IMPACT OF UNCERTAINTY IN MODEL INPUT DATA
ON PREDICTED PESTICIDE LEACHING

By

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Predicting the fate of agrochemicals in the environment is subject to imprecision in model input data. Although several methods are available to address uncertainty in the predicted fate of agrochemicals in the soil, no method has been accepted in a decision framework. This study focused on the development and application of a method to quantify uncertainty due to imprecision in input data for pesticide fate predictions in the soil profile.

The postulated method to quantify uncertainty relies on the development of probability functions for predicted and true pesticide mass emissions and travel times. The difference in probability between the two functions is used as a measure of uncertainty. Entropy and fuzzy logic methods are applied to quantify the uncertainty in predicted pesticide mass emissions and travel times to specified control depths in the soil profile.

Application of the entropy approach to compute the uncertainty in the predicted mass emissions and travel time revealed considerable spatial variability at the test site. Based on the hexazinone and simazine simulations, uncertainty increases with depth within the first 2.0m of the soil profile. Total site uncertainty in the hexazinone mass emission was 0.33, 0.38, and 0.46 for the 1.0-m, argillic horizon, and 2.0 m depths, respectively. For hexazinone travel time the total uncertainty for the site was 0.30, 0.40, and 0.47 for the 1.0m, argillic horizon, and 2.0m
depths, respectively. The soil map and organic carbon content in the surface horizon were identified as the most uncertain parameters in predictive modeling, whereas the curve number and precipitation were the least sensitive parameters.

Classification of uncertainty using fuzzy set theory revealed little uncertainty in the predictions for mass emissions and travel time. Also, it was concluded that fuzzy set classification is not suitable in the format used for quantifying uncertainty in the mass emissions and travel times because of the excess number of fuzzy maps required and the ease with which bias can be introduced in the classification.

This study demonstrated that predictive pesticide modeling is uncertain when site-specific data are not taken into account, and it remains uncertain even if site-specific data are used, though the uncertainty will be less.
CHAPTER 1
INTRODUCTION

Pesticide Modeling

In the U.S. alone, more than 2.2 billion kg of pesticide active ingredients have been used annually since the early 1990s. This includes conventional pesticides (0.5 billion kg) plus industrial wood preservatives and other chemicals used as pesticides. The application of these vast amounts of pesticides has raised concerns about their potential adverse affect on the environment -- including contamination of drinking water resources such as groundwater which has the potential to harm human health. Therefore, it is important to predict how much of that which is applied will potentially reach groundwater. However, there is much uncertainty in the predictions and this study will attempt to quantify some of the uncertainty in predictive pesticide leaching, because accurate data are required for making sound environmental decisions.

Pesticide behavior, including effects on groundwater quality, can be described with environmental-fate models. An environmental-fate model enables the user to estimate the amount of pesticide leached through the upper part of the soil profile to the underlying saturated zone, but such models generally require comprehensive data sets for chemicals, climate, and soils. Commonly, insufficient data are available for a selected study site. In order to predict pesticide behavior at that site, input data are estimated or derived from limited existing information; i.e., we use imported data to estimate pesticide leaching.

The need for more extensive data has grown in recent years. With the advent of geographic information systems (GIS), modelers are now capable of addressing the spatial component in environmental-fate and assessment studies. Several researchers (Loague et al., 1996; Hoogeweg and Hornsby, 1997, 1998) have successfully demonstrated that environmental-
fate models and GIS can be integrated and used to generate maps (e.g., probability of exceeding the health advisory level; Foussereau et al., 1993; Hoogeweg and Hornsby, 1995, 1997, 1998), thereby displaying the spatial distribution of predicted pesticide concentrations in the environment. A disadvantage of this approach, however, is the huge amount of data required to drive the spatial model. Not only are traditional model parameters required, but also maps portraying the distribution of model input parameters over the landscape. Available maps are often out-of-date or too generalized, or have been developed for differing purposes.

Modeling pesticide leaching is an integral part of vulnerability assessments and groundwater management. Predicting pesticide behavior is an imprecise exercise at best, as information about the spatial distribution of required data is either expensive to obtain or sparse. Consequently, assessment studies can only approximate the natural environment and, therefore, uncertainty is inherent in all pesticide leaching assessments (NRC, 1993).

**Hypothesis**

Several methods have been used to characterize, evaluate and quantify uncertainty in vulnerability assessments. Generally, these methods can be classified into four categories: 1) basic statistics; 2) stochastic simulation; 3) Monte Carlo simulations; and 4) fuzzy set theory.

Basic statistical methods usually involve estimating calculating the mean, variance, and confidence intervals of the observed population. These methods might work well for static data, but the natural environment is dynamic and variables change over time.

Stochastic simulations require fewer data but require a model that is capable of describing fate of agrochemicals in the environment. Recent developments show that this is a promising field, but it is not likely that decision managers will accept this technique as an alternative to the current regulatory models since no acceptable models are yet available.

Monte Carlo simulations are by far the most popular method for addressing uncertainty in assessments. A common problem, though not recognized by most users, is that many
researchers apply Monte Carlo simulations to account for variability in the input data and at the same time equate this to accounting for uncertainty. This application by itself does not account for uncertainty, as the uncertainty is hidden in the imprecision of the data.

Fuzzy set theory has found application in soil and landscape analysis. It shows promise as an alternative to statistical modeling, with uncertainty being embedded in this method. However, its application to pesticide fate has yet to be researched.

This study focuses on the development and application of a generic method that quantifies uncertainty in predictive pesticide modeling scenarios, independent of the model. It is postulated that: 1) uncertainty in model outputs can be quantified using the Shannon Entropy concept, and 2) uncertainty in model outputs can be quantified using fuzzy logic methodology. The model outputs considered are mass emissions and travel times to specified control depths in the vadose zone.

The above postulation is in agreement with the findings and recommendations of the Committee on Techniques for Assessing Ground Water Vulnerability to the National Research Council (NRC). In their final report (NRC, 1993), the committee recommended that more information be obtained on the uncertainty associated with vulnerability assessments and that ways be developed to display this uncertainty.

Methodology

The goal of this research was to develop a generic method to quantify uncertainty in predictive pesticide modeling. The predictive modeling scenario envisioned here is one that utilizes data that are available in the public domain. It does not include site-specific data, as such information is generally not available.

In formulating a definition of uncertainty for this study, only the uncertainty resulting from the input data was examined. More specifically only the uncertainty in model input data when non site-specific data are used to predicted pesticide leaching was studied.
The approach used applies uncertainty theory to pesticide behavior by two different methods: 1) entropy and 2) fuzzy logic. For both methods, spatial distribution of the uncertainty is determined. The focus of this study is the uncertainty in predicted mass emissions and travel times of two pesticides for a test site at the Santa Fe Beef Unit in Alachua County, FL, using the environmental-fate model CMLS98B (Nofziger et al., 1998).

Spatial distribution of the uncertainty is addressed using point data in conjunction with spatial interpolation methods and when needed discrete soil maps. For the purpose of this research, a discrete soil map is defined as a map in which the soil units are represented as polygons having discrete boundaries. Furthermore, each polygon is assumed to contain a single map unit having uniform soil attributes over the spatial domain represented by the polygon. An example of a discrete soil map is the county soil survey map. While it is well-known that soils represent a continuum in the landscape and that a map unit often contains inclusions of other soil series, the above simplifications were made to facilitate development of methods for determination of uncertainty. Dealing with inclusions will be left for future research efforts.

Overview

This paper begins with a review of the methods available to address uncertainty in modeling studies. Because no method was considered to be satisfactory for addressing uncertainty in a spatial predictive pesticide modeling scenario, a theory was developed to quantify the uncertainty. This theory and its application are described in Chapter 3. In Chapter 4, field methodology, database development, the model and model input parameters are described. Results from the pesticide modeling studies and associated uncertainties in pesticide mass emissions and travel times to selected control depths at the test site are presented in Chapter 5. Finally, a discussion of the method developed for quantifying uncertainty, results, and complications when dealing with a spatial environment is presented in Chapter 6. This chapter also includes recommendations for further research.
CHAPTER 2  
REVIEW OF LITERATURE

Definitions of Uncertainty

Often we associate uncertainty with terms like precision and accuracy, reflecting the confidence we have of a given value. Without defining any framework about what we are trying to achieve, any attempt at quantifying uncertainty will lack a clear, objective meaning. One of the frustrating aspects of dealing with uncertainty is that it is not always clear what a measurement of uncertainty will mean (Isaaks and Srivastava, 1989).

Imprecision in data and model procedures is often viewed as a source of uncertainty. Webster’s dictionary defines imprecision as a condition of being imprecise or inaccurate. This definition covers a wide variety of scenarios, in order to quantify uncertainty in environmental data (Cothern and Ross, 1994). Imprecision is most often used in relation to laboratory measurements of quantities, such as organic carbon content, percent sand, etc. In this context imprecision is the variability or variance of the measured values in comparison with the true value (Fig. 2-1: Goovaerts, 1997).

Terms like accuracy (exact, correct or true), precision (exactness or the degree to which given samples agree with their mean) and imprecise (not exact, vague, ill defined) all deal with the same concept, that the observed values might deviate from the true value.

Current definitions of uncertainty are not specific to the assessment of groundwater vulnerability to pesticides. However, all these definitions acknowledge that uncertainty arises from incomplete or imprecise knowledge:
Uncertainty is due to system complexity, incomplete information and imprecise human thought (Lueng, 1988).

Uncertainty appears in the form of imprecision, vagueness and ill-defined, ill-separable and doubtful data (Kaufmann and Gupta, 1985).

Uncertainty is a result of perception of reliability, confidence and accuracy (Isaaks and Srivastava, 1989).

Uncertainty arises from errors in obtaining data, natural spatial and temporal variations, computation, data processing, modeling and conceptual errors, and output and visualization errors (Burrough, 1986; NRC, 1993).

Uncertainty represents a lack of sureness as expressed in data, models and strategies (Mays, 1996).

Uncertainty results from scarcity of information concerning the inputs, the value of the parameters (measurement and sampling uncertainties), and the imperfection of the models (modeling uncertainties; Bogardi et al., 1996).

Uncertainty of measurement is indicated by the sample variance, because it indicates the precision of the mean and uniformity of the measurement (Corwin et al., 1997).

Connell (1986) defines three main sources of uncertainty in hydrologic modeling: model uncertainty, parameter uncertainty, and measurement error. Model uncertainty not only arises...
from incomplete understanding/description of hydrology, but is also due to uncertainty in the model’s input parameters. The greatest source of model uncertainty is the conceptualization of environmental processes. We commonly simplify complex processes in order to model them (Burrough, 1986; Burrough and McDonnel, 1998; Connell, 1986). Uncertainty in model parameters is attributed to measurement error (Klir, 1994) and estimation errors if the parameter of interest cannot be directly measured (Connell, 1986). Measurement error is introduced in the laboratory due to human handling and equipment limitations (Burrough, 1986). Use of erroneous or imprecise data leads in to uncertainty in model input parameters, which in turn results in uncertainty in the model predictions (Connell, 1986).

Assessing Uncertainty

Assessment of uncertainty in chemical, climatic and soil data with respect to groundwater vulnerability can be divided into several approaches: error analysis, statistical, stochastic, geostatistical, and fuzzy logic (Klir, 1994; McBratney, 1992). Klir (1994) considered various types of uncertainty. Among these are diagnostic uncertainty and predictive uncertainty. Diagnostic uncertainty represents a series of solutions rather than a single solution: for example, possible diseases and predictive uncertainty when an interval of values is obtained rather than a single value. Both types of uncertainty fall within classic set theory. The other classic uncertainty includes statistical and stochastic methods. In these, the number represents a likelihood that a unique value will happen. Fuzzy set theory is a novel way of dealing with uncertainty (Klir, 1994).

Uncertainty analysis, if performed at all, is usually restricted to some quantitative statement of confidence in the result (Hofmann and Hammonds, 1994). Thus, quantifying uncertainty is imprecise and biased (Lueng, 1988; Kosko, 1993). Identifying sources of uncertainty depends on the institutional context, objectives, disciplines, and views involved.
(Cothern and Ross, 1994). Examples are: no information or data, incomplete data, incompatible data, anecdotal data, variability, error, temporal and spatial variability, and estimations.

Before addressing uncertainty aspects, one first needs to determine model sensitivity to input parameters. Only sensitive parameters then should be used in the uncertainty analysis, with other model parameters fixed (Dankins, 1999; Kros et al., 1999; Zacharis et al., 1999).

Often, authors do not separate uncertainty and variability and treat them as a single process that influences the value of a variable. Therefore, the contribution of uncertainty to the assessment procedure is obscured in the final results.

Error

Error analysis as a means to quantify uncertainty has been proposed by Abbaspour et al. (1997), Clausnitzer et al. (1998), Isaaks and Srivastava (1989), Loague et al. (1990, 1996), and Tiktok (1999). Error can be defined as the difference between the true value of a parameter and the estimated or measured value for the same parameter. This is sometimes called the residual error (Loague et al., 1996), and is calculated as:

\[ r = v' - v \]  \hspace{1cm} [2-1]

where

\[ r = \text{error} \]
\[ v' = \text{observed value} \]
\[ v = \text{true value} \]

or, when comparing predicted values with the true value (Isaaks and Srivastava, 1989), the error is calculated as:

\[ r = \hat{v} - v \]  \hspace{1cm} [2-2]

where

\[ r = \text{error} \]
Analysis of residual errors has been used to evaluate model performance (Loague et al, 1996; Pennell et al., 1990; Tiktak, 1999). Several methods are available: maximum error (ME), coefficient of determination (CD), modeling efficiency (EF), root mean square error (RMSE), and the coefficient of residual mass (CRM):

\[
ME = \text{MAX} \left| P_i - O_i \right|_{i=1}^n
\]

\[
CD = \frac{\sum_{i=1}^{n} (O_i - \bar{O})^2}{\sum_{i=1}^{n} (P_i - \bar{O})^2}
\]

\[
EF = \frac{\left( \sum_{i=1}^{n} (O_i - \bar{O})^2 - \sum_{i=1}^{n} P_i^2 \right)}{\sum_{i=1}^{n} (O_i - \bar{O})^2}
\]

\[
RMSE = \left[ \frac{\sum_{i=1}^{n} (P_i - O_i)^2}{n} \right] \times \frac{100}{\bar{O}}
\]

\[
CRM = \frac{\sum_{i=1}^{n} (O_i - \sum_{i=1}^{n} P_i)}{\sum_{i=1}^{n} O_i}
\]

where

\[O_i = \text{observed value of the parameter}\]

\[P_i = \text{predicted value of the parameter}\]

Error sources and error propagation in geographic information systems have been the focus of many papers by Burrough and co-workers (Burrough, 1986; Burrough and McDonnel, 1998; Heuvelink and Burrough, 1993; Heuvelink et al., 1989). Burrough (1986) recognized eight categories of error sources (Table 2-1) when dealing with geographic data and analysis. Data quality and model assumptions are of greatest concern.
GIS do not analyze the effects of error in data or the propagation of error in spatial analysis. Burrough and coworkers proposed an error propagation theory based on Monte Carlo simulations. They assumed that each variable has an error that can be described by a Gaussian probability distribution function and that the error is stationary. This allowed them to quantify the error with mean $\mu$ and variance $\sigma^2$. As an alternative to Monte Carlo simulations they used an analytical approach based on bivariate models using the simple rules of adding, subtracting, multiplying and dividing the standard deviation of two parameters at a time.

Table 2-1. Error sources in geographic information systems.

<table>
<thead>
<tr>
<th>Error source independent of GIS</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Measurement errors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- instrumental inaccuracies</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data processing errors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- data editing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Errors due to changes in the field</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- discovery of new phenomena</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Error sources introduced by GIS      |                          |                          |
| Errors in data entry                 |                          |                          |
| - digitizing inaccuracies            |                          |                          |
| - entering attribute data            |                          |                          |
| Errors in data storage               |                          |                          |
| - insufficient numerical precision   |                          |                          |
| Errors in data manipulation          |                          |                          |
| - generalization                     |                          |                          |
| - interpolation                      |                          |                          |
| - conversion (vector to raster, raster to vector) | | |
| Errors in data presentation          |                          |                          |
| - plotter inaccuracies               |                          |                          |
| Modeling and conceptual errors       |                          |                          |
| - simplification                     |                          |                          |
| - inaccurate representation of natural processes | | |

Source: Burrough, 1986.

Isaaks and Srivastava (1989) proposed the error variance as a method to address uncertainty in geostatistical applications. The error variance accounts for both distance between samples and the number of samples when quantifying uncertainty. The error variance is calculated as:

$$\sigma_R^2 = C_{00} + \sum_{j=1}^{n} \sum_{i=1}^{n} w_j w_i C_{ij} - 2 \sum_{j=1}^{n} w_j C_{0j}$$

[2-8]
where

\[ \sigma_{\tilde{x}}^2 = \text{the error variance} \]

\[ C_{00} = \text{the variance of point values} \]

\[ C_{ij} = \text{the covariance between the } i^{\text{th}} \text{ sample and the } j^{\text{th}} \text{ sample} \]

\[ C_{i0} = \text{the covariance between the } i^{\text{th}} \text{ sample and the unknown value being estimated} \]

\[ w_i, w_j = \text{weighting factors} \]

The proposed equation can be adapted for block kriging estimations and for estimating the error based on the variance within a block.

Clausnitzer et al. (1998) proposed parameter optimization for infiltration parameters using the squared residual minimization in the Levenburg-Marquadt algorithm. This algorithm combines a standard steepest descent and a quadric extrapolation method using a dimensionless parameter. In addition, an objective function was developed to calculate the normalized residuals. Abbaspour et al. (1997) used the absolute error, the root mean square error (RMSE) and the logarithmic form of the RMSE to calculate the uncertainty. Operating under the assumption that each measurement has an error, each measured parameter was considered a random variable, so a Bayesian distribution could be developed (Cressie, 1993).

**Variability**

Variability or variance is defined as (McClave and Dietrich, 1982) the “spread” of the data. This term should not be confused with heterogeneity, which is the state of being composed of different parts (McBratney, 1992).

The variability or variance of a population is calculated as the average squared difference between the mean and each member of the population (McClave and Dietrich, 1982):
\[
\sigma^2 = \frac{\sum (x - \bar{x})^2}{n - 1}
\]  

[2-9]

where

- \( \sigma^2 = \text{variability} \)
- \( x = \text{value} \)
- \( \bar{x} = \text{mean value} \)
- \( n = \text{number of observations} \)

The spatial variability is estimated with a semi-variogram. The experimental semi-variogram is calculated as the average squared difference in z value between pairs of input sample points separated by a distance \( h \) (Burrough, 1986; Clark, 1984; Cressie, 1993; Isaaks and Srivastava, 1989) as:

\[
\gamma(h) = \frac{1}{2n} \sum_{i=1}^{n} [Z(x_i) - Z(x_i + h)]^2
\]  

[2-10]

where

- \( \gamma(h) = \text{spatial variance} \)
- \( n = \text{number of points} \)
- \( Z(x_i) = \text{value at location } i \)
- \( Z(x_i + h) = \text{value at location } i + h \)
- \( h = \text{distance between two selected sample points} \)

**Statistical methods**

Popular methods to address the variability or uncertainty in chemical, climatic and soils data revolve around common statistical analysis [variance, standard deviation, confidence intervals, interquartile ranges, probabilities, and T-tests (Bilisoy et al., 1997)] or stochastic methods [moment analysis: (Fetter, 1993; Gelhar, 1993) or transfer functions (Mallawarantri and...
Mulla, 1996; Jury et al., 1993). Several of these methods rely upon the assumption that populations are normally distributed. However, many environmental properties are non-normally distributed. The typical solution is to transform the distribution to a normal distribution (Bilisoy et al., 1997). Alternatively, non-parametric methods such as the Wilcoxon signed rank test or the signed test can be used (Bilisoy et al., 1997; Young et al., 1998).

**First order uncertainty analysis.** First order uncertainty analysis (FOUA) is an accepted method for evaluating error propagation in models with independent parameters (Burrough, 1986; Heuvelink et al., 1989; Loague et al., 1989, 1990; Nofziger et al., 1994a; Tiktok, 1999). The objective of FOUA is to estimate the uncertainty, such as the variance, in model output given the error in the independent parameters. FOUA was first proposed by Dettinger and Wilson (1984). It involves calculating the mean, variance and covariance of the model outputs from means, variances, covariances and sensitivity coefficients for the model inputs.

The model output variable, \( U \), is calculated as a function, \( f(X_1, X_2, \ldots, X_k) \), of independent variables, \( X_1, X_2, \ldots, X_k \). Assume that \( \bar{x}_i \) and \( \sigma^2_i \) represent the mean and variance of the independent variable \( i \), respectively and, assuming that the variables are uncorrelated, the mean (expected value), \( \bar{U} \), and the variance, \( \sigma^2_u \), of the dependent variable are given by:

\[
\bar{U} = f(\bar{X_1}, \bar{X_2}, \ldots, \bar{X_k})
\]

\[
\sigma^2_u = \Sigma_i^{k-1} \left( \frac{\partial U}{\partial X_i} \bigg|_{x_i = \bar{x}_i} \right)^2 \sigma^2_i
\]

In the case where the variables are correlated and \( r_{ij} \) is the correlation coefficient. The variance of \( U \) then is given by:

\[
\sigma^2_u = \Sigma_i^{k} \left( \frac{\partial U}{\partial X_i} \bigg|_{x_i = \bar{x}_i} \right)^2 \sigma^2_i + \Sigma_{ij}^{k} \left( \frac{\partial U}{\partial X_j} \bigg|_{x_j = \bar{x}_j} \right) \left( \frac{\partial U}{\partial X_i} \bigg|_{x_i = \bar{x}_i} \right) \sigma_i \sigma_j r_{ij}
\]

For the FOUA it is required that the independent variables be normally distributed. If this is not the case, a transformation must be applied. The FOUA technique is recommended when \( U \) can be specified by a differentiable and well-behaved function of the independent variables (NRC,
FOUA is the first-order Taylor series approximation of the dependent variable \( U \) with respect to the independent variable \( X_i \), summed over all variables.

The uncertainty for the \( i^{th} \) parameter of the model is calculated as (Loague et al., 1990; NRC, 1993):

\[
C_i = \frac{\partial AF}{\partial P_i} \sigma_{P_i}
\]  

[2-14]

where

\( C_i = \) uncertainty in the parameter of interest
\( \frac{\partial AF}{\partial P_i} = \) first-order partial derivative of the attenuation factor (AF)
\( \frac{\partial P_i}{\sigma_{P_i}} = \) first-order partial derivative of the parameter of interest
\( \sigma_{P_i} = \) variance of the parameter of interest

An example of FOUA applied to the pesticide half-life results in (Loague et al., 1990):

\[
C_{T50} = \left[ \frac{0.693 \bar{d} \bar{R} \Theta_{fe} AF}{\sigma_{T50}^2} \right] \sigma_{T50}
\]  

[2-15]

where

\( C_{T50} = \) uncertainty attributed by a single parameter
\( \bar{d} = \) mean depth
\( \bar{R} = \) mean retardation factor
\( \bar{\Theta}_{fe} = \) mean soil-moisture content at field capacity
\( AF = \) mean attenuation factor
\( \bar{q} = \) mean net recharge
\( \bar{T}_{50} = \) mean half-life (T)
\( \sigma_{T50} = \) variation of half-life (T²)

Loague et al. (1990, 1996) showed that FOUA can be used in conjunction with the Attenuation Factor (Rao et al., 1985) to address uncertainty in climate, chemical and soil
parameters when assessing groundwater vulnerability to pesticides. Tiktak (1999) used FUOA to
determine the uncertainty in cadmium leaching for Dutch soils.

Monte Carlo simulations. This is by far the most popular method to address uncertainty
or variability when assessing pesticide leaching to groundwater (Beltman et al., 1993; Carsel at
al., 1998; Clausnitzer et al., 1998; Fjed et al., 1989; Foussereau et al., 1993, 1999; Ginzburg et
al., 1984; Jury and Gruber, 1989; Loague et al., 1990, 1996; Nofziger et al., 1996; Soutter and
Pannatier, 1996; Tiktak, 1999; van der Zee and Boesten, 1991; Wu and Workman, 1999;
Zacharias et al., 1999), health exposure modeling (Frey, 1993; Hoffman and Hammonds, 1994)
and heavy metal distribution (Kros et al., 1999; Tiktak, 1999). Monte Carlo simulations are
preformed to generate probability and cumulative distribution curves for the model outputs.
Thus, a cumulative probability that a specific event will occur can be derived. The probability is
then viewed as an indicator of the uncertainty.

The principle of Monte Carlo simulations requires that at least one model parameter, X,
can be represented with a cumulative distribution function. Monte Carlo techniques involve the
repeated generation of pseudo-values for X, drawn from a known distribution within the range of
possible values. The generated pseudo-values are then used as input data for the model. A
Monte Carlo simulation session generally entails six steps (Carsel et al., 1998):

- Development of representative probability and cumulative density functions for
  selected model input parameters,
- Generation of a pseudo-value for each of the selected input parameters from the
distribution developed in the previous step,
- Execution of the model with the pseudo-values,
- Repeated application of the previous two steps,
- Presentation of the results in a cumulative distribution function, and
- Analysis of the cumulative distribution function for decision-making.

Depending on the input variable, the shape of the cumulative distribution function is dictated.
For dynamic soil properties such as the soil moisture content or soil hydraulic conductivity, the
distribution tends to be log-normal, whereas for static soil properties such as organic matter and bulk density the distribution functions tend to be normally distributed.

Jury (1986) stressed that Monte Carlo simulations cannot be used to estimate continuous spatial patterns in a field, because they represent different populations. However, advancements in geostatistics show that Monte Carlo simulations (stochastic imaging; Journel, 1989) can be used in a spatial environment. Another disadvantage of Monte Carlo simulations is that comprehensive knowledge is required of the population distribution for the parameter involved. Often parameter distributions are arbitrarily assigned (Clewell et al., 1999; Di and Aylmore, 1997; Diaz-Diaz et al., 1997; Swartout, 1999). The defined distributions are based upon sparse data and are therefore biased. Consequently, the outcome of the Monte Carlo simulations might behave erratically and the convergence of results, compared to analytical solutions, is a reflection of the arbitrarily assigned distribution functions (Corbett et al., 1989).

Foussereau et al. (1993) used bootstrapping in combination with Monte Carlo simulations to address variability within soil mapping units when assessing pesticide leaching to groundwater. Bootstrapping is a resampling technique to generate pseudo soil profiles based on existing data sets. This technique relies on the assumption that the variation of a soil parameter at a given depth within a taxonomic unit is separated into two independent components:

\[ \Theta = \mu + \alpha_i + \epsilon_{ij} \]  \[2-16\]

where

\[ \Theta \] = value of the soil property
\[ \mu \] = population mean
\[ \alpha_i \] = independent random variables with zero mean, representing the location effect and the random error
\[ \epsilon_{ij} \] = depth
\[ i \] = location
\[ j \] = depth

Estimated values of \( \Theta_{ij} \) can be calculated from:

\[ \Theta_{ij} = \mu_j - \alpha_i + \epsilon_{ij} \]  \[2-17\]
where

\[ \mu = \theta_i \]
\[ a = \theta_i - \theta \]
\[ \varepsilon = \theta_{ij} - \theta_i - \theta_j + \theta \]

From the estimates, the resampling distribution of a soil parameter in a pseudo-soil profile is generated by repeatedly selecting a location, i, from the set \( \{1, \ldots, 20\} \) and 20 associated errors with subscript i, selected with replacement from the set \( \{1, \ldots, j\} \) with subscript j. This computation involves the location effect for the profile and the remaining errors correspond to the soil layers.

2D Monte Carlo simulations. These simulations are used to address uncertainty and are often applied in risk exposure assessment analysis (Frey, 1993). An advantage of 2D Monte Carlo simulations is that variability and uncertainty allow for proper modeling of two conceptually different processes. The first step is to classify the model input parameters into variable and uncertain components. For the variable parameters, frequency distributions must be specified and, for the uncertain parameter, probability distribution functions must be specified. The latter distribution is arbitrarily assigned. Latin hyper cube sampling is applied to generate two sets of samples. Next, the model is repetitively evaluated for each combination of samples from the variable and uncertain parameters, and a matrix of values is generated. Any column in the matrix represents the frequency distribution of variable parameters in exposure levels for a given realization of uncertainties in each individual. Any row represents the probability distributions of uncertainty in exposure level for a given member of the population (Frey, 1993).

Uncertainty factors. Uncertainty factors are implemented in risk assessment methods to account for uncertainty. Usually an uncertainty factor is a pre-defined probability density function [double truncated normal, uniform or triangular distribution (Clewell et al., 1999; Portier, 1999; Swartout, 1999)] for the selected model parameters and is treated as a random variable. An example of the implementation of the uncertainty factor is:
\[ \text{RfD} = \frac{\text{NOAEL}}{\text{UF} \times \text{MF}} \]  
[2-18]

where

- \( \text{RfD} \) = Reference dose
- \( \text{NOAEL} \) = No observed adverse effect level
- \( \text{UF} \) = Uncertainty factor
- \( \text{MF} \) = Mass factor

In this example, the model is sensitive to the mass factor and not the NOAEL. Thus, the mass factor will be adjusted with an uncertainty factor. In this approach the values of the uncertainty distribution are arbitrarily chosen (Swartout, 1999). The uncertainty factor is used in combination with Monte Carlo simulations (Bartell, 1999; Clewell et al., 1999; Portier, 1999; Swartout, 1999). Sometimes, the uncertainty factor is a fixed number that is different for each model parameter (Clewell et al., 1999).

**Confidence intervals.** These values for the \( i^{\text{th}} \) percentile have been used to address uncertainty under the assumption that the distribution of the spatial phenomenon is normal (Gelhar, 1993; Isaaks and Srivastava, 1989). Using the student-T test for the mean and the \( \chi^2 \) distribution for the variance; confidence intervals can be calculated. These confidence intervals can be placed around a mean value, a population or any number to indicate uncertainty (Johnston, 1999). It is important to realize that the confidence interval of the variance will be wider than the interval for the mean of a given number of samples (Gelhar, 1993). Non-parametric confidence intervals are shown to be wide for most soil properties (Young et al., 1998), thus indicating a larger degree of uncertainty. The use of confidence intervals suggests that one can be \( i^{\text{th}} \) percent confident that the results fall inside the intervals, but this is only true if one is 100% confident in the model that has been used (Alder, 1997).

