 0.5 - 2. Distribution: uniform. Best estimate value: 1. Additional background: Ref. 103.
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: Ref. 103.
TDELAY	Time from accident warning to start of evacuation (hr). Defines element of MACCS input array EDELAY. Range: 1.25 - 3.25 hr. Distribution: uniform. Best estimate value: 2.3 hr.
TTOSH2	Time from accident warning to start of sheltering (hr). Range: 0.25 - 0.75 hr. Distribution: uniform. Best estimate value: 0.5 hr.
VDEPOS	Dry deposition velocity (m/s). Defines element of MACCS input array of same name. Range: 0.003 - 0.03 m/s. Distribution: loguniform. Best estimate value: 0.01 m/s. Additional background: Ref. 83.
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: Refs. 104, 105.
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: Refs. 104, 105.

4 were developed by the investigators in this study and are not the result of a comprehensive review process. It is hoped that this preliminary assessment of subjective uncertainty will 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 4 are rank correlations, which provide a measure of the extent to which variables tend to move up and down together.^{100,101} Rank correlations also have the desirable property that they are independent of the distributions assigned to the individual variables.

The reactor accident consequences selected for investigation in this study are listed in Table 5. The predicted values for these consequences correspond to the elements of the vector cS_i appearing in Eq. (1).

All of the variables in Table 4 are used in the calculation of the consequence vector cS_i appearing in Eq. (1). Thus, when the uncertainty in the variables in Table 4 is propagated in the analysis, the outcome will be of the form shown in Eq. (6). However, this does not have to be the case. For example, the probabilities pS_i are approximated by 1 year of weather data, as shown in Eq. (23), with the result that there is subjective uncertainty as to the appropriate values for these probabilities. This analysis does not include the uncertainty in the pS_i , although there is no conceptual problem in the inclusion of such uncertainty. The analysis also does not include a measure of the uncertainty in how to divide the set S in Eq. (7) into the sets S_i in Eq. (1), which would involve making the sets S_i and the number of sets nS functions of one or more imprecisely known variables. Again, although this analysis does not include uncertainty in nS and the S_i , there is no conceptual reason why this uncertainty could not be included.

Table 5. Reactor Accident Consequences Selected for Investigation.

CONSEQUENCE	DEFINITION
Early Fatalities	Number of fatalities occurring within 1 year of the accident. Cases: 100% evacuation, no evacuation, 100% sheltering, variable evacuation.
Prodromal Vomiting	Number of individuals experiencing prodromal vomiting. Cases: Same as for early fatalities.
Population Dose 0 - 10 mi	Population dose (Sv) resulting from exposure received by individuals within 10 mi of the reactor at accident initiation. Cases: Same as for early fatalities.
Population Dose 0 - 1000 mi	Population dose (Sv) resulting from exposure received by individuals within 1000 mi of the reactor at accident initiation. Cases: Same as for early fatalities.
Early Fatality Probability 0 - 1 mi	Probability that an individual within 1 mi of the reactor at accident initiation will become an early fatality. Cases: Same as for early fatalities.
Maximum Early Fatality Distance	Maximum distance (km) from reactor at which an individual has a probability of becoming an early fatality that exceeds 0.005. Case: No evacuation.

^aResults are based on exposures incurred within 7 days of the accident.

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5. 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 4 on the consequence results indicated in Table 5. To accomplish this, the LHS program¹⁰⁰ was used to generate a Latin hypercube sample of size 100 from the 34 variables in Table 4, with the Iman/Conover restricted pairing technique¹⁰⁰ being used to induce the indicated rank correlations. This produced a sample of the form shown in Eq. (5) with $nV = 34$ and $nLHS = 100$, which was then propagated through MACCS to produce the results shown in Eq. (6). As a reminder, the vector $cS_i(x_k)$ in Eq. (6) contains the values for the consequence results in Table 5 obtained for scenario S_i , where S_i is the set of similar weather conditions defined in Eq. (13). The analyses for the individual consequence results follow.

5.1. Early Fatalities

The number of early fatalities was estimated for four emergency response assumptions: (1) 100% evacuation, (2) no evacuation, (3) 100% sheltering, and (4) variable evacuation (i.e., the fraction EVFRAC of the population continues normal activities and the remaining fraction 1-EVFRAC of the population evacuates). Each sample element produces a CCDF of the form shown in Figure 1 for each of the preceding emergency response assumptions. When taken collectively, the CCDFs for each emergency response assumption produce a distribution of CCDFs of the form shown in Figure 2. Specifically, the distribution of CCDFs obtained in this analysis for number of early fatalities with 100% evacuation is shown in Figure 2.

Plots similar to the one appearing in Figure 2 can also be produced for each of the other analysis cases under consideration (i.e., no evacuation, 100% sheltering, and variable evacuation). Although these plots contain all 100 CCDFs generated in this analysis, they are difficult to examine and compare. A less congested summary of these distributions is provided by the mean and percentile curves shown in Figure 7. The summary results presented in the individual frames of Figure 7 are derived from results of the form shown in Figure 2. Specifically, at each point on the abscissa in Figure 2, a vertical line is drawn through the 100 CCDFs above this point. As a reminder, there is one CCDF for each sample element, which results in a total of 100 CCDFs. Further, the individual CCDFs do not really end at points in space as shown in Figure 2, 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 yield 100 exceedance probabilities, from which the mean and various percentiles (e.g., 5%, 50%, 95%) can be determined. The curves in Figure 7 result from connecting the mean and percentile values obtained for individual early fatality numbers. The mean and percentile curves in the upper left frame of Figure 7 for early fatalities with 100% evacuation are constructed from the results shown in Figure 2; the curves in the other frames of Figure 7 are constructed from similar distributions of CCDFs for number of early fatalities with no evacuation, 100% sheltering, and variable evacuation, respectively.

As examination of the results in Figure 7 shows, there is considerable uncertainty associated with the probability that a specified number of early fatalities will be exceeded. This uncertainty comes from the ranges and distributions assigned to the variables in Table 4. The percentile curves in Figure 7 can be used to provide a measure of confidence (i.e., degree of belief) as to where the exceedance probabilities are located for each number of early fatalities. However, these results are conditional on the distributions specified in Table 4 for the characterization of subjective uncertainty and also on the other modeling assumptions used in this analysis.

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Figure 7. Mean and Percentile Curves for Number of Early Fatalities for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering and Variable Evacuation.

An assessment of the subjective uncertainty in reactor accident consequence modeling parameters that appropriately incorporates the diverse body of information potentially available is a very large endeavor. Indeed, the present sensitivity study is being performed to help focus the resources of such an endeavor on the most important inputs used in modeling the consequences of reactor accidents. The ranges and distributions given in Table 4 were developed only to support this sensitivity study; the level of effort was not adequate to obtain and evaluate all information potentially available to the reactor safety community. Therefore, excessive emphasis should not be placed on the numeric values associated with uncertainty analysis results in this report. However, it is useful to present uncertainty results such as shown in Figures 2 and 7 because this information both provides the input to the sensitivity studies that are the primary focus of this presentation and forms a basis for assessing the effectiveness of the techniques in use. Further, the results in Figures 2 and 7 and other similar figures are conditional on the occurrence of the accident under consideration (i.e., SUR-11-3 as defined in Table 2), which was estimated in the NUREG-1150 analysis for internally initiated accidents at Surry to have a frequency of approximately $1.2 \times 10^{-7} \text{ yr}^{-1}$. Thus, the conditional probabilities appearing on the ordinates of Figures 2 and 7 and other similar figures must be multiplied by $1.2 \times 10^{-7} \text{ yr}^{-1}$ to obtain annual exceedance frequencies that incorporate the likelihood of the accident under consideration.

The identification of the variables in Table 4 that dominate the uncertainty displayed in Figures 2 and 7 is now addressed. Specifically, the PCCSRC program¹⁰⁷ is used to calculate partial rank correlation coefficients (PRCCs) for the probability that specified numbers of early fatalities will be exceeded. As a reminder, PRCCs provide a measure for the tendency of two variables to increase and/or decrease together after a correction has been made for the effects of the other variables in the analysis. Specifically, PRCCs are defined the same as ordinary partial correlation coefficients (PCCs) except that the independent and dependent variables are rank-transformed before the calculation of PRCCs. The use of the rank transform helps remove the effects of nonlinear relationships between variables that reduce the effectiveness of ordinary PCCs. For this presentation, all variables that have a PRCC above 0.5 in absolute value were identified. Typically, 4 to 9 variables satisfy this selection criterion.

As shown in Figure 8, a relatively compact display of this information can be achieved by plotting the PRCCs for the 4 variables that have the largest PRCCs in absolute value and simply listing the remaining variables whose PRCCs exceeded 0.5 in absolute value together with a + or - after the variable to indicate whether the coefficient is positive or negative when its absolute value exceeds 0.5. In a few instances, a variable will have both positive and negative partial correlations that exceed 0.5 in absolute value. In this case, the variable will be followed by +,- if the coefficient is positive and then negative and by -,+ if the coefficient is negative and then positive.

The analysis for number of early fatalities with 100% evacuation shown in the upper left frame of Figure 8 can be used to illustrate the presentation of the partial correlation results. The four variables with the largest PRCCs in absolute value are YSCALE (scaling factor for horizontal dispersion), ZSCALE (scaling factor for vertical dispersion), TDELAY (time from warning to start of evacuation) and ESPEED (evacuation speed); there is a partial correlation plot for each of these variables. For example, a vertical line drawn through one early fatality intersects the curves for YSCALE, ZSCALE, TDELAY, and ESPEED at -0.95, -0.85, 0.67, and -0.67 respectively. The numbers -0.95, -0.85, 0.67, and -0.67 are the PRCCs between YSCALE, ZSCALE, TDELAY, and ESPEED and the probability that one or more early fatalities will occur given the occurrence of the source term SUR-11-3. In addition to YSCALE, ZSCALE, TDELAY, and ESPEED, the variables SCLCRW (critical wind speed scaling factor), EFFACA1 (early fatality hazard function alpha value for bone marrow exposure), VDEPOS (dry deposition velocity) and CSFACTN (cloudshine shielding factor for nonevacuees) were found to have

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Figure 8. Partial Rank Correlation Coefficients for Probability that Specified Numbers of Early Fatalities Will Be Exceeded for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering and Variable Evacuation.

PRCCs that exceeded 0.5 in absolute value. As indicated by the + and - symbols following these variables, SCLCRW, EFFACA1, and VDEPOS have PRCCs that are less than -0.5 and CSFACTN has PRCCs that exceed 0.5; however, this summary does not contain enough information to identify the numbers of early fatalities for which these variables have PRCCs that exceed 0.5 in absolute value.

The sensitivity analysis results contained in Figure 8 for number of early fatalities with 100% evacuation are now discussed. As measured by the size of the PRCCs, the two most important variables are YSCALE (scaling factor for horizontal dispersion) and ZSCALE (scaling factor for vertical dispersion). Both of these variables have negative PRCCs, which indicates that increasing each of these variables tends to decrease the probability of exceeding a specified number of early fatalities. This effect occurs because increasing YSCALE and ZSCALE tends to spread the plume out and thus reduce the number of individuals receiving large radiation exposures. The variables YSCALE and ZSCALE consistently appear as important variables in the analyses presented in Figure 8.

The variable with the next largest PRCCs for number of early fatalities with 100% evacuation is TDELAY (time from warning to start of evacuation). The positive correlation indicated for TDELAY results because increasing TDELAY tends to increase the amount of radiation exposure that individuals receive before they begin evacuation. The partial correlation coefficients for TDELAY drop to approximately zero by 10 early fatalities. Thus, although increasing TDELAY tends to increase the probability of having a small number of early fatalities in this analysis, it does not appear to have an effect on the occurrence of a large number of early fatalities. However, it is important to recognize that all of the partial correlation plots will tend to zero as more and more of the individual CCDFs shown in Figure 7 drop to zero. The variable with the fourth largest PRCCs is ESPEED (evacuation speed). The negative correlation coefficients shown for ESPEED result because increasing ESPEED reduces the total time required for evacuation and thus reduces radiation exposure.

In addition to YSCALE, ZSCALE, TDELAY, and ESPEED, the following four variables were found to have PRCCs that exceeded 0.5 in absolute value for number of early fatalities with 100% evacuation: (1) SCLCRW (critical wind speed scaling factor) with negative PRCCs because increasing SCLCRW tends to increase plume rise and thus reduce the number of individuals receiving large radiation exposures, (2) EFFACA1 (early fatality hazard function alpha value for bone marrow exposure) with negative PRCCs because increasing EFFACA1 increases the dose that an individual must receive in order to have a probability of 0.5 of becoming an early fatality, (3) VDEPOS (dry deposition velocity) with negative PRCCs because increasing VDEPOS tends to increase the amount of radiation deposited near the reactor and thus decrease the amount of radiation deposited at greater distances from the reactor where more individuals are located, and (4) CSFACTN (cloudshine shielding factor for nonevacuees) with positive PRCCs because increasing CSFACTN tends to increase the radiation exposure received by individuals before they initiate evacuation.

The sensitivity analysis results in Figure 8 for number of early fatalities without evacuation are similar to those obtained for 100% evacuation. Increasing YSCALE (scaling factor for horizontal dispersion), ZSCALE (scaling factor for vertical dispersion), and SCLCRW (critical wind speed scaling factor) tends to decrease the probability of exceeding specified numbers of early fatalities while the opposite effect is indicated for GSHFACN (groundshine shielding factor for nonevacuees) and VDEPOS (dry deposition velocity). The analysis for 100% evacuation selected the cloudshine shielding factor for nonevacuees (CSFACTN) rather than the groundshine shielding factor for nonevacuees (GSHFACN). This difference results because cloudshine is more important when people are exposed to the plume but ultimately evacuate, while groundshine is more important when people do not evacuate at all. The

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variable VDEPOS shows an interesting pattern, going from positive correlation values for small numbers of early fatalities to negative correlation values for larger numbers of early fatalities. This pattern probably derives from the fact that large values for VDEPOS result in more deposition close to the reactor and hence in less deposition at greater distances from the reactor where more individuals are located, with the result that the probability of a small number of early fatalities goes up and the probability of a large number of early fatalities goes down. The variable TIMHOT (time at which individuals are relocated if their projected dose exceeds DOSHOT) was also identified in the analysis as having positive PRCCs that exceed 0.5, with this positive correlation resulting because increasing TIMHOT tends to increase the amount of radiation exposure that individuals receive before they are relocated.

Overall, the sensitivity analysis results in Figure 8 for number of early fatalities with 100% sheltering are similar to those obtained with and without evacuation. Increasing YSCALE (scaling factor for horizontal dispersion), ZSCALE (scaling factor for vertical dispersion), SCLCRW (critical wind speed scaling factor), EFFACA1 (early fatality hazard function alpha value for bone marrow exposure) and EFFTHR1 (early fatality threshold dose for bone marrow exposure) tends to decrease the probability of exceeding a specified number of early fatalities while the opposite effect is indicated for VDEPOS (dry deposition velocity) and GSHFACS (groundshine shielding factor for individuals who shelter). Of the preceding variables, only GSHFACS and EFFTHR1 were not identified in the analyses with and without evacuation. The variable GSHFACS has exactly the same role in the analysis with sheltering as the variable GSHFACN (groundshine shielding factor for nonevacuees) in the analysis for no evacuation. The variable EFFTHR1 defines the dose below which early fatalities due to bone marrow exposure will not occur. Thus, increasing EFFTHR1 tends to decrease the number of early fatalities. The variable EFFTHR1 also affects the number of early fatalities with and without evacuation; however, owing to the concurrent effects of other variables, it does not result in correlation coefficients with absolute values that exceed the selection criterion (i.e., 0.5) for these two cases.

The last sensitivity analysis results in Figure 8 are for the number of early fatalities that result when a fraction EVFRAC of the population within 10 mi of the reactor (i.e., within the emergency response zone) does not evacuate and the remaining fraction (i.e., 1-EVFRAC) of the population does evacuate. Increasing YSCALE (scaling factor for horizontal dispersion), ZSCALE (scaling factor for vertical dispersion), ESPEED (evacuation speed), SCLCRW (critical wind speed scaling factor), and EFFACA1 (early fatality hazard function alpha value for bone marrow exposure) tends to decrease the probability of exceeding a specified number of early fatalities while increasing VDEPOS (dry deposition velocity), GSHFACN (groundshine shielding factor for nonevacuees), EVFRAC (fraction of population in emergency response zone that does not evacuate) and TIMHOT (time at which individuals are relocated if their projected dose exceeds DOSHOT) tends to increase the probability of exceeding a specified number of early fatalities. With the exception of EVFRAC, all of the preceding variables were previously identified as having the same effects in either the analysis with or the analysis without evacuation. Increasing EVFRAC tends to increase the number of early fatalities by increasing the number of individuals who do not evacuate.

As discussed in conjunction with Figure 1, CCDFs are the basic summary display for analyses involving stochastic uncertainty. However, another more condensed summary is provided by the summation

$$\overline{cS} = \sum_{i=1}^{nS} pS_i cS_i, \quad (27)$$

where cS is a particular consequence value (e.g., number of early fatalities) in the vector cS appearing in Eq. (1). Here, $\overline{cS}$ is the expected value for the particular consequence value under consideration, where the expectation is being taken over stochastic uncertainty, and is the result of reducing the information in the CCDF in Figure 1 to a single number. In the presence of subjective uncertainty, the expression in Eq. (27) becomes

$$\overline{cS(x)} = \sum_{i=1}^{nS(x)} pS_i(x) cS_i(x), \quad (28)$$

where x is a vector of imprecisely known quantities required in the determination of the expression in Eq. (3).

