AN ABSTRACT OF THE THESIS OF

Terry A. Brock for the degree of Master of Science in Radiation Health Physics and Environmental Health Management presented on April 4, 1997. Title: A Comparison of Deterministic and Probabilistic Radiation Dose Assessments at Three Fictitious ^{137}Cs Contaminated Sites in California, Colorado, and Florida.

Redacted for Privacy

Abstract approved: ______________________________

Kathryn A. Higley

Redacted for Privacy

Abstract approved: ______________________________

Catherine M. Neumann

Two methods of radiation dose assessment were evaluated for the Cs-137 in soil ⇒ leafy vegetable ⇒ human consumption exposure pathway at three fictitious contaminated sites in California, Colorado, and Florida. An annual dose equation was developed and per USEPA risk assessment guidelines, traditional, single point annual dose estimates were calculated for all three sites at the central tendency (50th percentile) and the high end (95th percentile). Probability distributions were developed for the variables from the dose equation and used in a Monte Carlo simulation to create a range of probable doses to compare to the deterministic method. The Monte Carlo simulation was performed by using the software Crystal Ball® (an add-on program to the spreadsheet program Microsoft Excel®). Each fictitious site differed in soil type, so the effect of a site specific

parameter could be evaluated on the annual dose assessment from both methods. The deterministic dose at the 95th percentile was 19, 11, and 50 times greater than the probabilistic dose at the hypothetical California, Colorado, and Florida sites, respectively. The deterministic dose at the 50th percentile was 0.54, 0.74, and 0.17 times less than the probabilistic dose at the hypothetical California, Colorado, and Florida sites, respectively. The Florida site, due to soil type, had a greater annual dose than the other sites, regardless of computational method used.

A Comparison of Deterministic and Probabilistic Radiation Dose Assessments at Three Fictitious ^{137}Cs Contaminated Sites in California, Colorado, and Florida.

by

Terry A. Brock

A THESIS

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Master of Science

Presented April 4, 1997
Commencement June 1997

Master of Science thesis of Terry A. Brock presented on April 4, 1997.

APPROVED:

Redacted for Privacy

Co-Major Professor, representing Radiation Health Physics

Redacted for Privacy

Co-Major Professor, representing Environmental Health Management

Redacted for Privacy

Head or Chair of Department of Nuclear Engineering

Redacted for Privacy

Head or Chair of Department of Public Health

Redacted for Privacy

Dean of Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Redacted for Privacy

Terry A. Brock, Author

ACKNOWLEDGMENT

I would like to thank Dr. Higley for her guidance on this project, and her willingness to drop what ever she was doing to assist me. She deserves tenure as fast as she can get it.

Many thanks to Dr. Higginbotham and Rainier Farmer for finding a way to finance my graduate education. Without your efforts none of this would have been possible.

I would also like to thank Dr. Neumann and Dr. Harding for expanding my knowledge base on various environmental health issues, especially those not related to radiation. I have learned a lot from your courses!

I am greatly appreciative of my fellow graduate students: Tom Brannan, Mike Cantaloub, Darin Hekkala, Hsing Lee (Shining Star), Craig Marianno, Scott Menn, Robert Miller, Richard Pagh, Nate Potter, David Rynders, Donald Stewart, and Owen Stevens. Whether it was Doom, Woodstocks, Mary's Peak, or Wednesday afternoon. You guys provided enlightened conversation and an excuse to break from reality for awhile......Is grad school a reality?

Thanks to Holly Sherburne for sharing her file and experiences with Monte Carlo in risk assessment. Her prior work was greatly appreciated and utilized.

And finally, I would like to give my biggest thanks and love to my best friend and wife Kathryn Brock. She is the reason I get up in the morning and face the day. Her support and encouragement throughout this process has been totally positive.

TABLE OF CONTENTS

TABLE OF CONTENTS (Continued)

Page

LIST OF FIGURES

LIST OF FIGURES (CONTINUED)

Figure | Page

LIST OF TABLES

A Comparison of Deterministic and Probabilistic Radiation Dose Assessments at Three Fictitious ^{137}Cs Contaminated Sites in California, Colorado, and Florida.

1. INTRODUCTION

Traditional human exposure assessments from environmental contamination employ a deterministic calculation method, using conservative, single point parameters at the high end of data values (90-98th percentile) to estimate human exposure, dose, and subsequent health risk (USEPA, 1992a; USEPA, 1992b; USEPA, 1996; Hiatt, 1996). The results are highly conservative, frequently over-estimating exposure and risk (Chrostowski et al., 1994; Finley and Paustenbach, 1994; NCRP, 1996; Thompson et al., 1992). The influence of a single variable on the output is difficult to measure when using the deterministic method. Any uncertainty or variability in the exposure variables is neglected and no measurement of error associated with the final risk number is generated (NCRP, 1996).

One method to address these concerns is to use a probabilistic or Monte Carlo simulation for exposure assessments. Monte Carlo simulations use a distribution of data rather than a single data point to represent key exposure variables (Finley and Paustenbach, 1994; NCRP, 1996; USEPA, 1996). Monte Carlo allows for a more realistic exposure assessment by accounting for uncertainty and variability of the exposure variables and providing a descriptive sensitivity analysis of all exposure variables. For each realization, the computer draws one random value from the appropriate distribution for each of the random variables in the model, and computes a single result. This computation is repeated a large number of times to produce a complete distribution of modeled variables. Finally, the distributions can be plotted and various statistical summaries of the results can be produced to help interpret the data (Thompson et al., 1990).

In this study, a comparison was made between a Monte Carlo and deterministic exposure assessment for the Cs-137 in soil $\Rightarrow$ leafy vegetable (cabbage, lettuce, and spinach) $\Rightarrow$ human consumption pathway at three fictitious contaminated sites in different regions of the United States. To make the comparison, an exposure assessment equation was developed and used for all calculations. The final human exposure values were then converted to an annual radiation dose (Sv yr^{-1}). Per the United States Environmental Protection Agency's (USEPA) policy in assessing human health risk, all comparisons between the deterministic and probabilistic calculations were performed at the 50th (median) and 95th percentile (high end), with specific emphasis on the high end (USEPA, 1996; USEPA, 1992a; USEPA, 1992b).

Another aspect of this study was to investigate the effect of soil type on the annual dose assessment for this specific exposure pathway at the three fictitious sites in California, Colorado, and Florida. The choice of these three states was based on the differences of soil types to be expected in the different geographical regions they occupy. The objective was not to do an extensive soil science investigation, but to determine the impact of site specific data on data collection/analysis and the final annual radiation dose assessed from environmental contamination. This approach is important, because it is a common practice in risk assessment to apply a standard factor that may not always be applicable in all circumstances (USEPA, 1996; USEPA, 1992a; USEPA, 1992b).

An extensive data collection effort resulted in the accumulation of multiple data points for each exposure variable in the exposure assessment equation. The data analysis and distribution assignment of each exposure variable for the Monte Carlo simulation is explained in Section 2.3. The deterministic calculation was performed by the spreadsheet program Excel® by Microsoft™ and the Monte Carlo calculation was performed by the software Crystal Ball® by Decisioneering™, both are explained in Section 2.4. A comparison of the resultant annual doses from the two methods are compared and discussed in Section 3.

The dose equation developed, the calculations performed, and the results obtained are for demonstration purposes only. These were fictitious scenarios, where the actual annual dose values calculated are immaterial. The focus of the study was on the comparison of values obtained and illustration of the relationships between the two computational methods. This study served a cautionary tale for using data distributions in risk assessment and the subsequent impact on the values obtained.

2. MATERIALS AND METHODS

2.1 Fictitious Site Characterization

The California, Colorado, and Florida sites are identified by the soil type that could be expected in specific regions of the respective states. Soil type plays a major role in the uptake of contaminants into the leafy vegetable and subsequent intake into humans (Till and Meyer, 1983). By assigning specific soil types to the three sites, the impact of a site specific parameter could be assessed. The soil types in Table 1 were assigned using a general soil map of the United States (Miller and Donahue, 1990).

Table 1. Assigned Soil Type by State

State	Soil Type	Reference
California	loam	Miller and Donahue, 1990
Colorado	clay to clay loams	Miller and Donahue, 1990
Florida	sandy to sandy loams	Miller and Donahue, 1990

2.2 Exposure and Dose Rate Assessment Equation

The dose assessment equation was developed with the intent to have enough variables to develop probability distributions to make a comparison between the deterministic and probabilistic methods, while keeping it manageable enough to determine the effect of each variable on the outcome. The equation was developed for demonstration and comparative purposes only. In no way should this equation be considered a prescription for performing a dose assessment for the soil, leafy vegetable, and human consumption pathway.

The radiation dose equation includes two sections. The first section (bracketed) is the exposure assessment that calculates the annual movement of the contaminant from the soil to the leafy vegetable to the human body. The second bracketed section is the radiation dose assessment, it converts the ingested ^{137}Cs to an effective annual radiation dose H (Sv yr^{-1}):

$$H = [C_s \bullet B_{iv} \bullet W_{off} \bullet g \bullet r] \bullet [a \bullet IDC], \qquad (1)$$

where in the first bracketed section C_s is the concentration of ^{137}Cs in soil (Bq kg^{-1}), B_{iv} is the fraction of ^{137}Cs in the wet edible part of the leafy vegetable per unit of dry soil, W_{off} is the wash off fraction of contaminant during food preparation fraction, g is the percentage of leafy vegetables grown and consumed locally, r is the per capita annual ingestion rate of leafy vegetables (kg yr^{-1}), and in the second bracketed section a is the assimilation factor of ^{137}Cs from the gastrointestinal tract to the blood, and IDC is the ingestion dose coefficient (Sv Bq^{-1}) for ^{137}Cs (ICRP 67, 1993).