From a strict statistically point of view, confidence levels describe the interval in which we can place measurements for a given probability, usually 95 or 99 percent (McClave and Dietrich, 1982). Thus, in risk assessment or groundwater vulnerability assessments, confidence
intervals might be misplaced, because we are often interested only in data from the upper tail of a distribution. The upper tail represents the worst cases and, therefore, use of the complete distribution is preferred (Dankins, 1999).

**Stochastic modeling.** This is an alternative to statistical modeling using deterministic models (Fetter, 1993; Gelhar, 1993). In the stochastic approach the physical description of the framework is combined with a probabilistic description of the variability. Hence, the phenomenon of interest is described using stochastic processes and random fields. The stochastic equations are then solved to produce probabilistic results.

A stochastic process \(X(t)\) is defined as a random variable for any assigned time (Gelhar, 1993) and a stochastic model as a model in which there is statistical uncertainty in the value of input and output variables (Fetter, 1993). The probabilistic nature of the outcome is due to the fact that uncertainty is present in the distribution of the underlying parameters (Fetter, 1993). Graham (1990) states that stochastic analysis of flow and transport provides a tool to acknowledge explicitly the various sources of model prediction errors such as variability, along with spatial distribution of field data used to estimate model input parameters.

In the stochastic modeling approach the best estimates of a parameter are characterized by its moments and autocorrelation function. The best estimate for the parameter is calculated with the first moment of the ensemble mean (Fetter, 1993; Gelhar, 1993; Jury et al., 1993):

\[
\mu_x = E[X] = \int_{-\infty}^{\infty} x f(x) \, dx \quad [2-19]
\]

The variance or second moment is described with:

\[
\sigma_x^2 = E[(X - \mu_x)^2] = \int_{-\infty}^{\infty} (x-\mu_x)^2 f(x) \, dx \quad [2-20]
\]

and the zeroth moment represents the total mass in the system:

\[
M = \int_{-\infty}^{\infty} f(x) \, dx \quad [2-21]
\]

The autocorrelation function, \(\rho_x\), describes the correlation of the parameter \(X\) with itself over distance. It operates under the assumption that measurements of \(X\) at closer distances are more
similar than measurements of X at larger distances. Consequently, the value of the
autocorrelation function decreases with distance. An estimate for \( \rho_Y \) can be obtained with:

\[
\rho_Y = \frac{1}{\sigma_Y^2} \frac{1}{n} \sum_{i=1}^{n} (Y_i - \bar{Y})(Y_{i-k} - \bar{Y}) \tag{2-22}
\]

where

\( k = \) the lag distance representing a position in the sequence away from the
position \( i \)

The autocorrelation function can be represented in terms of the lag (\( \rho_{Y_k} \)) or distance (\( H \)). Doing
so introduces the concept of correlation distance. The correlation distance (\( \lambda_Y \)) is the distance
over which the parameter is correlated.

The autocovariance, \( \tau_Y \), is equal to the autocorrelation times the variance and represents
the variance of the variable with itself:

\[
\tau_Y(H) = \sigma_Y^2 \rho_Y(H) \tag{2-23}
\]

Using the mean, \( \mu \), variance, \( \sigma^2 \), and correlation length, \( \lambda \), stochastics can be used
to describe the distribution of heterogeneities (Fetter, 1993; Gelhar, 1993). The method of
moment analysis has been applied by researchers in the past to analyze tracer movement
(Freyberg, 1986; Garabedian et al., 1991; Rajaram and Gelhar, 1991; Sudicky, 1986), diffusion-
limited solute transport (Goltz and Roberts, 1987), degradation rates (Das and Kluitenberg,
1996), soil-water monitoring (Or, 1995), sorption (Espinoza and Valocchi, 1997), and transport
in unsaturated heterogeneous soils (Fousserau et al., 1999) with the intent to account for
uncertainty and to serve as a less computationally intense alternative to Monte Carlo simulations.
Espinoza and Valocchi (1997), James and Oldenburg (1997), and Zhang (1997) concluded from
their studies that Monte Carlo simulations, moment analysis, and stochastic models all predict
similar results with no significant differences.

Wu and Workman (1999), Wu et al. (1997) and Zacharias et al. (1999) used
deterministic models (GLEAMS and OPUS) in combination with stochastic modeling techniques
to predict pesticide fate to the groundwater zone. Both studies applied probability density
functions of selected input parameters to account for variability and uncertainty. The probability
density functions were used to generate input parameters for the Monte Carlo simulations. Wu
and Workman (1999) concluded that the stochastic approach yielded better results than
traditional methods.

**Entropy.** Shannon (1949) adapted the entropy concept to address uncertainty in the
mathematical theory of communication as a way to determine how much “choice” is involved in
the selection of an event, or how uncertain we are of the outcome. This enabled him to develop
an encryption method to reduce the noise in telephone lines.

In information theory, information is expressed as bits (Gimon, 1999; Shannon, 1949).
The more bits of information you have, the more uncertainty you have. The number of possible
messages, M, you can make with x number of bits will be two to the power of x. Shannon turned
this idea around, with the number of bits you need to transmit a message being the base-two
logarithm of the number of possible messages:

\[ 2^x = M \quad [2-24] \]

\[ \log_2 M = x \quad [2-25] \]

Shannon then developed an entropy function based on the three properties (Shannon, 1949):

- **Continuity.** \( U_S \) should be a continuous function of \( p_i \), i.e., \( U(p_1,p_2,...,p_n) \) (\( n \in \mathbb{N} \)).
  Often this is replaced by \( U_S(p,1-p) \) for the interval \([0,1]\), with \( p_i \) being the
  probability of a bit occurring.

- **Monotonicity.** If all \( p_i \) are equal (\( p_i = 1/n \)), then \( U_S \) is a monotonically increasing
  function of \( n \). With equal probability for each event, there is more choice or
  more uncertainty, when there are more possible events.

- **Branching.** If a choice were to be broken down into two successive choices, the
  original \( S \) should be the weighted sum of the individual values of \( U_S \).

The only function satisfying the three above assumptions is:

\[ U_S = - \sum p_i \log p_i \quad [2-26] \]

where
\[ U_S = \text{Shannon entropy} \]
\[ p_i = \text{probability of occurrence.} \]
\[ N = \text{number of probabilities} \]

It was proven by various authors (Aczel and Darczy, 1975; Mathai and Rathie, 1975) that the Shannon entropy is the only way to describe uncertainty in a framework when dealing with multiple choices and that the function applies to the natural logarithm and base-ten logarithm as well. Additionally, it was shown that the Shannon entropy adheres to the following rules (Aczel and Darczy, 1975; Klir and Weirman, 1998):

- **Additivity.** The uncertainty of any joint probability distribution that is non-interactive should be equal to the sum of the corresponding individual distributions.

- **Normalization.** To ensure (if desirable) that the measurements are bits, it is essential that:

  \[ U_{S2} \left( \frac{1}{2}, \frac{1}{2} \right) = 1 \quad [2-27] \]

- **Expansibility.** When a component with probability 0 is added to the probability distribution, the uncertainty should not change.

  \[ U_S(p_1, p_2, p_3, \ldots, p_n) = U_S(p_1, p_2, \ldots, p_n, 0) \quad [2-28] \]

**Geostatistical Methods**

Use of geostatistics to address error, variability or uncertainty is popular because it allows for a continuous spatial representation of the observed phenomenon and often presents the spatial variability as a means to estimate spatial error and uncertainty (Heuvelink and Burrough, 1993; Heuvelink et al., 1989). Commonly used kriging approaches include: ordinary kriging (Bourgalt et al., 1995; Burrough, 1989; Hamlett et al., 1986; Inakwu et al., 1992; Odeh et al., 1990; Rogowski, 1996a; Stein et al., 1995), block kriging (Odeh et al., 1990), co-kriging...
Ordinary kriging might not always provide sufficiently detailed information of the estimated parameter surface, so the use of additional data sets along with the original data set can improve the kriging estimate. The second data set should be larger than the original set and taken at different locations. Also, the data sets should be spatially correlated. This method of kriging is called co-kriging. Stein et al. (1988) showed an increase in precision of the predicted parameter by 10%; i.e., smaller kriging error.

Application of ordinary and co-kriging to estimate uncertainty implies use of the kriged variance surface. The variance surface is used as an indicator for the variability of the kriging estimate or is interpreted as an indicator for the error or accuracy of the resulting kriging surface (Isaaks and Srivastava, 1989; Stein et al., 1988). The larger the kriging variance, the less certain the results, although Journel (1989, 1995) states that the kriging variance is a ranking index of the data configuration, which is a poor estimate of the local accuracy. Only when the phenomena observed can be described with a Gaussian (normal) distribution, is the kriging variance an estimate of the accuracy (Bourgalt et al., 1995; Journel, 1989, 1995; Rogowski, 1996a).

Nonlinear kriging techniques to address spatial variability and uncertainty have been a topic of discussion in past years. These techniques allow implementation of a threshold and of probabilities in kriging estimates (Journel, 1989, 1995; Rogowski, 1996a).

Indicator kriging (Cressie, 1993; Isaaks and Srivastava, 1989) can be used to interpolate the probability that a given threshold will be exceeded. For each observed variable, the sequential indicator, i(q,x), determines the transformation with respect to the threshold (Cressie, 1993; Journel, 1989; Rogowski, 1996b):
\[ i(q,x) = 0 \quad \text{if} \quad Q(x) > q \]
\[ = 1 \quad \text{if} \quad Q(x) \leq q \]  

where

\[ Q(x) = \text{value of the phenomena at location } x \]
\[ q = \text{threshold value} \]

In essence, the original data are converted to a binary scale (Burrough and McDonell, 1998). For a set of measured and estimated values of parameters distributed across an area, the method converts them to indicator distributions for each threshold. If then it assigns an algorithm for adding values at the non-sampled locations based on the spatial structure (semivariogram) for the observed population at a particular threshold. If one interprets the indicator as a probability, with 0 being below the threshold and 1 above the threshold, then the use of ordinary kriging will produce estimates between 0 - 1 and the conditional probability distribution for the defined thresholds (Cressie, 1993; Isaaks and Srivastava, 1989). Therefore, indicator kriging is often called probabilistic kriging (Burrough and McDonell, 1998).

Uncertainty in indicator kriging, expressed in the soft data only (estimated values), ranges from 0 to 1. This information is called a soft indicator and is never greater than the threshold value. No uncertainty exists in the observed data points (Goovaerts, 1997). The 0 to 1 range does not say anything about how uncertain each value is.

Sequential indicator kriging (Journel, 1989, 1995; Rogowski, 1996b) is based on indicator kriging (Cressie, 1993; Isaaks and Srivastava, 1989; Journel, 1995) in that it converts the original data set to a binary scale and allows modeling of different portions of an irregular distribution by separating the observed population into various classes, each separated by a threshold. It can be used to proportion populations within a certain area or block (Isaaks and Srivastava, 1989). Rogowski (1996b) used sequential indicator kriging to develop a set of probability maps for hydraulic conductivity in the Mahantango Creek watershed of Pennsylvania. His results suggested that sequential indicator kriging can be used to reproduce spatial patterns or introduce a measure of uncertainty when performing multiple simulations.
Stochastic imaging (Journel, 1989) was developed to address the lack of measured data for each cell (location) and the probabilistic distribution for each location. In order to examine the impact of changing input values for a node, we might want to compute upper and lower boundaries for the original data and the kriged variance. The generated surfaces provide only an estimate of possible values (Burrough and McDonell, 1998; Journel, 1989), with each surface being equiprobable (Bourgalt et al., 1995; Journel, 1989, 1995). Monte Carlo simulations can be applied for each cell individually, such that the value is expressed as:

\[
Z(x) = P(z) \tag{2-30}
\]

where

\[
P(Z) = \text{normal probability distribution function with mean } \mu \text{ and variance } \sigma^2
\]

If the semi-variogram is known, this can be used to generate a new surface with the same statistical characteristics as the original. If the data are not fixed, the output would be a stationary random noise field (Burrough and McDonell, 1998). Stochastic imaging differs from ordinary kriging in that at least 500 surfaces will be generated and, additionally, the mean and the variance will be calculated (Burrough and McDonell, 1998; Journel, 1989, 1995), with the variance being an indicator of the uncertainty.

Rang et al. (1989) argued that the use of geostatistical tools in situations where pollutant levels are changed in steps is not appropriate, because they rely on the assumptions of gradual change and spatial dependence of the variable under consideration. In a case study for a Dutch sanitation project Rang et al. (1987) concluded that geostatistics were not an appropriate tool to estimate the extent of groundwater pollution, because of the severe lack of data.

Goovaerts (1997) listed various statistical and geostatistical methods as a means to display local uncertainty (Fig. 2-2). Among these are probabilities of exceeding a threshold (see indicator kriging), interquartile ranges, kriging variances and entropy measure. The entropy model (Christakos, 1990; Goovaerts, 1998; Journel and Deutsch, 1993) is based on a local conditional probability distribution function that was derived from n observations along a random path with the point of interest in the center, thus obtaining a different probability
function for each location. Each probability function was transformed to a normally distributed histogram of N classes, with the entropy calculated for the remaining classes.

Figure 2-2. Visualization of uncertainty using variances, entropy and interquartile ranges (Goovaerts, 1997).

Fuzzy Logic

An alternative to deterministic, probabilistic, stochastic, and geostatistical modeling is fuzzy logic (Burrough, 1993; Ganoulis, 1994; Lueng, 1988). It is very useful when only sparse data are available (Bogardi et al., 1996; Ganoulis, 1994) and for characterization of propagation of the uncertainty in imprecise data and functional relationships (Burrough, 1993; Ganoulis, 1994; Lueng, 1988).

Fuzzy logic is a concept that deals with natural imprecision. In traditional science, numbers are discrete and hard. Often phenomena are viewed as black or white, true or false, and in boolean terms 0 or 1. Although the real world represents the whole spectrum between black and white, everything is a matter of degree. This is called the fuzzy principle (Kosko, 1993). This fuzziness has a formal name in science: multivalence. Multivalence originated from work done by logisticians in the 1920s - 1930s to deal with Heisenberg’s uncertainty principle in
quantum mechanics. The principle resulting from their work allowed for three values: true, false or intermediate. Polish logician Jan Lukasiewicz divided the intermediate into multiple pieces and developed a continuum from 0 to 1 on the spectrum between false and true (Kosko, 1993).

In 1965, Lotfi Zadeh published a paper called “Fuzzy Sets” (Zadeh, 1965). In this paper the multivalence principle was applied to set theory with Zadeh introducing the term “fuzzy” for multivalence sets. The objects in these sets have a different degree of belonging to this set. The “degree of belonging to” is called the membership of an object. Thus, fuzzy sets are a generalization of discrete set theory and are characterized by three concepts (Burrough, 1993):

- generality - single concept
- ambiguity - single concept embraces more than one sub-concept
- vagueness - precise boundaries are not defined

Conventional or crisp sets allow only a true-false membership function, with elements either belonging to a set or not. Fuzzy sets, however, admit the possibility that a value has partial membership of a class. Thus, boundaries are not exactly defined. The general notation of fuzzy sets is (Burrough, 1993; Klir and Wierman, 1998):

\[ A(x) = [X, u_A(x)] \quad [2-31] \]

where

- \( A(x) = \) fuzzy set
- \( X = \) number \( x \)
- \( u_A(X) = \) degree of membership of \( x \) in \( A \)

Usually the degree of membership is a number in the range 0 to 1, with 1 representing full membership and 0 non-membership. The degree of membership does not depend on a probability but on an admitted possibility (Burrough, 1993; Burrough and McDonnel, 1998; Klir and Wierman, 1998; McBratney, 1992).

The membership function of a fuzzy set defines how the degree of membership of \( x \) in \( A \) is determined. A number of commonly used membership functions are available (Tab. 2-2), ranging from simple triangular functions to gaussian type distribution functions. The range over
which the functions operate depends on the type of function. The sinusoidal model (Burrough, 1993; Burrough and McDonnel, 1998) and the Guassian model have no limits for their ranges whereas trapezoid and triangular fuzzy sets have a defined range.

Table 2-2. Examples of commonly used fuzzy sets.

<table>
<thead>
<tr>
<th>Model</th>
<th>Membership Function</th>
<th>Range</th>
<th>Source</th>
</tr>
</thead>
</table>
| Gaussian | \[
\frac{(x - c)}{\sqrt{1 + a(x - c)^2}}
\] | \[a \leq x \leq b\] | McBratney and Odeh, 1997 [2-32] |
| Sinusoidal | \[
\frac{1}{1 + a(x - c)^2}
\] | \[0 \leq x \leq b\] | Burrough, 1993 [2-33] |
| Trapezoid | \[
\frac{x - a}{b - a} \quad \frac{b - a}{1} \quad \frac{d - x}{d - c} \quad \frac{0}{c - b}
\] | \[a < x \leq b \quad b \leq x \leq c \quad c < x \leq d \quad d < x\] | McBratney and Odeh, 1997 [2-34] |
| Triangular | \[
\frac{x - a}{b - a} \quad \frac{b - a}{c - b} \quad \frac{c - b}{0}
\] | \[a < x \leq b \quad b < x \leq c \quad c < x\] | McBratney and Odeh, 1997 [2-35] |

Note: a,b,c, and d indicate the range of the fuzzy set. The “c” in the gaussian and sinusoidal models refers to the centroid of the class.

Fuzzy numbers are a special case of fuzzy sets. A fuzzy number, X, has the following properties: a) it is defined on the set of real numbers, rather than a set of linguistic properties; b) its membership function reaches always the maximum value of 1, i.e. it is a normal fuzzy set; c) its membership function is unimodal: and d) a complete arithmetic is available to combine fuzzy numbers (Ganoulis, 1994; Kaufmann and Gupta, 1985; Leung, 1988).

Fuzzy logic models have been extensively applied in soil classification studies, as evidenced by publication of a special edition of the journal Geoderma, titled “Fuzzy sets in Soil
Science” (de Gruijter et al., 1997). In that issue, it is emphasized that fuzzy set theory offers the soil scientist the possibility of dealing with both the continuous variation of the soil and the vague nature of soil description. Prior to the Geoderma issue, much work has been done by McBratney and co-workers in this field. Odeh et al. (1990, 1992a, 1992b) used the fuzzy-k-means to determine optimal sample spacing, soil pattern recognition, and soil mapping. Fuzzy-k-means revolves around iterative methodology that establishes membership functions for fuzzy sets for which the central concept (k) is described in linguistic terms. The results suggested that fuzzy logic provides a more rapid soil pattern recognition and a minimum loss of information, since data are not classified into discrete classes. These results are supported by work of McBratney and de Gruijter (1992), Odeh and McBratney (1997) and Powell et al. (1991).

Burrough (1989) and Burrough et al. (1992) used the semantic import model for land use suitability classification. Juang et al. (1992) employed a similar method for mapping soil failure potential. Most of the previously mentioned researchers used fuzzy logic on point data sets. In order to embed the spatial and variable nature of soils, ordinary kriging was used to generate fuzzy soils maps (Burrough, 1993; Hendrick Franssen et al., 1997; McBratney and de Gruijter, 1992; Odeh et al., 1992a, 1992b; Powell et al., 1991).

Application of fuzzy logic in risk assessment is limited to a few studies. Bogardi et al. (1996) used fuzzy numbers to determine soil contamination caused by failure of a landfill. Exposure, threshold and exposed land surface were expressed as fuzzy numbers. Failure of the system was calculated for the case where one of its components fails. This was accomplished by using the fuzzy minimum of the fuzzy number for the three variables. In the second case, failure of the system was assumed if all of its components failed, i.e., the system is safe if one of the components is still working. System failure is then defined as the fuzzy maximum of the fuzzy numbers. The researchers concluded that chemical exposure and threshold levels are both uncertain and can be expressed as fuzzy numbers. Also, they suggested that the proposed method may be viable to conventional approaches in risk assessment, when uncertainty cannot be characterized by probabilistic models.
Fuzzy classification methods for mapping of soil pollutants and of soil properties have been compared to spatial interpolation techniques such as indicator kriging (Hendrick Franssen et al., 1997) and disjunctive kriging (Lark and Bolam, 1997). Both studies indicated that fuzzy sets are a viable alternative to traditional probabilistic methods, and at the same time, account for uncertainty inherent to the data.
CHAPTER 3
UNCERTAINTY THEORY

Uncertainty Analysis

Theory

Intuitively most people understand the concept of uncertainty. In this study, uncertainty relates to imprecision in predicted mass emissions and travel times for selected pesticides, introduced by imprecision in the model input data. Uncertainty is a subjective concept, being different for each person and many definitions of uncertainty have been published. It is imperative, therefore, for this research to define uncertainty within the framework of predictive pesticide modeling. For the purpose of this study, the following definition of uncertainty is used: Uncertainty is a measure of the degree of deviation between model outputs using imported input parameters as compared to model outputs using the “true” input parameters.

Imprecision in model input parameters can be classified as Type I and Type II imprecision. Type I imprecision is the inexactness associated with measured values of a parameter. These measured values tend to vary around the true value of that parameter. Type II imprecision is the inexactness of parameters, when non site-specific data are used instead of site-specific data. An example is the use of soil data collected elsewhere, for a location where no soil data were collected. Note that Type II imprecision contains Type I imprecision. In this research Type II imprecision is addressed.

Imprecision is commonly represented in terms of values distributed around the true value of the parameter of interest (Fig. 3-1). These deviations around the true value may be the result of such factors as human handling and machine limitations. If the true value of a parameter is
known, uncertainty can be easily quantified. For example, an observed value can be described as a function of the true value and the uncertainty, which can be expressed as:

\[ y = \mu_T + \epsilon \]  

[3-1]

Rearranging Eq. [3-1] to compute the uncertainty:

\[ \mu_T = y - \epsilon \]  

[3-2]

where

\[ y = \text{observed value} \]
\[ \mu_T = \text{true value} \]
\[ \epsilon = \text{uncertainty} \]

Knowing the true and observed values, the uncertainty can be described by a distribution function. Properties of the uncertainty distribution depends on presence of bias in the system. If bias is not present, the uncertainty distribution may be described with \( \epsilon(0,\sigma^2_\epsilon) \). The distribution has zero mean and \( \sigma_\epsilon \) standard deviation. If bias is present, the uncertainty distribution needs to be described with \( \epsilon(\mu,\sigma^2_\epsilon) \). Now the distribution has a mean of \( \mu \). In both cases, uncertainty can be described in terms of the variance of the distribution. This concept can be adapted for predictive modeling. First assume that, for a given site, only one “true” value exists: for example, the mass emission of a pesticide. The true value for that site could be obtained, for
example, by taking groundwater samples, measuring the pesticide concentrations, and converting these to a mass emission basis. As one attempts to predict the mass emissions for a site, multiple mass emissions are predicted by taking into account the variability of input parameters. Based on these multiple mass emissions, a distribution function can be developed (Fig. 3-2a) for the predicted values. In this scenario, uncertainty can be quantified in terms of the variance.

However, when dealing with natural systems, the true value for a parameter seldom can be expressed using a single number. For example, the mass emissions for a pesticide will be different from year to year, because of different rainfall patterns. Thus, for any given site, multiple "true" pesticide mass emissions exist (Fig. 3-2b). Theoretically, it is possible to calculate the uncertainty associated with each “true” mass emission. The total uncertainty $U_T$ in this scenario can be expressed as:

$$U_T = \sigma_{\mu}^2 + \sigma_{\epsilon}^2$$  \[3-3\]

where

- $U_T =$ total uncertainty expressed as the total variance
- $\sigma_{\mu} =$ variance of the true values
- $\sigma_{\epsilon} =$ variance of the predicted values

Taking this one step further, the true mass emission for a site can be represented with a probability distribution function (Fig. 3-2c). This distribution function would include all possible true mass emissions for that site. Similar to the mass emission distribution, a distribution function can be developed for the true travel time of a pesticide for a specific location at a site, using the same procedure.

Having two distributions, statistics can then be applied to compare the populations. Statistical tests, so could be used include the Chi-square test and the Kolmogorov-Smirnov test (Gilbert, 1987; Ott 1995). These tests allow us to determine whether the populations are significantly different. However, we cannot quantify the uncertainty with these tests alone. Thus, a different method needs to be used to quantify the uncertainty.
Figure 3-2. Representation of the true pesticide mass emission and the predicted pesticide mass emission. 
(a) Single true value; b) Multiple true values; c) True value as a probability distribution function.
Alternatively, the difference between the predicted and true mass emissions or travel time probability distribution functions can be calculated, as this might provide insight into uncertainty of the predicted mass emissions or travel times. This calculation involves subtracting both probability distribution functions and taking the absolute value of the difference in probability, |dP|. The absolute value is used rather than the relative value because we are primarily interested in the magnitude of the difference. This new function represents the uncertainty at each level of the predicted mass emissions or travel times (Fig. 3-3). It is postulated that smaller differences in probability indicate more accurate predictions, because the predicted probability density function for the mass emissions or travel times then becomes more nearly the same as the true mass emissions or travel times. If the differences are larger, we are less certain about our predictions. This function is named the probability difference function.

![Probability difference function of the difference between the predicted and true mass emission. This function represents the uncertainty of the system.](image)

**Figure 3-3.** Probability difference function of the difference between the predicted and true mass emission. This function represents the uncertainty of the system.

A question remains as to whether a model exists that will translate the derived probability difference function into a measure of uncertainty. The function by itself does not provide this information directly.
Entropy Approach

Shannon entropy

The Shannon entropy model Eq. [2-26], can be used to quantify uncertainty in a probabilistic framework. Entropy is a measure of similarity in a system, with increased entropy resulting in a higher state of disorganization. In our pesticide leaching framework, a small entropy value would equate to little difference between the distribution functions for the predicted and true mass emissions or travel times. On the other hand, a large entropy value would indicate dissimilar distributions for the predicted and true mass emissions or travel times.

As the shape of the |dP| function will most likely not adhere to a known distribution, it is not likely to be expressed as an analytical solution. However, the |dP| function can be expressed as a histogram, with K classes. Uncertainty is than expressed in terms of the overall probability of the classes, rather then the probability of individual choices. Consequently, the uncertainty is expressed as:

$$U_S = \sum_{i} p_i \log p_i$$  \[3-4\]

where

- $U_S$ = Shannon entropy
- $K$ = number of classes
- $p_i$ = probability of class $i$

Uncertainty in Eq. [3-4] is expressed as a function of log base 10. As long as the same logarithmic base is used the final uncertainty is the same as when logarithmic such as base 2, would be used. Maximum uncertainty is achieved when the probability of each of the classes is equal and could be calculated as log $K$ (Goovaerts, 1997; Shannon, 1949), but this relationship is only valid when dealing with a single probability distribution function. In the described framework, we deal with two probability functions: one for the predicted mass emissions or travel times and one for the “true” mass emissions or travel times. Theoretically, it is conceivable that the functions do not overlap in any of the classes. For example, one or two
classes could each have a value of \(|dP| = 1\), four classes could have values of \(|dP| = 0.5\), or eight classes could have \(|dP| = 0.25\), etc. In a system originally possessing two probability distribution functions, the sum of all probabilities is two. With each class having equal probability \((2/K)\) the maximum uncertainty, \(U_{\text{max}}\), of this system is calculated as:

\[
U_{\text{max}} = -\sum_{i=1}^{K} \frac{2}{K} \log \frac{2}{K} \tag{3-5}
\]

The normalized uncertainty \([0,1]\) in turn can be calculated as:

\[
U_H = \frac{U_S}{U_{\text{max}}} \tag{3-6}
\]

and, for \(U_H = 0\), we have complete certainty in the system. For \(U_H = 1\), there is total uncertainty in the system. Any deviation from 0 introduces more uncertainty to the system.

This system has two special cases, for both of which \(U_H = 0\):

1. Only two classes have a difference in probability and each has the maximum value of \(|dP| = 1\). \(\log(1) = 0\); thus, the sum equals 0. In this system, the calculated uncertainty is 0 but, in reality, it is larger than zero.
2. All classes have \(|dP| = 0\), indicating that the two distributions are identical and therefore that there is no uncertainty.

Although both cases can exist theoretically, it is assumed that these cases will not occur in any pesticide leaching scenario.

**Entropy application**

Application of the entropy approach requires the development of a standardized histogram to describe the pesticide mass emissions and travel times at selected depths. Often, pesticide leaching studies apply a lognormal scale to the mass emissions, enabling us to show very small and very large mass emissions in a single graph. Therefore, a logarithmic scale was used to classify the pesticide mass emissions.
The classification of mass emissions into selected classes was based upon the range of mass emissions predicted in the sensitivity analysis. These results indicated that mass emissions smaller than $10^{-23}$ kg active ingredient (a.i.) ha$^{-1}$ were sparsely predicted. Therefore, the lower boundary was set at $10^{-23}$ kg a.i. ha$^{-1}$. Predicted mass emissions smaller than $10^{-23}$ would belong to this class. The upper boundary was set at $10^1$ kg a.i. ha$^{-1}$. This is above the maximum application rate but, when using a logarithmic scale and maintaining the logarithmic class width, it was required to use $10^1$ as the maximum value. Environmental-fate models can predict that the pesticide did not leach to the specified depth within a specified time period. Such results were stored in a class for zero mass emissions and consequently the lower boundary was set to 0.

Based on this classification schematic, the $|dP|$ functions were transformed into a histogram with 26 classes (Table 3-1).

<table>
<thead>
<tr>
<th>Mass Emissions</th>
<th>Travel Times</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class</td>
<td>Range (kg a.i. ha$^{-1}$)</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$10^{-23}$</td>
<td>0 - 1 x $10^{-23}$</td>
</tr>
<tr>
<td>$10^{-22}$</td>
<td>1 x $10^{-23}$ - 1 x $10^{-22}$</td>
</tr>
<tr>
<td>$10^{-21}$</td>
<td>1 x $10^{-22}$ - 1 x $10^{-21}$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>$10^{-1}$</td>
<td>1 x $10^{-2}$ - 1 x $10^{-1}$</td>
</tr>
<tr>
<td>$10^0$</td>
<td>1 x $10^{-1}$ - 1 x $10^0$</td>
</tr>
<tr>
<td>$10^1$</td>
<td>1 x $10^0$ - 1 x $10^1$</td>
</tr>
</tbody>
</table>

Similar to the development of the standardized histogram for mass emissions, standard histogram classes were developed for the travel time as well. Classes with a class width of 100 days were used for the travel time, so each class covers a time period of approximately three months. With a maximum travel time for a pesticide of 40 years, this resulted in 147 different classes (Table 3-1). The 40-year time period is a model limitation when using CMLS98B (Nofziger et al., 1998) on personal computers. Whenever pesticides do not arrive within 40 years of application at a selected control depth, CMLS98B returns a value of -1 for the travel time.
However, the actual travel time is somewhat larger than 40 years (14600 days). All such observations were put in the class >14600 days.