Although the results of reactor accident consequence assessments are usually presented as CCDFs to maintain a separation between scenario probability and consequence magnitude, mean consequence results of the form shown in Eq. (27) are also used as summary measures. In the present study, the expression in Eq. (27) provides a way to reduce an entire CCDF to a single number (i.e., the expected number of consequences due to weather variability) to facilitate sensitivity analysis. Due to the imprecisely known variables listed in Table 4, this expected number of consequences is actually of the form shown in Eq. (28). For the present study, Eq. (28) can be evaluated for each CCDF in distributions of the form shown in Figure 2, where x takes on the values x_k , $k=1, \dots, nLHS=100$, of the elements of the Latin hypercube sample generated for the variables summarized in Table 4. The resultant mean consequence values for early fatalities are summarized in Figure 9. While each mean consequence value summarized in the distributions in Figure 9 results from stochastic uncertainty, the distributions themselves are displaying subjective uncertainty. Further, the single mean associated with each distribution in Figure 9, designated by a large dot, is a mean over subjective uncertainty.

Stepwise regression analysis provides a convenient tool with which to determine the importance of individual variables in influencing the uncertainty in mean number of early fatalities displayed in Figure 9. With stepwise regression 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 constructed in the stepwise process. The regression analyses contained in this presentation were performed with the STEP program.¹⁰⁸ Alpha values of 0.01 and 0.02 were required for variables to enter and remain in the regression models, respectively. Further, the PRESS criterion¹⁰⁹ was used to check for overfitting the data.

As illustrated in Tables 6 and 7, the analyses were initially tried with both raw (i.e., untransformed) data and rank-transformed data.¹¹⁰ The analyses with rank-transformed data consistently performed as well as or better than the analyses with raw data. For example, the regression analysis with raw data in Table 6 for mean number of early fatalities with 100% evacuation selected only the variable YSCALE (scaling factor for horizontal dispersion), which could account for 16% (i.e., $R^2 = 0.16$) of the observed variability. In contrast, the corresponding analysis in Table 7 with rank-transformed data selected 8 variables and the final regression model could account for 92% (i.e., $R^2 = 0.92$) of the

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Figure 9. Distribution of Mean Number of Early Fatalities for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Table 6. Stepwise Regression Analysis with Raw (i.e., untransformed) Data for Mean Number of Early Fatalities for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation

Step ^a	100% Evacuation			No Evacuation		
	Variable ^b	SRC ^c	R ² ^d	Variable ^b	SRC ^c	R ² ^d
1	YSCALE	-0.39	0.16	YSCALE	-0.59	0.50
2				GSHFACN	0.37	0.37
3				EFFACA1	-0.32	0.47
4				ZSCALE	-0.33	0.54
5				TIMHOT	0.25	0.60

Step ^a	100% Shelter			Variable Evacuation		
	Variable ^b	SRC ^c	R ² ^d	Variable ^b	SRC ^c	R ² ^d
1	YSCALE	-0.36	0.12	YSCALE	-0.40	0.16
2	EFFACA1	-0.31	0.22			

^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

Table 7. Stepwise Regression Analysis with Rank-Transformed Data for Mean Number of Early Fatalities for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation

Step ^a	100% Evacuation			No Evacuation		
	Variable ^b	SRC ^c	R ² ^d	Variable ^b	SRC ^c	R ² ^d
1	YSCALE	-0.68	0.65	YSCALE	-0.59	0.50
2	ESPEED	-0.28	0.72	GSHFACN	0.39	0.66
3	ZSCALE	-0.29	0.79	EFFACA1	-0.33	0.76
4	EFFACA1	-0.23	0.85	TIMHOT	0.27	0.83
5	GSHFACN	0.14	0.88	ZSCALE	-0.28	0.89
6	VDEPOS	-0.12	0.90			
7	CSFACTN	0.10	0.91			
8	TDELAY	0.08	0.92			

Step ^a	100% Shelter			Variable Evacuation		
	Variable ^b	SRC ^c	R ² ^d	Variable ^b	SRC ^c	R ² ^d
1	YSCALE	-0.64	0.57	YSCALE	-0.68	0.63
2	EFFACA1	-0.39	0.72	ZSCALE	-0.29	0.70
3	ZSCALE	-0.29	0.79	EFFACA1	-0.24	0.76
4	GSHFACS	0.22	0.84	ESPEED	-0.25	0.81
5	VDEPOS	0.12	0.85	GSHFACN	0.20	0.87
6	PROTINS	0.11	0.86	EVFRAC	0.14	0.89
7				TIMHOT	0.11	0.90
8				CSFACTN	0.09	0.91
9				SCLCRW	-0.08	0.92
10				VDEPOS	-0.08	0.92

^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.

observed variability. Further, the indicated effects for the variables in the regression model in Table 7 are consistent with their use in MACCS. Similarly unfavorable comparisons between regressions with raw and rank-transformed data also exist for the other three variables in Tables 6 and 7. As a result, the sensitivity analyses based on stepwise regression analysis contained in this report use rank-transformed data.

The individual analyses in Table 7 are now discussed. For mean number of early fatalities with 100% evacuation, the first variable selected in the regression analysis is YSCALE (scaling factor for horizontal dispersion), which can account for 65% of the observed variability. The variable YSCALE has a negative regression coefficient; thus, increasing YSCALE tends to decrease the mean number of early fatalities. This negative effect results because increasing YSCALE tends to spread the plume out and thus reduce the number of individuals receiving large radiation exposures. The next three variables selected in the analysis are ESPEED (evacuation speed), ZSCALE (scaling factor for vertical dispersion), and EFFACA1 (early fatality hazard function alpha value for bone marrow exposure), with each of these variables having a negative regression coefficient and accounting for approximately 7% of the observed variability. Increasing ESPEED and ZSCALE tends to decrease the number of the fatalities by decreasing individual exposure; in contrast, increasing EFFACA1 tends to decrease the number of fatalities by decreasing the probability that a specified radiation exposure will cause an early fatality. The last four variables selected in the analysis are GSHFACN (groundshine shielding factor for nonevacuees), VDEPOS (dry deposition velocity), CSFACTN (cloudshine shielding factor for nonevacuees) and TDELAY (time from warning to start of evacuation), with each of these variables accounting for 1 to 3% of the observed variability. The variables GSHFACN, CSFACTN, and TDELAY have positive regression coefficients; thus increasing each of these variables tends to increase the mean number of early fatalities. This positive effect results because increasing GSHFACN, CSFACTN, and TDELAY each increases the amount of radiation exposure that individuals receive before they begin to evacuate. The variable VDEPOS has a negative regression coefficient; thus, increasing VDEPOS tends to decrease the mean number of early fatalities. Large values for VDEPOS result in more of the release being deposited close to the reactor and hence in a reduction in the number of individuals receiving large radiation exposures. The final regression model containing all eight variables can account for 92% of the observed variability.

The analysis in Table 7 for mean number of early fatalities without evacuation is considered next. The first variable selected in the regression analysis is YSCALE (scaling factor for horizontal dispersion), which can account for 50% of the observed variability. As for the 100% evacuation case, increasing YSCALE decreases the mean number of fatalities by decreasing the number of individuals receiving large radiation exposures. After YSCALE, the regression analysis selects GSHFACN (groundshine shielding factor for nonevacuees) and EFFACA1 (early fatality hazard function alpha value for bone marrow exposure), which can account for 16% and 10%, respectively, of the observed variability. As for the 100% evacuation case, GSHFACN has a positive regression coefficient because increasing GSHFACN increases the dose that individuals receive, and EFFACA1 has a negative regression coefficient because increasing EFFACA1 decreases the probability that a given radiation exposure will cause a fatality. The last two variables selected in the regression analysis are TIMHOT (time at which individuals are relocated if their projected dose exceeds DOSHOT) and ZSCALE (scaling factor for vertical dispersion), which can account for 7% and 6%, respectively, of the variability. The positive regression coefficient for TIMHOT results because increasing TIMHOT increases the radiation exposure that individuals receive before they are relocated, and the negative regression coefficient for ZSCALE results because increasing ZSCALE tends to reduce the number of individuals receiving large radiation exposures. The final regression model containing all five variables can account for 89% of the observed variability.

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The next regression analysis in Table 7 is for mean number of early fatalities with 100% sheltering. This analysis is generally similar to the analyses with and without evacuation, with YSCALE (scaling factor for horizontal dispersion) identified as the most important variable and EFFACA1 (early fatality hazard function alpha value for bone marrow exposure) and ZSCALE (scaling factor for vertical dispersion) identified as the next two most important variables. Further, small effects are indicated for GSHFACS (groundshine shielding factor for individuals who shelter), VDEPOS (dry deposition velocity) and PROTINS (inhalation protection factor for individuals who shelter). The variable YSCALE was able to account for 57% of the variability, and all six variables together could account for 86%. As might be expected, this analysis selected the shielding factors GSHFACS and PROTINS for individuals who shelter rather than shielding factors for nonevacuees. The variable VDEPOS was selected with a positive regression coefficient, while it appears in the analysis for 100% evacuation with a negative regression coefficient. As examination of Figure 8 shows, VDEPOS plays a complex role in MACCS calculations by increasing the probability of a small number of early fatalities and decreasing the probability of a large number of early fatalities; it is probably a slight difference in the balance between these two roles that is causing VDEPOS to have a positive regression coefficient in one analysis and a negative regression coefficient in the other analysis.

The last regression analysis in Table 7 is for the variable evacuation case in which a fraction EVFRAC of the population does not evacuate and the remaining fraction 1-EVFRAC does evacuate. The number of early fatalities for this case is obtained by a combination of the results that underlie the cases with and without evacuation. The first five variables selected in the regression analysis are YSCALE (scaling factor for horizontal dispersion), ZSCALE (scaling factor for vertical dispersion), EFFACA1 (early fatality hazard function alpha value for bone marrow exposure), ESPEED (evacuation speed), and GSHFACN (groundshine shielding factor for nonevacuees), which are also the first five variables selected in the regression analysis for 100% evacuation. Although their order of selection varies somewhat, these five variables have identically signed regression coefficients in both analyses; further, they account for 88% and 87% of the variability in the 100% evacuation and variable evacuation cases, respectively. The next variable selected in the regression analysis is EVFRAC (fraction of population in emergency response zone that does not evacuate), which can account for approximately 2% of the variability. Thus, for this analysis problem, the fraction of the population not participating in evacuation does not have a large effect on the uncertainty in the mean number of early fatalities. After EVFRAC, four additional variables having small effects are identified. Collectively, the ten variables selected in the regression analysis can account for 92% of the variability, with 63% of the variability accounted for by YSCALE.

As shown in Table 8, the partial correlation analyses for exceedance probabilities in Figure 8 and the stepwise regression analysis for mean number of early fatalities in Table 7 produce similar, but not identical, sets of important variables and rankings of variable importance. Some differences between the two analyses should be expected as neither the dependent variables nor the analysis techniques are the same, although they are closely related. However, all analyses are consistent in the selection of YSCALE (scaling factor for horizontal dispersion) as the most important variable. Further, with the exception of VDEPOS (dry deposition velocity) in the analysis for variable evacuation, the analyses are consistent in indicating the same effect for variables identified in both analyses. As shown in Figure 8, VDEPOS can have both a positive and negative effect on the probability of exceeding specified numbers of early fatalities. If desired, the top-down correlation technique¹⁰⁹ could be used to provide a numerical measure of the similarity of the two variable rankings, although such a comparison is not needed in the present study.

Table 8. Comparison of Variable Selection for Number of Early Fatalities in Partial Correlation Analysis in Figure 8 and Stepwise Regression Analysis in Table 7

	Variables Selected in Both Analyses	Additional Variables Selected in Partial Correlation Analysis	Additional Variables Selected in Stepwise Regression Analysis
Early Fatalities with 100% Evacuation	YSCALE (1-, 1-) ^a ZSCALE (2-, 3-) TDELAY (3+, 8+) ESPEED (4-, 2-) EFFACA1 (6-, 4-) VDEPOS (7-, 6-) CSFACTN (8+, 7+)	SCLCRW (5-) ^b	GSHFACN(5+) ^c
Early Fatalities with No Evacuation	YSCALE (1-, 1-) GSHFACN (2+, 2+) ZSCALE (3-, 5-) TIMHOT (6+, 4+)	VDEPOS (4+) SCLCRW (5-)	EFFACA1 (3-)
Early Fatalities with 100% Sheltering	YSCALE (1-, 1-) ZSCALE (2-, 3-) VDEPOS (3+, 5+) GSHFACS (4+, 4+) EFFACA1 (5-, 2-)	SCLCRW (5-) EFFTHR1 (7-)	PROTINS (6+)
Early Fatalities with Variable Evacuation	YSCALE (1-, 1-) ZSCALE (2-, 2-) VDEPOS (3+, 10-) GSHFACN (4+, 5+) ESPEED (5-, 4-) SCLCRW (6-, 9-) EVFRAC (7+, 6+) EFFACA1 (8-, 3-) TIMHOT (9+, 7+)		CSFACTN (8+)

^a(i +/-, j +/-) indicates that the associated variable had i^{th} largest PRCC, in absolute value, in Figure 8, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5 and was also the j^{th} variable selected in the stepwise regression analysis in Table 7, with the regression coefficient being positive (+) or negative (-).

^b(i +/-) indicates that the associated variable had i^{th} largest PRCC, in absolute value, in Figure 8, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5.

^c(j +/-) indicates that the associated variable was the j^{th} variable selected in the stepwise regression analysis in Table 7, with the regression coefficient being positive (+) or negative (-).

5.2 Prodromal Vomiting

Prodromal vomiting and early fatalities are estimated in the same manner within MACCS. The only difference is in the values used in the expressions in Eqs. (25) and (26) for the threshold dose, hazard function alpha value (i.e., LD_{50}), and the hazard function beta value (i.e., shape factor). For prodromal vomiting, the hazard function alpha value is the variable EIFACA1 in Table 4, and the threshold dose and hazard function beta value are fixed at EITHRE1 = 0.5 Gy and EIFACB1 = 3.75, respectively. As a result, the analyses for prodromal vomiting are quite similar to the already presented analyses for early fatalities, with EIFACA1 (early injury hazard function alpha value for prodromal vomiting) playing the same role in the analyses for prodromal vomiting as EFFACA1 (early fatality hazard function alpha value for bone marrow exposure) in the analyses for early fatalities. Because of this similarity, Figures 10, 11, and 12 and Tables 9 and 10 are presented without discussion. The discussions of the corresponding results in Section 5.1 for early fatalities can be consulted for additional information. The similarity of the results for early fatalities and prodromal vomiting can be seen by comparing the variable rankings summarized in Tables 8 and 10.

5.3 Population Dose, 0-10 mi

The distributions of CCDFs for population dose received by individuals initially within 10 mi of the reactor are summarized by the mean and percentile curves presented in Figure 13. As examination of these curves shows, the analyses with evacuation actually yield higher doses than the analyses without evacuation. This pattern results because evacuees have larger shielding factors (i.e., less shielding) than nonevacuees and may also be under the plume for part of the time that they are evacuating.

The PRCC analyses for the probability of exceeding specified dose levels are given in Figure 14. For 100% evacuation, the most important variable, as measured by the absolute value of the PRCC, for the population dose to individuals initially within 10 mi of the reactor is TDELAY (time from warning to start of evacuation), with the exceedance probabilities for population doses tending to increase as TDELAY increases. As examination of the PRCC plot for TDELAY shows, a strong positive correlation exists between TDELAY and exceedance probability for small population doses, with this correlation decreasing as the population dose increases. This pattern may occur because, although increasing TDELAY tends to increase the dose to individuals before they begin to evacuate, large values for TDELAY also reduce the amount of time that evacuees might spend evacuating under the plume and thus reduce their doses while evacuating. The next variable identified in the analysis is YSCALE (scaling factor for horizontal dispersion), which has a negative correlation, with the probability of exceeding doses between approximately 1×10^3 and 1×10^5 Sv. This effect does not appear in the analyses for no evacuation and 100% sheltering and thus must be related to the doses received by individuals who undergo evacuation. In particular, individuals within 10 mi of the reactor are evacuating radially and are assumed to receive no additional dose after they are 20-mi from the reactor. The reduced exposure from increasing YSCALE results from a combination of shifting part of the plume to regions within 20 mi of the reactor from which evacuees have already departed and decreasing the distance from the reactor at which the plume edges start to move outside of the boundary of the 20-mi zone within which radiation exposures to evacuees are calculated. After YSCALE, negative effects are indicated for ESPEED (evacuation speed), VDEPOS (dry deposition velocity), and ZSCALE (scaling factor for vertical dispersion). Increasing ESPEED reduces the exposure to evacuees by reducing the transit time in evacuation; increasing VDEPOS results in more deposition close to the reactor and hence in less total exposure, and increasing ZSCALE tends to move the plume higher and hence reduce exposure to both radioactivity in the plume and radioactivity deposited on the ground. Finally, a positive effect is indicated

Figure 10. Mean and Percentile Curves for Number of Cases of Prodromal Vomiting for the Following Analysis Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

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Figure 11. Partial Rank Correlation Coefficients for Probability that Specified Numbers of Prodomal Vomiting Cases Will Be Exceeded for the Following Analysis Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Figure 12. Distribution of Mean Number of Cases of Prodromal Vomiting for the Following Analysis Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

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Table 9. Stepwise Regression Analyses with Rank-Transformed Data for Mean Number of Cases of Prodromal Vomiting for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation

Step ^a	100% Evacuation			No Evacuation		
	Variable ^b	SRC ^c	R ^{2 d}	Variable ^b	SRC ^c	R ^{2 d}
1	YSCALE	-0.66	0.67	YSCALE	-0.50	0.45
2	ZSCALE	-0.36	0.78	GSHFACN	0.44	0.65
3	ESPEED	-0.24	0.83	ZSCALE	-0.36	0.74
4	VDEPOS	-0.19	0.87	TIMHOT	0.31	0.84
5	GSHFACN	0.15	0.89	EIFACA1	-0.17	0.87
6	EIFACA1	-0.16	0.92			
7	TDELAY	0.12	0.93			
8	TIMHOT	0.08	0.94			
9	CSFACTE	0.07	0.94			

Step ^a	100% Shelter			Variable Evacuation		
	Variable ^b	SRC ^c	R ^{2 d}	Variable ^b	SRC ^c	R ^{2 d}
1	YSCALE	-0.68	0.73	YSCALE	-0.66	0.67
2	ZSCALE	-0.38	0.84	ZSCALE	-0.35	0.77
3	EIFACA1	-0.18	0.87	ESPEED	-0.23	0.82
4	GSHFACS	0.15	0.90	GSHFACN	0.17	0.86
5	GSHFACN	0.11	0.91	VDEPOS	-0.17	0.89
6	VDEPOS	-0.11	0.92	EIFACA1	-0.16	0.91
7	TIMHOT	0.10	0.93	TIMHOT	0.11	0.92
8	PROTINS	0.08	0.93	TDELAY	0.09	0.93

^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.