The focus of the Monte Carlo analysis in this study was on the exposure variables, the first bracketed section in equation (1). Consequently, the second half of the equation was not considered for development of distributions in the Monte Carlo simulation and should be addressed in future studies.

2.3 Data Collection, Analysis, and Distribution Assignment

An extensive literature review and data collection effort resulted in the accumulation of data points for the exposure variables in the first half of the equation. The data analysis and distribution assignments for the C_s, B_{iv}, and r, exposure variables were calculated by the statistical software SAS® for Windows 3.1®. SAS analyzed the exposure variable data set, and produced a summary output that included, but was not limited to, the mean, standard deviation, 50th and 95th percentiles. SAS also performed a distribution test by comparing the data sets against a known lognormal, normal, weibull, and exponential distribution. The output from the distribution test was a p-value that was used to determine whether to reject or accept the null hypothesis that the data are a random sample from the specified distribution.. The literature revealed the common practice of using a p-value of 0.05 as the level of significance when testing the null hypothesis (Taylor, 1982; Moore and McCabe, 1989). In this study, if the p-value was $<$ 0.05 then the distribution was rejected as not being indicative of the tested data set, or strong evidence against the null hypothesis. Conversely, if the p-value was > 0.05 then the distribution was accepted as being indicative of the tested data set, or strong evidence for the null hypothesis. So, the larger the p-value, the stronger the evidence for the null hypothesis, or the data set could be from the tested distribution. If the p-value exceeded

0.15, then SAS calculated the value as > 0.15, or very strong evidence for the null hypothesis.

The W_{off} and g variables' data sets were limited, so this presented a unique opportunity to utilize non-continuos distributions, instead of normal or lognormal distributions. This added value to the overall objective of the thesis by testing a variety of distributions that may be expected in an actual exposure assessment.

Each exposure variable is discussed in the following sections, followed by summary tables of the statistical analyses and distribution assignments.

2.3.1 C_s - Surface Soil Concentration of ^{137}Cs (Bq kg^{-1})

The C_s data used for the modeling at the three sites was from the Goiânia accident in Brazil. On 13 September 1987, a shielded radioactive ^{137}Cs source (50.9 TBq or 1375 Ci at the time) was removed from a teletherapy machine in an abandoned clinic in the city of Goiânia, Brazil. The source was ruptured in a residential garden, and the remnants of the source assembly were sold to a junkyard owner (Amaral et al., 1991). Surface soil samples were analyzed from the residential garden and the results are presented in Table 2. Each sample was taken from a 2 x 4 meter rectangle, one near the other. The data was analyzed by SAS and had a p-value of > 0.15 for a lognormal distribution. The lognormal distribution, as displayed in Figure 1, was applied to the three fictitious sites to demonstrate the probability of ^{137}Cs soil contamination concentrations that could be found at any one sampling point in the three fictitious sites.

Table 2. Distribution of ^{137}Cs radioactivity concentration in surface soil at the residential garden in Goiânia, Brazil (Amaral et al. 1991).

Sample Location	^{137}Cs Activity(Bq kg^{-1})	Sample Location	^{137}Cs Activity(Bq kg^{-1})
1	20000	9	7000
2	14000	10	7000
3	17000	11	12000
4	17000	12	4000
5	7000	13	17000
6	38000	14	115000
7	14000	15	14000
8	6000	16	41000

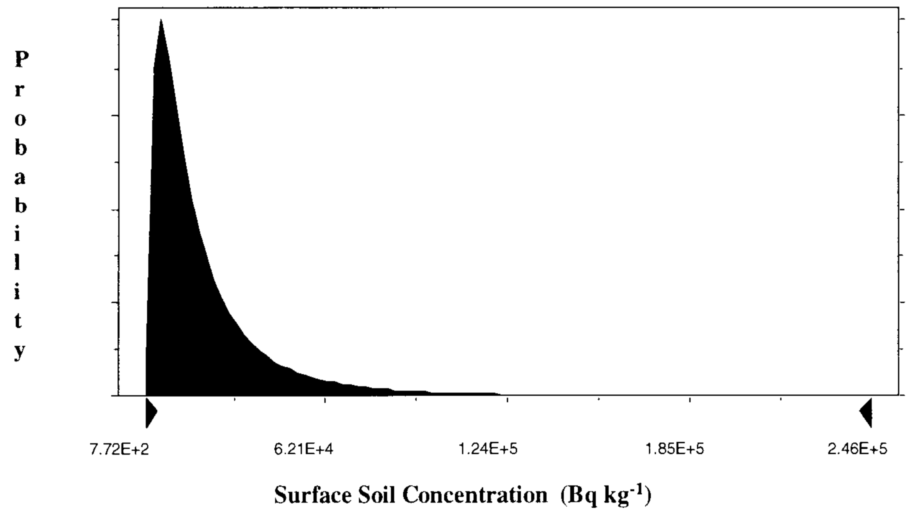

Figure 1. Goiânia, Brazil ^{137}Cs Surface Soil Concentration in 1987 as a Lognormal Distribution

2.3.2 B_{iv} - Soil-to-Plant Concentration Factor (Fresh Weight Vegetation)

The soil-to-plant concentration factor, B_{iv} is defined as the ratio of the concentration of a nuclide in the plant wet weight to that in dry soil (Till and Meyer, 1983). The B_{iv} is obtained from radioisotope experiments on plants grown in pots and other containers in laboratory greenhouses, or in containers or field plots outdoors. One should note that a B_{iv} value for a nuclide is an empirical relationship and is therefore not directly related to any of the many processes that play a role in effecting the transfer of the nuclide from soil to plants. However, these processes are included implicitly in estimates of B_{iv} (USNRC, 1982).

The assignment of various $B_{iv}s$ in Table 3, 4, and 5 are divided into the California, Colorado, and Florida sites, based on the predetermined soil type criteria associated with the B_{iv}. Following each California, Colorado, and Florida B_{iv} table are the respective lognormal distributions graphs generated by Crystal Ball and are displayed as figures 2,3, and 4.

Table 3. California B_{iv} Data Set

Crop	Soil Type	Biv (wet)	Reference
leafy veg	loam	0.0011	Till and Meyer, 1983
cabbage	loam	0.0079	NRC, 1982
cabbage	loam	0.0160	NRC, 1982
lettuce	loam	0.0003	NRC, 1982
lettuce	loam	0.0094	NRC, 1982
lettuce	loam	0.0031	NRC, 1982
lettuce	loam	0.0012	NRC, 1982
lettuce	loam	0.0007	NRC, 1982
lettuce	loam	0.0040	NRC, 1982
lettuce	loam	0.0290	NRC, 1982
spinach	loam	0.0036	NRC, 1982
spinach	loam	0.0400	NRC, 1982

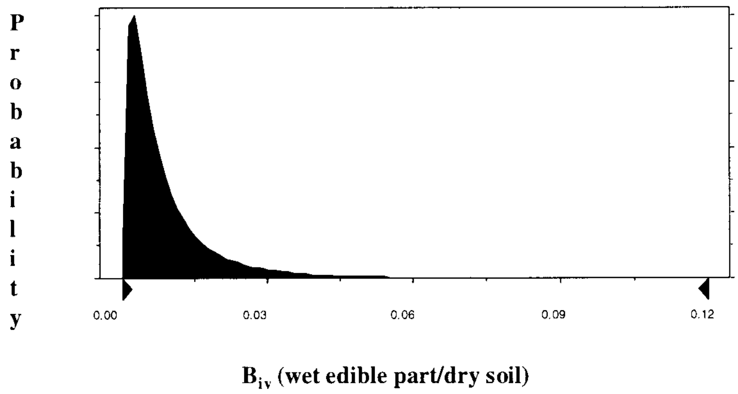

Figure 2. California B_{iv} as a Lognormal Distribution

Table 4. Colorado Biv Data Set

Crop	Soil Type	Biv (wet)	Reference
leafy veg	clay	0.0069	Till and Meyer 1983
lettuce	clay	0.0063	NRC, 1982
lettuce	clay	0.0043	NRC, 1982
cabbage	clay loam	0.0053	NRC, 1982
lettuce	clay loam	0.0140	NRC, 1982
spinach	clay loams	0.0210	NRC, 1982
lettuce	sandy clay loam	0.0036	NRC, 1982

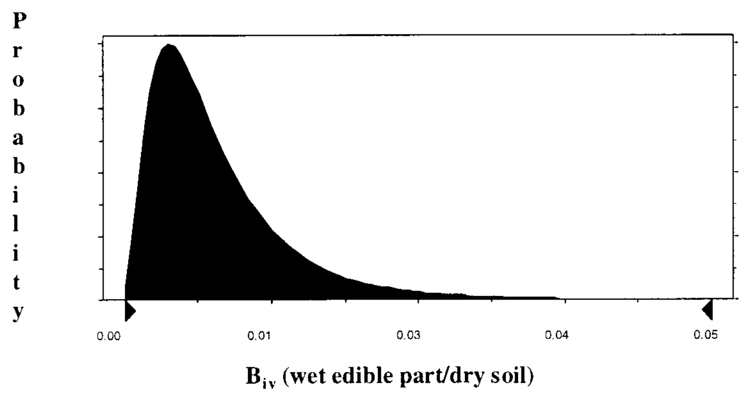

Figure 3. Colorado B_{iv} as a Lognormal Distribution

Table 5. Florida B_{iv} Data Set

Crop	Soil Type	Biv (wet)	Reference
leafy veg	Florida soils	1.4583	Till and Meyer, 1983
leafy veg	K<80 mg/kg	0.0267	Till and Meyer, 1983
leafy veg	sandy	0.0270	Till and Meyer, 1983
lettuce	sandy	0.2900	NRC, 1982
lettuce	sandy	0.0400	NRC, 1982
lettuce	sandy	0.0180	NRC, 1982
lettuce	sandy loam	0.0120	NRC, 1982
lettuce	sandy loam	0.0023	NRC, 1982
lettuce	sandy loam	0.0340	NRC, 1982
lettuce	sandy loam	0.0340	NRC, 1982
lettuce	sandy loam	0.0170	NRC, 1982
lettuce	sandy loam	0.0029	NRC, 1982
lettuce	sandy loam	0.0029	NRC, 1982
lettuce	sandy loam	0.0036	NRC, 1982
lettuce	sandy loam	0.0010	NRC, 1982