**Fuzzy Logic Approach**

**Fuzzy set classification**

As the notion of uncertainty varies from person to person, it does not seem suitable to treat it as a single number. What might be perceived as certain to one person might be perceived as less certain or even uncertain to another. Such vaguely formulated concepts must be translated in terms of the available basic units of information. Thus, lack of precision in both the data and the formulation requires a method that can handle imprecision.

Fuzziness is a type of imprecision which characterizes classes that, for various reasons, do not have crisp boundaries. These inexactly defined classes are called fuzzy sets. It is appropriate to think about fuzziness when dealing with ambiguity and vagueness. If one accepts that the concept of uncertainty has a range of possible meanings and values, fuzzy set theory can be applied to characterize uncertainty in pesticide risk assessment studies. The general notation of fuzzy sets (Burrough, 1993; Klir and Wierman, 1998) is:

\[
A(x) = [X, u_A(x)] \quad \text{[2-31]}
\]

where

\[
u_A(x) = \text{is the grade or degree of membership for } x \text{ in } A
\]

Usually the degree of membership is a number in the range 0 to 1, with 1 representing full membership and 0 representing non-membership. A possible approach to defining membership grades is the use of an *a priori* membership function to which each individual can be assigned a grade. This is known as the semantic import (SI) model (Burrough, 1993). The SI approach is useful whenever the user wants to define his/her own class boundaries or knows how to group the data.
There are several suitable functions for defining membership grades. A function that is suitable for use with the SI approach is given in Eq. [2-33]:

\[ u = (1 + a(x-c)^2)^{-1} \]  

where

- \( u \) = degree of membership
- \( a \) = shape parameter
- \( x \) = property of interest
- \( c \) = class centroid.

The shape and position of this model are governed by \( a \), which determines the shape, and \( c \), which determines the class centroid (Fig. 3-4). For smaller values of “\( a \)”, the function becomes more fuzzy. For larger number values of “\( a \)”, the membership function becomes more crisp.

Figure 3-4. Impact of changing the values of the shape parameter “\( a \)” on the form and values of the membership function; \( c = 0.25 \).
**Fuzzy logic application**

Based on the range of calculated differences in probability, $|dP|$, for mass emission, four fuzzy sets (Fig. 3-5) were developed. The four fuzzy sets were; 1) certain; 2) intermediate; 3) uncertain; and 4) extragrade. Each of the fuzzy classes was allowed a range in which the degree of membership, $\mu = 1.0$, and the fuzzy boundaries were described with a sinusoidal model making each fuzzy set a fuzzy interval. The fuzzy class “certain” expresses the highest degree of confidence in the predicted results, when the probability difference for a given mass emission is small. It thus indicates that there is little uncertainty in the predictions. The fuzzy set “intermediate” is considered the grey area in terms of certainty for the simulation results. Results are neither certain nor uncertain. The fuzzy set “uncertain” expresses the least degree of certainty in the outcome of the simulations. Values that fall within this class are highly uncertain and must be used with caution in the decision-making process. All variables that fall outside the boundaries of the three fuzzy sets are considered extragrades, because they fall outside the 0 - 0.30 range.

![Membership functions for four fuzzy classes that represent the difference in probability, $|dP|$ between the predicted and site-referenced mass emission.](image-url)

Figure 3-5. Membership functions for four fuzzy classes that represent the difference in probability, $|dP|$ between the predicted and site-referenced mass emission.
Each fuzzy set is described with an interval of maximum membership value and with sinusoidal functions at the boundaries. The fuzzy sets have the following characteristics:

\[
\text{Certain: } \mu = \begin{cases} 
1 & |dP| \leq 0.05 \\
\frac{1}{(1 + a(|dP| - 0.05)^4)} & |dP| > 0.05
\end{cases}
\]  
\[3-7\]

\[
\text{Intermediate: } \mu = \begin{cases} 
\frac{1}{(1 + a(|dP| - 0.10)^4)} & |dP| < 0.10 \\
1 & 0.10 \leq |dP| \leq 0.15 \\
\frac{1}{(1 + a(|dP| - 0.15)^4)} & |dP| > 0.15
\end{cases}
\]  
\[3-8\]

\[
\text{Uncertain: } \mu = \begin{cases} 
\frac{1}{(1 + a(|dP| - 0.20)^4)} & |dP| < 0.20 \\
1 & 0.20 \leq |dP| \leq 0.25 \\
\frac{1}{(1 + a(|dP| - 0.25)^4)} & |dP| > 0.25
\end{cases}
\]  
\[3-9\]

\[
\text{Extragrade: } \mu = \begin{cases} 
1 & |dP| \leq 0.30 \\
\frac{1}{(1 + a(|dP| - 0.30)^4)} & |dP| > 0.30
\end{cases}
\]  
\[3-10\]

where “a” was set equal to 1500, because the sets intersect at the cross-over points \(\mu=0.5\). These fuzzy intervals were applied to quantify \(|dP|\) in terms of uncertainty for the mass emissions.

Similar to the fuzzy classification of mass emissions is the fuzzy classification of probability difference, \(|dP|\), for the travel time. Four fuzzy intervals (certain, intermediate, uncertain, and extragrade) were developed, based on a sinusoidal function (Fig. 3-6). Because of

![Figure 3-6. Membership functions for four fuzzy sets to classify the uncertainty in the travel time.](image)
the fuzzy intervals for the travel time were smaller than for the the larger number of classes than for the mass emissions (147 vs 26), mass emission. Each fuzzy interval has a range of 0.02 |dP|, in which the membership values are constant. The shape parameter “a” was set to 1000 so that the fuzzy sets intersect at the cross-over point, μ=0.5. The four fuzzy sets have the following characteristics:

Certain: \[ \mu = \begin{cases} 1 & |dP| \leq 0.02 \\ \frac{1}{(1 + a(|dP| - 0.02)^{-1})} & |dP| > 0.02 \end{cases} \]  

Intermediate: \[ \mu = \begin{cases} (1 + a(|dP| - 0.04)^{-1}) & |dP| < 0.04 \\ \frac{1}{(1 + a(|dP| - 0.06)^{-1})} & 0.04 \leq |dP| \leq 0.06 \\ 1 & |dP| > 0.06 \end{cases} \]  

Uncertain: \[ \mu = \begin{cases} (1 + a(|dP| - 0.08)^{-1}) & |dP| < 0.08 \\ \frac{1}{(1 + a(|dP| - 0.10)^{-1})} & 0.08 \leq |dP| \leq 0.10 \\ 1 & |dP| > 0.10 \end{cases} \]  

Extragrade: \[ \mu = \begin{cases} (1 + a(|dP| - 0.12)^{-1}) & |dP| < 0.12 \\ \frac{1}{(1 + a(|dP| - 0.12)^{-1})} & |dP| > 0.12 \end{cases} \]  

Application of fuzzy intervals to the mass emission classes and selected travel time classes does not provide a final answer to the uncertainty in mass emissions and travel times at the Santa Fe Beef Unit test site. Therefore, the individual maps were combined into one final map. The concept of confusion may help us to combine maps of fuzzy memberships into easy-to-understand zones. If a particular site has a fuzzy membership value close to one, we are clear as to which class this site belongs. When the membership values of two or more classes are similar, however, it is not clear to which class the site belongs. Therefore, the situation is confusing. The degree of class overlap can be specified in terms of the confusion index (Burrough and McDonnell, 1998):

\[ CI = 1 - [\mu_{\text{max}} - \mu_{\text{max}2}] \]  

where

CI = confusion index
\[ \mu_{\text{max}} = \text{maximum membership value of all layers considered} \]
\[ \mu_{\text{max}2} = \text{second highest membership value for all layers considered} \]
The confusion index can be calculated for each mass emission class and travel time class at the soil sample locations. Degree of membership values can be computed using the sinusoidal model. Next, inverse distance weight interpolation can be used to generate maps showing spatial distribution of the degree of membership for each function and the confusion index.

Sensitivity Analysis

A first step in the uncertainty assessment process is a sensitivity analysis of the environmental-fate model used, CMLS98B (Nofziger et al., 1998). Sensitivity analysis is a first indication concerning the contribution of each parameter to the uncertainty of a model. If a model is sensitive to a parameter, it is expected that the parameter contributes more to uncertainty than a non-sensitive parameter (Dankins, 1999).

The sensitivity of a model refers to the change in a selected model output resulting from a change in an input parameter. Mathematically, the sensitivity coefficient, $S$, is defined for discrete change as (Nofziger et al., 1994a):

$$S = \frac{\Delta f}{\Delta x}$$  \hspace{1cm} [3-16]

with

$\Delta f = \text{change in output of the model (e.g., amount leached)}$

$\Delta x = \text{change in input parameter value}$

Sensitivity as defined above has units associated with it. This makes it difficult to compare the model’s sensitivity for various parameters. Therefore, the relative sensitivity, $S_r$, must be used. The relative sensitivity is a dimensionless number and is calculated by multiplying the sensitivity by the quotient of the parameter of interest and the mass leached. In mathematical terms:

$$S_r = \frac{f_i - f_{i*}}{f_e} \ast \left[ \frac{x_i - x_{i*}}{x_e} \right]^{-1}$$  \hspace{1cm} [3-17]
or

$$S_r = \frac{\Delta f}{\Delta x} \frac{x_c}{f_c}$$

[3-18]

where $c$ indicates the centroid value of the mass leached ($f_c$) for the parameter of interest ($x_c$).

The centroid value is defined for the purpose of this study as the value precisely between two $x$ values or $f$ values. Between the two points a linear relationship was assumed, because the value differences for $x$ were small for the parameters used in the sensitivity analysis.
CHAPTER 4
MATERIALS AND METHODS

Test Site: Santa Fe Beef Unit

The test site used for this study was located at the Sante Fe Beef Unit (SFBU) of the University of Florida (UF) in northwest Alachua County, Florida (Fig. 4-1). The SFBU is located east of County Road 241, approximately 12 km north of the town of Alachua in Sections 35 and 36, T6S, R18E. The test site encompassed 19.55 ha.

The landscape of the test site is characterized by gently sloping hills with pasture (bahiagrass: *Paspalum notatum*) on the higher elevations and deciduous forest at the lower elevations (Fig. 4-2). A streambed, flowing south to north through the forest, is usually dry from fall to spring. In the winter of 1998, the stream, the forest, and parts of the pasture were flooded from January through April, because of excessive rainfall in January and February. Elevations in the test site range from 29-32 m above mean sea level on the east and west sides of the test site, to 15 m above mean sea level in the streambed area (Fig. 4-3). Slopes of eight to 12 percent occur on the east site of the test site, and slopes of two to eight percent on the west side.

Geology at the site is dominated by presence of the Hawthorn formation, which at several places within the site is present near the landscape surface. The Hawthorn formation is of Middle Miocene age and overlies the older Ocala Group. The Hawthorn formation is characterized by quartz sands, high clay content, carbonates, and pebbles and grains of phosphate. Thickness ranges from a few meters to 55 m near Gainesville, and to 65 m near the northeastern part of Alachua County. The Ocala group is of Eocene age and consists mainly of soft, white to creamy colored chalky, cavernous limestone that is approximately 98 percent calcium carbonates. This limestone formation is found at depths greater than 55 m (Thomas et al., 1985) Alachua County.
Figure 4-1. Locator map of the Santa Fe Beef Unit test site in Alachua County, FL.
Figure 4-2. Land use at the Santa Fe Beef Unit test site.

Figure 4-3. Elevation (m) at the Santa Fe Beef Unit test site.
According to the Alachua County soil survey report (Thomas et al., 1985), 11 different soil map units (Fig. 4-4) occur within the boundaries of the test site. The Alachua County soil survey report was mapped at 1:15,840 scale and was recompiled to 1:24,000 when it was digitized. This digitized soil survey map was used throughout this research project and is referred to as the Alachua County soil survey map. Soil map units represent ten soil series and four soil orders. Dominant soil series phases are: Gainesville sand, 0 to 5 percent slopes (hyperthermic, coated Typic Quartzipsamments; 4.23 ha), Gainesville sand, 5 to 8 percent slopes (1.71 ha), Myakka sand (sandy, siliceous, hyperthermic Aeric Haplaquods; 3.64 ha) and Norfolk loamy fine sand, 5 to 8 percent slopes (fine-loamy, kaolinitic, thermic Typic Kandiudults; 4.06 ha). Other series mapped at the test site are: Blichton sand, 0 to 2 percent slopes (loamy, siliceous, hyperthermic Arenic Plinthic Paleaquults; 0.14 ha), Bonneau fine sand, 2 to 5 percent slopes (loamy, siliceous, subactive, thermic Arenic Paleudults; 1.78 ha), Chipley sand (thermic, coated Aquic Quartzipsamments; 1.10 ha), Micanopy loamy fine sand, 2 to 5 percent slopes (fine, mixed, hyperthermic Aquic Paleudalfs; 0.53 ha), Millhopper sand, 0 to 5 percent slopes (loamy, siliceous, hyperthermic Grossarenic Paleults; 1.26 ha), Sparr fine sand (loamy, siliceous, hyperthermic Grossarenic Paleudults; 0.27 ha), and Tavares sand, 0 to 5 percent slopes (hyperthermic, uncoated Typic Quartzipsamments; 0.83 ha; NRCS, 1999; Appendix A).

Soil Map Development

In order to develop the probability distribution functions for the true mass emissions and travel times the soil map and site characteristics had to be verified. Four soil maps were developed for this purpose; 1) two point-based soil maps and 2) two polygon-based soil maps. All field work, employed in development of the soil maps and associated databases is discussed in the following sections.
Figure 4-4. Spatial distribution of the soils mapped at the Santa Fe Beef Unit according to the Alachua County soil survey report (Thomas et al., 1985).
Sample Grid Design

An aligned square grid (Gilbert, 1987) with a 50 m surface distance between sample locations was laid out over the test site. For the purpose of this study, the surface distance is defined as the distance in meters between two points following the contours of the land surface. This design resulted in 90 sample locations approximately homogeneously distributed over the site (Fig. 4-5). The west border of the test site was chosen as the base line for the sample grid, because it is a north-south line. A hand-held compass was used to determine magnetic north and the straight border was confirmed with a survey transit. The first sample location had an offset of 5.0 m east and 5.0 m south from the northwest corner of the test site. Two nonmetallic 50 m tape measures (Kenson Fiberglass measuring tapes) were used to lay out the remaining sample locations. One tape was used for the north-south measurements and the second tape was used for the east-west measurements. The intersection of the two tape measures was the next sample location. A wooden stake was placed in the ground at each sample location. Sample locations 35 and 44 were lost due to high water during the sampling period.

Figure 4-5. Sample grid layout at the Santa Fe Beef Unit test site.
Global position system: data collection

A Magellan Pro Mark X-CM Global Position System (GPS) receiver was used to survey each soil sample location. This allowed us to rectify the sampling grid for latitude, longitude and elevation.

Magellan (Magellan, 1997a) recommends the following guidelines for collecting stationary differential GPS data at submeter accuracy:

\[
CM = 800 \text{ CM} + 100 \text{ credits/km of baseline} \quad [4-1]
\]

and for centimeter accuracy:

\[
CM = 1500 \text{ CM} + 100 \text{ credits/km of baseline} \quad [4-2]
\]

where CM is a GPS collection credit and a credit is a valid observation using four or more satellites with elevation angles of more than 25° for submeter accuracy and five or more satellites with elevation angles of more than 15° for centimeter accuracy; the baseline is the distance (km) between the base station and the rover. For this study the baseline was 33.3 km and \( T \) is the time (min) required to collect the GPS data.

Based on minimum satellite availability, the guidelines indicated that at least two hours were required to collect GPS data at centimeter accuracy. Because of this requirement only a control point and the four corners of the test site were surveyed at centimeter accuracy, while the remaining sample locations were surveyed at submeter accuracy. A time series analysis was performed to determine the required sampling time for the soil sample locations. GPS samples were collected for 25, 45, 60, 75, 90, 120, and 150 minutes.

Time series analysis of the control point (Fig. 4-6 and Fig. 4-7) indicated that sampling periods of less than 75 minutes produced highly variable results compared to the 120 min and 150 min sampling periods. The 75 minute samples produced results similar to those for 90, 120, and 150 minutes. Using Fig. 4-6 and Fig. 4-7, it was concluded that 75 min was sufficient to collect reliable submeter GPS data for all soil sample locations. Elevation or the height above
ellipsoid (HAE; Fig. 4-7) is the most sensitive parameter in GPS surveying, and the standard deviation of the HAE is usually three times larger than for the longitude or latitude (Kennedy, 1996). For each point, if necessary, the offset (bearing, distance, and elevation difference) was measured. An offset was required if the established sample location had significant interference from overhanging trees. The GPS receiver settings are described in Appendix B.
A control point was used at the site to estimate variability in the geographic location based on the developed GPS sampling design. The control point was surveyed once each week at different starting times, using the same sampling strategy as for the soil sample locations. The statistics indicated (Table 4-1) that GPS sampling time introduced little error in the obtained positions.

Table 4-1. Control point statistics.

<table>
<thead>
<tr>
<th></th>
<th>HAE † (m)</th>
<th>Longitude‡ (m)</th>
<th>Latitude‡ (m)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>3.49</td>
<td>545689.99</td>
<td>658296.25</td>
<td>6</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.05</td>
<td>0.07</td>
<td>0.07</td>
<td></td>
</tr>
</tbody>
</table>

† HAE: Height Above Ellipsoid.
‡ Longitude and latitude are reported for the Albers Equal Area projection

Global position system: postprocessing

GPS differential correction files were obtained from the GPS base station located on the campus of the University of Florida (Urban and Regional Planning Department). Base station files (RINEX format) were imported into MSTAR Professional GPS software (Magellan, 1997b)
for differential correction of the collected GPS data (MSTAR format). The collected GPS data were postprocessed at centimeter accuracy. If the differential correction data did not allow for a centimeter solution, a submeter solution was automatically obtained.

The differentially corrected GPS data were converted from the geographic coordinates to Albers conic equal area projection (Appendix C). Data in the Albers conic equal area projection are used for GIS data at the UF Soil and Water Science Department. ARC/INFO V 7.2.1 (ESRI, 1998a) GIS was used to change the projection system of the GPS data and to build new GIS layers.

**Grid sample distance**

The distance between the surveyed sample locations was calculated to verify that the surface distance was approximately 50m and to establish the impact of the elevation on the distance between sample locations. If the elevation significantly impacts the sample distance, this will affect the outcome of geostatistical applications at the test site. Therefore, the distance was calculated for; a) a 2-dimensional plane; b) a 3-dimensional plane; and c) along the landscape surface. The 2-dimensional distance was calculated as:

\[ d_2 = \sqrt{(x_n - x_{n+1})^2 + (y_n - y_{n+1})^2} \]  \[4-3\]

and the 3-dimensional distance was computed as:

\[ d_3 = \sqrt{(x_n + x_{n+1})^2 + (y_n + y_{n+1})^2 + (z_n + z_{n+1})^2} \]  \[4-4\]

where

- \(d_2, d_3\) = distance between two adjacent sample locations in the north-south or east-west direction.
- \(X_n\) = x coordinate for the \(n^{th}\) point.
- \(Y_n\) = y coordinate for the \(n^{th}\) point.
- \(Z_n\) = z coordinate for the \(n^{th}\) point.
\[ X_{n+1} = x \text{ coordinate for the first adjacent point south or east of the } n^{th} \text{ point.} \]
\[ Y_{n+1} = y \text{ coordinate for the first adjacent point south or east of the } n^{th} \text{ point.} \]
\[ Z_{n+1} = z \text{ coordinate for the first adjacent point south or east of the } n^{th} \text{ point.} \]

The surface distance was calculated using the SURFACELENGTH command in ARC/INFO 7.2.1. This command requires a surface elevation model and line coverage with arcs between the sample locations. A digital elevation model for the site was generated using the SPLINE function on the point data for which the elevation was surveyed. The line coverage was created using the GENERATE function. Lines were generated for the north-south and east-west directions of the grid.

**Soil Sampling**

Soil was sampled utilizing a bucket auger down to the 2.0-m depth. For each location, horizon depth (cm), color, texture, structure, consistency, roots, mottles, and other important features were described. The soil profile descriptions were interpreted and classified to the series level by Mr. S. Franz (Soil and Water Science Dept., UF) and Mr. W. Hurt (USDA-Natural Resources Conservation Service (NRCS)).

The soil surface horizon was sampled at each sample location to determine organic carbon content. It was assumed that management practices (fertilization, disk tillage and grazing by cows) at the test site altered the organic carbon content of the surface layer. Two soil samples were taken from each sample location, and the thickness of the surface horizon was recorded.

**Organic carbon analysis**

Organic carbon content of the surface horizon was determined using the Walkley and Black method (Houba et al., 1989).
The organic carbon content for six samples was also determined using the loss-on-ignition method (Houba et al., 1989) because the organic carbon content in these samples was too high to be determined with the Walkey-Black method. Approximately 2.0g of oven-dry soil sample was combusted in a muffle furnace at 550°C for 24 hrs.

Soil maps

Four soil survey maps were developed to display the spatial distribution of soil series at the Santa Fe Beef Unit test site. Two of the soil maps are point-based and two maps are polygon-based. The development and purpose of each map is described as follows.

Alachua County point-based soil map. For each of the soil sample locations the soil series was determined according to the Alachua County soil survey map (Thomas et al., 1985). The sample location map (Fig. 4-5) was overlaid with the Alachua County soil survey map (Fig. 4-4) in ArcView GIS 3.1. For each sample location it was determined in which map unit delineation the sample location fell and the soil series name of that map unit delineation was assigned to the sample location in consideration. This process was repeated for the 88 sample locations at the SFBU test site. This map was used as the base map for the predictive pesticide modeling scenario and is henceforth referred to as the ACPS map.

Site-specific point-based soil map. The site-specific point-based soil map was developed by assigning a soil series name, based on a soil profile description, at each sample location. This was done for the 88 sample locations at the SFBU test site. Soil profile descriptions were obtained from samples taken by bucket auger. This map was used to provide the spatial distribution of soils at the Santa Fe Beef Unit for the site-referenced modeling scenario and is referred to as the SSPS map.

High intensity soil survey map. The high intensity soil survey map (HISM) is a polygon-based map and was developed by combining the site-specific point-based soil map and a traditional field soil survey using landscape features and other site characteristics to establish soil boundaries. This map was solely used for soil area comparisons with the existing Alachua County soil survey map. The approximate map scale for the HISM is 1:2 000.
Recompiled high intensity soil survey map. The recompiled high intensity soil survey map (HISMR) is a recompiled version of the HISM and was generated by folding smaller map delineations into larger ones and down-scaling the HISM to 1:24 000 to allow for comparisons with the digitized Alachua County soil survey map comparison was used to determine the extent of change from the Alachua County soil survey map and the uncertainty that could be attributed to the Alachua County soil survey map.

Thematic site maps

Three thematic site maps were generated based on the point data. These maps are: 1) organic carbon content in the soil surface horizon; 2) depth to the argillic horizon; and 3) measured rooting depth.

For the organic carbon content the spatial structure was determined and modeled with a semivariogram. Next, ordinary kriging was applied to generate a map showing the spatial distribution of the parameter of interest.

Maps displaying the spatial distribution of the argillic horizon and the rooting depth were generated using splines in ArcView 3.1 Spatial Analyst.

Environmental-fate Model

The amount of pesticide leached to the groundwater was estimated using the CMLS98B model. CMLS98B (Nofziger et al., 1998) is the latest release of the 1994 version (Nofziger et al., 1994b). This model is an improved version of CMLS (Nofziger and Hornsby, 1986, 1987). Improvements include; functions for estimating daily infiltration and evapotranspiration, irrigation routines, a stochastic weather simulator (WGEN; Richardson and Wright, 1984), Monte Carlo capabilities for generating equiprobable weather sequences, and availability as a batch version.
CMLS98B estimates pesticide transport and degradation through a layered soil profile by estimating daily water flux and adjusting the depth to which the pesticide has moved. The program requires the soil-water content at field capacity, permanent wilting point, and saturation to calculate daily water flux. Water is moved in piston manner, with water already in the profile being pushed ahead of the newly incoming water flux. Precipitation is partitioned into runoff and infiltration, with runoff being estimated with the NRCS curve number technique (Knissel et al., 1993). Evapotranspiration is calculated with the NRCS variation of the Blaney-Criddle model or using a pan factor method. Evapotranspiration, leaching and runoff are the sources of water loss from the root zone.

Pesticide movement is assumed to occur only in the aqueous phase in the downward direction, and is estimated as the center of mass for a single application. Retardation is estimated with the retardation factor assuming a linear, reversible, equilibrium sorption model. The organic carbon content and bulk density are required for each soil horizon. The retardation coefficient is calculated based upon the soil-moisture content at field capacity. Degradation of pesticides is simulated using a first-order degradation function.

CMLS98B requires only a few input data (Table 4-2) and is suitable for regional pesticide leaching studies. The batch version can easily be integrated with geographic information systems (Hoogeweg and Hornsby, 1997, 1998).

The use of crop coefficients in CMLS98B is limited to 12 pairs of “day-crop coefficients” for each crop. Annual updates are not possible and, therefore, the crop coefficients were fixed. Since the crop in the test site is in continuous bahiagrass, use of fixed coefficients is realistic.

Pesticide degradation in CMLS98B is simulated as a first-order degradation process. The degradation rate can be fixed for the whole soil profile, implemented for each soil horizon, or can be temperature dependent degradation. In the latter option the Arrhenius equation is used to estimate the degradation rate with depth. For a full description of this option the reader is referred to Wu and Nofziger (1999) and, for the CMLS98B model, the reader is referred to the user’s manual (Nofziger et al., 1994b, 1998).
Table 4-2. Input data required by CMLS98B.

<table>
<thead>
<tr>
<th>Input Parameter</th>
<th>Units</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemical parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>activation energy</td>
<td>kJ mol$^{-1}$</td>
<td></td>
</tr>
<tr>
<td>application date</td>
<td>day-of-year</td>
<td></td>
</tr>
<tr>
<td>application rate</td>
<td>kg ha$^{-1}$</td>
<td></td>
</tr>
<tr>
<td>half-life</td>
<td>days</td>
<td></td>
</tr>
<tr>
<td>partition coefficient</td>
<td>mL g$^{-1}$</td>
<td></td>
</tr>
<tr>
<td>reference temperature</td>
<td>C or F</td>
<td></td>
</tr>
<tr>
<td>Climatic parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>crop coefficient</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>evapotranspiration</td>
<td>cm day$^{-1}$</td>
<td></td>
</tr>
<tr>
<td>precipitation</td>
<td>cm day$^{-1}$</td>
<td></td>
</tr>
<tr>
<td>Soil parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bulk density</td>
<td>g cm$^{-3}$</td>
<td>For each soil horizon</td>
</tr>
<tr>
<td>temperature damping depth</td>
<td>m</td>
<td></td>
</tr>
<tr>
<td>field capacity</td>
<td>cm$^{3}$ cm$^{-3}$</td>
<td>For each soil horizon</td>
</tr>
<tr>
<td>horizon depth</td>
<td>cm</td>
<td>For each soil horizon</td>
</tr>
<tr>
<td>permanent wilting point</td>
<td>cm$^{3}$ cm$^{-3}$</td>
<td>For each soil horizon</td>
</tr>
<tr>
<td>porosity</td>
<td>cm$^{3}$ cm$^{-3}$</td>
<td>For each soil horizon</td>
</tr>
<tr>
<td>organic carbon</td>
<td>%</td>
<td>For each soil horizon</td>
</tr>
<tr>
<td>Site parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>curve number</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>root depth</td>
<td>m</td>
<td></td>
</tr>
</tbody>
</table>

Source: Nofziger et al. 1998.

Sensitivity analysis

Nofziger et al. (1994a) and Wu and Nofziger (1999) suggested that all input parameters of the model are sensitive. Based on these results an additional sensitivity analysis was performed for a selected set of model parameters (Table 4-3) to confirm that these results are valid for Florida conditions. The pesticide amount passing a control depth (1.0m and 2.0m) was used in the sensitivity analysis. Multiple depths were desired because it was expected that the sensitivity of the model changes with depth. Climatic data from the Gainesville Regional Airport weather station were used to provide daily precipitation and temperature. The curve number, CN=25, for the soil series (Gainesville fine sand) was based upon non-contoured pasture (Knissel et al., 1993).
Table 4-3. Summary of the selected parameters used in the sensitivity analysis of CMLS98B.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value Range</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Chemical characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>activation energy</td>
<td>0.0 - 100.0</td>
<td>kJ mol⁻¹</td>
</tr>
<tr>
<td>application rate</td>
<td>0.25 - 5.0</td>
<td>kg ha⁻¹</td>
</tr>
<tr>
<td>half-life</td>
<td>0.0 - 1,000</td>
<td>d</td>
</tr>
<tr>
<td>partition coefficient</td>
<td>0.0 - 1,000</td>
<td>mL g⁻¹</td>
</tr>
<tr>
<td>reference temperature</td>
<td>30.0 - 90.0</td>
<td>F</td>
</tr>
<tr>
<td><strong>Climatic conditions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>average annual temperature</td>
<td>50.0 - 100.0</td>
<td>F</td>
</tr>
<tr>
<td>amplitude</td>
<td>2.0 - 20.0</td>
<td>F</td>
</tr>
<tr>
<td><strong>Site conditions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>curve number</td>
<td>5 - 95</td>
<td></td>
</tr>
<tr>
<td>root depth</td>
<td>0.05 - 1.95</td>
<td>m</td>
</tr>
<tr>
<td><strong>Soil profile</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>temperature damping depth</td>
<td>1.0 - 3.4</td>
<td>m</td>
</tr>
<tr>
<td>organic matter</td>
<td>0.0 - 12.0</td>
<td>%</td>
</tr>
</tbody>
</table>

**Pesticides**

Two pesticides were used to determine groundwater vulnerability at the Santa Fe Beef Unit. The selected pesticides were Velpar and Princep. The active ingredient (a.i.) in Velpar is hexazinone (3-cyclohexyl-6-(dimethylamino)-1-methyl-1,3,5-triazine-2,4-(1H,3H)-dione) and, in Princep, simazine (2-chloro-4,6-bis(ethylamino)-s-triazine). Both pesticides are herbicides that are used for weed control in grass and which target most seedling broadleaf weeds (Colvin et al., 1990).