Table 10. Comparison of Variable Selection for Number of Cases of Prodromal Vomiting in Partial Correlation Analysis in Figure 11 and Stepwise Regression Analysis in Table 9

	Variables Selected in Both Analyses	Additional Variables Selected in Partial Correlation Analysis	Additional Variables Selected in Stepwise Regression Analysis
Prodromal Vomiting with 100% Evacuation	YSCALE (1-, 1-) ^a ZSCALE (2-, 2-) TDELAY (3+, 7+) ESPEED (5-, 3-) VDEPOS (6-, 4-) EIFACA1 (7-, 6-) GSHFACN (8+, 5+)	SCLCRW (4-) ^b	TIMHOT (+) ^c CSFACTE (+)
Prodromal Vomiting with No Evacuation	YSCALE (1-, 1-) GSHFACN (2+, 2+) ZSCALE (3-, 3-) TIMHOT (5+, 4+) EIFACA1 (8-, 5-)	VDEPOS (4+) SCLCRW (5-) CWASH1 (7+)	
Prodromal Vomiting with 100% Sheltering	YSCALE (1-, 1-) ZSCALE (2-, 2-) GSHFACN (4+, 4+) VDEPOS (5+-, 6-) EFFACA1 (6-, 3-) GSHFACN (7+, 5+)	SCLCRW (3-)	TIMHOT (7+) PROTINS (8+)
Prodromal Vomiting with Variable Evacuation	YSCALE (1-, 1-) ZSCALE (2-, 2-) GSHFACN (3+, 4+) ESPEED (5-, 3-) VDEPOS (6+-, 5-) EIFACA1 (7-, 6-) TIMHOT (8+, 7+) EFFACA1 (8-, 3-) TIMHOT (9+, 7+)	SCLCRW (4-) EVFRAC (9+)	TDELAY (+)

^a(*i* +/-, *j* +/-) indicates that the associated variable had *i*th largest PRCC, in absolute value, in Figure 11, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5 and was also the *j*th variable selected in the stepwise regression analysis in Table 9, with the regression coefficient being positive (+) or negative (-).

^b(*i* +/-) indicates that the associated variable had *i*th largest PRCC, in absolute value, in Figure 11, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5.

^c(*j* +/-) indicates that the associated variable was the *j*th variable selected in the stepwise regression analysis in Table 9, with the regression coefficient being positive (+) or negative (-).

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Figure 13. Mean and Percentile Curves for Population Dose (Sv) for Individuals Initially within 10 mi of the Reactor for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Figure 14. Partial Rank Correlation Coefficients for Probability that Specified Doses (Sv) to the Population Initially within 10 mi of the Reactor Will Be Exceeded for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

for PROTINN (inhalation protection factor for nonevacuees), which results because increasing PROTINN increases the radiation exposure that individuals receive before they begin to evacuate.

For no evacuation, YSCALE (scaling factor for horizontal dispersion) has the largest PRCC in absolute value, with the probability of exceeding small population doses tending to increase as YSCALE increases. However, the impact of YSCALE decreases as dose increases, with YSCALE having essentially no impact on the probabilities of exceeding large doses. This is quite different from the effects indicated for YSCALE in the analysis for 100% evacuation, where increasing YSCALE tended to reduce the probability of exceeding large doses. In addition, positive effects are indicated for PROTINN (inhalation protection factor for nonevacuees) and GSHFACN (groundshine protection factor for nonevacuees), and negative effects are indicated for VDEPOS (dry deposition velocity) and ZSCALE (scaling factor for vertical dispersion). An interesting pattern is shown by VDEPOS, with this variable having a positive effect on the probability of exceeding small doses and a negative effect on the probability of exceeding large doses. This pattern probably results because large values of VDEPOS result in large doses to a small number of individuals while small values of VDEPOS result in small doses to a large number of individuals. The effect of VDEPOS is further complicated by the fact that both hotspot and normal relocation are based on projected individual dose, with the result that large values of VDEPOS may lead to more dose avoidance by relocation than small values of VDEPOS.

For 100% sheltering, the patterns of variable importance shown in Figure 14 are very similar to those shown for no evacuation with the exception that the shielding factors PROTINS (inhalation protection factor for individuals who shelter) and GSHFACS (groundshine shielding factor for individuals who shelter) are selected in the PRCC analysis rather than the corresponding shielding factors for nonevacuees. This similarity results because the shielding factors in use are the primary differences between these two analyses, although there are also differences related to the times at which sheltering and relocation take place.

For variable evacuation, the patterns of variable importance shown in Figure 14 are essentially the same as those shown for 100% evacuation. The positive effect indicated for EVFRAC (fraction of population in emergency response zone that does not evacuate) only occurs for small doses, where the variability is coming primarily from the evacuees, as shown in the upper two frames of Figure 13.

The distributions of CCDFs summarized in Figure 13 can be reduced to the distributions of expected dose shown in Figure 15. Then, as summarized in Table 11, stepwise regression analysis can be used to investigate the variability in these expected doses.

For 100% evacuation, the stepwise regression analysis in Table 11 indicates that YSCALE (scaling factor for horizontal dispersion) is the most important variable affecting expected population dose to individuals initially within 10 mi of the reactor, with expected dose tending to decrease as YSCALE increases. This is consistent with the negative influence on the probability of exceeding large doses indicated for YSCALE in Figure 14. Also in consistency with the results shown in Figure 14, negative effects are indicated for ESPEED (evacuation speed), VDEPOS (dry deposition velocity) and ZSCALE (scaling factor for vertical dispersion), and a positive effect is indicated for TDELAY (time from warning to start of evacuation). The variables YSCALE, ESPEED, and VDEPOS are the first three variables selected in the regression analysis and can account for 77% of the variability in mean dose; adding TDELAY and ZSCALE results in regression models that can account for an additional 7% and 3%, respectively, of the variability. On the basis of absolute value of the PRCC, the analysis shown in Figure 14 would rank TDELAY as the most important variable; however, TDELAY is less important in affecting

Figure 15. Distribution of Mean Population Dose (Sv) for Individuals Initially Within 10 mi of the Reactor for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Table 11. Stepwise Regression Analyses with Rank-Transformed Data for Mean Population Dose (Sv), 0-10 mi, for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation

Step ^a	100% Evacuation			No Evacuation		
	Variable ^b	SRC ^c	R ² ^d	Variable ^b	SRC ^c	R ² ^d
1	YSCALE	-0.60	0.48	VDEPOS	-0.55	0.34
2	ESPEED	-0.37	0.64	PROTINN	0.50	0.56
3	VDEPOS	-0.37	0.77	ZSCALE	-0.44	0.74
4	TDELAY	0.26	0.84	GSHFACN	0.25	0.80
5	ZSCALE	-0.21	0.87	TIMHOT	0.21	0.85
6				SCLEFP	0.11	0.86

Step ^a	100% Shelter			Variable Evacuation		
	Variable ^b	SRC ^c	R ² ^d	Variable ^b	SRC ^c	R ² ^d
1	VDEPOS	-0.61	0.37	YSCALE	-0.59	0.46
2	PROTINS	0.55	0.67	VDEPOS	-0.37	0.63
3	ZSCALE	-0.43	0.85	ESPEED	-0.36	0.76
4				TDELAY	0.25	0.82
5				ZSCALE	-0.23	0.86

^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.

mean dose than YSCALE, ESPEED, and VDEPOS because TDELAY primarily affects small doses while the other three variables primarily affect large doses.

For no evacuation, the first three variables selected in the regression analysis for mean population dose presented in Table 11 are VDEPOS (dry deposition velocity), PROTINN (inhalation protection factor for nonevacuees) and ZSCALE (scaling factor for vertical dispersion), which can account for 34%, 22% and 18% of the uncertainty in mean dose, respectively. In addition, GSHFACN (groundshine shielding factor for nonevacuees), TIMHOT (time at which individuals are relocated if their projected dose exceeds DOSHOT) and SCLEFP (plume rise scaling factor for stability classes E through F) account for 6%, 5% and 1% of the uncertainty in mean dose. Increasing VDEPOS results in more concentrated deposits of radioactivity and hence in more effective dose avoidance by relocation; increasing PROTINN and GSHFACN increases dose by reducing shielding; increasing TIMHOT increases dose by increasing the exposure that individuals receive before they are relocated, and increasing SCLEFP increases dose by reducing plume rise and thus increasing the amount of radioactivity that will be deposited within 10 mi of the reactor.

For 100% sheltering, the regression analysis in Table 11 selects VDEPOS (dry deposition velocity), PROTINS (inhalation protection factor for individuals who shelter) and ZSCALE (scaling factor for vertical dispersion), which can account for 37%, 30% and 18%, respectively, of the observed uncertainty in dose to individuals initially within 10 miles of the reactor. This selection is the same as the first three variables identified in the analysis for no evacuation, with the exception that PROTINS rather than PROTINN (inhalation protection factor for nonevacuees) appears in the regression model.

The regression analysis in Table 11 for variable evacuation is similar to the analysis for 100% evacuation, with the exception that the order of importance indicated for ESPEED (evacuation speed) and VDEPOS (dry deposition velocity) is reversed. This reversal probably occurs because VDEPOS is the third most important variable, accounting for 13% of the uncertainty for 100% evacuation and the most important variable, accounting for 34% of the uncertainty for no evacuation. For variable evacuation, VDEPOS is the second most important variable, accounting for 17% of the uncertainty. The variable ESPEED is of reduced importance for the variable evacuation case relative to 100% evacuation because although ESPEED affects the doses received by evacuees, it has no effect on the doses received by nonevacuees.

A comparison of the sensitivity analysis results for population dose to individuals initially within 10 mi of the reactor obtained with PRCCs and stepwise regression is presented in Table 12. Overall, the rankings of variable importance obtained with the two approaches are quite similar. The notable exception to this is the designation of YSCALE (scaling factor for horizontal dispersion) as being the most important variable in the PRCC analyses for population dose to individuals initially within 10 mi of the reactor under the assumptions of no evacuation and 100% sheltering, while YSCALE is not even selected in the corresponding regression analyses. However, as examination of the PRCC plots in Figure 15 shows, YSCALE has a large effect on the exceedance probabilities for small doses. Thus, because as the mean is dominated by the large doses, the absence of YSCALE from the regression analyses for mean dose is consistent with the effects indicated for YSCALE in the PRCC analysis.

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Table 12. Comparison of Variable Selection for Population Dose (Sv) to Individuals Initially Within 10 mi of the Reactor in Partial Correlation Analysis in Figure 14 and Stepwise Regression Analysis in Table 11

	Variables Selected in Both Analyses	Additional Variables Selected in Partial Correlation Analysis	Additional Variables Selected in Stepwise Regression Analysis
Population Dose, 0-10 mi, with 100% Evacuation	TDELAY (1+, 4+) ^a YSCALE (2-, 1-) ESPEED (3-, 2-) VDEPOS (4-, 3-) ZSCALE (5-, 5-)	PROTINN (6+) ^b	
Population Dose, 0-10 mi, with No Evacuation	VDEPOS (2+-, 1-) PROTINN (3+, 2+) ZSCALE (4-, 3-) GSHFACN (5+, 4+)	YSCALE (1+)	TIMHOT (5+) ^c SCLEFP (6+)
Population Dose, 0-10 mi, with 100% Sheltering	PROTINS (2+, 2+) VDEPOS (3-, 1-) ZSCALE (4-, 3-)	YSCALE (1+) GSHFACS (5+)	
Population Dose, 0-10 mi, with Variable Evacuation	YSCALE (1-, 1-) TDELAY (2+, 4+) ESPEED (3-, 3-) VDEPOS (4-, 2-) ZSCALE (7-, 5-)	EVFRAC (5+) PROTINN (6+)	

^a(i +/-, j +/-) indicates that the associated variable had ith largest PRCC, in absolute value, in Figure 14, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5 and was also the jth variable selected in the stepwise regression analysis in Table 11, with the regression coefficient being positive (+) or negative (-).

^b(i +/-) indicates that the associated variable had ith largest PRCC, in absolute value, in Figure 14, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5.

^c(j +/-) indicates that the associated variable was the jth variable selected in the stepwise regression analysis in Table 11, with the regression coefficient being positive (+) or negative (-).

5.4 Population Dose, 0-1000 mi

The distributions of CCDFs for population dose received by individuals within 1000 mi of the reactor are summarized in Figure 16. Because a substantial portion of this dose is received by individuals initially more than 10 mi from the reactor, the summaries in Figure 16 for the four emergency response assumptions under consideration are similar. However, as comparison of the CCDFs for 100% evacuation and no evacuation shows, a poorly chosen evacuation strategy can substantially increase the 1000-mi population dose.

The PRCC analyses for the CCDF distributions summarized in Figure 16 are presented in Figure 17. Given the similarity of the CCDF distributions, it is not surprising that the PRCC analyses in Figure 17 for the four emergency response assumptions are also similar. In particular, positive effects are indicated for PROTINN (inhalation protection factor for nonevacuees), GSHFACN (groundshine shielding factor for nonevacuees) and YSCALE (scaling factor for horizontal dispersion), and a negative effect is indicated for VDEPOS (dry deposition velocity). The only real difference in the analyses in Figure 17 involves YSCALE, which has a positive effect on the exceedance probabilities for small doses (i.e., 10^4 Sv) for all emergency response assumptions but a negative effect on the exceedance probabilities for large doses only for 100% evacuation and variable evacuation. As shown in Figure 14, this pattern results from the tendency of large values of YSCALE to produce a reduction of large doses to evacuees.

The result of reducing the CCDFs summarized in Figure 16 to distributions of expected doses is shown in Figure 18. Owing to the importance of emergency response assumptions about the population dose to individuals initially within 10 mi of the reactor, the distributions for expected dose, at 0-10 mi in Figure 15 are considerably broader than the distributions for expected dose at 0-1000 mi in Figure 18.

The stepwise regression analyses for the mean population doses presented in Figure 18 are summarized in Table 13. Owing to the importance of doses received by individuals initially outside the emergency response zone (i.e., more than 10 mi from the reactor), the four regression analyses summarized in Table 12 are quite similar. In particular, the first three variables selected in all four analyses are VDEPOS (dry deposition velocity), GSHFACN (groundshine shielding factor for nonevacuees), and PROTINN (inhalation protection factor for nonevacuees), with dose tending to decrease as VDEPOS increases and tending to increase as GSHFACN and PROTINN each increases. In each analysis, these three variables can account for 86% or 87% of the observed uncertainty. After VDEPOS, GSHFACN, and PROTINN, each of the regression analyses in Table 13 selects several additional variables that have small effects on the population dose.

A comparison of the sensitivity analysis results for population dose within 1000 mi of the reactor obtained with PRCCs and stepwise regression analysis is presented in Table 14. As examination of this table shows, both sensitivity analyses select VDEPOS (dry deposition velocity), GSHFACN (groundshine shielding factor for nonevacuees), and PROTINN (inhalation protection factor for nonevacuees) as the three most important variables with respect to each of the four population doses under consideration. There is considerable variability in the variables selected by the two techniques after VDEPOS, GSHFACN, and PROTINN; however, these additional variables are making relatively small contributions to the uncertainty in population dose within 1000 mi of the reactor.

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Figure 16. Mean and Percentile Curves for Population Dose (Sv) for Individuals within 1000 mi of the Reactor for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Figure 17. Partial Rank Correlation Coefficients for Probability that Specified Doses (Sv) to the Population within 1000 mi of the Reactor Will Be Exceeded for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Figure 18. Distribution of Mean Population Dose (Sv) for Individuals within 1000 mi of the Reactor for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Table 13. Stepwise Regression Analyses with Rank-Transformed Data for Mean Population Dose (Sv), 0-1000 mi, for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation

Step ^a	100% Evacuation			No Evacuation		
	Variable ^b	SRC ^c	R ^{2 d}	Variable ^b	SRC ^c	R ^{2 d}
1	VDEPOS	-0.78	0.66	VDEPOS	-0.74	0.59
2	GSHFACN	0.37	0.78	PROTINN	0.39	0.73
3	PROTINN	0.30	0.87	GSHFACN	0.38	0.87
4	P2DOS1	0.12	0.89	ZSCALE	0.16	0.90
5	ESPEED	-0.12	0.90	P2DOS1	0.14	0.92

Step ^a	100% Shelter			Variable Evacuation		
	Variable ^b	SRC ^c	R ^{2 d}	Variable ^b	SRC ^c	R ^{2 d}
1	VDEPOS	-0.78	0.64	VDEPOS	-0.78	0.66
2	GSHFACN	0.36	0.76	GSHFACN	0.38	0.78
3	PROTINN	0.32	0.86	PROTINN	0.30	0.87
4	ZSCALE	0.11	0.89	P2DOS1	0.12	0.89
5	P2DOS1	0.14	0.91	ESPEED	-0.12	0.90
6	PROTINS	0.11	0.93			
7	YSCALE	0.11	0.94			
8	SCLCRW	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.