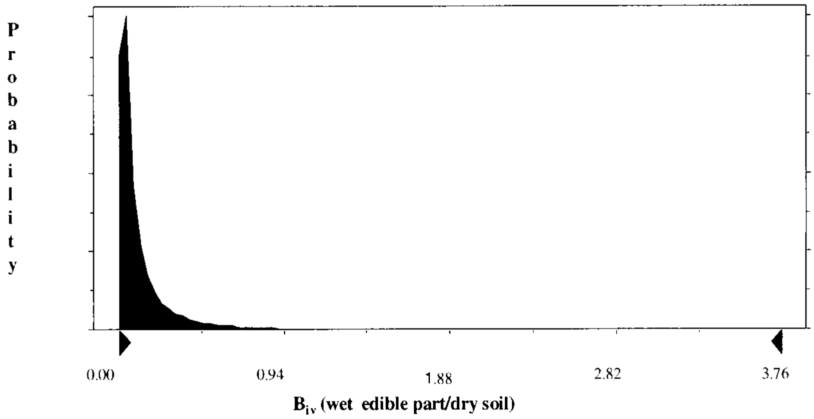

Figure 4. Florida B_{iv} as a Lognormal Distribution

2.3.3 W_{off} - The Wash Off Fraction of ^{137}Cs Contamination from Leafy Vegetable During Meal Preparation.

The W_{off} variable accounts for the common practice of washing fresh vegetables before consumption. Only one data point from one study was found for this variable, and the study claimed leafy vegetables used fresh for human consumption are assumed to contain 0.5 the concentrations of the "standard vegetable," which accounts for washing losses (Whicker and Kirchner, 1987). With this limited data, a uniform distribution was assigned to this variable with a range of 0.5 (best case) and 1.0 (worst case), or no contamination washed off the vegetable before consumption. In the uniform distribution, all values between the minimum and maximum occur with equal likelihood (Decisioneering, 1993). Figure 5 displays the Crystal Ball generated graph for the W_{off} uniform distribution.

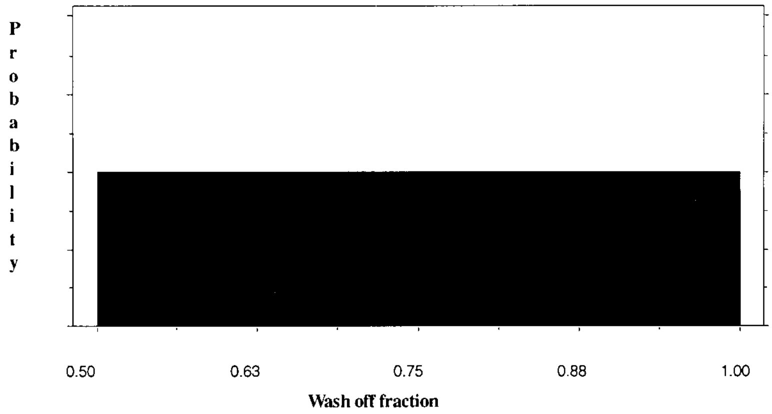

Figure 5. Wash Off Fraction of ^{137}Cs from Leafy Vegetable During Meal Preparation as a Uniform Distribution

2.3.4 g - The Percentage of Leafy Vegetables Grown and Consumed Locally

The *g* variable accounts for the exportation of local crops and those that are consumed locally. An analysis of national statistics revealed that between 4-75% of vegetables are grown and consumed locally, with a median of 25% (USEPA, 1987). With only three points, a triangle distribution was assigned. The triangle distribution describes a situation where you know the minimum, maximum, and most likely values to occur (Decisioneering, 1994). Figure 6 displays the Crystal Ball generated graph for the *g* triangle distribution.

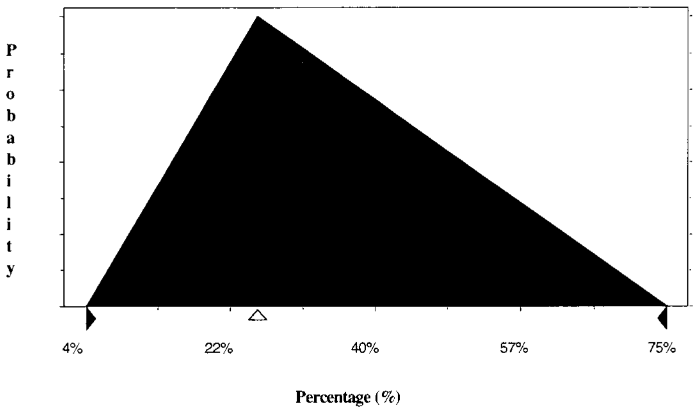

Figure 6. Percentage of Leafy Vegetables Grown and Consumed Locally as a Triangle Distribution

2.3.5 r - The Annual Leafy Vegetable Ingestion Rate (kg yr^{-1})

The *r* variable depicts the per capita annual leafy vegetable ingestion rate in the United States. The data in Table 2.3 summarizes the researched findings. SAS evaluated the data and calculated a p-value > 0.15 for a normal distribution. A normal distribution was assigned for *r*, truncated at zero, because consumption could never go below that quantity. Figure 7 displays the Crystal Ball generated graph for the *r* normal distribution.

Table 6. United States Annual Leafy Vegetable Consumption Rate Data Set

Rate(kg yr^{-1})	Reference	Comment
64.00	NRC Reg. Guide 1-109, 1977	
78.18	Rupp, 1980	
81.59	USDA, 1994	1984 rate
79.16	USDA, 1994	1985 rate
72.77	USDA, 1994	1986 rate
81.14	USDA, 1994	1987 rate
85.55	USDA, 1994	1988 rate
90.18	USDA, 1994	1989 rate
88.64	USDA, 1994	1990 rate
84.67	USDA, 1994	1991 rate
86.22	USDA, 1994	1992 rate
85.77	USDA, 1994	1993 rate

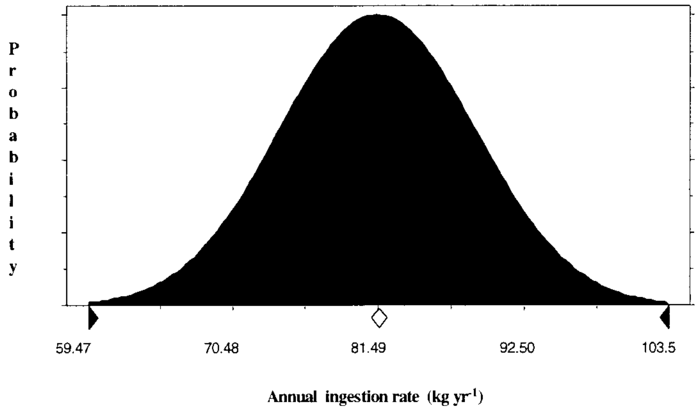

Figure 7. Annual Leafy Vegetable Ingestion Rate as a Truncated Normal Distribution

2.3.6 Summary Tables of Statistical Analysis and Distribution Assignments.

The summary information of the data analysis and distribution assignments are presented in Tables 7 and 8. The 50th and 95th percentile values in Table 7 are used in the deterministic calculation, while the mean and standard deviation are used by Crystal Ball when performing the Monte Carlo calculation.

Table 7. Summary of Statistical Analysis on Exposure Variables

Exposure Variable	50th percentile	95th percentile	mean	standard deviation
C_s (Bq kg^{-1})	1.4×10^4	1.15×10^5	2.19×10^4	2.69×10^4
California - B_{iv}	0.0038	0.04	0.00969	0.0127
Colorado - B_{iv}	0.0063	0.021	0.00878	0.00639
Florida - B_{iv}	0.018	1.4583	0.13	0.37
W_{off}	0.75	1.0	NA	NA
g (%)	25%	75%	NA	NA
r (kg yr^{-1})	83	90.18	81.49	7.34

Table 8. Summary of Exposure Variable Distribution Assignments

Exposure Variable	Distribution	p-value	Method
C_s	Lognormal	> 0.15	SAS
California - B_{iv}	Lognormal	> 0.15	SAS
Colorado - B_{iv}	Lognormal	> 0.15	SAS
Florida - B_{iv}	Lognormal	0.12	SAS
W_{off}	Uniform	NA	Data restrictions
g (%)	Triangle	NA	Data restrictions
r (kg yr^{-1})	Truncated Normal	> 0.15	SAS

2.4 Software Description and Application

The Monte Carlo exposure assessment was performed with the software Crystal Ball and Microsoft Excel. Crystal Ball is a stand-alone program which, in conjunction with Excel, allows a user to assign probability distributions to cells in the spreadsheet. With an intuitive graphical interface, Crystal Ball gives users powerful capabilities to perform uncertainty analyses based on Monte Carlo simulations (Burmaster and Udell 1990). With Crystal Ball, Monte Carlo simulations can be performed with the ease of a spreadsheet calculation and the sophistication of previously used custom codes. The output is equally user friendly, creating graphical presentations of projections, error analyses, inputs, and percentiles.