The environmental-fate properties (Table 4-4) of hexazinone and simazine were extracted from Hornsby et al. (1996). Only limited environmental-fate data were available for the selected pesticides. Rao and Davidson (1980) suggested that partition coefficient and half-life follow a log-normal distribution. The Shapiro and Wilks test (Gilbert, 1987) indicated that the pesticide properties were lognormal distributed.
Table 4-4. Pesticide health advisory level, application rate and environmental properties for three pasture pesticides.

<table>
<thead>
<tr>
<th>Active Ingredient</th>
<th>Health Advisory Level (HAL: ug L⁻¹)</th>
<th>Partition Coefficient (mL g⁻¹)</th>
<th>Half-life (d)</th>
<th>Application Rate (kg a.i. ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hexazinone</td>
<td>400</td>
<td>54</td>
<td>90</td>
<td>0.76 - 1.26</td>
</tr>
<tr>
<td>Simazine</td>
<td>1</td>
<td>130</td>
<td>60</td>
<td>2.58 - 5.58</td>
</tr>
</tbody>
</table>

Source: Colvin et al., 1990; Hornsby et al., 1996.

Pesticide degradation was simulated with first-order, temperature-dependent degradation. Proposed values for the activation energy range from 30 - 90 kJ mol⁻¹ and are normally distributed. The values are independent of soil type and pesticide (Boesten, 1986).

The pesticide application rate was assumed to follow a normal distribution, with minimum and maximum application rates determining the range of the distribution. The application window for the pesticides was set from February 1st to February 14th. This might not conform to the actual pesticide application period, but it was allowed here, as a standardized approach.

Environmental-fate of hexazinone was simulated for the 74 soil sample locations for which soil data were available. Simazine leaching was simulated for two selected locations at the test site to demonstrate that the entropy method will work with less mobile pesticides as well.

**Modeling Scenarios**

**Predictive Modeling**

In order to develop a probability distribution function for the predicted mass emissions and travel times, Monte Carlo simulations were performed. Therefore, for selected model input parameters a probability distribution function was developed. This would also allow us to account for variability in chemical, climatic, and soils data. To achieve stable solution of the
environmental-fate model, 10,000 simulations were executed. Each simulation was an unique combination of model input parameters.

A weather database was developed for a weather station located in Alachua County, FL. For the predictive modeling scenario the Gainesville Regional Airport weather station (Table 4-5) was used. Daily precipitation, maximum temperature and minimum temperature were extracted from the NCDC Summary of Day East CD-ROM (EarthInfo, 1996) and recompiled to a statistical file for use with the weather generator, WGEN. This enabled us to generate multi-year, equally likely weather sequences and, thus, perform Monte Carlo simulations on the weather. The crop coefficients, used to estimate evapotranspiration were set at the suggested values for pasture as published in the National Irrigation Handbook (USDA-NRCS, 1993).

Table 4-5. Geographic location and time period for the Gainesville Regional Airport weather station.

<table>
<thead>
<tr>
<th>Station Name</th>
<th>Elev. (m)</th>
<th>Latitude (Degrees)</th>
<th>Longitude (Degrees)</th>
<th>Period Start-End Date</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regional Airport</td>
<td>42.0</td>
<td>N29:41:00</td>
<td>W82:16:00</td>
<td>01/01/1961-12/31/1995</td>
<td>21</td>
</tr>
</tbody>
</table>

Source: EarthInfo, 1996.

The ACPS map was used to display spatial distribution of the soils at the research site. According to the Alachua County soil survey report, 10 different soil series were mapped at the site (Table 4-6). Soil data required by the environmental-fate model were extracted from the UF Soil Characterization database (Collins and Cantlin, 1992) and the soil survey geographic database (USDA-NRCS, 1995) of Alachua County. The extracted pedon data sets were normalized so that bootstrapping could be used to generate new pseudo soil profiles. This method requires at least three pedon data sets (Nofziger et al., 1994b).

Distribution functions for the environmental-fate properties of the pesticides were developed by setting the mean equal to selected values from the literature and setting the coefficient of variation (CV) arbitrarily at 20%. Computed CVs based on published values or arbitrarily values of 30% (see Diaz-Diaz et al., 1997; Di and Aylmore, 1997) produced negative
numbers which needed to be omitted from the data set as they are physically impossible. This, in turn, lead to statistically different distributions. Using a CV of 20% eliminated the negative

Table 4-6. Taxonomy placements for soil series found at the Santa Fe Beef Unit test site based upon the Alachua County soil survey report.

<table>
<thead>
<tr>
<th>Series Name</th>
<th>Taxonomic Description</th>
<th>Pedons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blichton</td>
<td>Loamy, siliceous, hyperthermic Arenic Plinthic Paleaquults</td>
<td>1</td>
</tr>
<tr>
<td>Bonneau</td>
<td>Loamy, siliceous, subactive, thermic Arenic Paleudults</td>
<td>7</td>
</tr>
<tr>
<td>Chipley</td>
<td>Thermic, coated Aquic Quartzipsammments</td>
<td>12</td>
</tr>
<tr>
<td>Gainesville</td>
<td>Hyperthermic, coated Typic Quartzipsammments</td>
<td>1</td>
</tr>
<tr>
<td>Micanopy</td>
<td>Fine, mixed, hyperthermic Aquic Paleudalfs</td>
<td>3</td>
</tr>
<tr>
<td>Millhopper</td>
<td>Loamy, siliceous, hyperthermic Grossarenic Paleudults</td>
<td>8</td>
</tr>
<tr>
<td>Myakka</td>
<td>Sandy, siliceous, hyperthermic Aeric Alaquods</td>
<td>11</td>
</tr>
<tr>
<td>Norfolk</td>
<td>Fine-loamy, kaolinitic, thermic Typic Kandiudults</td>
<td>4</td>
</tr>
<tr>
<td>Sparr</td>
<td>Loamy, siliceous, hyperthermic Grossarenic Paleudults</td>
<td>11</td>
</tr>
<tr>
<td>Tavares</td>
<td>Hyperthermic, uncoated Typic Quartzipsammments</td>
<td>13</td>
</tr>
</tbody>
</table>


values and avoided truncation of the distributions. The pesticide application rate was assumed to follow a normal distribution, truncated at the published minimum and maximum rates. Pesticide activation energy followed a normal distribution (Boesten, 1986; Wu and Nofziger, 1999) with a CV of 20%. The same distribution was used for both hexazinone and simazine in the predictive modeling scenario.

In the predictive modeling scenario, exact site conditions for parameters such as soil moisture conditions, crop coverage and rooting depth are assumed to be unknown. The NRCS curve number, which relies on soil moisture and crop coverage, encompassed all the possible soil moisture conditions (dry, average and wet) and crop coverage options (poor, fair and good). It was assumed that the curve number followed a uniform distribution. Pasture rooting depth was set to a typical value 0.60m (USDA-NRCS, 1993), with a CV of 20%.

The range of values of the CMLS98B model input parameters used in the predictive modeling scenario are summarized in Table 4-7.
Table 4-7. Recommended values for CMLS98B input parameters without ground truthing, used in the predictive modeling simulations.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Distribution</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Chemical parameters (hexazinone)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>application rate†</td>
<td>0.76 - 1.26</td>
<td>normal</td>
<td>Colvin et al., 1990</td>
</tr>
<tr>
<td>half-life (d)</td>
<td>90.0</td>
<td>lognormal</td>
<td>Hornsby et al., 1996</td>
</tr>
<tr>
<td>partition coefficient (mL g⁻¹)</td>
<td>54.0</td>
<td>lognormal</td>
<td>Hornsby et al., 1996</td>
</tr>
<tr>
<td><strong>Chemical parameters (simazine)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>application rate†</td>
<td>2.25 - 2.58</td>
<td>normal</td>
<td>Colvin et al., 1990</td>
</tr>
<tr>
<td>half-life (d)</td>
<td>60.0</td>
<td>lognormal</td>
<td>Hornsby et al., 1996</td>
</tr>
<tr>
<td>partition coefficient (mL g⁻¹)</td>
<td>130.0</td>
<td>lognormal</td>
<td>Hornsby et al., 1996</td>
</tr>
<tr>
<td><strong>Chemical parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>activation energy (kJ mol⁻¹)</td>
<td>49.4</td>
<td>normal</td>
<td>Boesten, 1986; Wu and Nofziger, 1999</td>
</tr>
<tr>
<td>reference temperature (°C)</td>
<td>25.0</td>
<td>normal</td>
<td>Boesten, 1986</td>
</tr>
<tr>
<td><strong>Site parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>root depth (m)</td>
<td>0.60</td>
<td>normal</td>
<td>USDA-NRCS, 1993</td>
</tr>
<tr>
<td>curve number (A)¶</td>
<td>25 - 73</td>
<td>uniform</td>
<td>Knissel et al., 1993</td>
</tr>
<tr>
<td>curve number (B)¶</td>
<td>52 - 82</td>
<td>uniform</td>
<td>Knissel et al., 1993</td>
</tr>
<tr>
<td>curve number (C)¶</td>
<td>68 - 87</td>
<td>uniform</td>
<td>Knissel et al., 1993</td>
</tr>
<tr>
<td>curve number (D)¶</td>
<td>78 - 90</td>
<td>uniform</td>
<td>Knissel et al., 1993</td>
</tr>
<tr>
<td><strong>Soil parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>profile properties‡</td>
<td>normalized by layer</td>
<td></td>
<td>Collins and Cantlin, 1992</td>
</tr>
</tbody>
</table>

† App. rate is the pesticide application rate in kg active ingredient per hectare.
¶: The character indicates the hydrologic group.
‡ Properties include: bulk density, organic carbon, field capacity, permanent wilting point and porosity.

Site-Referenced Modeling

For the site-referenced modeling scenario, site-specific input data were used when available. For climatic and pesticide data, no site-specific data could be obtained, due to: an absence of a weather station at the test site, and b: lack of a pesticide fate study at the test site. The latter is time-consuming and very expensive. For these input data other public and private data sources were used. Consequently, the term site-specific is perhaps misleading because for only selected input parameters actual site-specific data could be obtained. The term site-specific
modeling is used solely to distinguish this modeling scenario from the predictive modeling scenario.

Climatic data for the point locations were obtained from the Gainesville Regional Airport (Table 4-5) because no long-term, site-specific weather data was available for the site for a weather station located closer to the test site.

Pesticide properties for hexazinone were based upon field-experiment data obtained from Dupont Agricultural Products (Russel, 1999). For both the partition coefficient and the half-life, mean and standard deviation were calculated. Calculated values for the partition coefficient were smaller than the recommended value, published by Hornsby et al. (1996), whereas the half-life was approximately 30% larger. Environmental-fate properties for simazine were based on the pesticide registration data provided by the registrant (Novartis) to the Department of Agriculture and Consumer Services of the State of Florida (Howard, 1999).

As some of the site conditions (crop coverage and rooting depth) are known at each sample location, we can adjust these input data. The NRCS curve numbers used encompassed dry to wet soil moisture conditions and good crop coverage, so it was assumed that the curve number would follow a uniform distribution. The rooting depth for pasture grass was set to the measured depth at the sample location, or if that was unknown, to the mean for the soil series at the test site.

The SSPS map was used to display the spatial distribution of soils at the Santa Fe Beef Unit test site. At each sample location, the thickness of the surface horizon, the organic carbon content of the surface horizon and the depth to the argillie horizon were measured (Appendix E). These data were incorporated into the existing pedon data sets (Table 4-8) by adjusting the values of these properties in the corresponding horizons. The values of the other soil properties remained unchanged. In cases where multiple pedon data sets were available for a given soil, all pedon data sets were adjusted. Next, the adjusted pedon data sets were standardized for use with the bootstrapping technique to account for variability. Standardization of the soil pedon data sets involved computation of the depth-weighted average for each soil property for a horizon with a standard depth of 0.20m. Thus, each soil pedon data set was converted to a set with an equal
number of soil horizons (20). Note that, for the Bibb, Bruno, and Noboco soils, no pedon data sets were available. Bootstrapping also could not be performed for the Bigbee, Chipley, Gainesville, and Pickney soils, because of lack of sufficient (at least three) pedon data sets. For these soils, each pedon data set was used individually in the pesticide leaching simulations.

The parameter values used for the site-referenced modeling scenario are listed in Table 4-9.

Table 4-8. Taxonomic placement of soil series mapped at the point locations at the Santa Fe Beef Unit.

<table>
<thead>
<tr>
<th>Series Name</th>
<th>Taxonomic Description</th>
<th>Pedons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bibb</td>
<td>Coarse-loamy, siliceous, active, acid, thermic Typic Fluvaquents</td>
<td>0</td>
</tr>
<tr>
<td>Bigbee</td>
<td>Thermic, coated Typic Quartzipsamments</td>
<td>1</td>
</tr>
<tr>
<td>Bonneau</td>
<td>Loamy, siliceous, subactive, thermic Arenic Paleudults</td>
<td>7</td>
</tr>
<tr>
<td>Bruno</td>
<td>Sandy, mixed, thermic Typic Udifluvents</td>
<td>0</td>
</tr>
<tr>
<td>Chipley</td>
<td>Thermic, coated Aquic Quartzipsamments</td>
<td>12</td>
</tr>
<tr>
<td>Cowarts</td>
<td>Fine-loamy, kaolinitic, thermic Typic Kanhapudults</td>
<td>2</td>
</tr>
<tr>
<td>Gainesville</td>
<td>Hyperthermic, coated Typic Quartzipsamments</td>
<td>1</td>
</tr>
<tr>
<td>Millhopper</td>
<td>Loamy, siliceous, hyperthermic Grossarenic Paleudults</td>
<td>8</td>
</tr>
<tr>
<td>Noboco</td>
<td>Fine-loamy, siliceous, subactive, thermic Typic Paleudults</td>
<td>0</td>
</tr>
<tr>
<td>Norfolk</td>
<td>Fine-loamy, kaolinitic, thermic Typic Kandiudults</td>
<td>4</td>
</tr>
<tr>
<td>Osier</td>
<td>Siliceous, thermic Typic Psammaquents</td>
<td>6</td>
</tr>
<tr>
<td>Pickney</td>
<td>Sandy, siliceous, thermic Cumulic Humaquepts</td>
<td>1</td>
</tr>
</tbody>
</table>


Uncertainty in Selected Parameters

Uncertainty in selected model input parameters was addressed in a manner similar to the way one performs a sensitivity analysis. For each simulation session, the parameter of interest used the non-site specific input (Table 4-7) data and the remainder of the input parameters were site-specific (Table 4-9). This approach enabled us to study the uncertainty contribution from those model parameters for which site-specific data were available.
Table 4-9. Site-specific input parameters for CMLS98B.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Distribution</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Chemical parameters (hexazinone)</strong>‡</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>application rate††</td>
<td>1.12 - 1.57</td>
<td>normal</td>
<td>Colvin et al., 1990</td>
</tr>
<tr>
<td>half-life (d)</td>
<td>109.0 ± 11.6</td>
<td>lognormal</td>
<td>Russel, 1999</td>
</tr>
<tr>
<td>partition coefficient (mL g⁻¹)</td>
<td>38.0 ± 3.6</td>
<td>lognormal</td>
<td>Russel, 1999</td>
</tr>
<tr>
<td>reference temperature (°C)</td>
<td>22.0 ± 1.0</td>
<td>normal</td>
<td>Russel, 1999</td>
</tr>
<tr>
<td><strong>Chemical parameters (simazine)</strong>‡</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>application rate††</td>
<td>2.58 - 5.28</td>
<td>normal</td>
<td>Colvin et al., 1990</td>
</tr>
<tr>
<td>half-life (d)</td>
<td>60.0 ± 18.8</td>
<td>lognormal</td>
<td>Howard, 1999</td>
</tr>
<tr>
<td>partition coefficient (mL g⁻¹)</td>
<td>128.4 ± 22.4</td>
<td>lognormal</td>
<td>Howard, 1999</td>
</tr>
<tr>
<td>reference temperature (°C)</td>
<td>25.0 ± 1.0</td>
<td>normal</td>
<td>Boesten, 1986</td>
</tr>
<tr>
<td><strong>Chemical parameters‡</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>activation energy</td>
<td>49.4</td>
<td>normal</td>
<td>Boesten, 1986; Wu and Nofziger, 1999</td>
</tr>
<tr>
<td><strong>Site parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>root depth (m)</td>
<td>0.15 - 2.0</td>
<td>measured</td>
<td>Knissel et al., 1993</td>
</tr>
<tr>
<td>curve number (A)</td>
<td>25 - 51</td>
<td>uniform</td>
<td>Knissel et al., 1993</td>
</tr>
<tr>
<td>curve number (B)</td>
<td>52 - 67</td>
<td>uniform</td>
<td>Knissel et al., 1993</td>
</tr>
<tr>
<td>curve number (C)</td>
<td>68 - 77</td>
<td>uniform</td>
<td>Knissel et al., 1993</td>
</tr>
<tr>
<td>curve number (D)</td>
<td>78 - 83</td>
<td>uniform</td>
<td>Knissel et al., 1993</td>
</tr>
<tr>
<td><strong>Soil parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>organic carbon (%)</td>
<td>0.25 - 10.0</td>
<td>measured</td>
<td></td>
</tr>
<tr>
<td>argillic horizon (m)</td>
<td>0.20 - 2.00</td>
<td>measured</td>
<td></td>
</tr>
<tr>
<td>profile properties¶</td>
<td>normalized</td>
<td></td>
<td>Collins and Cantlin, 1992</td>
</tr>
<tr>
<td>by layer</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

† App. rate is the pesticide application rate in kg active ingredient per hectare.
‡ Pesticide environmental-fate properties based on field data other than for the Santa Fe Beef Unit.
¶ Properties include bulk density, organic carbon, field capacity, permanent wilting point, and porosity.

Climatic uncertainty. Uncertainty in precipitation was addressed by generating a WGEN-par file for a weather station (Gainesville, WNW) located 12 km southwest of the Santa Fe Beef Unit. Unfortunately, only six years of valid weather data were available for this weather station. Therefore, the simulation time frame was set to six years because longer time periods would not provide reliable weather sequences. The simulations were repeated with the weather data set from Gainesville Regional Airport, because the site-referenced data set was based on a 40-year time period.
Soil map uncertainty. In this modeling scenario, it was assumed that only the soil map was updated and that no additional updated information was available for the other input parameters: i.e., the same input parameters were used for the HISMR and the Alachua County soil survey map. Next, the soil maps were overlaid, to determine the unique combinations of overlaid soils so that a probability difference function could be developed. In this scenario, areas with matching soils have no uncertainty, areas with different overlaying soils have uncertainty, and areas for which no soils pedon data sets existed were set to no-data values.

Control Depth

For the predictive and the site-referenced modeling scenarios, pesticide leaching was computed to three depths in the soil profile: 1.0m, 2.0m, and the argillic horizon. The 1.0-m and 2.0-m depths were used to study the effect of depth of the control plane on the uncertainty with 2.0m being the maximum depth to which soil data were available for the SFBU test site.

Presence of the argillic horizon at the test site affects (retards and reroutes) pesticide movement and, therefore, should be taken into account. The measured depth to the argillic horizon was used as the third control depth. Note that this depth is different for each location in the field.

Statistical Analysis

Basic statistics. Basic statistical analyses were performed in Microsoft Excel, Professional Office 2000. Basic statistics included mean and variance of the mass emissions and travel time. Classification of the results into the proper mass emission and travel time classes was achieved by using the FREQUENCY command in Excel. For each class the probability was calculated by dividing the frequency count by the total number of simulations (10 000).
**Wilcoxon sum rank test.** To determine if the measured organic carbon content from the Santa Fe Beef Unit test site was statistically different from the UF soil characterization database data, the Wilcoxon rank sum test (Gilbert, 1987) in Systat 9.0 (SPSS, 1999), with $\alpha = 0.05$, was used.

**Distribution analysis.** Pesticide properties (half-life and partition coefficient) were tested for normality and lognormality using the Shapiro-Wilks test, with $\alpha = 0.05$. The data were first log$_{10}$-transformed for testing on lognormality, but only if a normal distribution was rejected.

**Kolmogorov-Smirnov test.** The distribution functions for the 26 mass emission and 147 travel time classes for the predicted and site-referenced modeling scenarios were statistically compared, using the Kolmogorov-Smirnov test at $\alpha = 0.05$ (Pfaffenberger and Patterson, 1987).

**Soil distribution analysis.** To determine the total area of matching soils at the levels of the soil taxonomy, grid-based overlay analysis were used. The Alachua County soil survey map and the recompiled high-intensity soil survey map for the test site were converted to ARC/INFO grid coverages with one-meter resolution. For each level of the soil taxonomy, the taxonomic placement was reclassified from a string item to a numeric item. Using the map calculator in ArcView 3.1 Spatial Analyst (ESRI, 1998b) the reclassified maps of the Alachua County soil survey report and the test site were subtracted. The total area of no-change was then divided by the total area of the test site, to compute the area percentage of matching soils.

**Spatial correlation.** The spatial correlation coefficient between the various data sets was computed using the CORRELATE command in ARC/INFO GRID (ESRI, 1998a). For these grid-based analysis, the forest area was set to no-data. Grid cells with no data were not considered in the computation of the spatial correlation coefficient.

**Spatial interpolation.** The geostatistical package, GSTAT (Pebesma, 1998) was used to estimate the experimental semivariogram and model the spatial structure. If a semivariogram was modeled, GTSAT was used to krige (ordinary kriging) to generate the surface maps. GSTAT ascii output files are compatible with ARC/INFO, so the ascii files were imported into ARC/INFO using the ASCIIGRID command. If kriging could not be applied, inverse distance
weight or splines were used, in ARC/INFO and ArcView 3.1 Spatial Analyst, to generate the surface map for the variable of interest.

**Zonal analysis.** Uncertainty in individual map unit delineations and, for the test site, were computed using zonal analysis in ARC/INFO. The Alachua County soil survey map was used as the zonal map for analysis of the individual map unit delineations and the Santa Fe Beef Unit test boundaries were used for the test-site analysis. Computation of the zonal mean gives the area-weighted average for the zones considered.
CHAPTER 5
RESULTS AND DISCUSSION

Sample Grid

Analysis of positional accuracy (Fig. 5-1) showed that most sample locations at the Santa Fe Beef Unit test site were collected at submeter accuracy or better, with some sample locations even being surveyed at centimeter accuracy. The base station (Geoplan Center, University of Florida) was located 33.3 km from the test site and the base station and the rover might not always have collected data from the same satellites, resulting in lapses in satellite coverage and, therefore, reduced accuracy. Also, the satellite constellation configuration could have been unsuitable (low angles, covering only part of the sky, not enough consecutive data) to obtain data of centimeter accuracy.

The precision dilution of precision (PDOP) is a measure of GPS satellite geometry, with a low PDOP indicating good geometry and a high PDOP indicating bad geometry. PDOPs for good geometry can be as high as 6 and differential PDOP should be less than 0.5. Differential PDOP values for the test site were less than 0.5, indicating exceptional signal quality. However, a few locations in the forested area had a differential PDOP above 1.0, indicating poorer signal quality. Tree canopy coverage was the major source of signal reduction for those samples.

The impact of site elevation on the distance between two adjacent sample locations at the Santa Fe Beef Unit test site was negligible (Table 5-1). When the 2D and 3D distances were compared with surface distance, the error was less than 1.0 percent in the worst case, with the error being larger for the east-west transects than for the north-south transects. Sample locations along the north-south transects of the site had less elevation change than along the east-west transects, and no significant differences were found between the 2D and 3D distances. Sample
location No. 40 had an offset from the sample grid, and the minimum and maximum distances between adjacent points in the north-south direction can be attributed to this offset. Using the 2D locations of samples for geostatistical applications would not introduce considerable errors into the mass emission estimates, because elevation did not appreciably affect distance between sample locations.

Table 5-1. Calculated distances between surveyed sample locations.

<table>
<thead>
<tr>
<th>Transect</th>
<th>Distance (m)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>×σ²</td>
<td>Max</td>
</tr>
<tr>
<td>North - South (2D)</td>
<td>50.1</td>
<td>1.7</td>
</tr>
<tr>
<td>North - South (3D)</td>
<td>50.1</td>
<td>1.7</td>
</tr>
<tr>
<td>East - West (2D)</td>
<td>49.8</td>
<td>0.7</td>
</tr>
<tr>
<td>East - West (3D)</td>
<td>49.8</td>
<td>0.7</td>
</tr>
<tr>
<td>Surface (north - south)</td>
<td>50.1</td>
<td>1.7</td>
</tr>
<tr>
<td>Surface (east - west)</td>
<td>49.9</td>
<td>0.7</td>
</tr>
</tbody>
</table>
Soil Map Development

Three new soil maps were developed during this research: 1) a soil series map by sample location, (SSPS map); 2) a high-intensity soil map (HISM) at 1:2 000 scale; and 3) a recompiled HISM to 1:24 000 (HISMR). The HISM and HISMR were developed primarily for map unit distribution comparisons with the Alachua County soil survey map, and to determine uncertainty contributed to the soil map and uncertainty within soil map units.

The soil series map for each sample location (Fig. 5-2) was established by comparing the soil profile description to official soil series descriptions and interpretations by soil scientists. Eleven soil series were established at the SFBU test site. Series not previously mapped at the site included Bibb, Bigbee, Bruno, Cowarts, Noboco, and Osier, while Blichton, Micanopy, Myakka, Sparr, and Tavares series, which were mapped at the SFBU test site during the original soil survey of Alachua County, were not mapped at the site during this survey.

Figure 5-2. Soil series by sample location at the Santa Fe Beef Unit test site.
A high-intensity soil map (HISM) was developed at a 1:2 000 map scale for the SFBU test site (Fig. 5-3). The HISM had 18 different soil mapping units, whereas the Alachua County soil survey map (scale 1:24 000) contained only 10 different soil mapping units. The increased number of soil mapping units was expected, because of the larger scale of the HISM. The four small delineations which were present east of the forest, representing two mapping units, were mapped because of the large scale of the HISM. At smaller map scales, these delineations (inclusions) would not shown on the soil map.

The HISM – 1:2 000 scale – was recompiled to 1:24 000 scale (Fig. 5-4), which resulted in a decrease in the number of soil series. This soil map (HISMR) showed seven different mapping units at the SFBU, representing six different soil series.

Soil Distribution

Analysis of the area distribution of the soils at three levels of Soil Taxonomy (order, great group and series) for the HISM (1:2 000), the HISMR (1:24 000), and the Alachua County soil survey map (Fig. 4-4; 1:24 000) showed that, at the order level, Entisols and Ultisols were the dominant orders (Fig. 5-5), with each representing over 40% of the total area. The areas covered by Spodosols according to the Alachua County soil survey map were not mapped as spodosols in this soil survey for the test site, which is notable.

The dominant presence of sandy soils at the SFBU was shown at the great group and subgroup level of Soil Taxonomy where Psammaquents (Osier-Bibb series), Quartzipsamments (Gainesville series), and Grossarenic Paleudults (Millhopper series) were the dominant soil series. The shift from Quartzipsamments to Paleudults at the great group level when the HISM and the HISMR were compared with the Alachua County soil survey map are notable, as well.

At the soil series level, the dominant soil series was Millhopper (39.7%) for the HISMR whereas, for the Alachua County soil survey map, Gainesville (30.6%) was the dominant series. Large areas that were mapped as Gainesville are now mapped as Millhopper. Millhopper and
Figure 5-3. High intensity soil survey map (1:2 000) for the Santa Fe Beef Unit test site.
Figure 5-4. Recompiled high-intensity soil survey map (1:24 000) for the Santa Fe Beef Unit test site.
Figure 5-5. Area distribution of soil mapped at the Santa Fe Beef Unit test site for the high-intensity soil map (HISM), the recompiled high-intensity soil survey map (HISMR) and the Alachua County soil survey map (ACSS).

a) Soil Order level; b) Soil Great Group level; c) Soil Series level.
Gainesville are geographically associated series and are often found in the same landscape, though Millhopper has an argillic horizon within 2.0m of the soil surface and Gainesville not.

The Bruno series delineated on the HISM and HISMR was not delineated at the time of the Alachua County soil survey report. Flood plain soils such as Bruno were not recognized in the county at that time and, therefore, could not be mapped.

The Alachua County soil survey map had the wooded area mapped as Myakka sand, with Myakka being a common upland soil series usually associated with Florida pine flatwoods. However, this mapping unit is mapped completely within the flood plain of the stream at the SFBU. If flood plains had been recognized at the time of the original soil survey, this area would have been mapped as Osier-Bibb complex, frequently flooded. The mapped area of Myakka encompassed 18.7%, and Osier-Bibb 17.6%, of the area of the test site.

The HISM and the HISMR were compared with the Alachua County soil survey map (1:24 000) using grid-based overlay analysis. Only patches of the Gainesville series in the northwest corner of the SFBU study site matched. Area analysis of the soil maps showed that 6.5% of the area matched when the HISM and the original Alachua County soil survey map were
compared, and 4.8% of the area had matching soils when the HISMR was compared with the Alachua County soil survey map (Fig. 5-6).

![Figure 5-6. Areas with matching soil series (shown in white) when the recompiled high-intensity soil survey map (1:24 000) and the Alachua County soil survey map (1:24 000) were compared. Only 4.8% of the test site had matching soil series.]

**Thematic Site Maps**

Three thematic site maps were developed during this project, showing the spatial distribution of site-specific parameters influencing or restricting leaching of pesticides in the soil matrix: organic carbon content in the surface horizon, depth to argilllic horizon, and rooting depth.