Table 14. Comparison of Variable Selection for Population Dose (Sv) to Individuals Within 1000 mi of the Reactor in Partial Correlation Analysis in Figure 17 and Stepwise Regression Analysis in Table 13

	Variables Selected in Both Analyses	Additional Variables Selected in Partial Correlation Analysis	Additional Variables Selected in Stepwise Regression Analysis
Population Dose, 0-1000 mi, with 100% Evacuation	VDEPOS (1-, 1-) ^a GSHFACN (2+, 2+) PROTINN (3+, 3+)	YSCALE (4+-) ^b CWASH1 (5-) ZSCALE (6+)	P2DOS1 (4+) ^c
Population Dose, 0-1000 mi, with No Evacuation	VDEPOS (1-, 1-) PROTINN (2+, 2+) GSHFACN (3+, 3+) YSCALE (4+, 4+)		P2DOS1 (5+)
Population Dose, 0-1000 mi, with 100% Sheltering	VDEPOS (1-, 1-) PROTINN (2+, 3+) GSHFACN (3+, 2+) YSCALE (4+, 7+) ZSCALE (5+, 4+)	CWASH1 (6-)	P2DOS1 (5+) PROTINS (6+) SCLCRW (7+)
Population Dose, 0-1000 mi, with Variable Evacuation	VDEPOS (1-, 1-) GSHFACN (2+, 2+) PROTINN (3+, 3+)	YSCALE (4+-) CWASH1 (5-) ZSCALE (6+)	P2DOS1 (4+) ESPEED (5-)

^a(i +/-, j +/-) indicates that the associated variable had i^{th} largest PRCC, in absolute value, in Figure 17, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5 and was also the j^{th} variable selected in the stepwise regression analysis in Table 13, with the regression coefficient being positive (+) or negative (-).

^b(i +/-) indicates that the associated variable had i^{th} largest PRCC, in absolute value, in Figure 17, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5.

^c(j +/-) indicates that the associated variable was the j^{th} variable selected in the stepwise regression analysis in Table 13, with the regression coefficient being positive (+) or negative (-).

5.5 Individual Early Fatality Probability, 0-1 mi

The distribution of CCDFs for the probability that an individual within 1 mi of the reactor will become an early fatality is summarized in Figure 19. The general patterns displayed by the mean and percentile curves in Figure 19 for the four emergency response assumptions are similar, although the CCDFs for 100% evacuation indicate lower early fatality probabilities than the CCDFs for the other three emergency response assumptions. The staircase pattern appearing in the CCDFs results from the nonuniform population distribution within 1 mi of the reactor (i.e., 19 individuals live within 1 mi, with 17 individuals in one wind direction, 1 individual in each of two additional wind directions, and the remaining wind directions having no resident individuals).

The PRCCs for the CCDFs summarized in Figure 19 are presented in Figure 20. For 100% evacuation, the two most important variables are SCLCRW (critical wind speed scaling factor) and YSCALE (scaling factor for horizontal dispersion), with the probability of exceeding a specified early fatality probability tending to decrease as SCLCRW and YSCALE each increases. These negative effects result because increasing SCLCRW increases the number of weather sequences for which plume liftoff will occur and increasing YSCALE causes more spreading out of the plume. Thus, increasing SCLCRW and YSCALE reduces individual radiation exposure. The next two variables in importance are TDELAY (time from warning to start of evacuation) and ESPEED (evacuation speed). The positive and negative effects indicated for TDELAY and ESPEED, respectively, result because increasing TDELAY causes individuals to receive more radiation exposure before they begin to evacuate while increasing ESPEED causes individuals to receive less radiation exposure during the time that they are actually evacuating. Smaller effects are indicated for ZSCALE (scaling factor for vertical dispersion), EFFTHR1 (early fatality threshold dose for bone marrow exposure), VDEPOS (dry deposition velocity) and EFFACA1 (early fatality hazard function alpha value for bone marrow exposure). Increasing ZSCALE tends to spread the plume vertically and thus reduce individual radiation exposure; increasing EFFTHR1 and EFFACA1 tends to reduce the probability that a specified radiation exposure will be fatal; and increasing VDEPOS tends to result in more radionuclide deposition close to the reactor and hence in higher individual radiation exposures. The sharp spikes in the PRCC plots between 0.01 and 0.1 in Figure 20 result from the nonuniform population distribution within 1 mi of the reactor.

For no evacuation, the four most important variables are YSCALE (scaling factor for horizontal dispersion), VDEPOS (dry deposition velocity), SCLCRW (critical wind speed scaling factor) and ZSCALE (scaling factor for vertical dispersion). For 100% evacuation, increasing YSCALE tended to decrease the probability of exceeding a specified individual early fatality probability; in contrast, the opposite effect is displayed for no evacuation, although the PRCCs for YSCALE show a sawtoothed pattern for both cases owing to the nonuniform population distribution within 1 mi of the reactor. The positive effect for YSCALE in the absence of evacuation probably results because increasing YSCALE tends to move radiation from unpopulated to populated grid cells, which is more important for the no evacuation case than for the 100% evacuation case because individuals remain in place longer and thus receive more radiation exposure in the absence of evacuation. The variables VDEPOS, SCLCRW and ZSCALE appear in the analysis for no evacuation for the same reasons that they appear in the analysis for 100% evacuation, although the ordering of importance is not the same. In addition, smaller positive effects are indicated for GSHFACN (groundshine shielding factor for nonevacuees) and TIMHOT (time at which individuals are relocated if their projected dose exceeds DOSHOT).

The analyses for 100% sheltering are similar to those for no evacuation in the sense that VDEPOS (dry deposition velocity), YSCALE (scaling factor for horizontal dispersion), SCLCRW (critical

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Figure 19. Mean and Percentile Curves for Probability that an Individual Within 1 mi of the Reactor Will Become an Early Fatality for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Figure 20. Partial Rank Correlation Coefficients for Probability that Specified Individual Risk Values (i.e., probability that an individual within 1 mi of the reactor will be an early fatality) Will Be Exceeded for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

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wind speed scaling factor), and ZSCALE (scaling factor for vertical dispersion) are again the four most important variables, although the order of VDEPOS and YSCALE is reversed. Further, these variables have similar effects in both analyses. The PRCCs for YSCALE display a complex sawtoothed pattern owing to the nonuniform population distribution within 1 mi of the reactor. In addition to VDEPOS, YSCALE, SCLCRW, and ZSCALE, the PRCC analysis for 100% sheltering also identifies positive effects for GSHFACS (groundshine shielding factor for individuals who shelter) and CWASH1 (linear term in wet deposition model) and negative effects for SCLEFP (plume rise scaling factor for stability classes E through F) and EFFACA1 (early fatality hazard function alpha value for bone marrow exposure). Increasing GSHFACS and CWASH1 tends to increase radiation exposure by reducing shielding to groundshine and increasing wet deposition, respectively, while increasing SCLEFP tends to reduce exposure by increasing plume rise. In contrast, increasing EFFACA1 reduces the probability that a specified radiation exposure will result in an early fatality.

For variable evacuation, the four most important variables are SCLCRW (critical wind speed scaling factor), YSCALE (scaling factor for horizontal dispersion), VDEPOS (dry deposition velocity), and ZSCALE (scaling factor for vertical dispersion), as was the case for no evacuation and 100% sheltering, although there is some shifting in order of importance. The variables SCLCRW, VDEPOS, and ZSCALE display the same effects, although to somewhat different degrees of importance, in all four PRCC analyses presented in Figure 20. In contrast, the indicated effects for YSCALE are less consistent. For variable evacuation, increasing YSCALE tends to increase the probability of exceeding a small individual early fatality probability and decrease the probability of exceeding a large individual early fatality probability, which is a pattern not displayed in any of the other analyses presented in Figure 20. Rather, this is a blending of the effects indicated for YSCALE in the analyses for 100% evacuation and no evacuation. After SCLCRW, YSCALE, VDEPOS, and ZSCALE, the PRCC analysis for variable evacuation identifies a number of additional variables that have small effects. With the exception of TDELAY (time from warning to start of evacuation), these variables have PRCCs that are consistent with their use in MACCS and what should be the resultant effects on individual early fatality probability with variable evacuation. The appearance of TDELAY with a negative PRCC does not make sense and is probably spurious.

The distributions of CCDFs summarized in Figure 19 can be reduced to the distributions of mean individual early fatality probability shown in Figure 21. Often, the production of mean reactor accident consequence results, where the mean is taken over weather variability as shown in Eqs. (27) and (28), produces results that are not very useful owing to the combining of consequence magnitude and consequence probability. The results shown in Figure 21 are somewhat more natural because they are equal to the annual probability that an individual currently living within 1 mi of the reactor will be killed given the occurrence of a reactor accident of the particular type under consideration (i.e., an accident producing the source term SUR-11-3 as defined in Table 2 for this analysis, which was estimated in the NUREG-1150 analysis for Surry to have a mean frequency of $1.2 \times 10^{-7} \text{ yr}^{-1}$ for internally initiated accidents).

The regression analyses for mean individual early fatality probability are presented in Table 15. For 100% evacuation, the uncertainty is dominated by variables that tend to reduce radiation levels in the plume close to the ground surface. In particular, negative effects are indicated for SCLCRW (critical wind speed scaling factor), YSCALE (scaling factor for horizontal dispersion), SCLEFP (plume rise scaling factor for stability classes E through F), and ZSCALE (scaling factor for vertical dispersion). These variables constitute four out of the first five variables selected in the regression analysis and can account for 57% of the uncertainty in mean individual early fatality probability. The variable EFFACA1 (early fatality hazard function alpha value for bone marrow exposure) was also among the first five

variables selected and can account for an additional 11% of the uncertainty. Increasing EFFACA1 reduces mean individual early fatality probability by reducing the probability that a specified radiation exposure will result in an early fatality. In addition to these variables, small positive effects are indicated for PROTINN (inhalation protection factor for nonevacuees), BUILDH (initial vertical height of plume) and CSFACTN (cloudshine shielding factor for nonevacuees), and small negative effects are indicated for ESPEED (evacuation speed) and EFFACA2 (early fatality hazard function alpha value for lung exposure).

For no evacuation, the uncertainty in mean individual early fatality probability is dominated by variables that affect groundshine dose. In particular, VDEPOS (dry deposition velocity), GSHFACN (groundshine shielding factor for nonevacuees), and TIMHOT (time at which individuals are relocated if their projected dose exceeds DOSHOT) account for 52% of the uncertainty in mean individual early fatality probability, with this probability tending to increase as each of these variables increases. The variables SCLCRW (critical wind speed scaling factor) and EFFACA1 (early fatality hazard function alpha value for bone marrow exposure) account for an additional 10% and 8%, respectively, of the uncertainty, with mean probability tending to decrease as each of these variables increases. In addition to VDEPOS, GSHFACN, TIMHOT, SCLCRW and EFFACA1, small positive effects are indicated for BUILDH (initial vertical height of plume), YSCALE (scaling factor for horizontal dispersion) and PROTINN (inhalation protection factor for nonevacuees), and small negative effects are indicated for SCLEFP (plume rise scaling factor for stability classes E through F) and ZSCALE (scaling factor for vertical dispersion). The small positive effect indicated for YSCALE contrasts with relatively strong negative effect indicated for YSCALE in the regression analysis for mean individual early fatality probability with 100% evacuation. As examination of the corresponding PRCC plots in Figure 20 shows, YSCALE does indeed have a negative effect in the analysis for 100% evacuation and a complex, but positive, effect in the analysis for no evacuation.

The analysis in Table 15 for mean individual early fatality probability with 100% sheltering is similar to the analysis for no evacuation with the exceptions that TIMHOT (time at which individuals are relocated if their projected dose exceeds DOSHOT) is not a relevant variable and thus does not appear in the regression analysis and also that protection factors for individuals who shelter rather than for nonevacuees appear in the regression analysis. The analysis in Table 15 for mean individual early fatality probability with variable evacuation is almost identical to the analysis for 100% evacuation.

A comparison of the sensitivity analysis results for individual early fatality probability within 1 mi obtained with PRCCs and stepwise regression is presented in Table 16. The two approaches generally agree on the most important variables, although there was less consistency than in the analyses summarized in Tables 8, 10, 12, and 14. This reduced consistency is probably due to the effects that result from a nonuniform population distribution within 1 mi of the reactor. In particular, YSCALE (scaling factor for horizontal dispersion) and TDELAY (time from warning to start of evacuation) show complex patterns of influence in Figure 20 that cannot be captured in the regression analyses for mean results presented in Table 15. Further, the large number of variables identified in the PRCC analyses in Figure 20 and the stepwise regression analyses in Table 15 indicates that the uncertainty in individual early fatality probability is influenced by many variables, with no single variable having a dominant effect.

Figure 21. Distribution of Mean Individual Early Fatality Probability for Individuals Living Within 1 mi of the Reactor for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering and Variable Evacuation.

**Table 15. Stepwise Regression Analyses with Rank-Transformed Data for Mean Individual Early Fatality Probability, 0-1 mi, for the Following Cases:
100% Evacuation, No Evacuation, 100% Sheltering and Variable Evacuation**

100% Evacuation				No Evacuation		
Step ^a	Variable ^b	SRC ^c	R ^{2 d}	Variable ^b	SRC ^c	R ^{2 d}
1	SCLCRW	-0.51	0.23	VDEPOS	0.53	0.26
2	YSCALE	-0.36	0.45	GSHFACN	0.37	0.40
3	EFFACA1	-0.34	0.56	TIMHOT	0.36	0.52
4	SCLEFP	-0.23	0.62	SCLCRW	-0.33	0.62
5	ZSCALE	-0.26	0.68	EFFACA1	-0.28	0.70
6	PROTINN	0.18	0.72	BUILDH	0.16	0.74
7	BUILDH	0.17	0.75	SCLEFP	-0.15	0.76
8	CSFACTN	0.17	0.78	YSCALE	0.28	0.78
9	ESPEED	-0.16	0.80	ZSCALE	-0.26	0.83
10	EFFACA2	-0.13	0.82	PROTINN	0.14	0.85

100% Shelter				Variable Evacuation		
Step ^a	Variable ^b	SRC ^c	R ^{2 d}	Variable ^b	SRC ^c	R ^{2 d}
1	VDEPOS	0.55	0.29	SCLCRW	-0.52	0.24
2	SCLCRW	-0.42	0.45	YSCALE	-0.33	0.43
3	EFFACA1	-0.35	0.57	EFFACA1	-0.35	0.55
4	GSHFACS	0.32	0.67	ZSCALE	-0.27	0.61
5	ZSCALE	-0.28	0.75	SCLEFP	-0.23	0.67
6	SCLEFP	-0.21	0.80	PROTINN	0.19	0.72
7	BUILDH	0.16	0.82	CSFACTN	0.17	0.74
8	PROTINS	0.14	0.84	ESPEED	-0.17	0.77
9				BUILDH	0.16	0.79
10				EFFACA2	-0.14	0.81
11				VDEPOS	0.13	0.83

^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.

Table 16. Comparison of Variable Selection for Individual Early Fatality Probability, 0-1 mi, in Partial Correlation Analysis in Figure 20 and Stepwise Regression Analysis in Table 15

	Variables Selected in Both Analyses	Additional Variables Selected in Partial Correlation Analysis	Additional Variables Selected in Stepwise Regression Analysis
Individual Early Fatality Probability, 0-1 mi, with 100% Evacuation	SCLCRW (1-, 1-) ^a YSCALE (2-, 2-) ESPEED (4-, 9-) ZSCALE (5-, 5-) EFFACA1 (8-, 3-)	TDELAY (3+-) ^b EFFTHR1 (6-) VDEPOS (7+)	SCLEFP (4-) ^c PROTINN (6+) BUILDH (7+) CSFACTN (8+) EFFACA2 (10-)
Individual Early Fatality Probability, 0-1 mi, with No Evacuation	YSCALE (1+, 8+) VDEPOS (2+, 1+) SCLCRW (3-, 4-) ZSCALE (4-, 9-) GSHFACN (5+, 2+) TIMHOT (6+, 3+)		EFFACA1 (5-) BUILDH (6+) SCLEFP (7-) PROTINN (10+)
Individual Early Fatality Probability, 0-1 mi, with 100% Sheltering	VDEPOS (1+, 1+) SCLCRW (3-, 4-) ZSCALE (4-, 5-) GSHFACS (5+, 4+) SCLEFP (6-, 6-) EFFACA1 (7-, 3-)	YSCALE (2-+) CWASH1 (8-)	BUILDH (7+) PROTINS (8+)
Individual Early Fatality Probability, 0-1 mi, with Variable Evacuation	SCLCRW (1-, 1-) YSCALE (2+-, 2-) VDEPOS (3+, 11+) ZSCALE (4-, 4-) ESPEED (7-, 8-) EFFACA1 (10-, 3-) BUILDH (11+, 9+) PROTINN (12+, 6+)	TDELAY (5-) EVFRAC (6+) GSHFACN (8+) TIMHOT (9+)	SCLEFP (5-) CSFACTN (7+) EFFACA2 (10-)

^a(i +/-, j +/-) indicates that the associated variable had i^{th} largest PRCC, in absolute value, in Figure 20, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5 and was also the j^{th} variable selected in the stepwise regression analysis in Table 15, with the regression coefficient being positive (+) or negative (-).

^b(i +/-) indicates that the associated variable had i^{th} largest PRCC, in absolute value, in Figure 20, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5.

^c(j +/-) indicates that the associated variable was the j^{th} variable selected in the stepwise regression analysis in Table 15, with the regression coefficient being positive (+) or negative (-).

5.6 Maximum Early Fatality Distance

The distribution of CCDFs for maximum early fatality distance with no evacuation is summarized in Figure 22. As examination of this figure shows, there is considerable variability in maximum early fatality distance owing to both weather and the imprecisely known variables listed in Table 4.

As shown in Figure 23, PRCCs can be used to identify the variables that contribute to the distribution of CCDFs summarized in Figure 22. The four most important variables are YSCALE (scaling factor for horizontal dispersion), VDEPOS (dry deposition velocity), ZSCALE (scaling factor for vertical dispersion), and GSHFACN (groundshine shielding factor for nonevacuees). Increasing YSCALE and ZSCALE tends to reduce maximum early fatality distance by spreading out the plume and thus reducing individual exposure; increasing VDEPOS shows a complex pattern of effects by both increasing the probability of exceeding small values for maximum early fatality distance and decreasing the probability of exceeding large scales; increasing GSHFACN tends to increase maximum early fatality distance by increasing individual radiation exposure. Smaller effects are also indicated for SCLCRW (critical wind speed scaling factor), SCLADP (plume rise scaling factor for stability classes A through D) and TIMHOT (time at which individuals are relocated if their projected dose exceeds DOSHOT). Increasing SCLCRW and SCLADP tends to decrease maximum early fatality distance by reducing plume liftoff, while increasing DOSHOT tends to increase maximum early fatality distance by increasing the radiation exposure that individuals receive before they are relocated.