Figure 8 is an example of the worksheet used in conjunction with Crystal Ball to perform the deterministic and Monte Carlo simulation. It is a simple spreadsheet calculation with the exposure variables in the left column and the deterministic values in the appropriate 95th or 50th percentile columns. An example of the results of the deterministic calculations are at the bottom of Figure 8 and are presented in the SI units of Sv yr^{-1} and the traditional English units of mrem yr^{-1}.

California Probabilistic Annual Radiation Dose Assessment

via the Cs-137 in soil > leafy vegetable > human ingestion exposure pathway

Parameters	**High End 95%**	**Median 50%**	**Distribution**	**Reference**
Soil Concentration (Bq/kg)	***1.15E+05***	***1.40E+04***	lognormal	Health Physics
Biv (wet edible part/dry soil)	***0.04***	***0.0038***	lognormal	NRC, NUREG/CR-2975, Till and Meyer
Wash off fraction	***1***	***0.75***	uniform	Health Physics
Leafy vegetables grown and consumed locally (%)	***75%***	***25%***	triangle	USDA 1977, Cullen and Frey
Annual ingestion rate (kg/yr)	***90.18***	***83***	truncated normal	USDA Consumption Survey 1994
Assimilation fraction	***1***	***1***	NA	ICRP 60
Ingestion Dose Coefficient (Sv/Bq)	***1.40E-08***	***1.40E-08***	NA	ICRP 67

Annual Radiation Dose Assessment

	High End	***Median***
Sv/year	***4.36E-03***	***1.16E-05***
mrem/yr	***435.5694***	***1.159095***

Figure 8. Example of Excel Worksheet used for the Deterministic and Monte Carlo Radiation Dose Rate Assessment

To assign a distribution to an exposure variable, the appropriate cell in the worksheet had to be selected from a gallery of distributions. When the desired distribution was selected, Crystal Ball prompted input for the distribution. Values from the data analysis section were entered into the appropriate input prompts. Figures 9 and 10 are examples of the Crystal Ball gallery screen and inputs needed for the lognormal distribution.

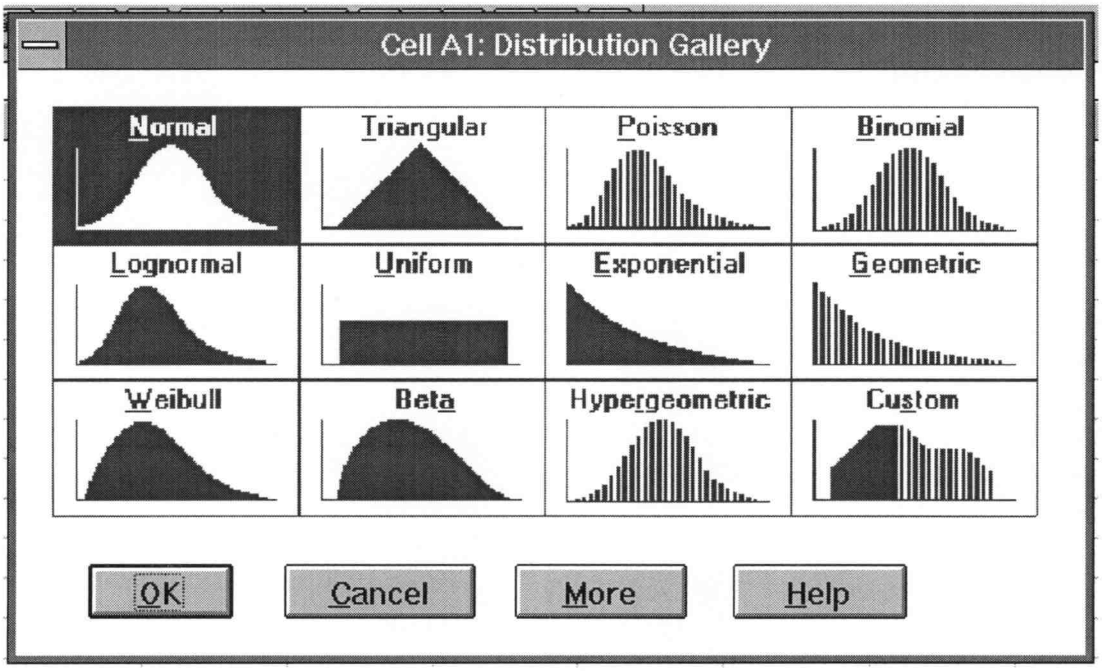

Figure 9. Crystal Ball Distribution Selection Gallery (reproduced with permission of Decisioneering, Inc.)

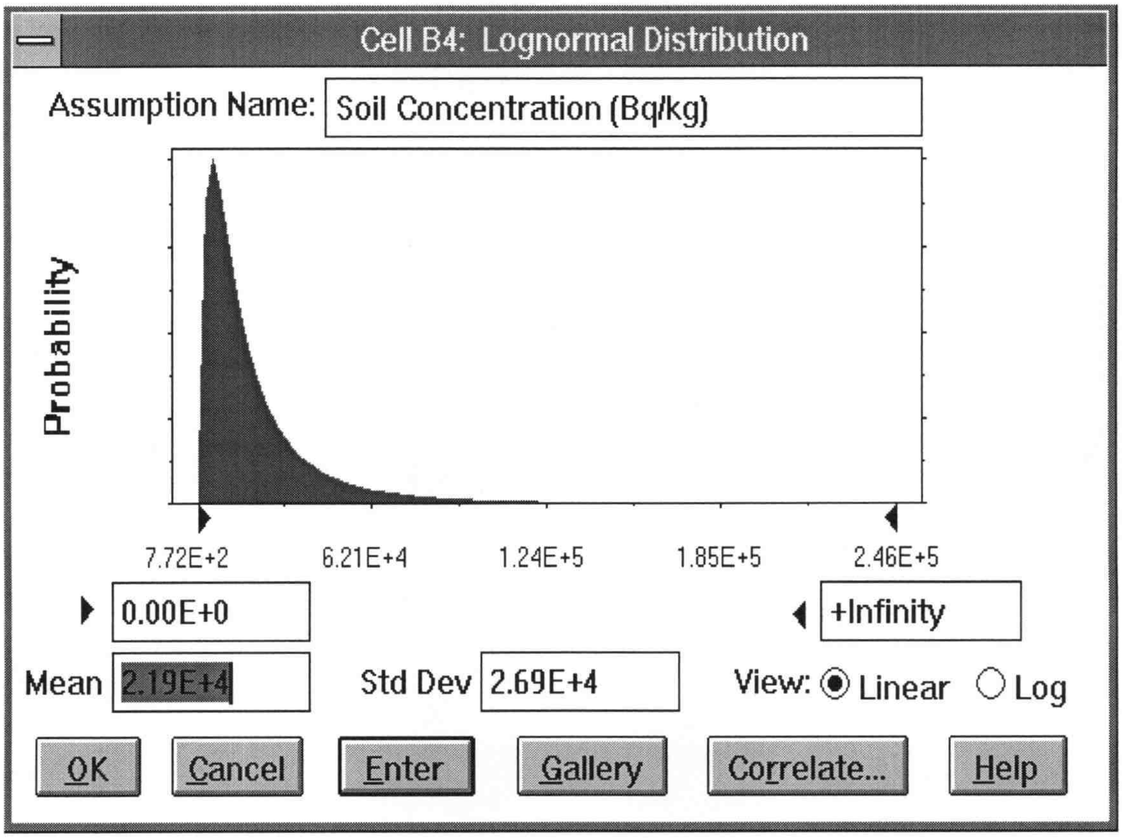

Figure 10. Crystal Ball Distribution Input Screen (reproduced with permission of Decisioneering, Inc.)

Figure 11 displays the inputs required to run the simulation. The main consideration on this screen is the number of iterations to run the Monte Carlo simulation. Based on a previous study, it was decided to use 10,000 iterations for each simulation. The results of the study indicated that 10,000 iterations was a sufficient number to ensure convergence and stability of the output distributions (Thompson, et al. 1991). To verify the study, a simulation was performed at 100,000 and 10,000 iterations. There was no significant difference observed in the simulation output between the 100,000 and 10,000 iterations.