Organic carbon content (OC%) in the surface horizon of the soils series mapped at the Santa Fe Beef Unit test site showed considerable variability between soil series (Table 5-2). Compared to the UF Soil Characterization database, the calculated average organic carbon content was higher for the collected samples at the SFBU. Application of fertilizers, cattle manure, and continuous cover with grass might have contributed to this increase. For the Bonneau, Millhopper, and Norfolk soils the differences were significant ($\alpha=0.05$) but, for the other soil series, insufficient data were available for testing. The highest values for OC% were
measured for the Chipley and Bibb series, though the Bibb series showed a large range of values for OC\% in the surface horizon. A higher organic carbon content will affect pesticide movement considerably, because the organic carbon content is an important governing factor in pesticide retardation. Higher organic carbon content will result in higher retardation factors, and thus slower pesticide movement.

Table 5-2. Organic carbon content (%) in the surface horizon determined for soil series identified at the sample locations at the Santa Fe Beef Unit compared to the average for the same series as extracted from the UF Soil Characterization database.

<table>
<thead>
<tr>
<th>Series</th>
<th>n</th>
<th>(\bar{x})</th>
<th>(\sigma)</th>
<th>(n_{UF})</th>
<th>(\bar{x}_{UF})</th>
<th>(\sigma_{UF})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bibb</td>
<td>6</td>
<td>4.37</td>
<td>3.78</td>
<td>0</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Bigbee</td>
<td>11</td>
<td>1.32</td>
<td>0.39</td>
<td>11</td>
<td>0.24</td>
<td>-</td>
</tr>
<tr>
<td>Bonneau</td>
<td>15</td>
<td>1.49</td>
<td>0.45</td>
<td>7</td>
<td>0.70</td>
<td>0.31</td>
</tr>
<tr>
<td>Bruno</td>
<td>5</td>
<td>1.51</td>
<td>0.70</td>
<td>0</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Chipley</td>
<td>1</td>
<td>10.24</td>
<td>-</td>
<td>12</td>
<td>1.06</td>
<td>0.55</td>
</tr>
<tr>
<td>Cowarts</td>
<td>1</td>
<td>2.92</td>
<td>-</td>
<td>2</td>
<td>1.01</td>
<td>0.18</td>
</tr>
<tr>
<td>Gainesville</td>
<td>9</td>
<td>1.86</td>
<td>0.37</td>
<td>1</td>
<td>1.17</td>
<td>-</td>
</tr>
<tr>
<td>Millhopper</td>
<td>24</td>
<td>1.71</td>
<td>0.47</td>
<td>8</td>
<td>1.00</td>
<td>0.15</td>
</tr>
<tr>
<td>Noboco</td>
<td>3</td>
<td>1.91</td>
<td>0.59</td>
<td>0</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Norfolk</td>
<td>7</td>
<td>2.57</td>
<td>1.09</td>
<td>4</td>
<td>1.02</td>
<td>0.19</td>
</tr>
<tr>
<td>Osier</td>
<td>6</td>
<td>2.22</td>
<td>0.85</td>
<td>6</td>
<td>1.80</td>
<td>0.78</td>
</tr>
</tbody>
</table>

UF: UF soil characterization database; -: no data available for Bibb, Bruno, and Noboco.

Spatial analysis for organic carbon in the surface soil of the pasture at the SFBU test site was modeled with an east-west directional semivariogram (Fig. 5-7). The east-west direction might suggest that elevation affected the organic carbon content, but the spatial correlation between organic carbon and elevation gave \(r^2 = 0.00\). This semivariogram was used to generate a map displaying the spatial distribution of organic carbon content in the surface horizon at the SFBU test site (Fig. 5-8). Soil series with higher organic carbon contents were generally located in the southern part of the flood plain, in the forest, at the lowest elevations on the site. At these locations, water collects after rainfall, and organic matter decomposes slowly.
Figure 5-7. Experimental and fitted semivariogram for the measured organic carbon content of the surface horizon at the Santa Fe Beef Unit.

Figure 5-8. Spatial distribution of the organic carbon content (percent) in the surface horizon at the Santa Fe Beef Unit test site. The red lines are the forest boundaries.
Presence of an argillic horizon was detected during ground-truthing of the Alachua County soil survey map, suggesting that the Hawthorn formation had several shallow outcroppings at the test site. Depth to the argillic horizon is shown in Fig. 5-9. At a few locations in the test site the argillic horizon was close to the surface, whereas at other locations an argillic horizon was not present in the top 2.0m of the soil profile. The argillic horizon was absent in the northwest section of the test site and under the forest. Absence of the argillic horizon in the eastern part of the test site is likely the result of the soil classification system used. During soil sampling an increase in clay content was detected below the 2.0m depth, suggesting presence of the clay layer, but official soil series description does not take soil information below 2.0m into account. Therefore, this information was not used in this study, although the underlying argillic horizon affects the drainage of water and leaching of pesticide.

Figure 5-9. Depth to the argillic horizon based on measured point data at the Santa Fe Beef Unit test site. The underlying grey area indicates the area of the test site.
Presence of an argillic horizon at the test site influences the taxonomic placement of soils mapped, though current taxonomic placements are only valid for the location at which each soil was sampled. For example, areas mapped currently as Millhopper would be mapped differently were the argillic horizon more shallow. Similarly, if the argillic horizon were below the 2.0-m depth, soils would have been classified as Gainesville rather than Millhopper. In either case, the soil classification would have had considerable influence on pesticide leaching predictions, as soil properties for the mentioned soils differ from those for Millhopper.

A map for the rooting depth at the test site (Fig. 5-10) was generated for the western half of the test site only. Too few data points were available for reliable interpolation of the rooting depth in the eastern half of the test site. The results show that there is considerable variability in the rooting depth, with rooting depths ranging from as shallow as 0.2m to as deep as 2.0m. When the maps of the rooting depth and the argillic horizon are compared visually, it appears that there was a strong correlation. However, the $r^2$ is only 0.24, indicating that poor spatial correlation actually exists.

Figure 5-10. Rooting depth in the western half of the Santa Fe Beef Unit test site. The underlying grey area indicates the area of the test site.
Sensitivity Analysis

A comprehensive sensitivity analysis of the environmental-fate model CMLS98B was not performed. Only those parameters for which site-specific data could be obtained were considered in the sensitivity analysis, because those parameters would be used in the uncertainty analysis. For each parameter the impact on predicted mass emissions of hexazinone was computed as well as relative sensitivity of the model to this parameter. The relative sensitivity allowed the parameters to be compared with each other, as this is a dimensionless number. Table 4-3 lists the ranges for the parameters used.

Chemical Parameters

CMLS98B was tested for sensitivity to changes in the application rate (Fig. 5-11), with the amount leached changing linearly with an increase in application rate. The relative sensitivity (Fig. 5-11b) is unity, for the range shown. A relative sensitivity of unity indicates that the relative change in model output (mass emission) is equal to the relative change in application rate. This relationship can be explained with Eq. [5-1]:

\[ M = M_0 \ e^{-rt} \]  

[5-1]

where \( M \) is the mass emission (kg active ingredient ha\(^{-1}\)): \( M_0 \) is the application rate (kg a.i. ha\(^{-1}\)): \( t \) is the travel time (d) and \( r \) is the degradation rate (d\(^{-1}\)). CMLS98B uses this relationship to calculate the mass emission for a given application rate, with an increase in \( M_0 \) resulting in an equal increase in mass leached.

The sensitivity of CMLS98B to pesticide degradation rate (expressed as the half-life) is shown in Fig. 5-12. With an increasing half-life (days), the mass leached past a specified depth increased. With increasing depth the model becomes more sensitive to the half-life,
because of increased residence time in the soil profile. However, for longer half-lives the differences between depths seemed to fade as the mass emission became less sensitive to the pesticide half-life. The relative sensitivity of the model indicated that, for half-lives of 70 - 100 days, the model is most sensitive. The increase and subsequent decrease in relative sensitivity of the model reflected the changes in slope of the mass emission curves of Fig. 5-12a.
Figure 5-12. Sensitivity of CMLS98B to the pesticide half-life at depths, d, of 1.0 and 2.0 meters
a) Mass emission; b) Relative sensitivity.
Increase of the partition coefficient resulted in a decreased mass emission at the specified depths (Fig. 5-13a). This was due to an increased residence time in the soil profile as pesticide movement was retarded by an increased partition coefficient. Relative sensitivity of the model increased with an increasing partition coefficient (Fig. 5-13b), with the spikes in the graph being attributed to non-uniform precipitation patterns.

Figure 5-13. Sensitivity of CMLS98B to the pesticide partition coefficient at depths, d, of 1.0 and 2.0 meters. 
(a) Mass emission; b) Relative sensitivity.
Because pesticide degradation is subject to temperature influences, the sensitivity of CMLS98B to temperature was computed for the reference temperature of degradation. The results indicated that, with increasing temperature, both the mass emission and the relative sensitivity increased (Fig. 5-14). The increasing and then decreasing relative sensitivity indicated that the model has an optimum level at which it is most sensitive to this parameter. Also, with increasing depth the model became more sensitive to the reference temperature, as this effect was enhanced by a longer residence time in the soil profile. An increasing mass emission with increased reference temperature might contradict the intuition conclusion that, at higher temperatures, pesticide degradation should be faster than at lower temperatures. However, analysis of Eq. [5-2] showed that, with increased reference temperature, the mass emission became larger, because the $1/T_{ref}$ term became smaller.

$$\frac{H}{H_{r_{ref}}} = \exp\left[\frac{E_a}{R} \left(\frac{1}{T} - \frac{1}{T_{r_{ref}}}\right)\right]$$  \[5-2\]

Here $H$ is the degradation rate, $H_{ref}$ is the reference degradation rate, $E_a$ the activation energy, $R$ the gas constant, $T$ the temperature and $T_{ref}$ the reference temperature (Wu and Nofziger, 1999).

Sensitivity to the activation energy is shown in Fig. 5-15. With increasing activation energy the mass leached past a selected depth increased, due to slower rate of pesticide degradation. With increasing depth the differences in mass emission became larger as the pesticide residence time in the soil profile became longer. For activation energies larger than 70 kJ mol$^{-1}$ the relative sensitivity of the model did not change apparently, because the exponential function, Eq. [5-2], had reached its limit.
Figure 5-14. Sensitivity of CMLS98B to the degradation reference temperature at depths, d, of 1.0 and 2.0 meters
a) Mass emission; b) Relative sensitivity.
Figure 5-15. Sensitivity of CMLS98B to the degradation activation energy at depths, d, of 1.0 and 2.0 meters.

a) Mass emission; b) Relative sensitivity.
Site Characteristics

The impact of the curve numbers on the amount of pesticide leached was limited to the higher curve numbers (Fig. 5-16). For curve numbers smaller than 70, the mass leached did not change but, for the highest curve numbers, the model was very sensitive. Most rainfall would disappear from the system as runoff rather than infiltrating into the soil profile under these conditions.

Sensitivity of CMLS98B to the rooting depth (Fig. 5-17) showed that, with increasing rooting depth, the amount leached decreased. However, results for the 1.0-m depth showed a slight increase in the amount leached when the rooting depth became larger than 1.0m. The rooting depth determines over which depth of the soil profile water will be extracted for evapotranspiration. With an increased rooting depth the fraction of water extracted from any given section of the root zone was less compared to the amount of water extracted from the same section for a smaller rooting depth. Thus, the water flux decreased less for larger rooting depths than for smaller rooting depths. Consequently, the water flux was higher for the larger rooting depths, travel times of the pesticide decreased and, therefore, mass emissions increased. Overall, the relative sensitivity of CMLS98B to the rooting depth decreased with increasing rooting depth and prediction depth did not affect relative sensitivity. The spikes in the graph were attributed to non-uniform precipitation.

Climatic Properties

The only climatic property of interest for the uncertainty analysis is the temperature damping depth (or simply the damping depth), because this is variable from soil to soil. Fig. 5-18 shows that the CMLS98B model was not sensitive to damping depth, as the mass leached remained unchanged and the relative sensitivity was less than 1.0. A relative sensitivity of less than 1.0 indicates that changes in the output were less than changes in the input. The only soil
property for which data were collected, organic carbon content, had a negligible influence on the damping depth (Wu and Nofziger, 1999).

Figure 5-16. Sensitivity of CML98B to the curve number at depths, d, of 1.0 and 2.0 meters. 

a) Mass emission; b) Relative sensitivity.
Figure 5-17. Sensitivity of CMLS98B to the rooting depth at depths, d, of 1.0 and 2.0 meters.
a) Mass emission; b) Relative sensitivity.
Figure 5-18. Sensitivity of CMLS98B to the soil damping depth at depths, d, of 1.0 and 2.0 meters.

a) Mass emission; b) Relative sensitivity.
Soil Properties

The effect of changing organic carbon content in the surface horizon is shown in Fig. 5-19. With increasing organic carbon content, the amount leached decreases, with minor changes in organic carbon content resulting in orders of magnitude changes in the amount leached. These changes were larger for the deeper depths in the soil profile as the residence time of the pesticide increased. The relative sensitivity of CMLS98B to organic carbon content increased as well and was the same for the 1.0-m and 2.0-m depths. The spikes in the relative sensitivity graph were attributed to non-uniform precipitation patterns.

Based on this sensitivity study of the CMLS98B model, it was concluded that temperature damping depth, application rate, and curve number were the least sensitive input parameters, whereas pesticide properties such as half-life, partition coefficient, and reference temperature were very sensitive parameters. Organic carbon content was the most sensitive parameter of all. Relative ranking of the parameters according to their sensitivity was: damping depth < application rate < curve number < activation energy < rooting depth < half-life < reference temperature < partition coefficient < organic carbon content.

Uncertainty Analysis

Uncertainty in predicted mass emissions and travel times was quantified for two pesticides; hexazinone and simazine, at three depths in the soil profile, 1.0m, 2.0m, and the depth to the argillic horizon. Depth to the argillic horizon henceforth referred to as the argillic depth, was variable for the test site (Fig. 5-9). For those sample locations where the argillic horizon was not present, the 2.0m depth results were used, because this was the maximum depth to which pesticide movement was simulated. Uncertainty analysis was addressed using basic statistics, the entropy approach, and the fuzzy set approach. First results for the basic statistics will be discussed, followed by results from the entropy and fuzzy set approaches.
Figure 5-19. Sensitivity of CMLS98B to the organic carbon content in the surface horizon at depths, d, of 1.0 and 2.0 meters.

a) Mass emission; b) Relative sensitivity.
**Statistical Analysis**

Descriptive statistics (mean and variance) of mass emissions and travel times were calculated for three depths in the soil profile for those locations at the test site for which soil profile data were available. In the following sections the results (statistical summary and uncertainty) for the mass emission will be discussed first, followed by results for the travel time.

**Mass emissions: hexazinone**

**Predicted mass emissions.** Predicted mean mass emissions for hexazinone at the Santa Fe Beef Unit test site at the 1.0m, 2.0m, and argillic depths showed a wide range of values (Table 5-3), but represented only a few orders of magnitude. Results from individual simulations were beyond the ranges presented in the table for all the soil series, but the mean mass emission was an indicator of relative sensitivity of the soils at the Santa Fe Beef Unit to pesticide leaching. The lowest predicted mass emission was 0.00 kg a.i. ha\(^{-1}\) and the highest was 1.26 kg a.i. ha\(^{-1}\) with the latter representing a case in which no degradation occurred before the pesticide leached to a specified control depth (argillic depth - 0.22m). Such a case is considered extreme but still possible, especially when heavy rainfall occurs shortly after application of the pesticide. With increasing depth the mean emission decreased, due to the longer residence time in the soil. Thus, more pesticide degraded.

From Table 5-3 one can conclude that Micanopy and Blichton are the least sensitive soils, with their respective mass emissions being an order of magnitude smaller than for the other soils. Tavares, with highest mass emissions at the 1.0m and 2.0m depths, seemed the most sensitive soil to pesticide leaching. However, when confining layers such as the argillic horizon were taken into account, soils with shallow argillic horizons could be interpreted as being more sensitive to pesticide leaching than soils with deeper or no argillic horizons. Bonneau and Micanopy had the most shallow argillic horizons and, therefore, had the highest mass emissions (travel time to the argillic horizon was short).
Table 5-3. Summary of descriptive statistics for the mass emission of hexazinone leaching as computed in the predictive modeling scenario.

<table>
<thead>
<tr>
<th>Soil series</th>
<th>Depth 1.0m</th>
<th>Mass Emission (kg a.i. ha⁻¹)</th>
<th>Depth 2.0m</th>
<th>Argillic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistics</td>
<td>σ²</td>
<td>σ²</td>
<td>σ²</td>
<td>σ²</td>
</tr>
<tr>
<td>Blichton</td>
<td>4.80 x 10⁻³</td>
<td>6.00 x 10⁻⁴</td>
<td>3.00 x 10⁻⁴</td>
<td>1.89 x 10⁻⁵</td>
</tr>
<tr>
<td>Bonneau</td>
<td>8.03 x 10⁻²</td>
<td>2.03 x 10⁻²</td>
<td>1.43 x 10⁻²</td>
<td>2.50 x 10⁻³</td>
</tr>
<tr>
<td>Chipley</td>
<td>5.40 x 10⁻²</td>
<td>1.34 x 10⁻²</td>
<td>1.04 x 10⁻²</td>
<td>2.20 x 10⁻³</td>
</tr>
<tr>
<td>Gainesville</td>
<td>2.90 x 10⁻²</td>
<td>5.10 x 10⁻³</td>
<td>3.20 x 10⁻³</td>
<td>4.00 x 10⁻⁴</td>
</tr>
<tr>
<td>Micanopy</td>
<td>1.50 x 10⁻³</td>
<td>2.00 x 10⁻⁴</td>
<td>1.00 x 10⁻⁴</td>
<td>2.87 x 10⁻¹</td>
</tr>
<tr>
<td>Millhopper</td>
<td>8.23 x 10⁻²</td>
<td>2.53 x 10⁻²</td>
<td>2.06 x 10⁻²</td>
<td>5.30 x 10⁻⁵</td>
</tr>
<tr>
<td>Myakka</td>
<td>3.62 x 10⁻²</td>
<td>1.14 x 10⁻²</td>
<td>8.40 x 10⁻³</td>
<td>1.90 x 10⁻³</td>
</tr>
<tr>
<td>Norfolk</td>
<td>4.12 x 10⁻²</td>
<td>8.40 x 10⁻³</td>
<td>5.50 x 10⁻³</td>
<td>8.00 x 10⁻⁴</td>
</tr>
<tr>
<td>Sparr</td>
<td>8.43 x 10⁻²</td>
<td>3.27 x 10⁻²</td>
<td>3.20 x 10⁻²</td>
<td>1.37 x 10⁻²</td>
</tr>
<tr>
<td>Tavares</td>
<td>1.34 x 10⁻¹</td>
<td>4.98 x 10⁻²</td>
<td>5.02 x 10⁻²</td>
<td>1.81 x 10⁻²</td>
</tr>
</tbody>
</table>

With increasing depth the variance of the mass emission decreased with variance at the 2.0-m depth was one to two orders of magnitude smaller, compared to the 1.0-m depth. This was to be expected, as time mufed differences between soil series. Increased variances for mass emissions at the argillic depth were explained by the shallower depth of the argillic horizon compared with the two other control depths.

Examples of pesticide leaching distribution curves (mass emissions) are shown in Fig. 5-20. These graphs are an example of the pesticide leaching distribution functions generated for soils mapped at the Santa Fe Beef Unit test site using the predictive input data set. Only the soils that were mapped according to the Alachua County soil survey map and the HISMR are shown, with the cumulative density functions for the four shown soils being similar for the 1.0-m and 2.0-m depths. However, when the argillic horizon was taken into account, considerable differences were visible. Soils without (e.g., Gainesville) or with a deep argillic horizon (e.g., Millhopper) showed lower mass emissions than soils with a shallow argillic horizon. This was expected, because the pesticides resided longer in the soil profile before reaching the control depth.
Figure 5-20. Cumulative density functions for the predicted mass emissions of hexazinone in four soils at three depths at the Santa Fe Beef Unit test site. 
a) 1.0-m depth; b) 2.0-m depth; c) Argillic depth.
The order in which the cumulative density functions appear in the graph is a measure of the relative sensitivity of each soil. Soils on the right in the graph are more sensitive than soils at the top. From this it can be concluded that Bonneau is a sensitive soil and Gainesville is not. When the other mapped soils were considered Micanopy, Norfolk, and Tavares soils could be added to the list of soils sensitive to pesticide leaching.

Next, spatial distribution of the mean mass emissions and variance were determined. For lag distances up to 300m, the variance increased and the maximum value had not been reached. With a continuously increasing semivariance, the exponential model was suitable to describe the spatial structure of mean and variance at the test site. The sill (Table 5-4) had little meaning for the exponential model as this function continuously increased, but was used as a parameter describing spatial variance at the site. Fig. 5-21 shows examples of semivariograms for hexazinone leaching to the depth of argillic horizon for the predictive modeling scenarios. In spite of the weak spatial structure, semivariograms could be described with the exponential model, and ordinary kriging was used to generate a map displaying spatial distribution at the test site (Fig. 5-22).

### Table 5-4. Semivariogram models for mean and variance of the predicted mass emissions for the pesticide hexazinone at three depths for the Santa Fe Beef Unit test site, using the Alachua County point-based soil map (ACPS).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Map</th>
<th>Depth (m)</th>
<th>Log</th>
<th>Model</th>
<th>Nugget</th>
<th>Range (m)</th>
<th>Sill</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>ACPS</td>
<td>1.0</td>
<td>no</td>
<td>exponential</td>
<td>$2.00 \times 10^{-4}$</td>
<td>158.22</td>
<td>$1.00 \times 10^{-3}$</td>
</tr>
<tr>
<td>mean</td>
<td>ACPS</td>
<td>2.0</td>
<td>yes</td>
<td>exponential</td>
<td>$4.98 \times 10^{-1}$</td>
<td>231.99</td>
<td>1.10</td>
</tr>
<tr>
<td>mean</td>
<td>ACPS</td>
<td>argillic</td>
<td>yes</td>
<td>exponential</td>
<td>$4.85 \times 10^{-1}$</td>
<td>153.08</td>
<td>2.37</td>
</tr>
<tr>
<td>variance</td>
<td>ACPS</td>
<td>1.0</td>
<td>no</td>
<td>exponential</td>
<td>-</td>
<td>74.42</td>
<td>$1.00 \times 10^{-4}$</td>
</tr>
<tr>
<td>variance</td>
<td>ACPS</td>
<td>2.0</td>
<td>no</td>
<td>exponential</td>
<td>-</td>
<td>67.71</td>
<td>$2.07 \times 10^{-5}$</td>
</tr>
<tr>
<td>variance</td>
<td>ACPS</td>
<td>argillic</td>
<td>yes</td>
<td>exponential</td>
<td>$1.10$</td>
<td>319.57</td>
<td>2.15</td>
</tr>
</tbody>
</table>

The interpolated maps (Fig. 5-22) showed a decrease in mass emissions and variances with increasing depth, with areas where Tavares and Bonneau soils were mapped showing the highest mass emissions at the 1.0-m depth. At the 2.0-m depth, mean mass emissions were of the
same order of magnitude. When the depth to argillic horizon was taken into account, the map (Fig. 5-23e) showed different results, with areas having a shallow argillic horizon showing the highest predicted mass emissions. Maps for the mass emission variance showed that, with increasing depth, the variance decreased. This could be explained by the fact that, with increased depth, the pesticide resided longer in the soil profile and differences in mass emissions between the soil series became less.

Figure 5-21. Semivariograms for the mean and variance of the mass emission at the argillic depth, computed in the predictive pesticide leaching scenario. a) Mass emission; b) Variance.
Figure 5-22. Spatial distribution of the mean mass emission and variance for hexazinone at the Santa Fe Beef Unit as modeled in the predictive pesticide leaching scenario. 
a) Mean at 1.0-m depth; b) Variance at 1.0-m depth; c) Mean at 2.0-m depth; d) Variance at 2.0-m depth; e) Mean at argillic depth; f) Variance at argillic depth.
Site-referenced mass emissions. Results for the site-referenced mean mass emissions and variances (Table 5-5) were presented as a range of values rather than a single value. In the site-referenced scenario, more than one sample location was mapped with the same soil. This resulted in different means and variances for the nine soil series mapped at the test site. Only Chipley and Cowarts were represented with a single sample location at the site, and had a single value for each statistic and depth.

Table 5-5. Summary of descriptive statistics for the mass emissions of hexazinone leaching as computed in the site-referenced modeling scenario. If more than one sample location was available for a soil series, the range of the calculated mean mass emissions and variance is listed.

<table>
<thead>
<tr>
<th>Soil series</th>
<th>Mass Emission (kg a.i. ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.0m</td>
</tr>
<tr>
<td>Statistics</td>
<td>μ</td>
</tr>
<tr>
<td>Bigbee</td>
<td>2.27 x 10⁻³</td>
</tr>
<tr>
<td></td>
<td>2.88 x 10⁻²</td>
</tr>
<tr>
<td>Bonneau</td>
<td>2.87 x 10⁻³</td>
</tr>
<tr>
<td></td>
<td>7.28 x 10⁻²</td>
</tr>
<tr>
<td>Chipley</td>
<td>6.27 x 10⁻⁷</td>
</tr>
<tr>
<td>Cowarts</td>
<td>9.90 x 10⁻³</td>
</tr>
<tr>
<td>Gainesville</td>
<td>6.79 x 10⁻³</td>
</tr>
<tr>
<td></td>
<td>9.91 x 10⁻³</td>
</tr>
<tr>
<td>Millhopper</td>
<td>2.12 x 10⁻²</td>
</tr>
<tr>
<td></td>
<td>1.30 x 10⁻¹</td>
</tr>
<tr>
<td>Norfolk</td>
<td>1.27 x 10⁻⁵</td>
</tr>
<tr>
<td></td>
<td>1.78 x 10⁻²</td>
</tr>
<tr>
<td>Osier</td>
<td>1.61 x 10⁻⁴</td>
</tr>
<tr>
<td></td>
<td>1.30 x 10⁻²</td>
</tr>
<tr>
<td>Pickney</td>
<td>2.90 x 10⁻²</td>
</tr>
</tbody>
</table>

For several soils, the mean mass emission showed a range of several orders of magnitude. Norfolk and Osier soils had the largest ranges at the 1.0-m and 2.0-m depth for mean mass emissions, with up to seven orders of magnitude difference. This indicated considerable variability between points, with the number of available pedons being one possible reason for this effect. However, for Gainesville, only one pedon data set was available and, for Millhopper,
seven. The range for Millhopper was smaller for both mass emissions and variance at any depth. This ruled out the possibility that the number of pedons had an impact on the mean and variance.

Taking restrictive layers such as the argillic horizon into account, the range for both mean mass emissions and variance became smaller. This could be explained by the suggestion that the argillic horizon was often within the first meter of the soil profile, thus decreasing residence time of the pesticides. These observations support the idea that, when predicting pesticide fate in the environment, confining layers should be accounted for. Otherwise, mass emissions might be underestimated for those soils that have confining layers.

For Gainesville, Bonneau, Millhopper, and Norfolk, the site-referenced mean mass emissions were smaller than for the predictive modeling scenario. This is illustrated by the position of the mass emissions cumulative density functions when Fig. 5-20 and Fig. 5-23 are compared. Smaller mass emissions resulted in a shift to the left of the cumulative distribution curves for the four soils, with the higher organic carbon content of the soil surface horizon being the most likely contributing factor to this phenomenon. The variance for site-referenced mass emissions was an order of magnitude smaller than for the predictive scenario, with a decrease of the variance indicating more homogeneous results.

The spatial structure for the mean and variance of the site-referenced simulations (Fig. 5-24) indicated that the spatial variability was accounted for within a 100m lag-distance. A sample grid with a shorter sampling distance might have provided a more distinct semivariogram but, for lag-distances over 100m, the variance remained constant. Using a natural logarithm transformation for mass emissions, the semivariograms were modeled with a spherical model. The semivariogram for the argillic depth revealed a more distinct spherical structure for both the mass emissions and their variance. At a lag distance of approximately 150m, the semivariance became constant. Contrary to the semivariogram model used for the predictive data set, the site-referenced data were modeled with a spherical model (Table 5-6), because it fitted the results better. Note that, for the mean at 1.0m and 2.0m, the nugget (variance at 0 lag distance) was 0 and was very small for the variance models. Maps for the mean mass emissions and variance of the mass emissions were generated using ordinary kriging.
Figure 5-23. Cumulative density functions for the mass emission of hexazinone at the Santa Fe Beef Unit test site.
a) 1.0-m depth; b) 2.0-m depth; c) Argillic depth.
Table 5-6. Semivariogram models for mean and variance of the predicted mass emissions for the pesticide hexazinone at three depths at the Santa Fe Beef Unit test site using the site-referenced point soil map (SSPS).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Map</th>
<th>Depth (m)</th>
<th>Log</th>
<th>Model</th>
<th>Nugget</th>
<th>Range (m)</th>
<th>Sill</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>SSPS</td>
<td>1.0</td>
<td>yes</td>
<td>spherical</td>
<td>-</td>
<td>101.18</td>
<td>4.41</td>
</tr>
<tr>
<td>mean</td>
<td>SSPS</td>
<td>2.0</td>
<td>yes</td>
<td>spherical</td>
<td>-</td>
<td>95.77</td>
<td>34.96</td>
</tr>
<tr>
<td>mean</td>
<td>SSPS</td>
<td>argillic</td>
<td>yes</td>
<td>spherical</td>
<td>9.98</td>
<td>152.58</td>
<td>39.85</td>
</tr>
<tr>
<td>variance</td>
<td>SSPS</td>
<td>1.0</td>
<td>no</td>
<td>spherical</td>
<td>$3.15 \times 10^{-5}$</td>
<td>108.33</td>
<td>$3.38 \times 10^{-5}$</td>
</tr>
<tr>
<td>variance</td>
<td>SSPS</td>
<td>2.0</td>
<td>no</td>
<td>spherical</td>
<td>$5.89 \times 10^{-8}$</td>
<td>70.66</td>
<td>$8.66 \times 10^{-7}$</td>
</tr>
<tr>
<td>variance</td>
<td>SSPS</td>
<td>argillic</td>
<td>no</td>
<td>spherical</td>
<td>$1.78 \times 10^{-5}$</td>
<td>145.42</td>
<td>$6.46 \times 10^{-5}$</td>
</tr>
</tbody>
</table>

The maps displaying mean mass emissions and the variance for hexazinone (Fig. 5-25) showed a few areas with mass emissions exceeding 0.1 kg a.i. ha$^{-1}$ at the 1.0-m depth. Similar to the predictive modeling scenario the variance decreased with increasing depth.