As shown in Figure 24, the CCDFs summarized in Figure 23 for maximum early fatality distance can be reduced to a distribution of mean early fatality distances, where the mean is taken over weather variability. Then, as shown in Table 17, stepwise regression analysis can be used to determine the variables that dominate the uncertainty in mean early fatality distance.

The variable YSCALE (scaling factor for horizontal dispersion) can account for 59% of the uncertainty in mean early fatality distance, with this distance tending to decrease as YSCALE increases due to spreading of the plume and a resultant reduction in individual radiation exposure. After YSCALE, similar effects (i.e., 6-10% of the uncertainty) are indicated for GSHFACN (groundshine shielding factor for nonevacuees), EFFACA1 (early fatality hazard function alpha value for bone marrow exposure), ZSCALE (scaling factor for vertical dispersion) and TIMHOT (time at which individuals are relocated if their projected dose exceeds DOSHOT). Increasing GSHFACN reduces radiation shielding and thus increases individual radiation exposure; increasing EFFACA1 reduces the probability that a small dose (i.e., a dose close to the threshold value EFFTHR1) will result in an early fatality; increasing ZSCALE tends to spread the plume out and thus reduce individual radiation exposure, and increasing TIMHOT increases the radiation exposure that individuals receive before relocation. In addition, a small negative effect is indicated for EFFACB1 (early fatality hazard function beta value for bone marrow exposure), and a small positive effect is indicated for VDEPOS (dry deposition velocity). Increasing EFFACB1 reduces the probability that a small dose will result in an early fatality. As shown in Figure 23, VDEPOS has a complex pattern of effects on maximum early fatality distance.

A comparison of sensitivity analysis results obtained with PRCCs and stepwise regression for maximum early fatality distance is presented in Table 18. Both analyses identify YSCALE (scaling factor for horizontal dispersion) as the most important variable. The variables ZSCALE (scaling factor for vertical dispersion), GSHFACN (groundshine shielding factor for nonevacuees) and TIMHOT (time at which individuals are relocated if their projected dose exceeds DOSHOT) also have similar importance rankings. There is considerable difference in the importance rankings for VDEPOS (dry deposition

Figure 22. Mean and Percentile Curves for Maximum Early Fatality Distance (km) with No Evacuation.

Figure 23. Partial Rank Correlation Coefficients for Probability that Specified Maximum Early Fatality Distances (km) with No Evacuation Will Be Exceeded.

Figure 24. Distribution of Mean Value for Maximum Early Fatality Distance (km) with No Evacuation.

Table 17. Stepwise Regression Analysis with Rank-Transformed Data for Mean Value of Maximum Early Fatality Distance (km) with No Evacuation

Step ^a	No Evacuation		
	Variable ^b	SRC ^c	R ² ^d
1	YSCALE	-0.62	0.59
2	GSHFACN	0.30	0.69
3	EFFACA1	-0.19	0.78
4	ZSCALE	-0.33	0.85
5	TIMHOT	0.22	0.91
6	EFFACB1	-0.16	0.92
7	VDEPOS	0.09	0.92

^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.

Table 18. Comparison of Variable Selection for Maximum Early Fatality Distance (km) with No Evacuation in Partial Correlation Analysis in Figure 23 and Stepwise Regression Analysis in Table 17

	Variables Selected in Both Analyses	Additional Variables Selected in Partial Correlation Analysis	Additional Variables Selected in Stepwise Regression Analysis
Maximum Early Fatality Distance with No Evacuation	YSCALE (1-, 1-) ^a VDEPOS (2+, 7+) ZSCALE (3-, 4-) GSHFACN (4+, 2+) TIMHOT (7+, 5+)	SCLCRW (5-) ^b SCLADP (6-)	EFFACA1 (3-) ^c EFFACB1 (6-)

^a(*i* +/-, *j* +/-) indicates that the associated variable had *i*th largest PRCC, in absolute value, in Figure 23, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5 and was also the *j*th variable selected in the stepwise regression analysis in Table 17, with the regression coefficient being positive (+) or negative (-).

^b(*i* +/-) indicates that the associated variable had *i*th largest PRCC, in absolute value, in Figure 23, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5.

^c(*j* +/-) indicates that the associated variable was the *j*th variable selected in the stepwise regression analysis in Table 17, with the regression coefficient being positive (+) or negative (-).

Determination of Dominant Variables

velocity) as a result of the bimodal effects indicated for VDEPOS in Figure 23. Finally, the PRCC analysis indicates negative effects for two variables related to plume liftoff, while the stepwise regression analysis indicates negative effects for two variables related to the shape of the early fatality hazard function in Eq. (25) for bone marrow exposure.

6. ROBUSTNESS OF ANALYSIS

This section presents the results of several investigations intended to provide perspective on the quality of the uncertainty and sensitivity analyses described in Section 5. A natural question to ask is "Would the uncertainty and sensitivity analysis results change if a different Latin hypercube sample is used?" The results of repeating the analyses in Section 5 with a second Latin hypercube sample are discussed in Section 6.1. The use of a second independent Latin hypercube of size 100 was found to produce uncertainty and sensitivity analysis results that were essentially the same as those produced with the first sample. Another natural question is "Will reducing the uncertainty in the dominant variables identified in the sensitivity analyses significantly reduce the uncertainty in the associated predicted variables?" As shown in Sections 6.2 and 6.3, fixing the dominant variables at "best estimate" values leads to substantial reductions in the uncertainty in the corresponding predicted variables, while fixing the less important variables at best-estimate values had little effect on uncertainty. Further, fixing the values for the dominate variables allows the effects of the less important variables to be assessed more accurately. Another question is "What effects do the assumed variable distributions have on the outcomes of the uncertainty and sensitivity analysis?" As shown in Section 6.4, similar sensitivity analysis results were obtained when the original uniform and loguniform distributions assigned to the 34 imprecisely known variables in Table 4 changed to left-triangular and then to right-triangular distributions, although there were shifts in the uncertainty analysis results. The original analyses were performed with rank-transformed data, which leads to the question "Would other data transformations produce similar sensitivity analysis results?" As shown in Section 6.5, both rank-transformed and logarithmically transformed data lead to similar sensitivity analysis results.

6.1 Results Obtained with Second Independent Sample

No formal results are currently known that define an appropriate or optimum sample size to use in an uncertainty/sensitivity study based on Latin hypercube sampling, although the experience of the authors in a number of such studies^{98, 112-117} suggests that a sample size that is approximately 1.5 to 3 times the number of variables is usually adequate. One way to test the stability of the results is to rerun the analysis with a second independently generated Latin hypercube sample and then compare the uncertainty and sensitivity analysis results obtained with the two samples. To this end, a second Latin hypercube sample of size 100 was generated from the variables in Table 4 and the analyses leading to the results in Section 5 were repeated with this sample. The uncertainty and sensitivity analysis results obtained with these two samples were very similar.

Owing to the large number of curves involved, it is difficult to directly compare distributions of CCDFs. However, the mean and percentile curves derived from such distributions can be readily compared. As an example, the mean and percentile curves for early fatalities obtained with the two samples are presented in Figure 25 and are essentially the same. Thus, the estimation of these curves is quite robust for the sample size in use (i.e., 100). Similarly close comparisons resulted for all predicted variables listed in Table 5.

The sensitivity analyses presented in Section 5 for the distributions of CCDFs are based on PRCCs. The sensitivity analyses obtained with the two samples are very similar. As an example, four selected partial rank correlation results are shown in Figure 26. Similarly close comparisons between PRCCs calculated with the two samples were obtained for all results presented in Section 5.

Robustness of Analysis

Figure 25. Comparison of Mean and Percentile Curves for Early Fatalities Obtained with Two Independent Latin Hypercube Samples for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Figure 26. Comparison of PRCCs Obtained with Two Independent Latin Hypercube Samples.

Each CCDF in Section 5 can be reduced to a single number by the calculation of an expected value as shown in Eq. (27). The result of the analysis for each variable in Table 5 can then be summarized with a cumulative distribution function for these expected values. A single mean value can also be calculated for each cumulative distribution function, which is equivalent to the reduction of a distribution of CCDFs to a single number. The results of these calculations for the two samples are illustrated in Figure 27 for early fatalities. As examination of this figure shows, the cumulative distribution functions and corresponding mean values obtained with the two samples are very close together. Similar results were obtained for all variables in Table 5.

As the comparisons in Table 19 show, the mean values and standard deviations obtained with the two samples are quite similar for all variables in Table 5. The biggest differences occur for early fatalities, with a -23.4% difference between the mean estimated with the first and second sample for 100% evacuation and a 31.8% difference between the standard deviation estimated with the first and second sample for 100% sheltering. As examination of Figure 27 shows, these differences are small compared with the almost four orders of magnitude uncertainty in the 100 expected values for each sample element that were used in the calculation of the means and standard deviations for early fatalities.

Stepsize regression analysis with rank-transformed variables was used in Section 5 to determine the dominant variables influencing the expected values for the variables in Table 5. Essentially the same results as presented in Section 5 were obtained when these analyses were repeated with the second Latin hypercube sample. As an example, summaries of the analyses for early health effects with the two samples are presented in Table 20. Although there are small variations in the order in which variables enter the analysis, the overall results are quite similar. For example, the analyses for each of the four cases in Table 20 select the same top four variables, and the analyses for three of the cases select the same top five variables. There is some variation in the variables selected near the end of the regression analysis; however, these variables tend to have small effects on the total uncertainty in the dependent variable under consideration (i.e., < 2%).

6.2 Important Variables Fixed at Best-Estimate Values

After the analyses presented in Section 5 were completed, a test was run to determine if fixing the important variables identified in the sensitivity analysis at their "best-estimate" values would produce a substantial reduction in the uncertainty in the associated predicted results.^{118,119} In particular, the early fatality results discussed in Section 5.1 were used as the basis for this test. The input variables identified as being important with respect to early fatalities are summarized in Table 21. In the test, the 14 variables listed at the bottom of Table 21 (i.e., EFFACA1, ..., ZSCALE and CSFACTN, ..., SCLCRW) were held fixed at their best-estimate values indicated in Table 4, and the remaining 20 variables were allowed to vary as before. In particular, the original Latin hypercube sample was modified by replacing the sampled values of the previously indicated 14 variables by their best-estimate values and leaving the sampled values for the remaining 20 variables unchanged. The resultant sample was then propagated through MACCS as before.

The resultant distributions of CCDFs for number of early fatalities are summarized in Figure 28. As comparison of Figures 7 and 28 shows, holding the important variables identified in the sensitivity analysis at their best-estimate values leads to a substantial reduction in the uncertainty in the CCDFs for number of early fatalities.

Figure 27. Comparison of Cumulative Distribution Functions and Mean Values for Early Fatalities Obtained with Two Independent Latin Hypercube Samples for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Table 19. Comparison of Mean Values and Standard Deviations Obtained with Two Independent Latin Hypercube Samples

Consequence	Mean			Standard Deviation		
	Sample 1	Sample 2	% Dif	Sample 1	Sample 2	% Dif
Early Fatalities						
100% Evacuation	2.25×10^1	2.94×10^1	-23.4	5.52×10^1	6.90×10^1	-20.0
No Evacuation	6.75×10^1	6.83×10^1	- 1.2	1.01×10^2	9.48×10^1	7.0
100% Shelter	1.64×10^1	1.58×10^1	3.9	4.39×10^1	3.33×10^1	31.8
Variable Evacuation	2.39×10^1	3.05×10^1	-21.6	5.59×10^1	6.90×10^1	-18.9
Prodromal Vomiting						
100% Evacuation	9.18×10^1	1.01×10^2	- 9.2	1.42×10^2	1.50×10^2	- 5.0
No Evacuation	1.77×10^2	1.81×10^2	- 2.1	1.72×10^2	1.68×10^2	2.3
100% Shelter	6.71×10^1	6.99×10^1	- 4.1	1.02×10^2	9.40×10^1	9.0
Variable Evacuation	9.43×10^1	1.03×10^2	- 8.7	1.43×10^2	1.50×10^2	- 4.6
Pop Dose (Sv), 0 - 10 mi						
100% Evacuation	5.68×10^3	5.92×10^3	- 3.9	5.96×10^3	6.22×10^3	- 4.2
No Evacuation	6.74×10^3	6.69×10^3	0.7	2.86×10^3	2.81×10^3	1.5
100% Shelter	2.95×10^3	2.93×10^3	0.8	1.60×10^3	1.56×10^3	2.7
Variable Evacuation	5.72×10^3	5.94×10^3	- 3.7	5.86×10^3	6.10×10^3	- 3.9
Pop Dose (Sv), 0 - 1000 mi						
100% Evacuation	3.26×10^4	3.27×10^4	- 0.3	1.36×10^4	1.32×10^4	3.0
No Evacuation	3.37×10^4	3.35×10^4	0.5	1.31×10^4	1.29×10^4	1.7
100% Shelter	2.99×10^4	2.97×10^4	0.5	1.17×10^4	1.16×10^4	1.0
Variable Evacuation	3.27×10^4	3.28×10^4	- 0.3	1.36×10^4	1.32×10^4	3.0
Early Fat Prob, 0 - 1 mi						
100% Evacuation	2.01×10^{-2}	2.05×10^{-2}	- 1.9	8.88×10^{-3}	9.20×10^{-3}	- 3.5
No Evacuation	5.03×10^{-2}	4.99×10^{-2}	0.7	2.28×10^{-2}	2.15×10^{-2}	6.1
100 % Shelter	2.54×10^{-2}	2.58×10^{-2}	- 1.3	1.22×10^{-2}	1.37×10^{-2}	-10.6
Variable Evacuation	2.09×10^{-2}	2.13×10^{-2}	- 1.7	8.91×10^{-3}	9.26×10^{-3}	- 3.8
Max Early Fat Dist (km)						
No Evacuation	7.07×10^0	7.18×10^0	- 1.5	3.14×10^0	3.36×10^0	- 6.6

Table 20. Comparison of Stepwise Regression Analyses with Rank-Transformed Data for Two Independent Latin Hypercube Samples for Mean Number of Early Fatalities for the Following Cases:
100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation

Step ^a	Sample 1			Sample 2		
	Variable ^b	SRC ^c	R ² ^d	Variable ^b	SRC ^c	R ² ^d
Early Fatalities: 100% Evacuation						
1	YSCALE	-0.68	0.65	YSCALE	-0.68	0.68
2	ESPEED	-0.28	0.72	EFFACA1	-0.27	0.76
3	ZSCALE	-0.29	0.79	ZSCALE	-0.28	0.81
4	EFFACA1	-0.23	0.85	ESPEED	-0.20	0.85
5	GSHFACN	0.14	0.88	VDEPOS	-0.17	0.88
6	VDEPOS	-0.12	0.90	GSHFACN	0.14	0.90
7	CSFACTN	0.10	0.91	TDELAY	0.13	0.92
8	TDELAY	0.08	0.92	TIMHOT	0.08	0.93
Early Fatalities: No Evacuation						
1	YSCALE	-0.59	0.50	YSCALE	-0.63	0.59
2	GSHFACN	0.39	0.66	TIMHOT	0.35	0.72
3	EFFACA1	-0.33	0.76	EFFACA1	-0.29	0.81
4	TIMHOT	0.27	0.83	GSHFACN	0.22	0.88
5	ZSCALE	-0.28	0.89	ZSCALE	-0.24	0.92
6				VDEPOS	0.09	0.93
7				CSFACTN	0.09	0.94
8				BUILDW	-0.07	0.94
Early Fatalities: 100% Shelter						
1	YSCALE	-0.64	0.57	YSCALE	-0.63	0.63
2	EFFACA1	-0.39	0.72	EFFACA1	-0.39	0.80
3	ZSCALE	-0.29	0.79	ZSCALE	-0.29	0.86
4	GSHFACS	0.22	0.84	GSHFACS	0.19	0.89
5	VDEPOS	0.12	0.85	VDEPOS	0.10	0.90
6	PROTINS	0.11	0.86	TIMHOT	0.09	0.91

Table 20 (concluded)

Step ^a	Sample 1			Sample 2		
	Variable ^b	SRC ^c	R ² ^d	Variable ^b	SRC ^c	R ² ^d
Early Fatalities: Variable Evacuation						
1	YSCALE	-0.68	0.63	YSCALE	-0.68	0.69
2	ZSCALE	-0.29	0.70	EFFACA1	-0.29	0.78
3	EFFACA1	-0.24	0.76	ZSCALE	-0.28	0.83
4	ESPEED	-0.25	0.81	ESPEED	-0.16	0.85
5	GSHFACN	0.20	0.87	GSHFACN	0.15	0.88
6	EVFRAC	0.14	0.89	TIMHOT	0.14	0.90
7	TIMHOT	0.11	0.90	VDEPOS	-0.13	0.91
8	CSFACTN	0.09	0.91	TDELAY	0.11	0.92
9	SCLCRW	-0.08	0.92			
10	VDEPOS	-0.08	0.92			

^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.

**Table 21. Important Input Variables Identified in
Sensitivity Analyses for Early Fatalities**

First Four Variables in PRCC Analysis	Additional Variables in PRCC Analysis	Additional Variables in Stepwise Regression Analysis
ESPEED GSHFACN GSHFACS TDELAY VDEPOS YSCALE ZSCALE	CSFACTN EFFACA1 EFFTHR1 EVFRAC SCLCRW TIMHOT	PROTINS
First Four Variables in Stepwise Regression Analysis	Additional Variables in Stepwise Regression Analysis	Additional Variables in PRCC Analysis
EFFACA1 ESPEED GSHFACN GSHFACS TIMHOT YSCALE ZSCALE	CSFACTN EVFRAC PROTINS SCLCRW TDELAY VDEPOS	EFFTHR1
First Four Variables in Either Analysis	Additional Variables	
EFFACA1 ESPEED GSHFACN GSHFACS TDELAY TIMHOT VDEPOS YSCALE ZSCALE	CSFACTN EFFTHR1 EVFRAC PROTINS SCLCRW

Figure 28. Mean and Percentile Curves for Number of Early Fatalities with Variables Listed in Table 21 Fixed at Best-Estimate Values for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

A similar comparison can also be made for the mean number of early fatalities, with the mean defined as shown in Eq. (28). The distributions for the mean number of early fatalities obtained with the variables in Table 21 held fixed at their best-estimate values are shown in Figure 29. As comparison of Figures 9 and 29 shows, holding the important variables at their best-estimate values again leads to a substantial reduction in uncertainty.