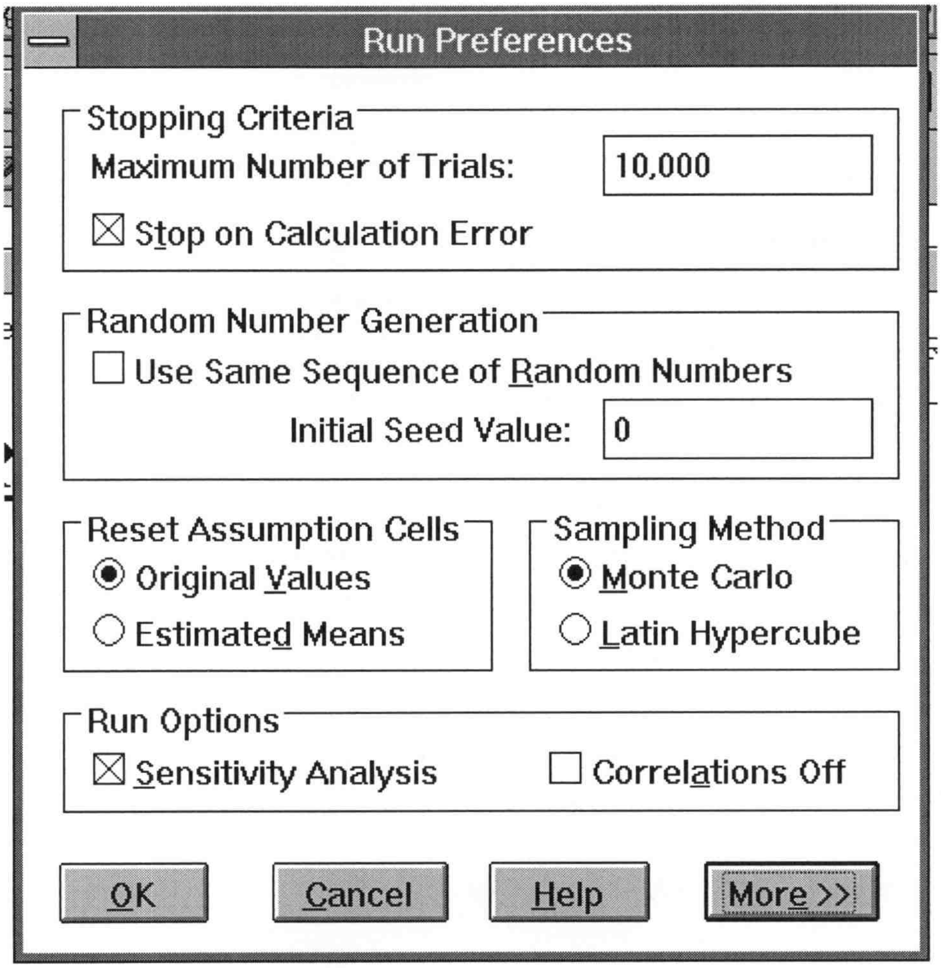

Figure 11. Crystal Ball Forecast Input Screen (reproduced with permission of Decisioneering, Inc.)

3. RESULTS AND DISCUSSION

3.1 Dose Rate Frequency Distribution Output

The results of the Monte Carlo simulation are presented as a probability distribution graph of dose rates for each state. Crystal Ball conveniently generates dose rate frequency distribution (dfd) graphs for each simulation. The dfd graph allows for a more thorough analysis of the possible ranges of dose rates by graphically presenting where the majority of probable dose rates can be expected in a population. Figures 12, 13, and 14 are the dfd graphs from the Crystal Ball simulations at the three sites. Table 9 depicts the range of doses calculated for each site and the respective percentiles.

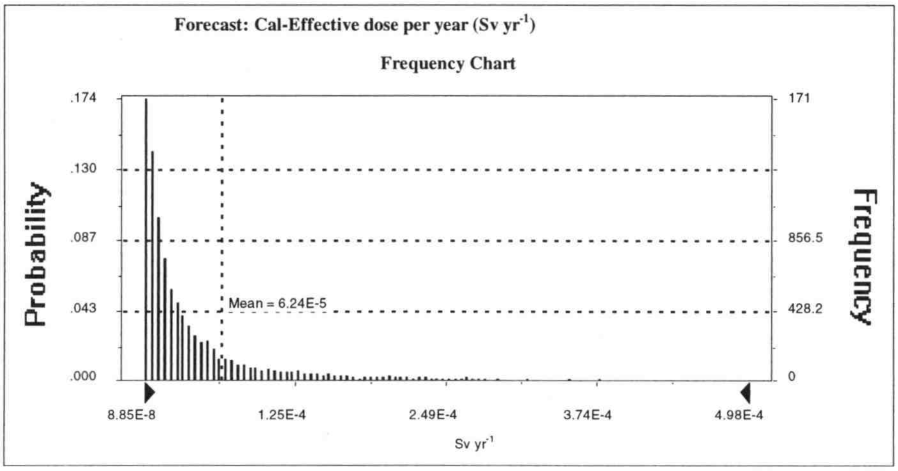

Figure 12. California Dose Rate Frequency Distribution (Sv yr^{-1})

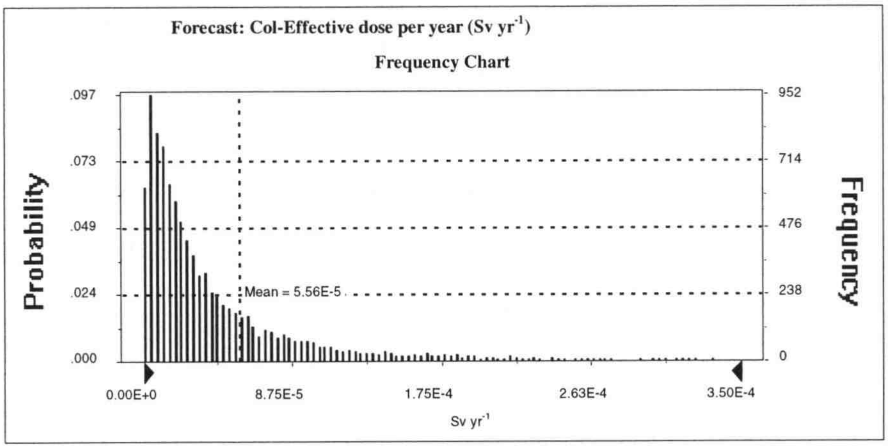

Figure 13. Colorado Dose Rate Frequency Distribution (Sv yr^{-1})

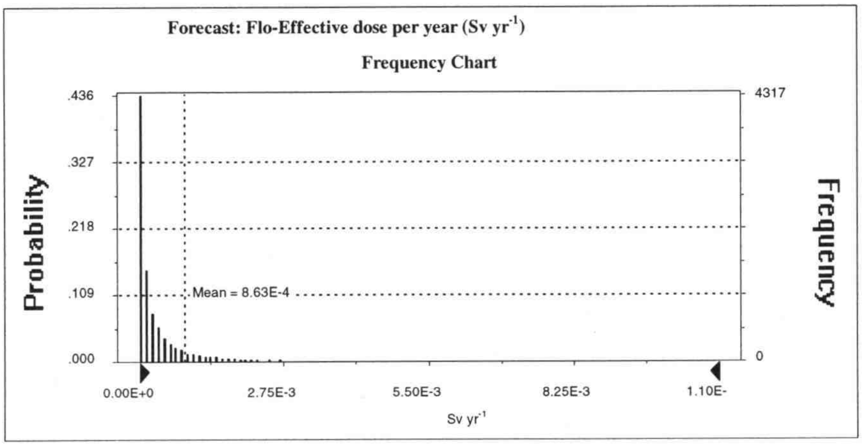

Figure 14. Florida Dose Rate Frequency Distribution (Sv yr^{-1})

Table 9. Results of California, Colorado, and Florida Monte Carlo Simulation by Dose Rate Range and Percentile.

	California Sv yr^{-1}	Colorado Sv yr^{-1}	Florida Sv yr^{-1}
Dose Rate Range	8.85E-08 to 6.71E-03	2.89E-07 to 2.16E-03	1.24E-07 to 1.54E-01
Percentile			
0.0%	8.85E-08	2.89E-07	1.24E-07
2.5%	1.17E-06	1.35E-06	1.74E-05
5.0%	2.25E-06	2.41E-06	3.47E-05
50.0%	2.17E-05	2.59E-05	3.45E-04
95.0%	2.40E-04	2.03E-04	3.43E-03
97.5%	3.79E-04	3.11E-04	6.15E-03
100.0%	6.71E-03	2.16E-03	1.54E-01

An interesting comparison was made with the deterministic dose rate at the 95th percentile and the point where it appeared in the dfd graph of the respective Monte Carlo simulation. The California deterministic dose rate at the 95th percentile of 4.36×10^{-3} Sv yr^{-1}, per the Monte Carlo analysis, would fall within the 97.5% to 100% percentile range. The Colorado deterministic dose rate at the 95th percentile of 2.29×10^{-3} Sv yr^{-1}, per the Monte Carlo analysis, would fall within the 95% to 97.5% percentile range. The Florida deterministic value at the 95th percentile of 1.59×10^{-1} Sv yr^{-1}, per the Monte Carlo analysis, exceeded the 100% value. So, after 10,000 iterations, the Florida deterministic dose rate at the 95th percentile of 1.59×10^{-1} Sv yr^{-1} never occurred in the Monte Carlo simulation, indicating an improbable event of anyone receiving that dose in a year.

3.2 Deterministic and Monte Carlo Dose Rate Comparison

At the California, Colorado, and Florida sites the deterministic dose rate at the 95th percentile exceeded the Monte Carlo dose rate at the 95th percentile by a factor of 18, 11, and 46, respectively. Conversely, the dose rate calculated with the Monte Carlo method exceeded the deterministic method at the 50th percentile, but not to the same extreme. Specific emphasis should be given to the 95th percentile, because most risk assessments use the high end value, not the median value for decision making (US EPA 1992).

Table 10. Summary Results at the 50th and 95th Percentile (Sv yr^{-1})

	Deterministic 95th %	Probabilistic 95th %	D/P	Deterministic 50th %	Probabilistic 50th %	D/P
California	4.36E-03	2.40E-04	18	1.16E-05	2.47E-05	0.47
Colorado	2.29E-03	2.03E-04	11	1.92E-05	2.39E-05	0.80
Florida	1.59E-01	3.43E-03	46	5.49E-05	3.45E-04	0.16

While the intent of the deterministic method was to predict a dose rate at the 95th percentile, conservative assumptions usually combine in multiplicative ways, resulting in unintended conservatism in the final answer. This phenomena is explained by using a simple relationship from probability, the multiplication of three 95th percentile numbers yields a value close to this percentile for the exposure equation:

$1 - (1-0.95)^3 = 0.999875$ or 99.9875th percentile (Burmaster and Lehr 1991).

3.3 Sensitivity Analysis

Another beneficial function of Crystal Ball was the ability to perform a sensitivity analysis on the exposure variables in the dose rate equation. The sensitivity analysis provided information on the exposure variables and their individual influence on the outcome or annual dose. Two types of sensitivity analysis were calculated, the contribution to variance and the rank correlation.