Cumulative distribution functions for the predicted and site-referenced mass emissions were statistically compared using the Kolmogorov-Smirnov test ($\alpha=0.05$). Results suggested that predicted and site-referenced mass emission cumulative distribution functions were statistically not different for 58.1%, 26.7%, and 41.9% of the sample locations at the 1.0m, 2.0m, and argillic depths, respectively.

Travel time: hexazinone

Predicted travel time. Travel time of a pesticide is not often used in risk assessments as an indicator, because it cannot be compared with drinking water standards. However, it provides important information regarding the time frame in which pesticides will likely reach the specified control depth or groundwater zone. Similar to mass emissions, travel times can be expressed as a variable.
Figure 5-24. Semivariograms for the mean and variance for the mass emission of hexazinone at the depth of the argillic horizon for the site-referenced modeling scenario.

a) Mass emission; b) Variance.
Figure 5-25. Spatial distribution of the mean mass emission and variance at selected depths at the Santa Fe Beef Unit based on site-referenced modeling.
a) Mean at 1.0-m depth; b) Variance at 1.0-m depth; c) Mean at 2.0-m depth; d) Variance at 2.0-m depth; e) Mean at argillic depth; f) Variance at argillic depth.
Analysis of the mean and variance for the predicted travel times of hexazinone (Table 5-7) showed that there is considerable variability. Predicted mean travel times ranged from as short as 106 days to as long as 9829 days, depending on the depth considered. According to travel time, soils such as Bonneau and Micanopy were very sensitive to pesticide leaching at the 1.0m depth. However, Micanopy became less sensitive to pesticide leaching with increasing depth, with the mean travel time estimated as 9829 days. One reason was the presence of the argillic horizon between the 1.0 and 2.0m depths. This layer retards pesticide movement and, thus, increases travel time. Predicted travel times ranged from as short as 22 days to more than 14600 days. The latter included a fraction of predictions in which the pesticide did not leach to the specified control depth within the simulated time period of 40 yrs.

Table 5-7. Summary of descriptive statistics for the travel time of hexazinone leaching as computed in the predictive modeling scenario.

<table>
<thead>
<tr>
<th>Soil Series</th>
<th>Travel Time (d)</th>
<th>Depth</th>
<th>Statistics</th>
<th>1.0m</th>
<th>2.0m</th>
<th>Argillic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>×</td>
<td>σ²</td>
<td>×</td>
<td>σ²</td>
</tr>
<tr>
<td>Blichton</td>
<td>2611</td>
<td>994708</td>
<td>6496</td>
<td>6185601</td>
<td>1555</td>
<td>362333</td>
</tr>
<tr>
<td>Bonneau</td>
<td>106</td>
<td>3614</td>
<td>1906</td>
<td>817220</td>
<td>111</td>
<td>3916</td>
</tr>
<tr>
<td>Chipley</td>
<td>1575</td>
<td>4994702</td>
<td>3436</td>
<td>10974463</td>
<td>1201</td>
<td>3773466</td>
</tr>
<tr>
<td>Gainesville</td>
<td>1132</td>
<td>118990</td>
<td>2784</td>
<td>537936</td>
<td>2784</td>
<td>537936</td>
</tr>
<tr>
<td>Micanopy</td>
<td>209</td>
<td>6599</td>
<td>9829</td>
<td>8465619</td>
<td>209</td>
<td>6599</td>
</tr>
<tr>
<td>Millhopper</td>
<td>1176</td>
<td>1217561</td>
<td>2829</td>
<td>6833387</td>
<td>1962</td>
<td>3542084</td>
</tr>
<tr>
<td>Myakka</td>
<td>5020</td>
<td>2573457</td>
<td>7958</td>
<td>30558910</td>
<td>5947</td>
<td>17892229</td>
</tr>
<tr>
<td>Norfolk</td>
<td>1055</td>
<td>220385</td>
<td>2621</td>
<td>1281406</td>
<td>1836</td>
<td>636129</td>
</tr>
<tr>
<td>Sparr</td>
<td>2045</td>
<td>11303453</td>
<td>3641</td>
<td>15644435</td>
<td>1223</td>
<td>4927381</td>
</tr>
<tr>
<td>Tavares</td>
<td>1572</td>
<td>7993896</td>
<td>2984</td>
<td>14693144</td>
<td>2903</td>
<td>14461714</td>
</tr>
</tbody>
</table>

The variance of the travel time showed a wide range of values. This reflected considerable variability in the travel time, not only between soils, but also within a soil series. Part of this variability could be attributed to the number of soil pedons used in the pesticide
leaching simulations, with soils having more pedon data sets displaying more variability. Chipley, for which 13 pedon were used, had the largest variability followed by Myakka and Spar. Soils with only one pedon data set, such as Gainesville and Bigbee, had smaller variances. These results are contrary to the results of mass emissions, estimated in which the variance decreased with an increase in the number of pedon data sets.

Both the mean and the variance showed the largest ranges of possible values at the depth of the argillic horizon. This was due to the position of the argillic horizon at the test site, which ranged from as shallow as 0.22m to 2.0m. Consequently there were considerable differences in travel times to the argillic depth.

Application of cumulative density functions allows for easier comparison of the travel times for various soils. An example for the predicted travel times is shown in Fig. 5-26. From this figure it easy to see that Bonneau is a very sensitive soil to pesticide leaching, as travel times were short and little variable. This is expressed as a steep curve. Millhopper, on the other hand, showed a more gradual increase in the cumulative density function as well as a change of slope at a probability of approximately 0.7. Generally, the flatter tail of a cumulative distribution function is evidence of drier weather years and, thus, of conditions under which pesticides required more time to leach to a specified depth. However, a change in slope can also be attributed to differences in soil properties of the soil pedons used. In the case of Millhopper, some pedons had higher organic carbon contents in the soil subsurface horizons than others. Also, organic carbon content in the surface horizon ranged from 0.73 to 1.20%, which was variable enough to cause considerable differences between the soil pedons used.

Spatial distributions of the mean and variance of the predicted travel times were modeled with semivariograms and inverse distance weighting (Table 5-8). For the variance of the travel time at the 2.0-m and argillic depths, the semivariogram could not be modeled, because of lack of spatial structure. In this case inverse distance weight modeling was used instead.
Figure 5-26. Cumulative density functions for the travel time in four soils and three depths for hexazinone on the Santa Fe Beef Unit test site.

a) 1.0-m depth; b) 2.0-m depth; c) Argillic depth.
Table 5-8. Spatial structure models for the predicted mean and variance of hexazinone travel time.

<table>
<thead>
<tr>
<th>Depth (m)</th>
<th>Model</th>
<th>Nugget</th>
<th>Sill</th>
<th>Range (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>Exponential</td>
<td>142618</td>
<td>4.26 x 10^6</td>
<td>165.96</td>
</tr>
<tr>
<td>mean</td>
<td>Spherical</td>
<td>409539</td>
<td>6.40 x 10^6</td>
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</tr>
<tr>
<td>mean</td>
<td>Argillic Spherical</td>
<td>350681</td>
<td>7.27 x 10^6</td>
<td>236.35</td>
</tr>
<tr>
<td>variance</td>
<td>Spherical</td>
<td>1.26 x 10^{13}</td>
<td>1.18 x 10^{14}</td>
<td>250.37</td>
</tr>
<tr>
<td>variance</td>
<td>IDW†</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>variance</td>
<td>Argillic</td>
<td>IDW†</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Interpolated maps for the spatial distribution of the predicted mean travel time of hexazinone and its associated variance (Fig. 5-27) showed little spatial variability. This is primarily a result of the classification method, in which each class was set to 1000 days, or more than 3 years. In the predicted modeling scenario, the largest travel times and variances were located at the forest’s edge, where higher organic carbon content in the surface or subsurface layers was a potential factor.

Site-referenced travel time. As for the mass emissions, the statistical summary of the travel time of hexazinone under the site-referenced scenario was presented as a range rather than a single value. The mean travel time and variance (Table 5-9) showed that several soil series had ranges for both mean travel time and variance that varied by a factor of 3-4. Since only the organic carbon content in the surface horizon and depth of the argillic horizon were adjusted, differences in travel time within a soil series could be contributed to these factors. The most extreme case was for the variance at the argillic depth for the Norfolk soils, where the upper mean was over 100 times larger than the lower mean. In such a situation, one might ask whether of all the pedons were properly classified or whether one of the Norfolk pedons was incorrectly classified and, therefore, caused these differences.
Figure 5-27. Spatial Distribution of the mean and variance of the travel time of hexazinone as computed in the predictive modeling scenario.
a) Mean at 1.0-m depth; b) Variance at 1.0-m depth; c) Mean at 2.0-m depth; d) Variance at 2.0-m depth; e) Mean at argillic depth; f) Variance at argillic depth.
Table 5-9. Summary of descriptive statistics for the travel time of hexazinone leaching as computed in the site-referenced modeling scenario. If more than one sample location had the same soil series, the range of the calculated mean and variance is listed.

<table>
<thead>
<tr>
<th>Soil Series</th>
<th>1.0m Mean</th>
<th>1.0m Variance</th>
<th>2.0m Mean</th>
<th>2.0m Variance</th>
<th>Argillic Mean</th>
<th>Argillic Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>×</td>
<td>σ²</td>
<td>×</td>
<td>σ²</td>
<td>×</td>
<td>σ²</td>
</tr>
<tr>
<td>Bigbee</td>
<td>975</td>
<td>119238</td>
<td>3619</td>
<td>542267</td>
<td>2092</td>
<td>834141</td>
</tr>
<tr>
<td></td>
<td>1819</td>
<td>25728021</td>
<td>6871</td>
<td>30556605</td>
<td>6678</td>
<td>2910206</td>
</tr>
<tr>
<td>Bonneau</td>
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<td>1729</td>
<td>542889</td>
<td>232</td>
<td>21020</td>
</tr>
<tr>
<td></td>
<td>1832</td>
<td>25728327</td>
<td>6032</td>
<td>30569027</td>
<td>4332</td>
<td>4715112</td>
</tr>
<tr>
<td>Chipley</td>
<td>5767</td>
<td>25716828</td>
<td>13457</td>
<td>30565678</td>
<td>13456</td>
<td>4242590</td>
</tr>
<tr>
<td>Cowarts</td>
<td>817</td>
<td>4231</td>
<td>1909</td>
<td>815499</td>
<td>226</td>
<td>5326</td>
</tr>
<tr>
<td>Gainesville</td>
<td>855</td>
<td>119122</td>
<td>2929</td>
<td>543977</td>
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<td>489168</td>
</tr>
<tr>
<td></td>
<td>1071</td>
<td>119143</td>
<td>5520</td>
<td>6838893</td>
<td>5519</td>
<td>2148708</td>
</tr>
<tr>
<td>Millhopper</td>
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<td></td>
<td>2363</td>
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<td>6148</td>
<td>30563443</td>
<td>5119</td>
<td>16022381</td>
</tr>
<tr>
<td>Norfolk</td>
<td>879</td>
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<td>2319</td>
<td>816508</td>
<td>71</td>
<td>1479</td>
</tr>
<tr>
<td></td>
<td>2750</td>
<td>7996237</td>
<td>8428</td>
<td>14725950</td>
<td>8428</td>
<td>4747943</td>
</tr>
<tr>
<td>Osier</td>
<td>3066</td>
<td>119148</td>
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<td>539679</td>
<td>5492</td>
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</tr>
<tr>
<td></td>
<td>6273</td>
<td>25729070</td>
<td>10584</td>
<td>30571188</td>
<td>10582</td>
<td>34051069</td>
</tr>
<tr>
<td>Pickney</td>
<td>1792</td>
<td>1810738</td>
<td>4476</td>
<td>7664200</td>
<td>4476</td>
<td>7664200</td>
</tr>
</tbody>
</table>

Cumulative density functions for the site-referenced travel time (Fig. 5-28) for selected soils showed more variability with increasing depth. The previously mentioned change in slope for the Millhopper soil was even more distinctly visible at the 2.0-m and argillic depths. Organic carbon content in the surface horizon was kept constant in this scenario; thus, the differences must have been due to the subsurface profiles and could have been due to any given soil property used for the environmental-fate simulations. Also, based on the site-referenced data, Norfolk soils were more sensitive to pesticide leaching than in the predictive modeling scenario, because the travel times were shorter.

The spatial structures of the site-referenced mean and variance for the travel time were difficult to model with a semivariogram. Only for half of the variables considered could a semivariogram be modeled (Table 5-10). For the remaining variables, inverse distance
Figure 5-28. Cumulative distribution functions for the site-referenced travel time of hexazinone to three depths. 
a) 1.0-m depth; b) 2.0-m depth; c) Argillic depth.
weight was used to interpolate a map. The resulting surface maps (Fig. 5-29) showed considerable spatial variability for both the mean and variance of the travel time.

Cumulative distribution functions for the predicted and site-referenced travel times at the 1.0m, 2.0m and argillic depths were statistically compared using the Kolmogorov-Smirnov test ($\alpha=0.05$). Results indicated that the predicted and site-referenced travel time distributions were statistically not different for 14.9%, 4.1% and 12.2% of the 74 sample locations for which travel time cumulative distribution functions could be generated for the three respective depths.

Table 5-10. Spatial structure models for mean and variance of hexazinone travel time using site-referenced data.

<table>
<thead>
<tr>
<th>Depth (m)</th>
<th>Model</th>
<th>Nugget</th>
<th>Sill</th>
<th>Range (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>Spherical</td>
<td>213 258</td>
<td>$1.97 \times 10^6$</td>
<td>146.42</td>
</tr>
<tr>
<td>Mean</td>
<td>Spherical</td>
<td>734 549</td>
<td>$4.60 \times 10^6$</td>
<td>131.95</td>
</tr>
<tr>
<td>Mean</td>
<td>Argillic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>Spherical</td>
<td></td>
<td>$1.27 \times 10^{13}$</td>
<td>250.35</td>
</tr>
<tr>
<td>Variance</td>
<td>IDW$^\dagger$</td>
<td></td>
<td>$1.18 \times 10^{14}$</td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>Argillic</td>
<td>IDW$^\dagger$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^\dagger$: All inverse distance models used second-order interpolation.

**Simazine leaching**

Leaching of simazine was modeled for two sample locations (Points 2 and 11) at the Santa Fe Beef Unit to demonstrate that the developed uncertainty method also works for less-mobile pesticides. The results (statistical summaries for both mass emissions and travel times, and the uncertainty analysis) will be discussed in the following sections.

**Mass emission and travel time.** Environmental-fate properties of simazine (Table 4-7 and Table 4-9) are sufficiently different from those of hexazinone that leaching behavior is considerably different. Simazine moves slower and degrades faster in the soil profile than does hexazinone.
Figure 5-29. Spatial distribution of the mean and variance of the site-referenced travel time.

a) Mean travel time to 1.0-m depth; b) Variance at 1.0-m; c) Mean travel time to 2.0-m; d) Variance at 2.0-m; e) Mean travel time to argillic depth; f) Variance at argillic depth.
At the two sample locations (2 and 11), Gainesville soil had been mapped originally. The site verification study revealed that Gainesville soil is present at location 2, but that Millhopper is present at location 11. Millhopper has an argillic horizon which, at this location, was found at the 1.7m depth.

Simazine leaching showed considerable variability in both the predicted and site-referenced modeling scenarios for both the Gainesville and Millhopper soils (Table 5-11). However, such results need to be interpreted with considerable care. Simazine’s partition coefficient is large enough to retard simazine movement in the soil profile sufficiently that the herbicide might not leach past the selected control depths in the soil profile within the time period simulated (40 yrs). In the predictive modeling scenario, simazine reached the 2.0-m depth in all cases but, in the site-referenced modeling scenario, it did not. For the Gainesville soil 6.2% and 67.7% of the simulations resulted in no arrival at the 1.7-m and 2.0-m depths, respectively. For

Table 5-11. Statistical summary for simazine mass emissions (kg a.i. ha⁻¹) and travel time (d) for Gainesville and Millhopper, at selected depths in the soil profile for the predicted and site-referenced modeling scenarios. The 1.7m depth is the measured depth at which an argillic horizon is present in the Millhopper profile.

<table>
<thead>
<tr>
<th>Control Depth (m)</th>
<th>Gainesville fine sand</th>
<th>Millhopper sand</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>×σ²</td>
<td>×σ²</td>
</tr>
<tr>
<td>1.0</td>
<td>5.03 x 10⁻³ 1.83 x 10⁻³ 4.77 x 10⁻⁴ 1.05 x 10⁻⁴ 2.28 x 10⁻⁴ 4.16 x 10⁻⁵</td>
<td>3.20 x 10⁻³ 1.09 x 10⁻³ - - 7.12 x 10⁻⁶ 1.58 x 10⁻⁷</td>
</tr>
<tr>
<td>1.7</td>
<td>2452 369790 4992 1491761 6022 2158114</td>
<td>4204 15049824 9342 22374154 11129 18817062</td>
</tr>
<tr>
<td>2.0</td>
<td>3071 589010 - - 13886 1947187</td>
<td>4204 15049824 9342 22374154 11129 18817062</td>
</tr>
</tbody>
</table>

† Data as modeled in the predictive scenario, ‡ Data as modeled in the site-specific scenario.
simulations with the Millhopper soil, 4.7%, 32.0% and 50.2% of the simulations resulted in no
arrival at the 1.0-m, 1.7-m, and 2.0-m depths, respectively. Consequently, mass emissions was
underestimated as the environmental-fate model predicted 0.0 kg a.i. ha\(^{-1}\) mass emission for no-
arrivals. The travel time can be approximated by setting the no-arrival time equal to 40 years
plus one day (14601 days), but this resulted in underestimation of the mean travel time and
introduced a bias into the statistics. The larger the percentage of no-arrivals, the greater the bias.
This is not evident in the summary statistics presented, but is clearly evident in the cumulative
distribution functions for the mass emissions and travel times of simazine to the argillic horizon
(Fig. 5-30) in both soils. For both the Gainesville and Millhopper soils, the cumulative
probability of mass emissions smaller than 10\(^{-23}\) kg a.i. ha\(^{-1}\) is fairly large, with overall
probabilities larger than 0.6. This is partly due to the percentage of the simulations that resulted
in no arrival and partly due to smaller mass emissions. Presence of no-arrival simulations is best
shown in the travel time (Fig. 5-30b) for Millhopper soil. The graph makes a 0.3 probability
jump at 14600 days. This is solely due to the no-arrivals. For Gainesville soil the jump is much
smaller only (0.06 probability).

The cumulative distribution functions for the predicted and site-referenced travel times
were statistically compared using the Kolmogorov-Smirnov test ($\alpha=0.05$). The cumulative
distributions functions were statistically not different with respect to the travel time for 4.05%,
4.05%, and 2.70% of the sample locations at the 1.0m, 2.0m, and the argillic depths, respectively.
This was lower than for to the mass emission cumulative distribution functions, and was
attributed to the larger number of classes used to define the cumulative distribution functions.
The Kolmogorov-Smirnov test statistic decreased with increased number of classes and became
less tolerable to large differences between the cumulative distribution functions.
Figure 5-30. Cumulative density functions for simazine leaching at the depth of the argillic horizon for the predictive and site-referenced modeling scenarios.

(a) Mass emission; (b) Travel time.
Entropy Approach

In the following sections the uncertainty in predicted mass emissions and travel times for hexazinone and simazine are quantified using the entropy approach. Uncertainty, $U_H$, refers to the uncertainty calculated with Eq. [3-6]. First the uncertainty analysis for hexazinone is presented and discussed, followed by the results for simazine.

Uncertainty in hexazinone mass emissions

Uncertainty is a measure of imprecision in the predicted mass emissions of a selected pesticide for a defined leaching scenario. Different scenarios will result in different values for the uncertainties for the same site. The measure of uncertainty, $U_H$, used in this part of the study depends on the probability difference between the predicted and site-referenced mass emissions. Larger differences in probability will result in more uncertainty, whereas smaller values of $\mid dP \mid$ indicate less uncertainty.

Examples of mass emission probability functions for the predicted and site-referenced modeling scenarios and the resulting probability difference function, $\mid dP \mid$, are shown for three sample locations (2, 11, and 82) at the Santa Fe Beef Unit test site for the three control depths in Fig. 5-31. These three sample locations represented examples of various computed leaching results. Consider first the mass emission curves at sample location 2 (Fig. 5-31a and b), where Gainesville was mapped in both modeling scenarios. At this location no argillic horizon is present within the first two meters of the soil profile, and the computed mass emissions differed only moderately at the 1.0-m depth. Most mass emissions were within the $10^{-5} - 1.0$ kg a.i. ha$^{-1}$ range, and predicted mass emissions showed more tailing towards smaller values. The site-referenced mass emissions were, on the other hand, distributed around $10^{-3}$ kg a.i. ha$^{-1}$. The resulting $\mid dP \mid$ curve showed three peaks, which were the result of taking the absolute difference rather than the relative difference in probability. For mass emissions larger than $10^{-8}$ kg a.i. ha$^{-1}$, $\mid dP \mid \approx 0$ and did not contribute to uncertainty. All uncertainty results from $\mid dP \mid$ were in the range...
$10^{-7} - 10^1$ kg a.i. ha$^{-1}$. With increasing depth the differences between the two mass emission curves were enhanced (Fig. 5-31). Consequently the ldPl curve had larger values over a larger range of mass emissions and, therefore, uncertainty increased from 0.33 to 0.64 at the 1.0-m and 2.0-m depths, respectively.

At the second location (Point 11: Fig. 5-31c,d, and e), two different soils were mapped in the two scenarios. According to the ACPS map, Gainesville was mapped whereas the SSPS indicated Millhopper. The argillic horizon was found at the 1.71-m depth. At the 1.0m depth both mass emission curves remained similar. Consequently, the difference in probability curve had small values over the entire range and $U_H = 0.17$. With increased depth, the curves had demonstrated differences in shape; i.e., more tailing was visible. Uncertainty increased to 0.35 and 0.28 at the 2.0-m and argillic depths, respectively. The smaller uncertainty at the 2.0-m depth could be explained by the fact that this was deeper in the soil profile, with differences decreasing due to increased travel time.

The third location (Point 82: Fig 5-31f, g, and h), represented a case in which the uncertainty was large and was dominated by a single mass emission curve. At this location Micanopy was mapped according to the ACPS map, whereas ground-truthing mapped Norfolk. The argillic horizon was found at 0.20-m depth. As is shown in Fig. 5-31f - 5-31h, the probability difference function was dominated by the shape of the mass emission curve for Norfolk. Mass emissions predicted for Micanopy soil were fairly uniformly distributed between 0.0 - 1.0 kg a.i. ha$^{-1}$. This, by itself, indicated considerable variability for this soil pair. At the 1.0-m and 2.0-m depths, ldPl values were high for several mass emission classes; consequently, the uncertainty values, were $U_H = 0.69$ and $U_H = 0.66$, respectively. However, when the argillic horizon was taken into account, the uncertainty decreased to $U_H = 0.22$. This could be explained by the shorter travel time to the argillic depth and, therefore, by the fact that degradation and leaching did not have a large enough impact to introduce differences in the system sufficient to result in sizable uncertainty.
Figure 5-31. Probability density functions for the predicted and site-referenced mass emissions of hexazinone, and difference in probability, \(|dP|\), for selected locations and depths at the Santa Fe Beef Unit test site. a) Point 2 - 1.0-m depth; b) Point 2 - 2.0-m depth; c) Point 11 - 1.0-m depth; d) Point 11 - 2.0-m depth; e) Point 11 - argillic depth; f) Point 82 - 1.0-m depth; g) Point 82 - 2.0-m depth; h) Point 82 - argillic depth.
Figure 5-31–continued.
Figure 5-31—continued.
The spatial structure of the uncertainty was modeled with a semivariogram for the 1.0m and argillic depths, and with splines for the 2.0-m depth. For the 2.0-m depth, the experimental semivariogram could not be described with any specific model, but by a pure nugget effect and splines were used instead to generate a surface map for uncertainty at the 2.0-m depth. The other two depths were described with a spherical model and a gaussian model for the 1.0-m and argillic depths, respectively.

Uncertainty in the mass emissions of hexazinone (Fig. 5-32) at the 1.0-m depth showed areas of little uncertainty: e.g., $U_H < 0.2$ and only a few areas with increased, $U_H > 0.2$. Little uncertainty at this depth could be explained by the short residence time of the pesticide in the soil. Differences between the predicted mass emissions and the site-referenced mass emissions were not large enough to cause considerable uncertainty, with the area-weighted uncertainty for the site being $U_H = 0.33$. With increasing depth, uncertainty increased in the system. Evidently, areas were present with high uncertainty, $U_H > 0.6$. Notable was the increased uncertainty where Gainesville was mapped for both the ACPS map and the SSPS map.

The uncertainty for the site is $U_H = 0.46$. Accounting for presence of the argillic horizon, the spatial distribution of uncertainty showed both low values, $U_H < 0.1$, and high values, $U_H > 0.6$. At this depth, areas with high uncertainties where generally those areas were Gainesville and Micanopy soils were originally mapped. The area-weighted uncertainty for the site, based on mass emissions at the argillic depth, was $U_H = 0.38$.

Spatial distribution of the uncertainty at the Santa Fe Beef Unit test site seemed to follow a similar pattern as depth to the argillic horizon, with the spatial correlation coefficient being 0.55. This indicated a weak correlation between uncertainty and depth to the argillic horizon. Based on results from the hexazinone study, uncertainty in the predicted mass emissions could be ranked as follows: 1.0-m < argillic < 2.0-m depth.

Uncertainty in the predicted mass emissions, displayed for the map unit delineations of the Alachua County soil survey map (Fig. 5-33), suggested lower uncertainty in the predicted mass emissions compared to values from the spatial interpolated maps. However, the site’s area-
Figure 5-32. Spatial distribution of the uncertainty in the predicted mass emission of hexazinone. a) 1.0-m depth; b) 2.0-m depth; c) Argillic depth.
weighted uncertainty was the same as the site’s area-weighted uncertainty based upon the spatially interpolated maps for all three depths, though there was less variability in the uncertainty itself. Extreme values were not present, because they were averaged within the boundaries of the Alachua County soil survey map delineations.

Gainesville and Bonneau soils are the only soils that were mapped at the same sample locations in the Alachua County soil survey report and the site-referenced soil survey. Uncertainty in the predicted mass emissions of hexazinone for these soils (Table 5-12) showed little variability for Gainesville whereas, for Bonneau, $U_{ir}$ differs by a factor of 1.5 - 2 when the two points are compared.

<table>
<thead>
<tr>
<th>Soil</th>
<th>Point</th>
<th>1.0m</th>
<th>2.0m</th>
<th>Argillic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gainesville</td>
<td>1</td>
<td>0.37</td>
<td>0.66</td>
<td>-</td>
</tr>
<tr>
<td>Gainesville</td>
<td>2</td>
<td>0.33</td>
<td>0.64</td>
<td>-</td>
</tr>
<tr>
<td>Gainesville</td>
<td>12</td>
<td>0.36</td>
<td>0.59</td>
<td>-</td>
</tr>
<tr>
<td>Gainesville</td>
<td>19</td>
<td>0.33</td>
<td>0.65</td>
<td>-</td>
</tr>
<tr>
<td>Gainesville</td>
<td>21</td>
<td>0.31</td>
<td>0.63</td>
<td>-</td>
</tr>
<tr>
<td>Bonneau</td>
<td>16</td>
<td>0.43</td>
<td>0.63</td>
<td>0.27</td>
</tr>
<tr>
<td>Bonneau</td>
<td>25</td>
<td>0.21</td>
<td>0.43</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Uncertainty in hexazinone travel times

Travel time of a pesticide is influenced by fewer model input parameters than the mass emission. Degradation rate and reference temperature are examples of such parameters. If fewer parameters affect the results, it is expected that uncertainty should be less for the travel time than for the mass emissions.
Figure 5-33. Uncertainty in the predicted mass emissions for individual map units at the Santa Fe Beef Unit test site. a) 1.0-m depth; b) 2.0-m depth; c) Argillic depth.
Similar to mass emissions, the uncertainty in the travel time was calculated based on differences in probability between the predicted and site-referenced travel times. For the same three points used in Fig. 5-23, the probability difference curves for the travel time (Fig. 5-34) showed a variety of possible probability distribution curves. The choppy behavior of the probability difference curves was traced back to the classification method. Generated random numbers showed spikes if too many classes were specified when generating a histogram of distributions for this variable. 147 classes were too many classes, and spikes became visible.

The uncertainty for sample point 2 (Fig. 5-34a and b), where Gainesville soil was mapped in both the Alachua County soil survey report and the site-specific soil survey, was 0.14 and 0.65 at 1.0-m and 2.0-m, respectively. Compared to the uncertainty in mass emissions this was lower for the 1.0-m depth and virtually the same for the 2.0-m depth. The lower uncertainty for the 1.0m depth was explained by the predicted and site-referenced travel time probability curves. They were very similar; thus, the uncertainty was low. For the 2.0-m depth, however, the curves were shifted, and the \( |dP| \) curve had higher values over a larger range, consequently giving a higher uncertainty.

Uncertainties in the travel time at the Gainesville-Millhopper location (Point 11; Fig 5-34c, d, and e) were 0.40, 0.57, and 0.54 for the 1.0-m, 2.0-m, and argillic depths respectively. These values were higher than the corresponding mass emission uncertainties, by a factor 1.5 to 2. This indicated that fewer input parameters did not necessarily result in less uncertainty. For some parameters, differences might still diminish between the predictive and site-referenced modeling scenarios with respect to travel time.

Travel time uncertainty in the Micanopy-Norfolk overlay (Sample location 82: Fig. 5-34f, g, and h) is an example where one of the data sets determined the shape of the probability difference function. At this location, Norfolk was the dominant data set. Like other locations at the test site, the uncertainty increased with depth, \( U_1 \), being 0.38, 0.84, and 0.15 for the 1.0-m, 2.0-m, and argillic depths, respectively. The argillic horizon was close to the surface (0.22m); thus, the uncertainty was expected to be small because the travel time was small for shallow layers, whereas deeper in the profile the difference in travel time became larger and thus the uncertainty should increase. These results confirmed the results found for mass emissions, in
Figure 5-34. Probability distribution functions for predicted, site-referenced, and probability difference, |dP|, for hexazinone travel time at three locations at the Santa Fe Beef Unit test site. 

a) Point 2 - 1.0-m depth; b) Point 2 - 2.0-m depth; c) Point 11 - 1.0-m depth; d) Point 11 - 2.0-m depth; e) Point 11 - argillic depth; f) Point 82 - 1.0-m depth; g) Point 82 - 2.0-m depth; h) Point 82 - argillic depth.
Figure 5-34–continued.
Figure 5-34–continued.
that uncertainty increased with depth. Note that this was valid only for the first two meters of the soil profile, which was the extent of this study.