Once the calculations leading to Figures 28 and 29 have been completed, additional sensitivity analyses can be performed to determine the important variables when the variables in Table 21 are held fixed at their best-estimate values. For example, the PRCCs for the CCDFs summarized in Figure 28 are shown in Figure 30. Such analyses provide perspective on what would become the important variables if the uncertainty in the most important variables identified in the first analysis could be substantially reduced. For example, EFFACB1 (early fatality hazard function beta value for bone marrow exposure) is now identified as the most important variable in all four analyses presented in Figure 30, with the probability of exceeding a specified number of early fatalities tending to decrease as EFFACB1 increases. This negative effect results because increasing EFFACB1 decreases the probability of becoming an early fatality at doses below EFFACA1 (early fatality hazard function alpha value for bone marrow exposure) (See Eq. 25). After EFFACB1, the PRCC analyses presented in Figure 30 selected a number of additional variables with effects that are consistent with their implementation within MACCS.

An interesting pattern is displayed by SCLEFP (plume rise scaling factor for stability classes E through F) in the analyses for no evacuation and 100% sheltering, with this variable having a negative effect on the probability of exceeding 1 or more early fatalities and a positive effect on the probability of exceeding 100 or more early fatalities. In contrast, only the negative effect is displayed in the analyses with evacuation. Increasing SCLEFP increases plume rise for stability classes E through F, with the result that less radioactive material is deposited close to the reactor and correspondingly more is deposited farther away from the reactor. This reduces the number of early fatalities among evacuees by reducing the high-concentration deposits that are necessary to produce radiation exposures with the potential to cause an early fatality before evacuation precludes additional exposure. For analyses without evacuation, the spreading of the release due to increased plume rise results in more individuals receiving potentially lethal radiation exposures for some weather sequences owing to the longer time period for exposure in the absence of evacuation.

Stepwise regression analyses for mean number of early fatalities are presented in Table 22. The original analysis with all variables is given in Table 7. Again, the impact of variables whose effects were too small to be identified in the original analysis can now be seen. As already observed in the PRCC analysis in Figure 30, increasing EFFACB1 (early fatality hazard function beta value for bone marrow exposure) has a negative effect in all analyses. Also in accord with the results obtained in the PRCC analysis, SCLEFP (plume rise scaling factor for stability classes E through F) has a positive effect for the no evacuation case and negative effects for the other three cases. The dominant variable in the analysis for 100% evacuation is EFFACA2 (early fatality hazard function alpha value for lung exposure), with the number of early fatalities tending to decrease as EFFACA2 increases. Interestingly, EFFACA2 does not appear in the analysis for either no evacuation or 100% sheltering, which suggests that lung exposure is more important in the evacuees than in the nonevacuees. A difference between the PRCC analyses in Figure 30 and the regression analyses in Table 22 is that the former indicates a small positive effect for BUILDH (reactor building height) while the latter indicates a small negative effect. However, the overall effect of BUILDH is small, and this difference probably results from BUILDH having both a positive and a negative effect for the probability of exceeding different numbers of early fatalities.

**Figure 29. Distribution of Mean Number of Early Fatalities with Variables Listed in Table 21 Fixed at Best-Estimate Values for the Following Cases:
100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.**

Figure 30. Partial Rank Correlation Coefficients for Probability that a Specified Number of Early Fatalities Will Be Exceeded with the Variables in Table 21 Fixed at Best Estimate Values for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

Table 22. Stepwise Regression Analysis with Rank-Transformed Data for Mean Number of Early Fatalities with Variables in Table 21 Set to Best-Estimate Values for the Following Cases: 100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation

Step ^a	100% Evacuation			No Evacuation		
	Variable ^b	SRC ^c	R ² ^d	Variable ^b	SRC ^c	R ² ^d
1	EFFACA2	-0.57	0.30	SCLEFP	0.65	0.42
2	EFFACB1	-0.51	0.58	EFFACB1	-0.39	0.57
3	PROTINN	0.36	0.70	BUILDH	-0.33	0.68
4	SCLEFP	-0.32	0.79	PROTINN	0.33	0.78
5	CSFACTE	0.25	0.85			
6	BUILDH	-0.15	0.88			

Step ^a	100% Shelter			Variable Evacuation		
	Variable ^b	SRC ^c	R ² ^d	Variable ^b	SRC ^c	R ² ^d
1	EFFACB1	-0.67	0.44	EFFACB1	-0.54	0.29
2	SCLEFP	-0.43	0.63	EFFACA2	-0.55	0.58
3	CSFACTS	0.40	0.79	PROTINN	0.40	0.73
4	TTOSH2	0.20	0.83	CSFACTE	0.24	0.79
5				SCLEFP	-0.23	0.84
6				BUILDH	-0.19	0.87

^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.

This section has presented analyses for number of early fatalities with the important variables identified in Section 5.1 fixed at their best-estimate values. Similar analyses could be performed for each of the other dependent variables considered in Sections 5.2 through 5.6. For obvious reasons, this gets to be rather tedious. However, as comparison of the important variables listed in Tables 8, 10, 12, 14, 16 and 18 shows, the important input variables for the other dependent variables are essentially the same as those listed in Table 21 for number of early fatalities. Thus, the MACCS calculations with the variables in Table 21 held fixed also provides perspective on fixing the important input variables for the other dependent variables. The results of sensitivity analyses for these dependent variables with the variables in Table 21 fixed are summarized without discussion in Table 23.

Table 23. Summary of Sensitivity Analysis Results Based on PRCCs and Stepwise Regression Analysis with the Variables in Table 21 Fixed at Best-Estimate Values

100% Evacuation	No Evacuation	100% Shelter	Variable Evacuation
Early Fatalities			
EFFACB1 (1-, 2-) ^a PROTINN (2+, 3+) SCLEFP (3-, 4-) EFFACA2 (4-, 1-) BUILDH (5+, 6-) CSFACTE (6+, 5+)	EFFACB1 (1-, 2-) SCLEFP (2-, 1+) ^b PROTINN (3+, 4+) BUILDH (5+, 4-) CWASH1 (4+, *) ^c	EFFACB1 (1-, 1-) SCLEFP (2-, 2-) CSFACTS (4+, 3+) TTOSH2 (5+, 4+) CWASH1 (3+, *) BUILDH (6+, *)	EFFACB1 (1-, 1-) PROTINN (2+, 3+) EFFACA2 (3-, 2-) SCLEFP (4-, 5-) CSFACTE (5+, 4+) BUILDH (6+, 6-)
Prodromal Vomiting			
EIFACA1 (1-, 1-) PROTINN (2+, 4+) CSFACTE (3+, 2+) BUILDH (4+, 3-) GSHFACE (6+, 5+) SCLEFP (5+, *)	EIFACA1 (1-, 1-) PROTINN (2+, 3+) SCLEFP (3+, 2+) BUILDH (4+, 4-) CWASH1 (5+, *)	EIFACA1 (1-, 1-) SCLEFP (2+, 2+) CSFACTS (3+, 3+) BUILDH (4+, 4-) CWASH1 (5+, 6+) TTOSH2 (*, 5+)	EIFACA1 (1-, 1-) PROTINN (2+, 4+) SCLEFP (3+, 6+) BUILDH (4+, 3-) CSFACTE (5+, 2+) GSHFACE (6+, 5+)
Population Dose (Sv), 0-10 mi			
PROTINN (1+, 1+) SCLEFP (2+, 3+) BUILDH (5+, 2-) SCLADP (3-, *) CWASH1 (4-, *) VDEPOS (*, 4-) GSHFACE (*, 5+)	PROTINN (1+, 1+) SCLEFP (3+, 2+) P2DOS1 (4+, 3+) SCLADP (2-, *) BUILDH (5+, *) VDEPOS (*, 4-)	SCLEFP (1+, 1+) BUILDH (3+, 2-) CSFACTS (4+, 3+) CWASH1 (5+, 4-) SCLADP (2-, *)	PROTINN (1+, 1+) SCLEFP (3+, 3+) BUILDH (4+, 2-) SCLADP (2-, *) CWASH1 (4-, *) P2DOS1 (5+, *) VDEPOS (*, 4-) GSHFACE (*, 5+)
Population Dose (Sv), 0-1000 mi			
PROTINN (1+, 1+) SCLEFP (2+, 3+) CWASH1 (3-, 4-) P2DOS1 (4+, 2+) BUILDH (5-, 5-) PHS2T2 (*, 6+)	PROTINN (1+, 1+) CWASH1 (2-, 4-) SCLEFP (3+, 2+) P2DOS1 (4+, 3+) PHS2T2 (*, 5+)	PROTINN (1+, 1+) SCLEFP (2+, 3+) CWASH1 (3-, 4-) P2DOS1 (4+, 2+)	PROTINN (1+, 1+) SCLEFP (2+, 3+) CWASH1 (3-, 4-) P2DOS1 (4+, 2+) BUILDH (5-, *) BUILDW (*, 5-) PHS2T2 (*, 6+)

Table 23 (concluded)

100% Evacuation	No Evacuation	100% Shelter	Variable Evacuation
Individual Early Fatality Probability, 0-1 mi			
SCLEFP (1-, 1-) PROTINN (2+, 2+) BUILDH (4+, 3+)	PROTINN (3+, 2+) SCLEFP (4-, 1-) BUILDH (5+, 3+) BUILDW (6+, 4+)	EFFACB1 (1-, 5-) SCLEFP (2-, 1-) CWASH1 (3+, 4+) BUILDH (4+, 2+) CSFACTS (6+, 3+)	SCLEFP (1-, 1-) PROTINN (2+, 2+) BUILDH (4+, 3+)
EFFACB1 (3-, *) EFFACA2 (*, 4-)	CWASH1 (1+, *) EFFACB1 (2-, *) EFFACA2 (*, 5-)	BUILDW (5+, *) TTOSH2 (7+, *)	EFFACB1 (3-, *) EFFACA2 (*, 4-)

^a($i+/-j+/-$) indicates that the associated variable had the i^{th} largest PRCC, in absolute value, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5 and was the j^{th} variable selected in the stepwise regression analysis, with the corresponding regression coefficient being positive (+) or negative (-).

^b+/- indicates that a PRCC is first positive and then negative when it exceeds 0.5 in absolute value; the opposite pattern is indicated by -+.

^c* indicates variable not identified in analysis.

6.3 Important Variables Fixed at Different Best-Estimate Values

As shown in Section 6.2, fixing the important variables at their best-estimate values leads to a substantial reduction in the uncertainty in predicted results. The effect of different best-estimate values is now considered.

The results presented in this section are based on two Latin hypercube samples from the variables in Table 4. The first sample, which is represented by

$$x_i, i = 1, \dots, nS = 20, \quad (29)$$

is of size 20 and is constructed from all variables in Table 4 (i.e., $nV = 34$). The second sample, which is represented by

$$y_i, i = 1, \dots, nS = 5, \quad (30)$$

is of size 5 and is constructed from the variables in Table 4 that are not listed in Table 21 (i.e., $nV = 34 - 14 = 20$). Thus, the second sample contains the variables that were not identified as being important in the sensitivity analyses in Section 5.1 for number of early fatalities. Due to the small size of the samples in Eqs. (29) and (30), they were generated without use of the Iman/Conover restricted pairing technique.¹⁰⁰

The two preceding samples can now be used to construct a new sample

$$(x_i, y_j), i = 1, \dots, 20, j = 1, \dots, 5, \quad (31)$$

from the variables in Table 4, with the convention that the variable values in y_j replace the corresponding variable values in x_i for each pair (x_i, y_j) . The new sample is of size 100 with $nV = 34$, but only five values are used for each of the variables not listed in Table 21. The sample indicated in Eq. (31) can also be viewed as 20 samples of size 5, that is

$$(x_i, y_j), j = 1, \dots, 5, \quad (32)$$

for $i = 1, \dots, 20$, and as 5 samples of size 20, that is

$$(x_i, y_j), i = 1, \dots, 20, \quad (33)$$

for $j = 1, \dots, 5$. For the 20 samples indicated in Eq. (32), values for the variables in Table 21 are fixed and the remaining variables from Table 4 are allowed to take on different values. The opposite occurs for the 5 samples indicated in Eq. (33), with the values for the variables in Table 21 changing and values for the remaining variables in Table 4 fixed.

If the analyses in Section 5.1 were successful in identifying the important variables influencing the number of early fatalities, then variability between results obtained with the different samples in Eq. (32) should be greater than the variability associated with the individual sample elements within a sample. In contrast, the opposite pattern should hold for the samples in Eq. (33). To test this, the associated 100 MACCS runs were made, and the indicated comparisons were performed.

For the samples in Eq. (32), 20 sets of 5 CCDFs result for each dependent variable. Three of these sets are shown in Figure 31 for number of early fatalities with variable evacuation. As examination of this figure shows, the variation between the three sets of CCDFs is greater than the variation within each set. As suggested by Figure 28, the variation within each set would increase with a larger sample size (i.e., > 5) for the variables not listed in Table 21 but not enough to equal the between set variation. For additional perspective, Figure 32 shows the median CCDF for each of the 20 samples in Eq. (32); the variation between these CCDFs is much greater than the variation within each set of CCDFs in Figure 31 or, for that matter, within the sets in Figure 28. The results in Figures 31 and 32 indicate that the position of the CCDF for number of early fatalities with variable evacuation is controlled by the uncertainty in the variables listed in Table 21, with little influence due to the other 20 variables considered in the analysis (i.e., those variables listed in Table 4 but not in Table 21). In particular, the results in Figures 31 and 32 indicate that the substantial reduction of uncertainty shown in Figure 22 is not a function of the particular set of best-estimate values selected for the variables in Table 21, although this selection does determine where the resultant distribution of CCDFs is located.

For the samples in Eq. (33), 5 sets of 20 CCDFs result for each dependent variable. The mean and selected percentile curves for number of early fatalities with variable evacuation are presented in Figure 33. As this figure shows, changing the values for the variables not contained in Table 21 has only a small effect on the distribution of CCDFs for early fatalities with variable evacuation. A similar pattern is also displayed by the other dependent variables under consideration. Thus, as indicated by the results in Figures 31, 32 and 33, the analysis has been successful in identifying the dominant variables that influence number of early fatalities. Similar comparisons also show that the variables in Table 21 are the dominant variables with respect to the other MACCS predictions under consideration.

6.4 Effect of Different Distributions on Sensitivity Analysis Results

The variables in Table 4 were assigned either uniform or loguniform distributions for the analyses presented in Section 5. These distributions were selected to provide sampled values across the full range of each variable. Although the distributions of predicted variables can be quite sensitive to the distributions assigned to input variables, the results of regression-based sensitivity analyses are often fairly insensitive to the actual distributions selected for use. To illustrate this point, the analyses in Section 5 were repeated with the variables in Table 4 first assigned left-triangular distributions and then assigned right-triangular distributions (i.e., distributions that have density functions that are triangular in shape, with the modes appearing at the left and right ends of the range of each variable, respectively). In this way, the original variable ranges were preserved but the selected distributions weighted the left and right ends of these ranges, respectively.

The use of left-triangular as opposed to right-triangular distributions for the variables in Table 4 caused observable, but not large, changes in the location of the mean and percentile curves for individual consequences. The exceedance probabilities for individual consequence values typically changed by a factor of 2 to 10 for these two distributional assumptions. A typical comparison is shown in Figure 34 for number of early fatalities with variable evacuation; the corresponding mean and percentile curves obtained with the original distributions are shown in Figure 7.

The box plots shown in Figure 35 for mean number of early fatalities obtained with each of the distributional assumptions provide another comparison of the effects of different distributional assumptions. As a reminder, the endpoints of the boxes in Fig. 35 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, $x_{.50}$.

Figure 31. Three Sets of CCDFs for Number of Early Fatalities with Variable Evacuation with Variables in Table 21 Set to Different Best-Estimate Values.

Figure 32. Median CCDFs for Number of Early Fatalities with Variable Evacuation for 20 Sets of CCDFs with Variables in Table 21 Set to Different Best-Estimate Values.

Figure 33. Mean and Percentile Curves for Number of Early Fatalities with Variable Evacuation for Variables Not Contained in Table 21 Set to Five Different Sets of Best-Estimate Values.

Figure 34. Mean and Percentile Curves for Number of Early Fatalities with Variable Evacuation for Left-Triangular Distributions (left frame) and Right-Triangular Distributions (right frame) Assigned to the Variables in Table 5.

Figure 35. Box Plots for Mean Number of Early Fatalities for Left-Triangular Distributions, Original Distributions and Right-Triangular Distributions Assigned to the Variables in Table 5 for the Following Cases:
100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation.

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.

The sensitivity analyses based on PRCCs appearing in Figures 8, 11, 14, 17 and 20 were repeated with left-triangular and right-triangular distributions, respectively. The results of the analyses with the three distributional assumptions (i.e., left-triangular, original as defined in Table 4, and right-triangular) are summarized in Table 24. As examination of this table shows, a similar set of important variables is picked with each distributional assumption, although there is some variation in the order of variable importance.

The similarity of the sensitivity analysis results obtained with the three distributional assumptions is particularly apparent when the set of all variables identified in the analysis at a specific level of importance is considered. For example, the sets L_{Pi} , O_{Pi} and R_{Pi} defined in Table 25 contain the top i variables identified in the analyses presented in Table 24 for left-triangular distributions, the original distributions and right-triangular distributions, respectively. Thus, L_{Pi} contains all variables listed in Table 24 for which the first integer following the variable is less than or equal to i ; the sets O_{Pi} and R_{Pi} are defined similarly for the second and third integers, respectively. As examination of Table 25 shows, the sets L_{Pi} , O_{Pi} and R_{Pi} tend to be similar. The changing membership of the sets $U_{Pi} - L_{Pi}$, $U_{Pi} - O_{Pi}$ and $U_{Pi} - R_{Pi}$, where $U_{Pi} = L_{Pi} \cup O_{Pi} \cup R_{Pi}$, indicates that the differences between L_{Pi} , O_{Pi} and R_{Pi} are due primarily to order of variable selection rather than inherent differences between these sets as i increases.