Per the Crystal Ball User Manual, the sensitivity is calculated via the following:

> "Crystal Ball calculates sensitivity by computing Spearman rank correlation coefficients between every assumption and every forecast cell while the simulation is running. Correlation coefficients provide a meaningful measure of the degree to which assumptions and forecasts change together. If an assumption and a forecast have a high correlation coefficient, it means that the assumption has a significant impact on the forecast (both through its uncertainty and its model sensitivity). Positive coefficients indicate that an increase in the assumption is associated with an increase in the forecast. Negative coefficients imply the reverse situation. the larger the absolute value of the correlation coefficient, the stronger the relationship.
>
> An option in the Sensitivity Preference dialog box lets you display the sensitivities as a percentage of the contribution to the variance of the target forecast. This option, called Contribution to Variance, doesn't change the order of the items listed in the Sensitivity Chart and makes it easier to answer questions such as "what percentage of the variance or uncertainty in the target forecasts is due to assumption X?". However, it is important to note that this method is only an approximation and is not precisely a variance decomposition. Crystal Ball calculates Contribution to Variance by squaring the rank correlation coefficients and normalizing them to 100%." (Decisioneering, 1993).

The following Crystal Ball output in Sections 3.3.1 and 3.3.2 display the sensitivity analysis performed for each exposure variable for the California, Colorado, and Florida sites, respectively. The exposure variables are ranked in descending order by the influence on the forecast.