The spatial distribution of uncertainty in travel time was modeled with semivariograms and an inverse-distance weighting model (Table 5-13). The semivariogram could not be modeled at the depth of the argillic horizon, because of lack of spatial structure at this depth for this variable. All spatial variability was accounted for at lag-distances less than 50m.

Table 5-13. Spatial models used to generate surface maps for the travel time uncertainty.

<table>
<thead>
<tr>
<th>Depth (m)</th>
<th>Model</th>
<th>Nugget</th>
<th>Sill</th>
<th>Range (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>Spherical</td>
<td>0.011</td>
<td>0.083</td>
<td>141.13</td>
</tr>
<tr>
<td>2.0</td>
<td>Spherical</td>
<td>0.015</td>
<td>0.152</td>
<td>123.90</td>
</tr>
<tr>
<td>Argillic</td>
<td>IDW†</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

†: Inverse distance weighting used a second-order power.

Spatial distribution of the uncertainty in the travel times (Fig. 5-35) followed similar patterns as uncertainties in the predicted mass emissions. Notable is the low uncertainty, $U_H$, being approximately 0.20, at those areas east of the forest where the argillic horizon was shallow. However, this was not observed for the western half of the test site. Spatial correlation between the argillic depth and the computed uncertainty at the argillic depth was 0.64, thus indicating only weak correlation.

Based on the maps for travel time uncertainty, the area-weighted uncertainty was $U_H = 0.30, 0.47,$ and $0.40$ for the 1.0-m, 2.0-m, and argillic depths, respectively. These values were similar to the site uncertainties for the mass emissions, $U_H = 0.33, 0.46,$ and $0.38$, for the respective depths.
Figure 5-35. Uncertainty in the predicted travel time at three depths.

(a) 1.0m depth; (b) 2.0m depth; (c) Argillic depth.

Uncertainty

0.0  1.0

Figure 5-35. Uncertainty in the predicted travel time at three depths.

a) 1.0m depth; b) 2.0m depth; c) Argillic depth.
Uncertainty in simazine leaching

Uncertainty in mass emissions at site location 2 (Gainesville - Gainesville) was governed by the shape of the predicted mass emission probability curve (Fig. 5-36a) and the computed mass emissions for the site-referenced scenario. The almost uniform distribution for this difference in probability curve, $|dP|$, indicated that there was considerable uncertainty in the system at the 2.0m depth. Similar results were obtained for site location 11 (Fig 5-36b), though the resulting $|dP|$ function looked fairly uniform. However, the value of $|dP|$ shown for mass emissions over the entire range did not exceed 0.05. Total uncertainty in this system was low, with $U_H$ being 0.22.

The $|dP|$ functions for the travel time (Fig. 5-37) clearly showed the effect of the no-arrival simulations, with the calculated values for $|dP|$ exceeding the shown graphics range. This by itself indicated that there was considerable uncertainty in the system. The calculated uncertainties were 0.64 and 0.51 for locations 2 and 11, respectively.

Table 5-14 lists the computed uncertainty for simazine leaching at the two site locations. The computed uncertainties for travel time were larger than for mass emissions at any depth, and, similar to results obtained from the hexazinone study, the uncertainty increased with depth.

| Table 5-14. Uncertainty in simazine leaching for the Gainesville and Millhopper soils. |
|---------------------------------|---|---|---|---|---|---|
|                                | Control depth (m) | Mass Emission | Travel Time |
|                                |                | 1.0 | 1.7 | 2.0 | 1.0 | 1.7 | 2.0 |
| Gainesville fine sand          | 0.22           | -   | 0.46 | 0.32 | -   | 0.64 |
| Millhopper sand                | 0.33           | 0.36 | 0.37 | 0.52 | 0.58 | 0.51 |

- : No argillie horizon was present in this soil profile within the 2.0m depth.

Simulations that produced a no-arrival result were used in the calculation of uncertainty with no arrival as a result telling us that, within the simulated time frame, the pesticide did not leach to the specified depth. This information must be taken into account when computing uncertainty.
Figure 5-36. Probability distribution functions for the mass emission of simazine at the depth of the argillic horizon and the probability difference function.

a) Site location 2; b) Site location 11.
Figure 5-37. Probability density functions for the travel time of simazine to the argillic horizon and the difference in probability function for two different locations at the Santa Fe Beef Unit.

a) Site location 2; b) Site location 11.
Uncertainty in selected parameters

Contribution to uncertainty of selected input parameters was expected to be variable, based on results of the sensitivity analysis. Results from the uncertainty analysis of selected model input parameters for hexazinone (Table 5-15) and simazine (Table 5-16) support this.

Table 5-15. Uncertainty for selected model input parameters for different soils and depths using the pesticide hexazinone. The 1.7m depth is the measured depth at which the argillic horizon is present in the Millhopper soil profile.

<table>
<thead>
<tr>
<th>Control Depth (m)</th>
<th>Mass Emission</th>
<th>Travel Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.0</td>
<td>1.7</td>
</tr>
<tr>
<td>Gainesville fine sand</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Curve number</td>
<td>0.03</td>
<td>-</td>
</tr>
<tr>
<td>Partition coefficient</td>
<td>0.28</td>
<td>-</td>
</tr>
<tr>
<td>Organic carbon</td>
<td>0.31</td>
<td>-</td>
</tr>
<tr>
<td>Precipitation</td>
<td>0.06</td>
<td>-</td>
</tr>
<tr>
<td>Rooting depth</td>
<td>0.32</td>
<td>-</td>
</tr>
<tr>
<td>Half-life</td>
<td>0.22</td>
<td>-</td>
</tr>
<tr>
<td>Reference temperature</td>
<td>0.33</td>
<td>-</td>
</tr>
<tr>
<td>Millhopper sand</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Curve number</td>
<td>0.14</td>
<td>0.29</td>
</tr>
<tr>
<td>Partition coefficient</td>
<td>0.25</td>
<td>0.36</td>
</tr>
<tr>
<td>Organic carbon</td>
<td>0.34</td>
<td>0.44</td>
</tr>
<tr>
<td>Precipitation</td>
<td>0.14</td>
<td>0.28</td>
</tr>
<tr>
<td>Rooting depth</td>
<td>0.25</td>
<td>0.35</td>
</tr>
<tr>
<td>Half-life</td>
<td>0.19</td>
<td>0.33</td>
</tr>
<tr>
<td>Reference temperature</td>
<td>0.24</td>
<td>0.38</td>
</tr>
</tbody>
</table>

- : No argillic horizon was present in this soil profile within the 2.0m depth.

As expected, contribution of the curve number to uncertainty was minimal, since the CMLS98B model was not sensitive to curve numbers. Notable was the increase in uncertainty with depth for hexazinone, whereas the uncertainty decreased with depth for simazine. At the 2.0-m depth the probability curves for mass emissions were shifted enough to cause increased
uncertainty for this mobile pesticide, though curve numbers affected the travel time uncertainty less. Simazine, with its larger partition coefficient, showed a smaller change in the probability density functions, and consequently less uncertainty. For both herbicides, the uncertainty was larger for the travel time than for the mass emission.

Table 5-16. Uncertainty in selected model input parameters for different soils and depths using the herbicide simazine. The 1.7m depth is the measured depth to the argillic horizon which is present in the Millhopper soil profile.

<table>
<thead>
<tr>
<th>Control Depth (m)</th>
<th>Mass Emission</th>
<th>Travel Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.0</td>
<td>1.7</td>
</tr>
<tr>
<td>Gainesville fine sand</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Curve number 0.11</td>
<td>-</td>
<td>0.05</td>
</tr>
<tr>
<td>Organic carbon 0.43</td>
<td>-</td>
<td>0.35</td>
</tr>
<tr>
<td>Partition coefficient 0.10</td>
<td>-</td>
<td>0.06</td>
</tr>
<tr>
<td>Precipitation 0.08</td>
<td>-</td>
<td>0.00†</td>
</tr>
<tr>
<td>Rooting depth 0.27</td>
<td>-</td>
<td>0.17</td>
</tr>
<tr>
<td>Millhopper sand</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Curve number 0.11</td>
<td>0.10</td>
<td>0.09</td>
</tr>
<tr>
<td>Organic carbon 0.35</td>
<td>0.33</td>
<td>0.34</td>
</tr>
<tr>
<td>Partition coefficient 0.12</td>
<td>0.09</td>
<td>0.08</td>
</tr>
<tr>
<td>Precipitation 0.00†</td>
<td>0.00†</td>
<td>0.00†</td>
</tr>
<tr>
<td>Rooting depth 0.18</td>
<td>0.16</td>
<td>0.22</td>
</tr>
</tbody>
</table>

† Simazine did not leach to the control depth within the specified time period of six years following application; - : No argillic horizon was present in this soil profile within the 2.0m depth.

Uncertainty due to soil organic carbon content was considerable. This was to be expected, as the measured organic carbon content on-site was significantly higher than for data from the UF soil characterization database. Consequently, the distribution curves for both the mass emissions and travel times would shift enough to cause considerable uncertainty. The impact was larger for simazine than for hexazinone and was larger for travel time than for mass emissions. That the uncertainty due to soil organic carbon content was the greatest of all
parameters tested was not surprising, because the CMLS98B model was highly sensitive to soil organic carbon content and pesticide movement is strongly governed by the organic carbon content of the soil.

Impact of the partition coefficient was similar to that of soil organic carbon content, with pesticide movement being strongly affected by this parameter. The larger uncertainty due to the partition coefficient for hexazinone compared to simazine was caused by the larger difference between the predicted and site-referenced values. Small differences between the distribution functions result in relatively little uncertainty.

Generally, precipitation is considered one of the more uncertain parameters in a model, as we cannot predict the weather accurately nor precisely. The relatively small uncertainty of the precipitation at the 1.0m depth was caused by relatively small differences in long-term weather between the Gainesville Regional Airport weather station and the Gainesville Northwest weather station. Also, distances between the test site and the two weather stations did not greatly affect this uncertainty. For the 2.0m depth the uncertainty in precipitation was larger, because of failure for hexazinone to arrive at this depth within the simulated time frame. The uncertainty at depths deeper than 1.0m could not be assessed for simazine, because the six-year time period was insufficient to leach simazine to these depths.

Uncertainty due to the rooting depth tended to increase with depth, as was shown for both pesticides and soils except for simazine and Gainesville fine sand. In the latter case the uncertainty decreased with depth for both the mass emissions and travel times.

Uncertainty in the travel time was smaller than uncertainty in mass emissions, for hexazinone, though the contrary was true for simazine. Such results seem to indicate that the uncertainty increases for less mobile pesticides as the travel time increases and, therefore, that those differences are enhanced. Hexazinone followed the expectation that the uncertainty in travel time is less than the uncertainty in mass emissions. Pesticide half-life and degradation reference temperature do not influence travel time. Calculated values of the uncertainty for these parameters, were merely an effect of differences in weather patterns generated during this uncertainty study, with actual values for the uncertainty being zero in this case.
Uncertainties due to pesticide half-life and degradation reference temperature were computed for hexazinone only. For simazine, no site-specific pesticide environmental-fate properties data were available. As expected, these parameters did not affect the uncertainty in travel time, for such parameters do not influence pesticide movement but, only mass emissions. With increasing depth, uncertainty due to both parameters increased, because the residence time in the profile was longer and differences between the scenarios became larger.

Results of the uncertainty analysis for selected parameters for hexazinone and simazine were often contrary to each other. Whereas the uncertainty increased with depth for hexazinone it decreased for simazine. The main differences are the environmental-fate properties of the two herbicides. For mobile pesticides, uncertainty tends to increase with depth in the soil profile whereas, for less mobile pesticides, the uncertainty decreases with depth.

Uncertainty in the Alachua County soil survey map is similar to the total uncertainty, as shown in Fig. 5-38. The uncertainty differs with each map unit was on the order of 0.4 - 0.6, and increased with depth. Using an area-weighted estimator, total uncertainty at the test site ranged from 0.44 to 0.73 (Table 5-17), with the highest uncertainty for predicted travel times at the depth of the argillic horizon. This information indicated that it is imperative to verify soil map units when conducting predictive risk assessment studies at any given site.

Table 5-17. Area-weighted uncertainty in the predicted mass emissions and travel times of hexazinone at the Santa Fe Beef Unit test site.

<table>
<thead>
<tr>
<th>Depth (m)</th>
<th>Mass Emissions</th>
<th>Travel Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>0.44</td>
<td>0.47</td>
</tr>
<tr>
<td>2.0</td>
<td>0.47</td>
<td>0.56</td>
</tr>
<tr>
<td>Argillic</td>
<td>0.68</td>
<td>0.73</td>
</tr>
</tbody>
</table>

If parameters were to be ranked with regard to their contributions of uncertainty based on these results, it would be as follows for mass emissions: curve number < precipitation < pesticide half-life < partition coefficient < organic carbon content in the surface horizon < rooting depth < soil map. However, for travel time the ranking would be: curve number < pesticide half-life <
Figure 5-38. Uncertainty in the mass emission and travel time of hexazinone introduced by the soil map.

a) Mass emission at 1.0-m depth; b) Travel time to 1.0-m depth; c) Mass emission at 2.0-m depth; d) Travel time to 2.0-m depth; e) Mass emission at argillic depth; f) Travel time to argillic depth.
precipitation < partition coefficient < rooting depth < organic carbon content in the surface horizon < soil map.

Uncertainty in pesticide leaching

Uncertainty analysis for the predicted mass emissions and travel times for two pasture herbicides indicated that there was considerable uncertainty in model input data. Computed mass emission uncertainties, $U_{m}$, ranged from 0.10 - 0.76 for hexazinone depending on depth and location, whereas the uncertainty in travel time for hexazinone was 0.05 - 0.84. For simazine, $U_{m}$ = 0.22 - 0.64 for both mass emissions and travel times, but this was based on the results for only two sample locations in the field. These ranges suggest that considerable spatial variability exists. The amount of uncertainty in the predicted mass emissions and travel times might invalidate any environmental assessment studies done at the Santa Fe Beef Unit. If we were to accept any specified level of uncertainty, we might be able to accept or reject any predictive modeling results. In the case of the Santa Fe Beef Unit, any threshold for $U_{m} > 0.3$ results in rejection of the predicted mass emissions and travel times for much of the test site. Based on the area-weighted uncertainty, the estimated mass emissions and travel times would be rejected as $U_{m} > 0.30$ for all depths.

If the Santa Fe Beef Unit test site is a typical example for predictive pesticide modeling, one should be careful when applying predicted mass emissions and travel times to a groundwater management scenario. For the defined pesticide leaching scenarios at the Santa Fe Beef Unit, estimated pesticide leaching is highly uncertain.

One of the questions that arises from this research is whether $U_{m}$-mass emissions and $U_{m}$-travel times can be compared, because uncertainty in each case was based on a different number of classes, 26 classes for the mass emission and 147 classes for the travel time. Maximum uncertainty in a system, $U_{max}$, is affected by the number of classes. With increasing number of classes the maximum uncertainty increases (Fig. 5-39). For a system with only one probability density function originally, the maximum entropy or uncertainty was calculated as $\log(K)$, with
K being the number of classes in the system (Goovaerts, 1997; Shannon, 1949). The maximum uncertainty in a system with two distribution functions originally was calculated using Eq. [3-5]. Both functions are logarithmic distributions and increase less rapidly with increasing numbers of classes.

In this study, $U_{\text{max}}$ was used to normalize the computed uncertainty. This allowed us to compared the uncertainty in the predicted mass emissions with the uncertainty in the predicted travel times, if the number of classes would not affect the uncertainty in a system. Results from a reclassification study in which the uncertainty in mass emissions was computed for different numbers of classes (Table 5-18), revealed that: 1) the uncertainty in a system increased when the number of classes decreased, irrespective of the classification method and; 2) the classification method affects the uncertainty in the system. A conclusion from these observations is the fact that computed uncertainties for the mass emissions and travel times cannot be compared directly, because the number of classes for the two variables were not equal. Taking into account the fact that the computed $U_H$ for the travel times is greater than the $U_H$ for the mass emissions and that the travel time is based on 147 classes vs 26 for the mass emission, the predicted travel time was more uncertain than the predicted mass emission.
Table 5-18. Uncertainty in the predicted mass emissions at the 1.0-m depth for hexazinone leaching as a function of the number of classes. Uncertainty was computed for sample location two at the Santa Fe Beef Unit test site.

<table>
<thead>
<tr>
<th>Number of Classes</th>
<th>Uncertainty</th>
<th>Class Width</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logarithmic Scale</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>0.334</td>
<td>10</td>
</tr>
<tr>
<td>13</td>
<td>0.390</td>
<td>100</td>
</tr>
<tr>
<td>7</td>
<td>0.299</td>
<td>1000</td>
</tr>
<tr>
<td>4</td>
<td>0.440</td>
<td>10000</td>
</tr>
<tr>
<td>Linear Scale</td>
<td></td>
<td></td>
</tr>
<tr>
<td>102</td>
<td>0.130</td>
<td>0.008</td>
</tr>
<tr>
<td>51</td>
<td>0.144</td>
<td>0.016</td>
</tr>
<tr>
<td>26</td>
<td>0.166</td>
<td>0.032</td>
</tr>
<tr>
<td>14</td>
<td>0.196</td>
<td>0.065</td>
</tr>
<tr>
<td>8</td>
<td>0.244</td>
<td>0.130</td>
</tr>
</tbody>
</table>

† Mass emissions smaller than 10^{-23} kg a.i ha^{-1} were added to the smallest class.

Reclassification of the mass emissions using a logarithmic scale or based on a linear scale resulted in different uncertainties in the system. The logarithmic scale had considerably higher uncertainty than the uncertainty based on a linear scale and its range. A logarithmic scale was used to classify the mass emissions because the model computed mass emissions based on first-order degradation and, therefore, a non-linear scale was expected to better reflect the distribution of mass emissions. Use of different classification scales is another reason why the uncertainty in the predicted mass emissions and travel times cannot be compared directly.

It can be concluded that the developed uncertainty method is not scalable and that different parameters can only be compared when the number of classes and the scale (linear, logarithmic) are the same.

In several simulations it was observed that the uncertainty decreased (Table 5-16), rather than increased, with depth. This suggested that the uncertainty in the system might decrease at depths deeper than 2.0m. Therefore, hexazinone leaching was simulated for depths up to 5.0m using sample location 2 as an example. The results (Fig. 5-40) showed that uncertainty in the
system initially increased, and then decreased deeper in the soil profile. The results showed that the differences between predicted and site-referenced mass emissions and travel times should be damped with depth. The increased uncertainty for the travel time at depths greater than 4.0m was caused by a high percentage of simulations in which hexazinone did not arrive at this depth within the 40-year time period.

Figure 5-40. Uncertainty in the predicted mass emissions and travel times as a function of depth. The uncertainty is calculated for sample location 2.

Of concern is the uncertainty introduced by the Alachua County soil survey map. Of all the selected input parameters, it ranked the highest in uncertainty for both the predicted mass emissions and travel times. Initial overlay analysis of the Alachua County soil survey map and the developed recompiled high intensity soil survey map indicated that the Alachua County soil survey map was of poor quality, with up to 95% of the area of the test site being inaccurate at the series level. At different levels in the soil taxonomy this percentage was smaller. At the soil order level the Alachua County soil survey map and the HISMR matched for 55.5% of the area, though decreased to 36.4% at the soil suborder level. The next greatest change in matching areas happened at the soil subgroup level, where only 6.8% of the soil map areas matched. One of the sources of uncertainty and mismatches in the Alachua County soil survey map was the absence
of flood plain soils at the time of the original Alachua County soil survey, such as Osier-Bibb and Bigbee. These soils were not recognized when the soil survey report for Alachua County was established. Secondly, the presence of an argillic horizon near the soil surface at various locations throughout the test site might have gone undetected, as at several locations this layer was near the 2.0-m depth. Consequently, soils that were classified as Entisols might actually have been Ultisols if the sample was taken at a location when the argillic horizon occurred within the 2.0-m depth. An example at the test site were those areas where originally Gainesville was mapped but where presence of the argillic horizon reclassified the soil as Millhopper. The Alachua County soil survey map used might only be an example of a low quality county soil survey report, at least at the test site, and might actually be an exception when compared with other soil surveys in the state of Florida, but rarely if ever can one expect a county soil survey to have 50m times 50m intensity of soil survey.

With the advent of desktop GIS, more researchers are using digitized soil maps for modeling and assessment studies. Currently, the digitized county soil survey map is often the only source of spatial information regarding the distribution of soils over the landscape for field, farm, watershed or county. Many of the users, mostly non-soil scientists, are often not aware of the limitations and “general” character of the survey. First of all, when developing the soil survey, at only a few selected locations is the soil actually sampled, with other information obtained from the landscape and vegetation. When applying the county soil survey map for large-scale studies, ground-truthing of the soil map for that site is a necessity.

Results from the field study and the subsequent uncertainty analysis indicated that the organic carbon content of the soil surface horizon had a significant impact on the uncertainty in predicted pesticide leaching for both hexazinone and simazine. Measured organic carbon content was 2-fold higher than corresponding data from the UF soil characterization database. Soil characterization data from UF and the Natural Resources Conservation Service usually describe a typical pedon for a series from a undisturbed area and, therefore, are of limited usefulness in an agricultural setting. As agricultural activities impact the surface horizon, it becomes important to update the pedon data sets for the agricultural setting. Ideally, all the required input parameters
for environmental-fate predictions should be characterized for the surface horizon but, if nothing else, at least the organic carbon content should be measured for this governs pesticide movement and, therefore, both mass emissions and travel times.

In many environmental-fate models the presence of a restricting layer, such as the argillic horizon, is treated like any other soil horizon, except that its drainage properties are different. This is especially true for environmental-fate models in which movement of water and pesticides is governed by the redistribution of water between field capacity and the permanent wilting point. Presence of an argillic horizon in the soil profile might alter patterns of pesticide movement, where, instead of continued vertical downward movement, water and pesticides might flow on top of the clay layer to deeper depths or downslope locations or might collect on top of the clay layer. Current lack of data to describe water and pesticide flow in these environmental settings limits our ability to model pesticide movement under such conditions. At best we should be able to model pesticide movement to the argillic layer or any other confining layer and then use those results in assessment studies rather than just considering leaching to an arbitrary depth.

In this research the site-referenced modeling scenario was presented as being free of error and uncertainty. However, these data are prone to error and imprecision as well, with examples including the variability in measured organic carbon content for point locations, and single values for the rooting depth and depth of the argillic horizon. Consequently, the site-referenced computed mass emissions and travel times remain uncertain. The uncertainty should be less than for the predicted modeling scenario, because more information was collected regarding the site-specific conditions. Updated information including several site-specific parameters (rooting depth, organic carbon content, depth to argillic horizon, and soil map), and better estimates of the pesticide environmental-fate properties, were collected and used. It was assumed that these data better reflected conditions at the Santa Fe Beef Unit. To determine actual uncertainty in the predictive modeling scenario, pesticide-fate field experiments should be carried out to determine actual pesticide fate properties (half-life and partition coefficient) for this site.
Predictive pesticide modeling will always be an uncertain exercise, because it will be difficult to obtain suitably accurate and precise information for any given site. Also, our inability to predict the climate limits the reliability of our predictions and, thus, introduces uncertainty.

**Fuzzy Logic Approach**

Fuzzy set theory has been used as an alternative method to the entropy method to classify uncertainty in pesticide leaching within the vadose zone. Fuzzy set classification accounts for uncertainty by means of the degree of membership to a fuzzy set. The higher the degree, the more a given value belongs to that class. In this study four fuzzy sets (certain, intermediate, uncertain, and extragrades) were used to classify the probability difference function, \( |dP| \), for the mass emissions and travel times of hexazinone at the three control depths. The fuzzy set “extragrades” is an overflow class into which all the extremely large values of \( |dP| \) are placed. One might interpret this set as being extremely uncertain, and that predictions thus are unreliable for use. Unlike the entropy approach, the fuzzy set approach does not produce a single final map representing uncertainty at the Santa Fe Beef Unit. The use of multiple classes for mass emissions and travel times resulted in an equal number of fuzzy maps. Therefore, for both mass emissions and travel times, selected examples were used to illustrate the use and application of fuzzy set theory in this research.

**Mass emissions; hexazinone**

The application of fuzzy sets to classify uncertainty in the predicted mass emissions of hexazinone at the Santa Fe Beef Unit test site is shown for three classes \( (10^{-1}, 10^{-6}, 10^{-9}) \) kg a.i. ha\(^{-1}\) and depths (1.0m, 2.0m, and depth to the argillic horizon). Each of the figures (Figs. 5-41 - 5-49) show the degree of membership for each of the four fuzzy classes (Fig. 5-41a - d) and the confusion index (Fig. 5-41e). The degree of membership ranges from 0 to 1, with 0 being no
member and 1 being a full member of the fuzzy set. Membership values of 0.5 are considered to represent the cross-over point. The cross-over point indicates the lowest membership value of interest to which one believes that a value belongs to the fuzzy set. When multiple fuzzy sets are used for classification of the same variable, the confusion index (CI) can be used as a measure of dominance. Lower CI values indicate less confusion as to which fuzzy set a value belongs, because one set has a high degree of membership. Higher CI values indicate that more confusion is present in the system and thus it is not clear to which fuzzy set a particular value belongs.

Fuzzy classification of the mass emissions between $10^{-2}$ - $10^{-1}$ kg a.i. ha$^{-1}$ (Fig. 5-41) at the 1.0-m depth showed that most areas were classified as belonging to the fuzzy sets “certain” or “intermediate”; i.e., the predicted mass emissions were considered to have little to moderate uncertainty, as $|dP|$ was small. Only a few points were classified as being members of the fuzzy sets “uncertain” or “extragrades”. The resulting CI map (Fig. 5-41e) showed that, for the greater part of the test site, the CI was low. Thus suggests little confusion as to which classes the calculated $|dP|$ values belong. A few areas, mainly where Gainesville soil series was originally mapped, had high CI values, indicating that the $|dP|$ values did not belong to a large degree to any of the four fuzzy classes.

With increasing depth the degree of membership changed. At the 2.0-m depth (Fig. 5-42) there was a shift towards higher degrees of membership for both the “certain” and “intermediate” fuzzy sets. At this depth, only one location and its directly surrounding area was classified as being uncertain. Originally, Gainesville was mapped at this location, but ground-truthing mapped a Millhopper instead. At this location the predictions had to be considerably different to be classified as uncertain. Since the membership maps displayed higher degrees of membership for the various fuzzy classes, the CI map showed very confusion, and only a few areas had moderate confusion. When the degree of membership at the depth of the argillic horizon was considered (Fig. 5-43), the spatial distribution followed yet another spatial pattern. The spatial distribution of the fuzzy set “intermediate” resembles similar patterns as the 2.0-m depth, and the presence of several locations with high membership values resembled the 1.0-m depth. The final CI map indicated that there were several locations with confusion, but that the CI was low overall.
Figure 5-41. Membership functions and confusion index for mass emissions between $10^{-1}$ and $10^{-2}$ kg a.i. ha$^{-1}$ at the Santa Fe Beef Unit of hexazinone at 1.0m depth.  
(a) Certain; b) Intermediate; c) Uncertain; d) Extragrade; e) Confusion index.
Figure 5-42. Membership functions and confusion index for mass emissions between $10^{-2}$ and $10^{-1}$ kg a.i. ha$^{-1}$ at the Santa Fe Beef Unit of hexazinone at 2.0m depth. a) Certain; b) Intermediate; c) Uncertain; d) Extragrade; e) Confusion index.
Fuzzy classification of the mass emissions between $10^{-5} - 10^{-6}$ kg a.i. ha$^{-1}$ indicated that the $|dP|$ values were sufficiently small at the 1.0-m depth in the soil profile to be considered “certain” (Fig. 5-44), and only a few locations were classified as having intermediate certainty. The resulting CI map showed little confusion. At the 2.0-m depth (Fig. 5-45) and the depth of the argillic horizon (Fig. 5-46), the degree of membership for the fuzzy class “certain” became smaller but all the membership values remained above the 0.5 level. Only for a few locations in the field did the uncertainty increase, because of increased membership values for the fuzzy sets “intermediate” and “uncertain”. The uncertainty for this mass emission class was traced back to areas where Bonneau or Norfolk were mapped during ground-truthing of the soil map.

Mass emissions for the $10^{-8} - 10^{-9}$ kg a.i. ha$^{-1}$ class were not often predicted at the 1.0-m depth for hexazinone in both the predictive and site-referenced modeling scenarios. As the probability difference became smaller, the degree of membership of the fuzzy set “certain” increased and the overall uncertainty increased. Often, high degrees of membership for the fuzzy set “certain” resulted from a lack of observations in a mass emission class or a low probability of occurrence in the considered class. Thus, the fuzzy map (Fig. 5-47) shows a strong bias towards certainty and little to no confusion regarding the class to which $|dP|$ values belong. With increasing depth, it became increasingly more common that smaller mass emissions (e.g., $< 10^{-9}$ kg a.i. ha$^{-1}$) were predicted. Consequently, the probability of the lower mass emission classes increased, as did the probability difference. Thus, the uncertainty in the system increased (Fig. 5-48 and Fig. 5-49). In spite of the increasing uncertainty, confusion in the system did not increase and the CI remained small over the entire test site.