The sensitivity analyses based on stepwise regression analysis appearing in Tables 7, 9, 11, 13 and 15 were also repeated with left-triangular and right-triangular distributions. As shown in Table 26, the results of these analyses with the three distributional assumptions are quite similar. In particular, the different distributional assumptions tend to lead to the identification of the same variables, although the order of importance can be different.

As was the case for the sensitivity analysis results based on PRCCs in Table 24, the similarity of the sensitivity analysis results based on stepwise regression analysis in Table 26 is particularly apparent when the set of all variables identified in the analysis at a specific level of importance is considered. The sets L_{Ri} , O_{Ri} and R_{Ri} defined in Table 27 contain the top i variables identified in the analyses presented in Table 26 for left-triangular distributions, the original distributions and right-triangular distributions, respectively, and are analogous to the sets L_{Pi} , O_{Pi} and R_{Pi} used in Table 25 to summarize results based on PRCCs. The sets L_{Ri} , O_{Ri} and R_{Ri} shown in Table 27 tend to be similar. Further, as was the case for groupings based on PRCCs in Table 25, the changing membership of the sets $U_{Ri} - L_{Ri}$, $U_{Ri} - O_{Ri}$ and $U_{Ri} - R_{Ri}$ indicates that the differences between L_{Ri} , O_{Ri} and R_{Ri} are due primarily to order of variable selection rather than inherent differences between these sets as i increases.

**Table 24. Comparison of Sensitivity Analysis Results Obtained with PRCCs for
Left-Triangular Distributions, Original Distributions as Defined in Table 4
and Right-Triangular Distributions**

100% Evacuation	No Evacuation	100% Shelter	Variable Evacuation
Early Fatalities			
YSCALE (1-, 1-, 1-) ^a ZSCALE (2-, 2-, 5-) TDELAY (3+, 3+, 2+) ESPEED (4-, 4-, 7-) SCLCRW (5-, 5-, 6-) VDEPOS (6-, 7-, 4+) CSFACTN (8+, 8+, *) EFFACA1 (*, 6-, *) EFFTHR1 (7, *, *) GSHFACN (*, *, 3+) SCLEFP (*, *, 8-)	YSCALE (1-, 1-, 3-) GSHFACN (2+, 2+, 1+) ZSCALE (3-, 3-, 6-) VDEPOS (5+-, 4+-, 2+) TIMHOT (6+, 6+, 5+) SCLCRW (4-, 5-, *) EFFTHR1 (7-, *, *) CWASH1 (*, *, 4+) EFFACA1 (*, *, 7-)	YSCALE (1-, 1-, 2-) ZSCALE (2-, 2-, 4-) VDEPOS (3+, 3+, 1+) GSHFACS (5+, 4+, 3+) SCLCRW (4-, 5-, 6-) EFFACA1 (6-, 6-, 5-) EFFTHR1 (7-, 7-, *)	YSCALE (1-, 1-, 1-) ZSCALE (2-, 2-, 6-) VDEPOS (5+-, 3+, 3+) ^b GSHFACN (6+, 4+, 2+) EVFRAC (8+, 7+, 5+) TIMHOT (7+, 9+, 7+) ESPEED (3-, 5-, *) SCLCRW (4-, 6-, *) EFFACA1 (*, 8-, 8-) TDELAY (*, *, 4)
Prodromal Vomiting			
YSCALE (1-, 1-, 1-) ZSCALE (2-, 2-, 5-) TDELAY (3+, 3+, 2+) VDEPOS (5-, 6-, 7-) EIFACA1 (6-, 7-, 4-) SCLCRW (7-, 4-, *) ESPEED (4-, 5-, *) GSHFACN (*, 8+, 3+) TIMHOT (*, *, 6+)	YSCALE (1-, 1-, 3-) GSHFACN (2+, 2+, 1+) ZSCALE (3-, 3-, 5-) VDEPOS (5+-, 4+, 2+) TIMHOT (6+, 6+, 4+) SCLCRW (4-, 5-, *) EIFACA1 (*, 8-, 6-) CWASH1 (*, 7+, *)	YSCALE (1-, 1-, 1-) ZSCALE (2-, 2-, 4-) SCLCRW (3-, 3-, 8-) GSHFACS (4+, 4+, 5+) VDEPOS (5+-, 5+-, 3+) EIFACA1 (6-, 6-, 6-) GSHFACN (7+, 7+, 2+) TIMHOT (*, *, 8+)	YSCALE (1-, 1-, 2-) ZSCALE (2-, 2-, 3-) GSHFACN (6+, 3+, 1+) VDEPOS (5+-, 6+-, 4+) EIFACA1 (7-, 7-, 7-) TIMHOT (9+, 8+, 5+) SCLCRW (4-, 4-, *) ESPEED (3-, 5-, *) EVFRAC (*, 9+, 6+) TDELAY (8+, *, *)
Population Dose (Sv), 0-10 mi			
TDELAY (1+, 1+, 1+) YSCALE (3-, 2-, 2-) ESPEED (2-, 3-, 5-) VDEPOS (4-, 4-, 4-) ZSCALE (5-, 5-, 6-) PROTINN (6+, 6+, 3+)	YSCALE (1+, 1+, 1+) VDEPOS (2-, 2+-, 3+) PROTINN (3+, 3+, 2+) ZSCALE (4-, 4-, 4+) GSHFACN (5+, 5+, 5+) TIMHOT (6+, *, 7+) SCLEFP (7+, *, 6+) P2DOS1 (8+, *, 8+)	YSCALE (1+, 1+, 2+) PROTINS (2+, 2+, 1+) VDEPOS (3-, 3-, 3-) ZSCALE (4-, 4-, 4-) GSHFACS (5+, 5+, 5+) SCLEFP (6+, *, 6+) SCLCRW (7-, *, *)	YSCALE (1-, 1-, 2+) TDELAY (3+, 2+, 1+) ESPEED (2-, 3-, 7-) VDEPOS (5-, 4-, 4-) EVFRAC (4+, 5+, 5+) PROTINN (6+, 6+, 3+) ZSCALE (7-, 7-, 6+) SCLEFP (*, *, 8+) SCLADP (*, *, 9-)

Table 24 (concluded)

100% Evacuation	No Evacuation	100% Shelter	Variable Evacuation
Population Dose (Sv), 0-1000 mi			
VDEPOS (1-, 1-, 1-) GSHFACN (2+, 2+, 2+) PROTINN (3+, 3+, 4+) YSCALE (4+-, 4+-, 5+) CWASH1 (6-, 5-, 6-) ZSCALE (5+, 6+, 3+)	VDEPOS (1-, 1-, 1-) PROTINN (2+, 2+, 3+) GSHFACN (3+, 3+, 2+) YSCALE (4+, 4+, 4+) ZSCALE (5+, *, 5+)	VDEPOS (1-, 1-, 1-) PROTINN (3+, 2+, 4+) GSHFACN (2+, 3+, 2+) YSCALE (5+, 4+, 5+) ZSCALE (4+, 5+, 3+) CWASH (7-, 6-, 6-)	VDEPOS (1-, 1-, 1-) GSHFACN (2+, 2+, 2+) PROTINN (3+, 3+, 4+) YSCALE (4+-, 4+-, 5+) CWASH1 (6-, 5-, 6-) ZSCALE (5+, 6+, 3+)
SCLEFP (8+, *, 7+) P2DOS1 (9+, *, 8+) ESPEED (7-, *, *)	CWASH (6-, *, *) SCLEFP (*, *, 6+) P2DOS1 (*, *, 7+)	PROTINS (6+, *, *) SCLCRW (8+, *, *) SCLEFP (*, *, 7+) P2DOS1 (*, *, 8+)	SCLEFP (8+, *, 7+) P2DOS1 (9+, *, 8+) ESPEED (7-, *, *)
Individual Early Fatality Probability, 0-1 mi			
SCLCRW (1-, 1-, 2-) YSCALE (2-, 2-, 3-) TDELAY (4+-, 3+, 1+) ESPEED (8-, 4-, 7-) EFFTHR1 (5-, 6-, 9-) EFFACA1 (7-, 8-, 8-) ZSCALE (3-, 5-, *) VDEPOS (*, 7+, 4+) PROTINN (6+, *, *) GSHFACN (*, *, 5+) SCLEFP (*, *, 6-)	YSCALE (1+, 1+, 3+) VDEPOS (2+, 2+, 1+) SCLCRW (5-, 3-, 5-) GSHFACN (6+, 5+, 2+) TIMHOT (4+, 6+, 4+) ZSCALE (3-, 4-, *) CWASH1 (7+, *, *)	VDEPOS (1+, 1+, 1+) YSCALE (2+-, 2+-, 3+) SCLCRW (3-, 3-, 2-) ZSCALE (4-, 4-, 6-) GSHFACS (5+, 5+, 4+) EFFACA1 (6-, 7-, 7-) EFFTHR1 (7-, *, 5-) SCLEFP (*, 6-, *) PROTINS (8+, *, *)	SCLCRW (1-, 1-, 1-) YSCALE (2+-, 2+-, 2+) VDEPOS (3+, 3+, 3+) ZSCALE (4-, 4-, 11-) TDELAY (5-, 5-, 4+) EVFRAC (6+, 6+, 5+) ESPEED (11-, 7-, 9-) GSHFACN (8+, 8+, 6+) TIMHOT (7+, 9+, 10+) EFFACA1 (9-, 10-, 8-) PROTINN (10+, 11+, *) SCLEFP (*, *, 7-)

^a($i+/-j+/-, k+/-$) indicates that the associated variable had the i^{th} largest PRCC, in absolute value, in the analysis when left-triangular distributions are assumed for the variables in Table 4, with this coefficient being positive (+) or negative (-) when its absolute value exceeds 0.5; $j+/-$ and $k+/-$ provide similar information when the original distributions and right-triangular distributions, respectively, are assumed for the variables in Table 4; * indicates that the variable was not selected in the associated analysis.

^b+/- indicates that a PRCC is first positive and then negative when it exceeds 0.5 in absolute value; the opposite pattern is indicated by -+.

Table 25. Comparison of Sets of Variables Identified in Sensitivity Analyses with PRCCs for Left-Triangular Distributions, Original Distributions as Defined in Table 4 and Right-Triangular Distributions

Notation	
$L_{Pi} = \{VAR:$	VAR is one of the top i variables (i.e., rank $1, 2, \dots, i$ as defined by the maximum value of the PRCC) for at least one of the predicted variables in Table 24 when left-triangular distributions are assumed}
O_{Pi}, R_{Pi} are defined the same as L_{Pi} but for the original distributions in Table 4 and right-triangular distributions, respectively.	
$U_{Pi} = L_{Pi} \cup O_{Pi} \cup R_{Pi}$	
nU_{Pi} = number of variables in U_{Pi}	
First Variable in One or More Analyses	
$U_{P1} = \{GSHFACN, PROTINN, SCLCRW, TDELAY, VDEPOS, YSCALE\}, nU_{P1} = 6$	
$U_{P1} - L_{P1} = U_{P1} - O_{P1} = \{GSHFACN, PROTINN\}$	
$U_{P1} - R_{P1} = \emptyset$	
Top 2 Variables in One or More Analyses	
$U_{P2} = U_{P1} \cup \{ESPEED, SCLCRW, ZSCALE\}$ $= \{ESPEED, GSHFACN, PROTINN, PROTINS, SCLCRW, TDELAY, VDEPOS, YSCALE, ZSCALE\}, nU_{P2} = 9$	
$U_{P2} - L_{P2} = \emptyset$	
$U_{P2} - O_{P2} = \{ESPEED\}$	
$U_{P2} - R_{P2} = \{ESPEED, ZSCALE\}$	
Top 3 Variables in One or More Analyses	
$U_{P3} = U_{P2} \cup \{GSHFACS\}$ $= \{ESPEED, GSHFACN, GSHFACS, PROTINN, PROTINS, SCLCRW, TDELAY, VDEPOS, YSCALE, ZSCALE\}, nU_{P3} = 10$	
$U_{P3} - L_{P3} = U_{P3} - O_{P3} = \{GSHFACS\}$	
$U_{P3} - R_{P3} = \{ESPEED\}$	

Table 25 (concluded)

Top 4 Variables in One or More Analyses

$$\begin{aligned}
 U_{P4} &= U_{P3} \cup \{\text{CWASH1, EIFACA1, EVFRAC, TIMHOT}\} \\
 &= \{\text{CWASH1, EIFACA1, ESPEED, EVFRAC, GSHFACN, GSHFACS, PROTINN,} \\
 &\quad \text{PROTINS, SCLCRW, TDELAY, TIMHOT, VDEPOS, YSCALE, ZSCALE}\}, \\
 nU_{P4} &= 14
 \end{aligned}$$

$$\begin{aligned}
 U_{P4} - L_{P4} &= \{\text{CWASH1, EIFACA1}\} \\
 U_{P4} - O_{P4} &= \{\text{CWASH1, EIFACA1, EVFRAC, TIMHOT}\} \\
 U_{P4} - R_{P4} &= \{\text{ESPEED, EVFRAC}\}
 \end{aligned}$$

Top 5 Variables in One or More Analyses

$$\begin{aligned}
 U_{P5} &= U_{P4} \cup \{\text{EFFACA1, EFFTHR1}\} \\
 &= \{\text{CWASH1, EFFACA1, EFFTHR1, EIFACA1, ESPEED, EVFRAC, GSHFACN,} \\
 &\quad \text{GSHFACS, PROTINN, PROTINS, SCLCRW, TDELAY, TIMHOT, VDEPOS,} \\
 &\quad \text{YSCALE, ZSCALE}\}, nU_{P5} = 16
 \end{aligned}$$

$$\begin{aligned}
 U_{P5} - L_{P5} &= \{\text{CWASH1, EFFACA1, EIFACA1}\} \\
 U_{P5} - O_{P5} &= \{\text{EFFACA1, EFFTHR1, EIFACA1, TIMHOT}\} \\
 U_{P5} - R_{P5} &= \emptyset
 \end{aligned}$$

Top 6 Variables in One or More Analyses

$$\begin{aligned}
 U_{P6} &= U_{P5} \cup \{\text{SCLEFP}\} \\
 &= \{\text{CWASH1, EFFACA1, EFFTHR1, EIFACA1, ESPEED, EVFRAC, GSHFACN,} \\
 &\quad \text{GSHFACS, PROTINN, PROTINS, SCLCRW, SCLEFP, TDELAY, TIMHOT,} \\
 &\quad \text{VDEPOS, YSCALE, ZSCALE}\}, nU_{P6} = 17
 \end{aligned}$$

$$U_{P6} - L_{P6} = U_{P6} - O_{P6} = U_{P6} - R_{P6} = \emptyset$$

Table 26. Comparison of Sensitivity Analysis Results Obtained by Stepwise Regression Analysis with Rank-Transformed Data for Left-Triangular Distributions, Original Distributions as Defined in Table 4 and Right-Triangular Distributions

100% Evacuation	No Evacuation	100% Shelter	Variable Evacuation
Early Fatalities			
YSCALE (1-, 1-, 1-) ^a ESPEED (2-, 2-, 7-) EFFACA1 (4-, 4-, 3-) GSHFACN (6+, 5+, 2+) TDELAY (7+, 8+, 4+) ZSCALE (3-, 3-, *) VDEPOS (5-, 6-, *) CSFACTN (*, 7+, *) SCLEFP (*, *, 5-) BUILDH (*, *, 6+)	YSCALE (1-, 1-, 2-) GSHFACN (2+, 2+, 1+) EFFACA1 (3-, 3-, 4-) TIMHOT (4+, 4+, 3+) ZSCALE (5-, 5-, 5-) VDEPOS (*, *, 6+)	YSCALE (1-, 1-, 1-) EFFACA1 (2-, 2-, 2-) ZSCALE (4-, 3-, 5-) GSHFACS (3+, 4+, 3+) VDEPOS (*, 5+, 4+) PROTINS (5+, 6+, *)	YSCALE (1-, 1-, 1-) ZSCALE (3-, 2-, 7-) EFFACA1 (4-, 3-, 3-) GSHFACN (6+, 5+, 2+) EVFRAC (8+, 6+, 6+) ESPEED (2-, 4-, *) TIMHOT (+, 7+, 4+) VDEPOS (5-, 10-, *) TDELAY (7+, *, 5+) CSFACTN (*, 8+, *) SCLCRW (*, 9-, *)
Prodromal Vomiting			
YSCALE (1-, 1-, 1-) ZSCALE (2-, 2-, 8-) ESPEED (3-, 3-, 6-) VDEPOS (4-, 4-, 7-) GSHFACN (7+, 5+, 2+) EIFACA1 (6-, 6-, 3-) TDELAY (5+, 7+, 5+) TIMHOT (*, 8+, 4+) CSFACTE (*, *, 9+)	YSCALE (1-, 1-, 2-) GSHFACN (2+, 2+, 1+) ZSCALE (3-, 3-, 5-) TIMHOT (4+, 4+, 3+) EIFACA1 (7-, 5-, 4-) SCLEFP (5+, *, 6+) VDEPOS (6-, *, *) PROTINN (8+, *, *)	YSCALE (1-, 1-, 1-) ZSCALE (2-, 2-, 5-) EIFACA1 (4-, 3-, 2-) GSHFACS (3+, 4+, 3+) TIMHOT (6+, 7+, 6+) GSHFACN (*, 5+, 4+) VDEPOS (5-, 6-, *) PROTINS (7+, 8+, *) CWASH1 (*, *, 7+)	YSCALE (1-, 1-, 1-) ZSCALE (2-, 2-, 5-) ESPEED (3-, 3-, 8-) GSHFACN (7+, 4+, 2+) VDEPOS (4-, 5-, 7-) EIFACA1 (6-, 6-, 4-) TIMHOT (*, 7+, 3+) TDELAY (5+, 8+, *) EVFRAC (*, *, 6+)
Population Dose (Sv), 0-10 mi			
YSCALE (1-, 1-, 1-) ESPEED (2-, 2-, 6-) VDEPOS (3-, 3-, 3-) TDELAY (4+, 4+, 2+) ZSCALE (5-, 5-, 5-) PROTINN (*, *, 4+)	VDEPOS (1-, 1-, 4-) PROTINN (2+, 2+, 2+) ZSCALE (3-, 3-, 5-) GSHFACN (5+, 4+, 1+) TIMHOT (4+, 5+, 3+) SCLEFP (6+, 6+, 7+) P2DOS (7+, *, 6+)	VDEPOS (1-, 1-, 2-) PROTINS (2+, 2+, 1+) ZSCALE (3-, 3-, 3-) SCLEFP (4+, *, 4+) GSHFACS (5+, *, 5+) CWASH1 (6+, *, *) EFFACA1 (7-, *, *)	YSCALE (1-, 1-, 1-) VDEPOS (3-, 2-, 3-) ESPEED (2-, 3-, 6-) TDELAY (4+, 4+, 2+) ZSCALE (5-, 5-, 5-) PROTINN (*, *, 4+)