3.3.1 Crystal Ball Sensitivity Analysis by Rank Correlation

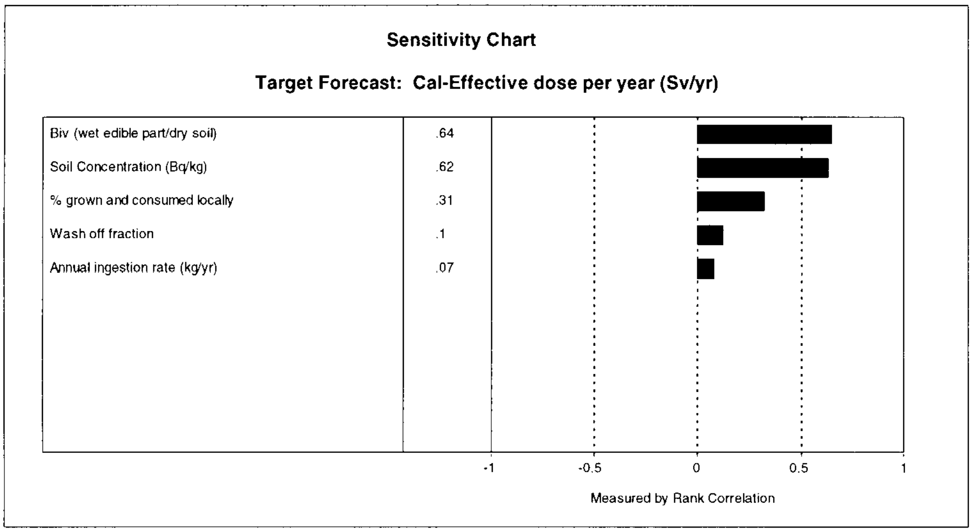

Figure 15. California Sensitivity Analysis by Rank Correlation

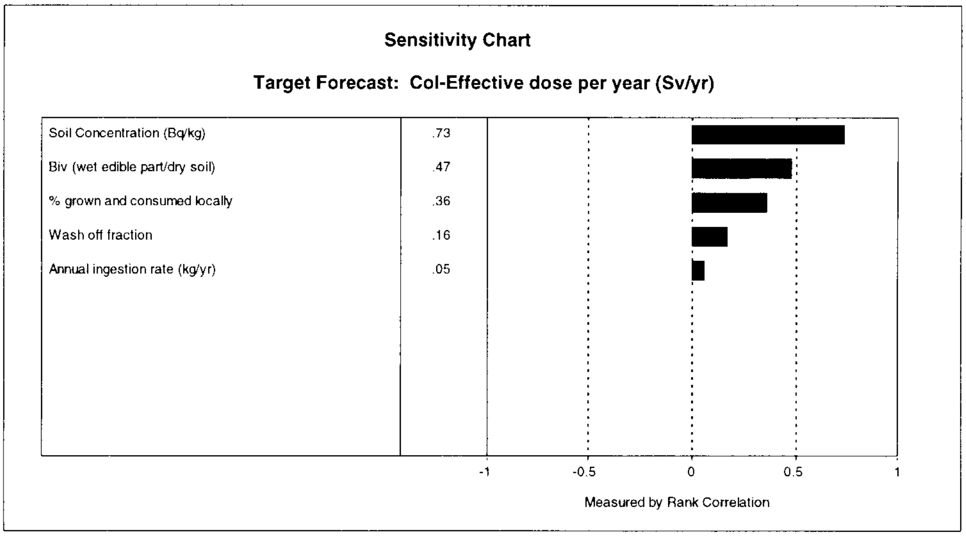

Figure 16. Colorado Sensitivity Analysis By Rank Correlation

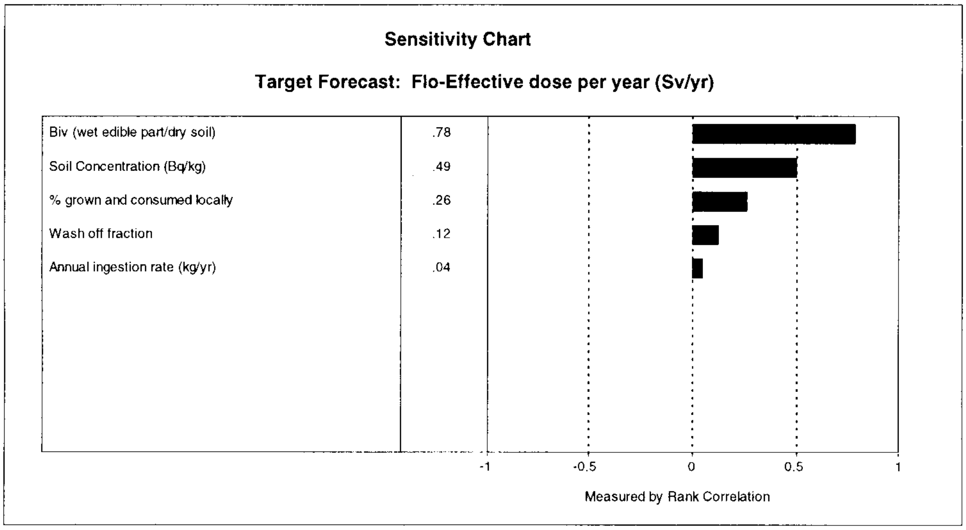

Figure 17 Florida Sensitivity Analysis by Rank Correlation

3.3.2 Crystal Ball Sensitivity by Contribution to Variance

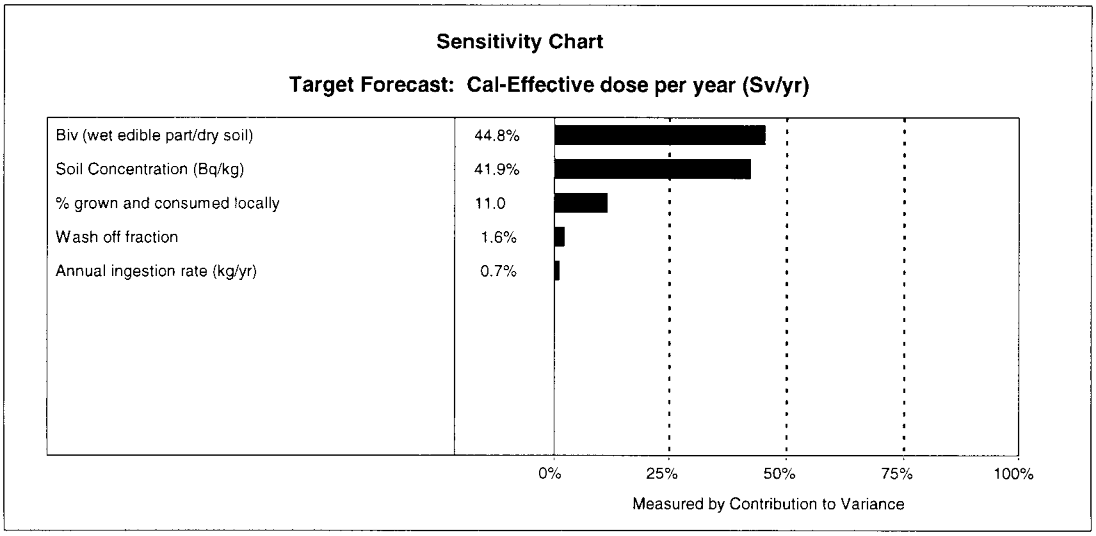

Figure 18. California Sensitivity Analysis by Contribution to Variance

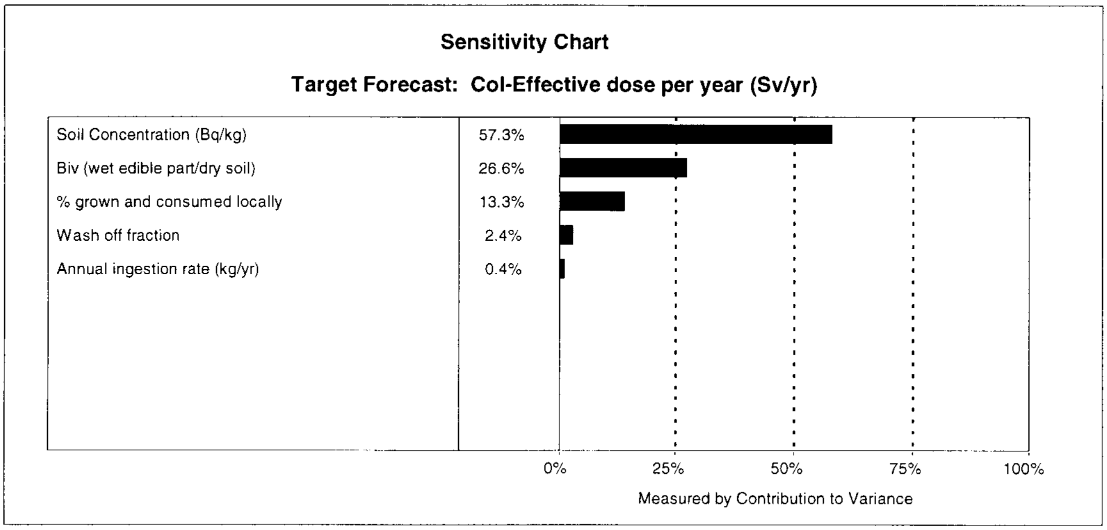

Figure 19. Colorado Sensitivity Analysis by Contribution to Variance

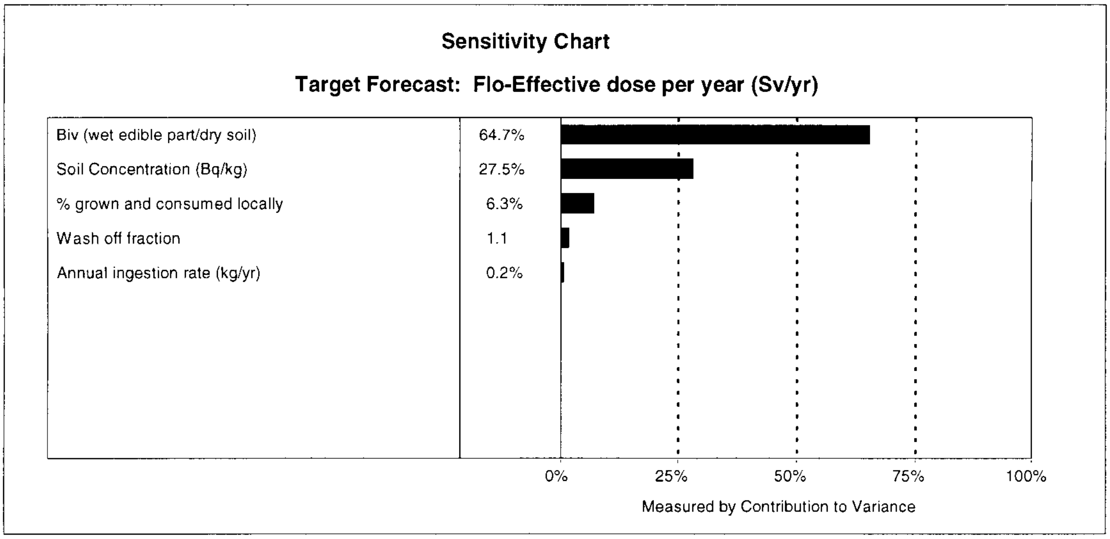

Figure 20. Florida Sensitivity Analysis by Contribution to Variance

3.4 California, Colorado, and Florida Dose Rate Comparisons

The soil type and associated B_{iv} had an obvious influence on the outcome for this model. Figures 10 -13 demonstrate the difference of dose rates calculated for each site in the respective state. To evaluate the difference, the dose rates at the 50th and 95th percentile were compared for both the probabilistic and deterministic methods. The deterministic dose rates at the 95th percentile ranged from 4.36E-03 Sv yr^{-1} at the California site to 1.59E-01 Sv yr^{-1} at the Florida site, a factor of 46 times greater at the Florida site. The probabilistic dose rates at the 95th percentile ranged from 2.4E-04 Sv yr^{-1} at the California site to 3.43E-03 Sv yr^{-1} at the Florida site, a factor of 14 times greater at the Florida site. The deterministic dose rates at the 50th percentile ranged from 1.16E-05 Sv yr^{-1} at the California site to 5.49E-05 Sv yr^{-1} at the Florida site, a factor of 4.7 greater at the Florida site. The probabilistic dose rates at the 50th percentile ranged from 2.47E-05 Sv yr^{-1} at the California site to 3.45E-04 Sv yr^{-1} at the Florida site, a factor of 14 greater at the Florida site. Consistently for all scenarios, the Florida dose rates exceeded the California and Colorado sites.

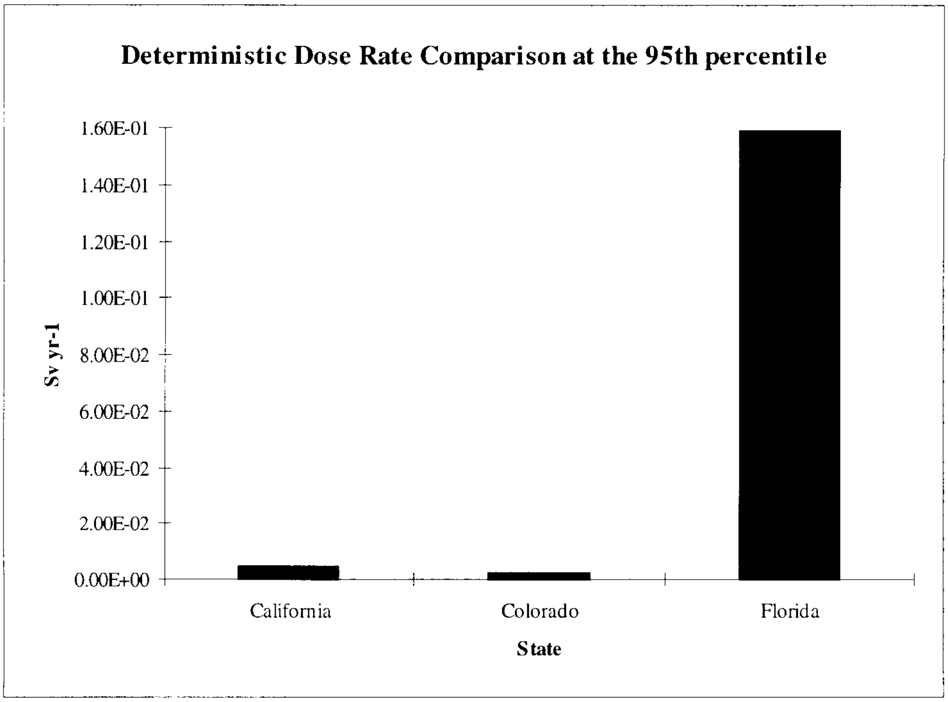

Figure 21. A State Comparison of the Deterministic Dose Rates at the 95th Percentile

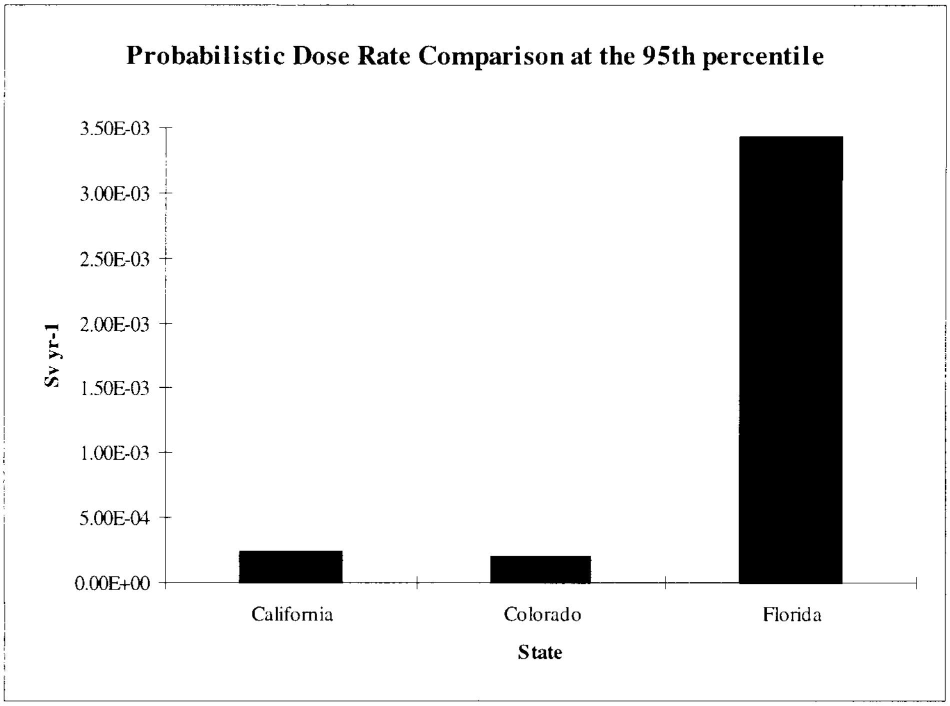

Figure 22. A State Comparison of the Probabilistic Dose Rates at the 95th Percentile