Table 26 (concluded)

100% Evacuation	No Evacuation	100% Shelter	Variable Evacuation
Population Dose (Sv), 0-1000mi			
VDEPOS (1-, 1-, 2-) GSHFACN (2+, 2+, 1+) PROTINN (3+, 3+, 4+) P2DOS1 (4+, 4+, 5+) ESPEED (5-, 5-, *) ZSCALE (*, *, 3+) CWASH1 (*, *, 6-)	VDEPOS (1-, 1-, 2-) PROTINN (3+, 2+, 4+) GSHFACN (2+, 3+, 1+) ZSCALE (7+, 4+, 3+) P2DOS1 (5+, 5+, 5+) YSCALE (4+, *, 6+) PHS2T2 (6+, *, *) SCLCRW (8+, *, *) CWASH2 (9-, *, *) CWASH1 (*, *, 7-) SCLEFP (*, *, 8+)	VDEPOS (1-, 1-, 2-) GSHFACN (2+, 2+, 1+) PROTINN (3+, 3+, 4+) ZSCALE (4+, 4+, 3+) P2DOS1 (5+, 5+, 5+) YSCALE (7+, 7+, 6+) PROTINS (6+, 6+, *) SCLCRW (8+, 8+, *) CWASH1 (9-, *, 7-)	VDEPOS (1-, 1-, 2-) GSHFACN (2+, 2+, 1+) PROTINN (3+, 3+, 4+) P2DOS1 (4+, 4+, 5+) ESPEED (5-, 5-, *) ZSCALE (*, *, 3+) CWASH1 (*, *, 6-)
Individual Early Fatality Probability, 0-1 mi			
SCLCRW (2-, 1-, 7-) YSCALE (4-, 2-, 2-) EFFACA1 (3-, 3-, 1-) SCLEFP (9-, 4-, 4-) PROTINN (5+, 6+, 9+) BUILDH (7+, 7+, 11+) ESPEED (8-, 9-, 10-) ZSCALE (1-, 5-, *) CSFACTN (6+, 8+, *) EFFACA2 (*, 10-, *) TDELAY (*, *, 3+) GSHFACN (*, *, 5+) VDEPOS (*, *, 6+) TIMHOT (*, *, 8-)	VDEPOS (2+, 1+, 1+) GSHFACN (3+, 2+, 2+) TIMHOT (1+, 3+, 3+) SCLCRW (5-, 4-, 5-) EFFACA1 (4-, 5-, 4-) BUILDH (9+, 6+, *) YSCALE (7+, 8+, *) ZSCALE (6-, 9-, *) PROTINN (8+, 10+, *) SCLEFP (*, 7-, *)	VDEPOS (1+, 1+, 1+) SCLCRW (4-, 2-, 4-) EFFACA1 (2-, 3-, 2-) GSHFACS (3+, 4+, 3+) ZSCALE (5-, 5-, 6-) SCLEFP (8-, 6-, 5-) BUILDH (7+, 7+, *) PROTINS (6+, 8+, *) CSFACTE (*, *, 7-) YSCALE (*, *, 8-)	SCLCRW (2-, 1-, 7-) YSCALE (4-, 2-, 2-) EFFACA1 (3-, 3-, 1-) SCLEFP (7-, 5-, 3-) ZSCALE (1-, 4-, *) PROTINN (5+, 6+, *) CSFACTN (6+, 7+, *) ESPEED (9-, 8-, *) BUILDH (8+, 9+, *) VDEPOS (*, 11+, 6+) EFFACA2 (*, 10-, *) TDELAY (*, *, 4+) GSHFACN (*, *, 5+)

^a(*i*+/-, *j*+/-, *k*+/-) indicates that the associated variable was the *i*th variable selected in the stepwise regression analysis when left-triangular distributions are assumed for the variables in Table 4, with the corresponding regression coefficient being positive (+) or negative (-); *j*+/- and *k*+/- provide similar information when the original distributions and right-triangular distributions, respectively, are assumed for the variables in Table 4; * indicates that the variable was not selected in the associated analysis.

Table 27. Comparison of Sets of Variables Identified in Sensitivity Analyses Based on Stepwise Regression Analysis with Rank-Transformed Data for Left-Triangular Distributions, Original Distributions as Defined in Table 4 and Right-Triangular Distributions

Notation	
$L_{Ri} = \{VAR:$	VAR is one of the top i variables (i.e., rank $1, 2, \dots, i$ as defined by the order of entry into a stepwise regression analysis) for at least one of the predicted variables in Table 26 when left-triangular distributions are assumed}
O_{Ri}, R_{Ri} are defined the same as L_{Ri} but for the original distributions in Table 4 and right-triangular distributions, respectively.	
$U_{Ri} = L_{Ri} \cup O_{Ri} \cup R_{Ri}$	
nU_{Ri} = number of variables in U_{Ri}	
First Variable in One or More Analyses	
$U_{R1} = \{EFFACA1, GSHFACN, PROTINS, SCLCRW, TIMHOT, VDEPOS, YSCALE, ZSCALE\}, nU_{R1} = 8$	
$U_{R1} - L_{R1} = \{EFFACA1, GSHFACN, PROTINS, SCLCRW\}$	
$U_{R1} - O_{R1} = \{EFFACA1, GSHFACN, PROTINS, TIMHOT, ZSCALE\}$	
$U_{R1} - R_{R1} = \{SCLCRW, TIMHOT, ZSCALE\}$	
Top 2 Variables in One or More Analyses	
$U_{R2} = U_{R1} \cup \{EIFACA1, ESPEED, PROTINN, TDELAY\}$ $= \{EFFACA1, EIFACA1, ESPEED, GSHFACN, PROTINN, PROTINS, SCLCRW, TDELAY, TIMHOT, VDEPOS, YSCALE, ZSCALE\}, nU_{R2} = 12$	
$U_{R2} - L_{R2} = \{EIFACA1, TDELAY\}$	
$U_{R2} - O_{R2} = \{EIFACA1, TDELAY, TIMHOT\}$	
$U_{R2} - R_{R2} = \{ESPEED, SCLCRW, TIMHOT, ZSCALE\}$	
Top 3 Variables in One or More Analyses	
$U_{R3} = U_{R2} \cup \{GSHFACS, SCLEFP\}$ $= \{EFFACA1, EIFACA1, ESPEED, GSHFACN, GSHFACS, PROTINN, PROTINS, SCLCRW, SCLEFP, TDELAY, TIMHOT, VDEPOS, YSCALE, ZSCALE\}, nU_{R3} = 14$	
$U_{R3} - L_{R3} = \{EIFACA1, SCLEFP, TDELAY\}$	
$U_{R3} - O_{R3} = \{GSHFACS, SCLEFP, TDELAY\}$	
$U_{R3} - R_{R3} = \{ESPEED, GSHFACS, SCLCRW\}$	

Table 27 (concluded)

Top 4 Variables in One or More Analyses

$$\begin{aligned}
 U_{R4} &= U_{R3} \cup \{P2DOS1\} \\
 &= \{EFFACA1, EIFACA1, ESPEED, GSHFACN, GSHFACS, PROTINN, PROTINS, \\
 &\quad P2DOS1, SCLCRW, SCLEFP, TDELAY, TIMHOT, VDEPOS, YSCALE, \\
 &\quad ZSCALE\}, nU_{R4} = 15
 \end{aligned}$$

$$\begin{aligned}
 U_{R4} - L_{R4} &= U_{R4} - O_{R4} = \emptyset \\
 U_{R4} - R_{R4} &= \{ESPEED, P2DOS1\}
 \end{aligned}$$

Top 5 Variables in One or More Analyses

$$U_{R5} = U_{R4} \cup \emptyset = U_{R4}, nU_{R5} = 15$$

$$\begin{aligned}
 U_{R5} - L_{R5} &= U_{R5} - O_{R5} = \emptyset \\
 U_{R5} - R_{R5} &= \{P2DOS1\}
 \end{aligned}$$

Top 6 Variables in One or More Analyses

$$\begin{aligned}
 U_{R6} &= U_{R5} \cup \{BUILDH, CSFACTN, CWASH1, EVFRAC, PHS2T2\} \\
 &= \{BUILDH, CSFACTN, CWASH1, EFFACA1, EIFACA1, ESPEED, EVFRAC, \\
 &\quad GSHFACN, GSHFACS, PROTINN, PROTINS, PHS2T2, P2DOS1, SCLCRW, \\
 &\quad SCLEFP, TDELAY, TIMHOT, VDEPOS, YSCALE, ZSCALE\}, nU_{R6} = 20
 \end{aligned}$$

$$\begin{aligned}
 U_{R6} - L_{R6} &= \{BUILDH, EVFRAC\} \\
 U_{R6} - O_{R6} &= \{CSFACTN, CWASH1, PHS2T2\} \\
 U_{R6} - R_{R6} &= \{CSFACTN, PHS2T2\}
 \end{aligned}$$

6.5 Effect of Logarithmic Transformations

The analyses presented to this point have used rank-transformed data. As indicated in Section 5.1, the use of rank-transformed data led to better sensitivity analysis results than use of the original untransformed (i.e., raw) data. Other transformations are also possible. For example, the logarithmic (i.e., $\log_{10}$) transformation is often effective. The logarithmic transformation is difficult to use in the analysis of distributions of CCDFs of the form shown in Figure 2 owing to the occurrence of zero exceedance probabilities as the consequence values increase. However, all of the mean results analyzed in Section 5 are nonzero and so use of the logarithmic transform presents no problems. As shown in Table 28 for mean number of early fatalities, use of rank-transformed data and logarithmically transformed data lead to similar sensitivity analysis results. Similar comparisons between sensitivity analysis results with rank-transformed data and logarithmically transformed data were obtained for all the mean consequence values considered in Section 5.

Table 28. Comparison of Stepwise Regression Analysis Results with Rank-Transformed Data and Logarithmically Transformed Data for Mean Number of Early Fatalities for the Following Cases:
100% Evacuation, No Evacuation, 100% Sheltering, and Variable Evacuation

Step ^a	Rank-Transformed		Log-Transformed	
	Variable ^b	R ² ^c	Variable ^b	R ² ^c
Early Fatalities: 100% Evacuation				
1	YSCALE	0.65(-)	YSCALE	0.64(-)
2	ESPEED	0.72(-)	ZSCALE	0.72(-)
3	ZSCALE	0.79(-)	ESPEED	0.78(-)
4	EFFACA1	0.85(-)	EFFACA1	0.84(-)
5	GSHFACN	0.88(+)	GSHFACN	0.88(+)
6	VDEPOS	0.90(-)	VDEPOS	0.90(-)
7	CSFACTN	0.91(+)		
Early Fatalities: No Evacuation				
1	YSCALE	0.50(-)	YSCALE	0.51(-)
2	GSHFACN	0.66(+)	GSHFACN	0.66(+)
3	EFFACA1	0.76(-)	EFFACA1	0.77(-)
4	TIMHOT	0.83(+)	TIMHOT	0.85(+)
5	ZSCALE	0.89(-)	ZSCALE	0.91(-)
Early Fatalities: 100% Shelter				
1	YSCALE	0.57(-)	YSCALE	0.57(-)
2	EFFACA1	0.72(-)	EFFACA1	0.74(-)
3	ZSCALE	0.79(-)	ZSCALE	0.80(-)
4	GSHFACS	0.84(+)	GSHFACS	0.85(+)
5	VDEPOS	0.85(+)	GSHFACN	0.87(+)
6	PROTINS	0.86(+)	VDEPOS	0.88(+)
7			TIMHOT	0.89(+)

Table 28 (concluded)

Step ^a	Rank-Transformed		Log-Transformed	
	Variable ^b	R ² ^c	Variable ^b	R ² ^c
Early Fatalities: Variable Evacuation				
1	YSCALE	0.63(-)	YSCALE	0.64(-)
2	ZSCALE	0.70(-)	ZSCALE	0.71(-)
3	EFFACA1	0.76(-)	EFFACA1	0.76(-)
4	ESPEED	0.81(-)	ESPEED	0.82(-)
5	GSHFACN	0.87(+)	GSHFACN	0.87(+)
6	EVFRAC	0.89(+)	TIMHOT	0.89(+)
7	TIMHOT	0.90(+)	EVFRAC	0.90(+)
8	CSFACTN	0.91(+)	VDEPOS	0.91(-)
9	SCLCRW	0.92(-)	SCLCRW	0.92(-)
10	VDEPOS	0.92(-)		

^aSteps in stepwise regression analysis.

^bVariables listed in order of selection in stepwise regression analysis.

^cCumulative R² value with entry of each variable into regression model, with the "+/-" in parentheses after the R² value indicating whether the variable selected at that step has a positive (+) or negative (-) regression coefficient.

7. DISCUSSION

An uncertainty/sensitivity analysis for the early health effects associated with a severe accident at a nuclear power station has been performed with the MACCS reactor accident consequence model. The primary purpose of this study is to identify important variables for further review to improve the quality of results obtained in future uncertainty analyses. To facilitate the identification of important variables, a source term that involves a large release and results in large exposures to evacuees was selected for use in the analysis.

In the presented analyses, care is taken to distinguish between stochastic uncertainty, which leads to a single CCDF, and subjective uncertainty, which leads to a distribution of CCDFs. Stochastic uncertainty enters the analysis through weather sequence probabilities and thus is a property of the system under study. Subjective uncertainty enters the analysis because of lack of knowledge about quantities that are assumed to be fixed within the computational implementation of the analysis and thus is a property of both how the system is modeled and the analysts performing the analysis.

Thirty-four imprecisely known variables are considered in this study and used in the calculation of the following predicted variables: number of fatalities occurring within 1 yr of the accident, number of individuals experiencing prodromal vomiting, population dose (Sv) from exposure received by individuals initially within 10 mi of the reactor, population dose (Sv) from exposure received by individuals within 1000 mi of the reactor, probability that an individual initially within 1 mi of the reactor will become an early fatality, and maximum distance from the reactor at which an individual has a nonzero probability of becoming an early fatality. Conditional on the characterizations of subjective uncertainty in use, the corresponding uncertainty in the preceding reactor accident consequences typically spanned several orders of magnitude for both the exceedance probabilities associated with CCDFs and mean values derived from CCDFs. However, excessive emphasis should not be placed on the observed uncertainty ranges until after additional review can be performed for the dominant variables identified in the sensitivity analyses.

Of the 34 variables treated as being uncertain, a relatively small number had substantial effects on the predicted variables under consideration. When the predicted variables are considered collectively, the following input variables were found to be the dominant contributors to uncertainty: YSCALE (scaling factor for horizontal dispersion), VDEPOS (dry deposition velocity), PROTINN (inhalation protection factor for nonevacuees), GSHFACN (groundshine shielding factor for nonevacuees), EFFACA1 (early fatality hazard function alpha value for bone marrow exposure), and ZSCALE (scaling factor for vertical dispersion).

Several tests were conducted to provide a check on the robustness of the results obtained in this study. Concern is often expressed that a different sample from the input variables will lead to different uncertainty and sensitivity analysis results. To provide a check, the analyses were repeated with a second independent Latin hypercube sample. Both samples were of size 100 and produced similar results.

The dominant variables were identified with procedures based on PRCCs and stepwise regression analysis. Several checks were then performed to provide further verification of the importance of these variables. Setting the dominant variables to best-estimate values led to a substantial reduction in uncertainty. Further, with the dominant variables set to best-estimate values, sensitivity analyses were performed to provide an indication of what would become the new set of dominant variables if the uncertainty in the initial set of dominant variables could be substantially reduced or eliminated.

Discussion

In addition, the effects of different choices for best-estimate values were investigated. When the best-estimate values for the dominant variables were changed, the uncertainty in the predicted variables remained small but the actual location of the uncertainty distributions showed considerable variability. In contrast, when the dominant variables were allowed to vary and the less important variables were set to best-estimate values, little effect on the uncertainty in the predicted variables resulted.

Concern is often expressed about the distributions assigned to input (i.e., independent) variables in sampling-based sensitivity analyses because of the possibility that the resultant variable rankings will be highly dependent on these distributions. As a check, the analyses presented in this report were repeated with the variables assigned first left-triangular distributions and then right-triangular distributions. The sensitivity analysis results obtained with these two distributions were quite similar to the results obtained with the original uniform and loguniform distributions. Thus, maintaining the ranges in use and switching between emphasizing the left and right ends of these ranges does not have a large effect on the sensitivity analysis results in this presentation. However, it should be recognized that extreme changes in distributions may cause substantial changes in sensitivity analysis results. For example, the results given in this report of the effects of assigning the dominant variables their best-estimate values can be viewed as a redefinition of their distributions in which the density functions become Dirac delta (i.e., impulse) functions.

This analysis used rank-transformed data, which were found to yield better sensitivity analysis results than raw (i.e., untransformed) data. The logarithmic transformation is another possible transformation. Logarithmic transformations are not very convenient for the analysis of CCDFs owing to the large number of zeros present in the analysis. However, the mean consequence results obtained from CCDFs were always nonzero in this analysis. Sensitivity analyses of these mean results with rank-transformed data and logarithmically transformed data yielded similar rankings of variable importance.

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