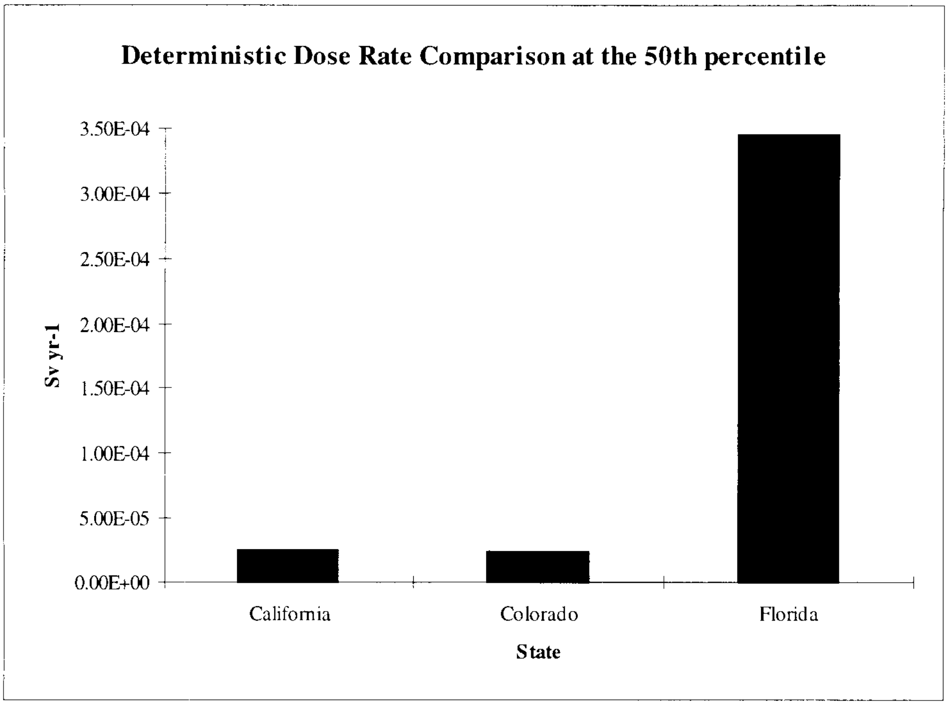

Figure 23. A State Comparison of the Deterministic Dose Rates at the 50th Percentile

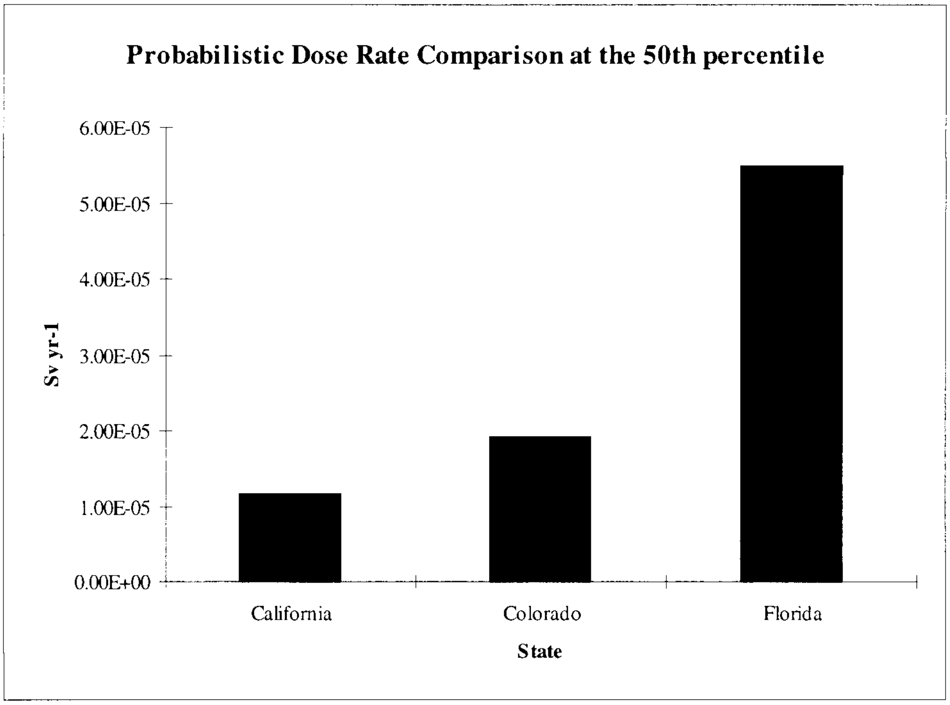

Figure 24. A State Comparison of the Probabilistic Dose Rates at the 50th Percentile

4. CONCLUSION

From this study there is strong evidence that different methods of assessing exposure and dose can affect the outcome greatly. The point estimates and generic exposure variables were conservative and tended to over estimate at the higher end when compared to the Monte Carlo values at the 95th percentiles. By developing distributions for the exposure variables, the exposure assessment accounts for variability and uncertainty in the specific exposure variable. As shown with Crystal Ball, the ability to perform sensitivity analysis on the exposure variables provides the assessor an understanding of where and how much each variable in the equation is impacting the assessment.

In this study it was shown by applying site specific data to the B_{iv} variable that soil type variability can affect the dose rates assessed from site to site. It was demonstrated that a generic B_{iv} value would not be appropriate for all sites, because soil types can vary greatly from place to place, and in turn affecting the transfer of ^{137}Cs from soil to the edible leafy vegetables. An attempt should be made to employ site specific data whenever possible to ensure a more realistic exposure assessment.

A caveat to this study: no matter what method is used to perform an exposure assessment, the analysis is only as accurate as the data utilized. To facilitate the use of accurate data in Monte Carlo exposure assessments, the author recommends an easily accessible data base of exposure parameters, preferably on the world wide web.

BIBLIOGRAPHY

Amaral, E.C.S; Vianna, M.E.C.; Godoy, J.M.; Rochedo, E.R.R; Campos, M.J.; Pires do Rio, M.A.; Oliveira, J.P.; Pereira, J.C.A; Reis, W.G. Distribution of ^{137}Cs in Soils Due to the Goiania Accident and Decisions for Remedial Action During the Recovery Phase. Health Physics. 60:91-98; 1991.

Burmaster, D.E.; Udell E.C. A Review of Crystal Ball. Risk Analysis. 10:343-345; 1990.

Chrostowski, P.; Foster, S.A.; Dolan, D. Monte Carlo Analysis of the Reasonable maximum Exposure (RME) Concept. Health and Endangerment. 577-583; 1994.

Decisioneering, Inc. Crystal Ball Users Manual. Denver, Colorado; 1993.

Finley, B.; Paustenbach, D. The Benefits of Probabilistic Exposure Assessment: Three Case Studies Involving Contaminated Air, Water, and Soil. Risk Analysis. 14:53-73; 1994.

Hiatt, G. United States Environmental Protection Agency Risk Assessment Workshop Overhead Handouts. United States Environmental Protection Agency, Region IX. San Francisco; 1996.

The International Commission on Radiological Protection (ICRP). Age-dependent Doses to Members of the Public from Intake of Radionuclides: Part 2 Ingestion Dose Coefficients, ICRP Publication 67. New York; 1993.

Lipton J., Shaw D. Selecting Distributions for Use in Monte Carlo Simulations. Submitted to the Science Policy Branch and Office of Policy Analysis of the United States Environmental Protection Agency by RCG/Hagler, Inc. Boulder, Colorado; June 1992.

McKone, T.E.; Bogen, K.T. Predicting the Uncertainties in Risk Assessment. Environmental Science Technology. 25:1674-1681; 1991.

Miller, R.M.; Donahue, R.L. Soils, An Introduction to Soils and Plant Growth, 6th Edition. New York: Prentice Hall; 1990.

Moore D.S., McCabe, G. Introduction to the Practice of Statistics. New York: W.H. Freeman and Company; 1989. p. 468.

National Council on Radiation on Radiation Protection and Measurements. A Guide for Uncertainty Analysis In Dose and Risk Assessments Related to Environmental Contamination. Bethesda, Maryland, NCRP Commentary No. 14; 1996.

Schuller, P.; Handl, J.; Trumper, R.E. Dependence of the 137Cs Soil-to-Plant Transfer Factor on Soil Parameters. Health Physics. 50:575-577; 1988.

Taylor, J.R. An Introduction to Error Analysis. University Science Books; 1982. p.201.

Thompson, K.; Burmaster, D.E.; Crouch, E.A.C. Monte Carlo Techniques for Quantitative Uncertainty Analysis in Public Health Risk Assessment. Risk Analysis. 12:53-61; 1992.

Till, J.E. ed.; Meyer, R.H. ed. Radiological Assessment: A Textbook on Environmental Dose Analysis. USNRC NUREG/CR-3332; 1983.

United States Environmental Protection Agency. Municipal Waste Combustor Study. Office of Solid Waste and Emergency Response, Office of Air and radiation, Office of Research and Development. Washington D.C., EPA/530-SW-87-021; June 1987.

United States Environmental Protection Agency. Guidelines for Exposure Assessment. Federal Register, 57(104):22888-22938; May 29, 1992.

United States Environmental Protection Agency. Risk & Decision Making: A Workshop in Risk Assessment, Risk Management, and Risk communication. Office of the Senior Science Advisor, Region IX. San Francisco; October 1992.

United States Environmental Protection Agency (USEPA). Summary Report for the Workshop On Monte Carlo Analysis. Office of Research and Development. Washington D.C., EPA/630/R-96/010; September 1996.

United States Department of Agriculture (USDA). National Agricultural Statistics Service, Agricultural statistics 1994. Washington D.C., U.S. Government Printing Office; 1994.

United States Nuclear Regulatory Commission (USNRC). Soil-to-Plant Factors for Radiological Assessments. Office of Nuclear Regulatory Research. Washington D.C., NUREG/CR-2975; 1982.

USNRC. Calculation of Annual Doses to Man from Routine Release of Reactor Effluents for the Purpose of Evaluating Compliance with 10 CFR Part 50, Appendix I. Regulatory Guide 1-109; 1977.

Whicker, F.; Kirchner, T.B. Pathway: A Dynamic Food-Chain Model to Predict Radionuclide Ingestion After Fallout Deposition. Health Physics. 52:717-737; 1987.