The results presented in Fig. 5-41 - 5-49 are a sample of the 26 mass classes. It is clear that there is some bias towards the fuzzy set “certain”, with this being the the most dominant class in all mass emission classes. The fuzzy interval $0 < |dP| < 0.05$ was perhaps too wide and, therefore, most results had a high degree of membership in the fuzzy set “certain”. Also, for several mass classes $|dP| = 0$ was calculated, because no mass emissions were computed that fell within the boundaries of these classes. This was also classified as being “certain”. However, it is always possible that those mass emissions still were predicted, though they were not predicted in this study.
Figure 5-43. Membership functions and confusion index for mass emissions between $10^{-2}$ and $10^{-1}$ kg a.i. ha$^{-1}$ at the Santa Fe Beef Unit of hexazinone at argillic depth. a) Certain; b) Intermediate; c) Uncertain; d) Extragrade; e) Confusion index.
Figure 5-44. Membership functions and confusion index for mass emissions between $10^{-6}$ and $10^{-5}$ kg a.i. ha$^{-1}$ at the Santa Fe Beef Unit of hexazinone at 1.0m depth. 
a) Certain; b) Intermediate; c) Uncertain; d) Extragrade; e) Confusion index.
Figure 5.45. Membership functions and confusion index for mass emissions between $10^{-6}$ and $10^{-5}$ kg a.i. ha$^{-1}$ at the Santa Fe Beef Unit of hexazinone at 2.0m depth. 

a) Certain; b) Intermediate; c) Uncertain; d) Extragrade; e) Confusion index
Figure 5-46. Membership functions and confusion index for mass emissions between $10^{-6}$ and $10^{-5}$ kg a.i. ha$^{-1}$ at the Santa Fe Beef Unit of hexazinone at argillic depth. 
a) Certain; b) Intermediate; c) Uncertain; d) Extragrid; e) Confusion index.
Figure 5-47. Membership functions and confusion index for mass emissions between $10^{-9}$ and $10^{-8}$ kg a.i. ha$^{-1}$ at the Santa Fe Beef Unit of hexazinone at 1.0m depth. 

a) Certain; b) Intermediate; c) Uncertain; d) Extragrade; e) Confusion index.
Figure 5-48. Membership functions and confusion index for mass emissions between $10^{-9}$ and $10^{-8}$ kg a.i. ha$^{-1}$ at the Santa Fe Beef Unit of hexazinone at 2.0m depth. a) Certain; b) Intermediate; c) Uncertain; d) Extragrade; e) Confusion index.
Figure 5-49. Membership functions and confusion index for mass emissions between $10^{-9}$ and $10^{-8}$ kg a.i. ha$^{-1}$ at the Santa Fe Beef Unit of hexazinone at argillic depth. a) Certain; b) Intermediate; c) Uncertain; d) Extragrade; e) Confusion index.
Travel time; hexazinone

Travel time is an important indicator of the time period in which a pesticide might actually leach to a specified depth or groundwater zone. Uncertainty in the predicted travel time was classified using fuzzy sets for the 147 travel time classes and three control depths in the soil profile. The results for three of the classes are discussed in the following section as an example of the application of fuzzy set classification to travel time.

Travel time uncertainty as expressed in the degree of membership values at the 1.0-m depth for the 300-400 day period showed considerable variability in degrees of membership (Fig. 5-50). Maximum membership values were computed for the fuzzy sets “certain”, “intermediate” and “uncertain”. The resulting confusion index (CI) map showed that several zones of confusion were present at this depth. For these areas (Millhopper was mapped during ground-truthing, whereas Gainesville was mapped according to the Alachua county soil survey report) it was confusing as to what fuzzy sets the difference in probability, |dP|, belonged. At the 2.0-m depth most of the test site was classified as being “certain”. This was mainly due to the lack of observations of travel times to the 2.0-m depth (Fig. 5-51) for this time class. Hexazinone would not normally leach to this depth within the 300 - 400 day time period. In fact, only along the eastern border of the test site, where Tavares originally was mapped, did hexazinone leach to this depth within the 300 - 400 day period. The degree of membership in this region indicates partial membership in the fuzzy sets “certain” and “intermediate”. Consequently, the CI is high. More interesting is the classification of travel time to the depth of the argillic horizon, because the depth of the argillic horizon varies between 0.22m and over 2.0m at the test site. Therefore, the travel time showed significant variation. It was expected that, for locations with a shallow argillic horizon, the travel times would be shorter and the differences between the predicted and site-referenced modeling scenarios would be smaller. An increased degree of membership for the fuzzy set “certain” should result. Fuzzy classification of the 300 - 400 day time period (Fig. 5-52) showed the contrary. Areas with a shallow argillic horizon had low degrees of membership in the fuzzy set “certain”, with the spatial correlation between the argillic depth and the travel time being 0.11.
Figure 5-50. Membership values and confusion index for the travel time of hexazinone to 1.0m depth for 300 - 400 days.

a) Certain; b) Intermediate; c) Uncertain; d) Extragrades; e) Confusion index.
Figure 5-51. Membership values and confusion index for the travel time of hexazinone to 2.0m depth for 300 - 400 days.
a) Certain; b) Intermediate; c) Uncertain; d) Extragrades; e) Confusion index.
Figure 5-53. Membership values and confusion index for the travel time of hexazinone to 1.0m depth for 1000 - 1100 days.
a) Certain; b) Intermediate; c) Uncertain; d) Extrarades; e) Confusion index.
Fuzzy classification of the predicted travel times of 1000 - 1100 days to the 1.0-m depth (Fig. 5-53) was an example in which the fuzzy set “certain” did not dominate classification of the $|dP|$. At this depth, the classification indicated a shift towards the “intermediate” uncertainty fuzzy set. However, the degrees of membership for a few locations reached the maximum value for the four fuzzy classes. Thus, the resulting CI map showed considerable confusion in results. The $|dP|$ values for these locations being neither full member of the “certain” nor “intermediate” fuzzy sets, but with values instead in-between those fuzzy sets. One might consider such values intergrades. Intergrades were a result of insufficient classes to cover the range of predicted travel times. With increasing depth, our predictions become more certain for this time class. Both at the 2.0-m depth (Fig. 5-54) and the depth of the argillic horizon (Fig. 5-55), there was decreased uncertainty in the predictions because the degree of membership increased for the fuzzy set “certain”.

Uncertainty in the travel time for the 2500 - 2600 day period at the 1.0-m depth (Fig. 5-56), 2.0-m depth (Fig. 5-58), and depth of argillic horizon (Fig. 5-59) were examples in which the uncertainty was very low. Probability difference values were small enough (< 0.02) to have full degree of membership in the fuzzy set “certain”. This is partly caused by the fact that predicted and site-referenced travel time probabilities were similar for this class, and also because there were no observations available. Thus, uncertainty defaults to full degree of membership in the fuzzy class “certain”. Depending on the soil, hexazinone did not arrive (e.g., Chipley sand) at this depth or had already leached below (e.g., Bonneau fine sand) the control depth within the given 2500 - 2600 days. Thus, uncertainty defaulted to the highest degree of membership in the fuzzy set “certain”. Maps for the CI followed an inverse pattern for this fuzzy set.

Maps displaying the spatial distribution of the degree of membership for fuzzy sets and the associated CI map for other time periods than the ones shown could be roughly divided into two groups. One group could be summarized as having results similar to those shown in Fig. 5-56 - 5-58, with the travel times for this particular group being larger than 10 000 days. Complete confidence or no-uncertainty is caused by the lack of observations to introduce some differences between the predicted and site-referenced travel times. The other group showed considerable
Figure 5-52. Membership values and confusion index for the travel time of hexazinone to the argillic depth for 300 - 400 days.
(a) Certain; (b) Intermediate; (c) Uncertain; (d) Extragrades; (e) Confusion index.
Figure 5-54. Membership values and confusion index for the travel time of hexazinone to 2.0m depth for 1000 - 1100 days.

a) Certain; b) Intermediate; c) Uncertain; d) Extragrades; e) Confusion index.
Figure 5-55. Membership values and confusion index for the travel time of hexazinone to the argillic depth for 1000 - 1100 days.
a) Certain; b) Intermediate; c) Uncertain; d) Extragrades; e) Confusion index.
Figure 5-56. Membership values and confusion index for the travel time of hexazinone to the 1.0-m depth for 2500 - 2600 days.

a) Certain; b) Intermediate; c) Uncertain; d) Extragrades; e) Confusion index.
Figure 5-57. Membership values and confusion index for the travel time of hexazinone to the 2.0-m depth for 2500 - 2600 days.

a) Certain; b) Intermediate; c) Uncertain; d) Extragrades; e) Confusion index.
Figure 5-58. Membership values and confusion index for the travel time of hexazinone to the argillic depth for 2500 - 2600 days.
a) Certain; b) Intermediate; c) Uncertain; d) Extragrades; e) Confusion index.
confusion for one or more soils series at any particular travel-time class. This related to travel times shorter than 10 000 days. The greatest confusion was found for predictions to the depth of the argillic horizon. Hexazinone had leached past all depths for these travel times and the calculated $|dP| = 0$. Thus, all these values had the highest degree of membership for the fuzzy set “certain”. For other travel-time classes, the confusion index seemed to follow no particular pattern other than that each soil series exhibited some confusion depending on the travel-time class.

**Fuzzy sets and uncertainty classification**

Uncertainty is different for each person. One person might classify results as being uncertain when $|dP|$ exceeds a set threshold of, for example, 0.10, whereas for another person this might be for example 0.05. These are examples of typical true-or-false classifications; a.k.a. boolean classifications. Any values greater than the threshold are uncertain and anything smaller than the threshold is certain. Fuzzy sets address uncertainty in the predictions by means of the degree of membership in a set. Herein lies a difficulty similar to the traditional boolean classification. How does one establish acceptable fuzzy classes? Fuzzy sets can vary in shape and range, they can be represented by an interval having maximum degree of membership, or they can have just a single value to which the maximum degree of membership is assigned. In this study, fuzzy sets had an interval to which the maximum degree of membership was assigned. Additionally, a sinusoidal model was used to compute the degree of membership outside the maximum membership value range. The interval length was set to 0.05 for the mass emissions and to 0.02 for the travel times. Distance between the intervals for the maximum membership values of the fuzzy sets was set to the same width as the interval width of maximum degree of membership. In this study intervals were biased towards the fuzzy set “certain”, considering the high degree of membership that was computed for this fuzzy set for most classes of both mass emissions and travel time. Membership values for the three other fuzzy sets occasionally reached a maximum degree of membership, but not nearly as frequently as the fuzzy set “certain”. The
high degree of membership for the fuzzy set “certain” is either due to low uncertainty in the predictions or to bias towards the fuzzy class. If different values for the interval width and shape parameter of the sinusoidal model were used, the fuzzy map would be different.

Also, why can a single fuzzy set not be used to classify the uncertainty in predictions? If one is merely interested in the certainty of the predictions and not in additional classification of results, it should be possible to use only a single fuzzy set to classify results. The degree of membership of the fuzzy set “certain” might then be used as an indicator of the uncertainty for the predictions. Similar to the fuzzy classification itself, high degrees of membership indicate little uncertainty, whereas low degrees of membership indicate uncertainty. This approach would be easy and straightforward to apply and would eliminate the need for additional fuzzy sets and the computation of a confusion index.

Information provided by the confusion index includes a measure of dominance and provides additional information on variability of the fuzzy classification in the system. The confusion index has little meaning when it is simply presented by itself, for one cannot determine what the dominant fuzzy class was. In the fuzzy classification study presented here, application of the confusion index did not add more information to the results, since it was generally clear what the dominant fuzzy set was.

A disadvantage of using fuzzy set classification was the number of maps generated for interpretation and classification of uncertainty in the predictions. For mass emissions 26 times five maps and for travel times 147 times five maps were generated to classify |dP| in terms of fuzzy sets. Although it is possible to analyze each of these maps in detail, it is not practical to quantify uncertainty in pesticide leaching.

An alternative to fuzzy set classification would be the application of fuzzy numbers in the computation of pesticide fate in the environment. Fuzzy numbers are similar to fuzzy sets, but are described in terms of numbers and have the additional advantage that complete arithmetic is available. A fuzzy number, like a fuzzy set, has a central concept and degrees of memberships for values deviating from the central concept. This embeds uncertainty in the input data. Application of fuzzy numbers would embed uncertainty directly into the input parameters of the
model; however, current environmental-fate models are not capable of using fuzzy numbers. Fuzzy arithmetic follows different rules and, therefore, two fuzzy numbers cannot be subtracted in a manner similar to that used for crisp numbers. Simple environmental-fate models such as the attenuation factor (Rao et al., 1985) could be used, if the proper fuzzy numbers (at each degree of membership) were implemented in the model. The fuzzy number output for the mass emissions and travel times could then be used as an alternative to quantify or embed uncertainty in pesticide leaching.

To Krige or Not To Krige

Application of spatial interpolation methods based on Krige’s work has become increasingly popular over the past two decades. Kriging, using a best unbiased estimator, is useful when point data are available and a surface map for a spatial phenomenon needs to be generated. One of the underlying assumptions of kriging is that the phenomenon of interest is normally distributed or can be transformed to a normal distribution. For the latter, the lognormal transformation is often chosen. More complex transformation methods are available but are not generally used, because the back transformations of the interpolated maps may introduce unwanted and unforeseen errors (Cressie, 1993; Isaaks and Srivastava, 1989).

The application of spatial interpolation by means of kriging was often unsuccessful in this research. Modeling of the spatial structure using nontransformed and transformed data often revealed that the sampling distance of 50m was insufficient to capture the short-range spatial variability and model it with a semivariogram (Fig. 5-59). This semivariogram is a good example of a pure nugget effect, with a pure nugget effect being the result of complete lack of spatial correlation between the data values at any location in the field (Cressie, 1993; Isaaks and Srivastava, 1989). The pure nugget effect shown is the result of sampling distance, with the 50m sampling distance being too great to capture the spatial structure. Mathematically, a nugget effect should not happen (Cressie, 1993), because this is the spatial semivariance at lag-distance
0. At lag-distance 0, the spatial variance is computed for the point with itself, which is by definition 0 (see Eq. [2-10]). Additional exploratory data analysis revealed that the data set was non-normally distributed and that transformations did not provide a distribution resembling a normal distribution, which is an underlying assumption of kriging. Consequently, kriging could not be used to generate a surface for the variables at the site.

For several variables, the spatial structure could be modeled with a semivariogram, but the resulting surface map showed results that are impossible. Examples include negative mass emissions, travel times, and variances (Fig. 5-60). For cases such as these, alternative methods of spatial interpolation were used. Available methods included splines and inverse-distance weighting (IDW). The advantage of splines is that they give visually nice maps and take local trends into account. Also, the generated surface maps go through each point location in the field. Examples of maps generated using splines include the digital elevation map (Fig. 3-3) and the depth to argillic horizon (Fig. 4-10). However, the nature of this method (fitting a curve through a series of points) allows for predicted negative values for mass emissions, travel times, and variance for mass emission and travel time, even though such values are impossible. As a last alternative, IDW was used to generate surface maps in order to display the spatial distribution of each variable considered. IDW uses the distance between neighboring points as a weighting factor to interpolate between the points. Maps generated with IDW usually show a sphere of influence for the central point in the calculation, thereby not always being representative of what really happens in nature. One advantage to this method is that it will not predict negative values if only positive values are present in the data set.

Even when the semivariogram could be modeled, the kriged surface map did not always produce acceptable results (Fig. 5-60). The semivariogram showed that spatial correlation exists for the travel of hexazinone to the depth of the argillic horizon. However, the semivariogram showed four outliers. These are only a few of the point-pairs for which the semivariance was calculated and they have little influence on computation of the semivariogram parameters. The black areas in the kriged surface map represent negative values for the estimated travel time. This is more surprising when one realizes that the points surrounding the negative values were all
positive values (travel time > 300 days). Clearly, the semivariogram model was incorrect, but application of different semivariogram models produced similar results. Next, splines were used to model spatial variability for mean travel time to the argillic horizon (Fig. 5-58c). The results produced with splines were worse than those produced with kriging. Finally, IDW was used to generate a surface map for the travel time variance to the depth of the argillic horizon. Although a relatively crude map was generated, the values were positive and the main spatial distribution could be visualized.
Figure 5-60. Spatial distribution of the mean travel time of hexazinone to the argillic depth. The black areas indicate negative numbers. 
a) Semivariogram; b) Kriged surface map; c) Splined surface map; d) Inverse distance surface map.

The issue here is that often the short-range variability cannot be modeled because sampling distances are too large to be captured. Consequently, kriging was not a suitable method with which to generate surface maps for the spatial phenomena under study. However, some researchers argue that a pure nugget effect can be modeled with ordinary point kriging. Results here indicate that ordinary kriging produced some unrealistic and impossible results for mass emissions, travel time and variances. For the same reason, splining did not produce acceptable results and IDW had to used to generate maps displaying the spatial distributions for the variables of interest.
In this study a method was developed to quantify the uncertainty in predictive pesticide assessments. For a selected 19.55 ha test site at the Santa Fe Beef Unit, Alachua County, FL, the uncertainty in predicted mass emissions and travel times for two herbicides – Velpar (hexazinone) and Princep (simazine) -- was quantified for three control depths in the soil profile. The soil profile considered was 0.0 - 2.0m depth and conclusions are valid for this range only.

- Current county soil survey maps need to be ground-truthed before being used in a pesticide leaching study.
- When predicting pesticide leaching in agricultural areas and using imported data, at least organic carbon content and rooting depth should be obtained from the site, because they strongly affect the model predictions. In the case of the Santa Fe Beef Unit test site, site-specific data for the organic carbon content of the surface horizon were significantly ($\alpha = 0.05$) higher than for data obtained from the UF soil characterization database, which contains data for typical pedons representing the same soil series in the state of Florida.
- Depending on the environmental-fate model used, the rooting depth might be a sensitive parameter. For the CMLS98B model, the rooting depth is sensitive and, therefore, site-specific data need to be obtained.
- Pesticide leaching studies should at least compute mass emissions and travel times to confining or impervious layers in the soil profile.
- Uncertainty in the predicted mass emissions and travel times can be quantified using the normalized Shannon entropy with regards to the absolute difference in
probability between the predicted and site-referenced probability distribution functions. The advantage of this approach is that the method is independent of the environmental-fate model and the uncertainty can be expressed as a number in the range [0,1].

- It has been demonstrated that the entropy approach works well in a spatial environment, which allows us to quantify the uncertainty for any region of interest and to show the spatial variability of the uncertainty within a selected field.
- The entropy approach is capable of calculating the contribution to uncertainty of each model input parameter. However, the method does not allow us to calculate the fraction of total uncertainty for each parameter, as the sum of the uncertainty of individual model parameters is larger than the total uncertainty.
- This study demonstrated that uncertainty increased with depth. For mass emissions, the uncertainty for the test site increased in the order 0.33 < 0.38 < 0.46 for the 1.0 m, argillic-depth, and 2.0 m depths, respectively. The uncertainty in the travel time increased from 0.30 < 0.40 < 0.47 for the three control depths (1.0 m, argillic-depth, and 2.0 m).
- The uncertainty contributed by the soil map in predicting mass emissions was 0.30 - 0.64 depending on the depth, with corresponding values of 0.37 - 0.67 with respect to predicted travel times.
- Uncertainty in the predicted mass emissions based on each input parameter increased in the order: curve number < precipitation < pesticide half-life < partition coefficient < organic carbon content < rooting depth < soil map. For the predicted travel times the ranking was: curve number < pesticide half-life < precipitation < partition coefficient < organic carbon content < rooting depth < soil map.
- Uncertainty at the Santa Fe Beef Unit test site ranged from 0.17 - 0.84 at the [0,1] scale for both mass emissions and travel times. This suggested that
considerable uncertainty existed locally with respect to pesticide leaching predictions. Without a measure of uncertainty pesticide leaching studies are of little value, because predictions might be misleading. Consequently, any leaching study should provide a measure of uncertainty along with the predicted pesticide fate. However, the uncertainty in predictive modeling can only be quantified when site-specific data are available. Even these data are prone to imprecision and, thus, introduce uncertainty into the predictions.

- Fuzzy set classification is an alternative way of describing uncertainty in predicted pesticide mass emissions and travel times. Fuzzy set classification maps indicated that predicted mass emissions and travel times contained little uncertainty. However, the results seemed to have a strong bias towards certainty, as the fuzzy set “certain” consistently had a high degree of membership.

- Fuzzy set classification, as used in this study, did not appear to be suitable for quantifying uncertainty in predicted pesticide leaching to specific control depths.

- Kriging and splining are often not suitable methods to generate interpolated maps of a spatial phenomena, especially when the data can not be transformed to a normal distribution.

- Predicting pesticide fate in the environment is an uncertain exercise.

**Recommendations**

The current study was of limited scope because of the number of pesticides used and the limited amount of site-referenced data available. Based on this study it is recommended that:

- The entropy method be tested to quantify uncertainty for a number of pesticides in different areas for which site-specific soil maps and data are available.
Pesticides used in these studies encompass different categories – not only herbicides but also insecticides, nematicides, etc. – and should have different properties from the ones used in this research, for example, larger partition coefficients and half-lives.

The entropy approach be tested in an area without confining layers in the soil profile where water and dissolved pesticides can freely drain to the groundwater (for example, the Central Florida Ridge). This should enable us to study the impact of uncertainty on predicted mass emissions and travel times at greater depths than the current 2.0m, and take aquifer properties into account as well as considering the impact of exceeding the drinking water standards for a given pesticide or group of pesticides.

The entropy approach be tested with another model and the outcomes compared with results from the CMLS98B model. This would demonstrate that the method is model-independent and show the difference in uncertainty for both models.

The entropy approach be tested for all model parameters in order to determine what model parameters contribute most to uncertainty. The current study lacked sufficient site-specific data to determine the contribution of all model parameters to uncertainty.

Environmental simulations be performed using a fuzzy number representation of the input parameters used in both the predictive and site-referenced scenarios. The use of fuzzy numbers is desired over fuzzy classification, as it allows the generation of fuzzy maps for the predicted mass emissions and travel time rather than a series of maps representing the degree of membership for various mass-emission and travel-time classes.
Closing Remarks

As with any research project, it became clear over the course of this study that several improvements could be made which would enable better results. Such changes might include the following.

- Address the uncertainty introduced by Type I imprecision in the model input data and not only Type II imprecision. Having information regarding the uncertainty introduced by Type I imprecision would enable us to better quantify uncertainty introduced by Type II imprecision.

- Use a different test plot than the one used at the Santa Fe Beef Unit. The new test plot should be located at the western half of the current test site and be extended westwards, past the current boundaries into the adjacent pastures. This would enable us to deal with a system that is not strongly influenced by a stream and a deciduous forest.

- Use a randomized sampling design instead of a uniform sampling design. A randomized sampling design has the advantage of: a) additional spatial population statistics which can be computed to describe the spatial phenomena of interest, and b) the semivariogram can be better described as more lag distances become available.

- Verify the results of the interpolated maps by collecting data for additional sample locations in the field. For these locations, the collected data should be compared with the interpolated data because this will address the accuracy of the interpolations. Additionally compute the uncertainty for the additional sample locations and compare the results with the interpolated values for the uncertainty at these locations.
APPENDIX A
OFFICIAL SOIL SERIES DESCRIPTION

This appendix lists the official soil series description (USDA-NRCS, 1999) for soil series mapped at the Santa Fe Beef Unit.

**Bibb**

A 0.00-0.10m brown (10YR 4/3) sandy loam; weak fine granular structure; friable; common fine roots and pores; strongly acid; abrupt wavy boundary.

Ag 0.10-0.15m mottled dark gray (N 4/) and dark grayish brown (10YR 4/2) sandy loam; weak fine granular structure; friable; few fine roots and pores; common fine strong brown (7.5YR 5/6) stains around old roots; strongly acid; clear wavy boundary.

Cg1 0.15-0.94m gray (5Y 5/1) sandy loam; massive; friable; few fine roots and pores; common medium strong brown (7.5YR 5/6) stains around old roots; common thin strata of silt loam to loamy sand; some strata have bits of partially decomposed organic materials; very strongly acid; clear wavy boundary.

Cg2 0.94-1.50 m gray (N 5/) silt loam; massive; slightly sticky; common strata of sandy loam and loamy sand; common thin strata with partially decomposed organic materials; strongly acid.

**Bigbee**

Ap 0.00-0.20m dark yellowish brown (10YR 3/4) loamy sand; structureless; loose; few fine roots; strongly acid; clear smooth boundary.

C1 0.20-0.42 m yellowish red (5YR 4/8) loamy sand; structureless; loose, very friable; few fine roots; strongly acid; abrupt smooth boundary.

C2 0.42-0.82m yellowish brown (10YR 5/4) sand; structureless; loose; very strongly acid; clear smooth boundary.

C3 0.82-2.00 m pale brown (10YR 6/3) sand; structureless; loose; very strongly acid.

**Blichton Series**

Ap 0.00-0.13m very dark gray (N 3/0) sand; weak medium granular structure; very friable; common fine and medium roots; few pebbles of ironstone and weathered phosphatic nodules; medium acid; abrupt wavy boundary.

E 0.13-0.66m gray (10YR 6/1) sand; few coarse faint light gray (10YR 7/1) mottles and few, fine, distinct very pale brown streaks along root channels in upper part; single grained; loose; common fine and
medium roots; about 2 percent fine pebbles of ironstone and weathered phosphatic nodules; medium acid; clear wavy boundary.

**BEg** 0.66-0.75 m
gray (10YR 5/1) sandy loam; moderate medium and coarse granular structure; friable; common fine and medium roots; few fine sand bodies; about 4 percent pebbles of ironstone and weathered phosphatic nodules; strongly acid; clear wavy boundary.

**Btgl** 0.75-1.14 m
dark gray (N 4/0) sandy clay loam; common coarse prominent red (2.5YR 4/8) and yellowish red (5YR 5/8) mottles; moderate medium angular and subangular blocky structure; friable; few fine and medium roots; distinct clay films on faces of peds; about 12 percent nodules of plinthite; few pebbles of ironstone and weathered phosphatic nodules; few rod shaped siliceous bodies about 1/4 inch in diameter and 0.03 to 0.05 m in length; very strongly acid; gradual wavy boundary.

**Btg2** 1.14-1.65 m
dark gray (N 4/0) sandy clay loam; gray (N 5/0) crushed; common medium distinct yellowish red (5YR 4/8) and few, fine light gray mottles; moderate medium angular blocky structure; friable; few fine and medium roots; distinct clay films on faces of peds; about 10 percent nodules of plinthite; common medium pebbles of ironstone; very strongly acid; gradual wavy boundary.

**BCg** 1.65-1.93 m
gray (5Y 5/1) sandy clay loam; common fine distinct very pale brown and common fine prominent yellowish red mottles; weak subangular blocky structure; friable; very strongly acid; few light gray (10YR 7/1) lenses of sandy loam; gradual wavy boundary.

**Cg** 1.93-2.03 m
gray (N 5/0) stratified sandy loam, loamy sand, and sandy clay loam; common medium to coarse yellowish brown (10YR 5/6) and common medium prominent yellowish red (5YR 5/6) mottles; massive; friable; very strongly acid.

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**Bonneau Series**

**A** 0.00-0.08 m
very dark grayish brown (2.5Y 3/2) loamy sand; weak fine granular structure; very friable; many fine and medium roots; very strongly acid; abrupt wavy boundary.

**E1** 0.08-0.18 m
light yellowish brown (2.5Y 6/4) loamy sand; common fine faint very dark grayish brown (10YR 3/2) accumulations of organic matter coatings; weak fine granular structure; very friable; many fine and medium roots; very strongly acid; clear wavy boundary.

**E2** 0.18-0.56 m
light yellowish brown (2.5Y 6/4) loamy sand; weak fine granular structure; very friable; common fine and medium roots; strongly acid; abrupt wavy boundary.

**Bt1** 0.56-0.68 m
brownish yellow (10YR 6/6) sandy loam; weak coarse subangular blocky structure; very friable; few fine roots; strongly acid; clear wavy boundary.

**Bt2** 0.68-1.00 m
brownish yellow (10YR 6/6) sandy clay loam; common medium faint yellowish brown (10YR 5/6) soft masses of iron accumulations; weak coarse subangular blocky structure; friable; few fine roots; sand grains coated and bridged with clay; very strongly acid; clear wavy boundary.

**Bt3** 1.00-1.27 m
yellowish brown (10YR 5/8) sandy clay loam; many medium distinct gray (10YR 6/1) iron depeltions and common medium faint dark yellowish brown (10YR 4/4) soft masses of iron
accumulations; weak coarse subangular blocky structure; friable; few fine roots; few medium tubular pores; sand grains coated and bridged with clay; few faint clay films on faces of some peds; few fine uncoated sand grains (in old root pores); very strongly acid; clear wavy boundary.

Bt4 1.27-1.88m light gray (10YR 6/1) and yellowish brown (10YR 5/8) sandy clay loam; weak coarse subangular blocky structure; friable; sand grains coated and bridged with clay; very strongly acid.

Bruno
Ap 0.00-0.20m brown (10YR 4/3) sandy loam; weak fine granular structure; very friable; neutral; abrupt smooth boundary
C1 0.20-0.50m dark grayish brown (10YR 4/2) loamy sand; single grained; loose; neutral; abrupt smooth boundary.
C2 0.50-0.60m brown (10YR 5/3) loam; weak fine granular structure; very friable; neutral; abrupt smooth boundary.
C3 0.60-0.95m grayish brown (10YR 5/2) loamy sand; single grained; loose; neutral; abrupt smooth boundary.
C4 0.95-1.05m dark grayish brown (10YR 4/2) silt loam; weak fine granular structure; very friable; neutral; abrupt smooth boundary.
C5 1.05-1.50m light brownish gray (10YR 6/2) sand; single grained; loose; neutral.

Chipley Series
A1 0.00-0.08 m very dark gray (10YR 3/1) sand; single grained; loose; many fine roots; strongly acid; gradual smooth boundary.
A2 0.08-0.15m dark gray (10YR 4/1) sand; single grained; loose; many fine roots; strongly acid; gradual irregular boundary.
C1 0.15-0.41m light yellowish brown (10YR 6/4) sand; common fine and medium distinct yellowish brown coats and few medium distinct dark gray (10YR 4/1) streaks along the root channels; single grained; loose; few fine roots; strongly acid; gradual irregular boundary.
C2 0.41-0.82m brownish yellow (10YR 6/6) sand; common fine and medium faint strong brown (7.5YR 5/6) soft masses of iron accumulation and few fine faint streaks of light gray iron depletions; single grained; loose; few fine roots; strongly acid; gradual wavy boundary.
C3 0.82-1.40m coarsely multicolored brownish yellow (10YR 6/6), light gray (10YR 7/2) and strong brown (7.5YR 5/6) sand; single grained; loose; few fine roots; strongly acid; gradual irregular boundary.
Cg 1.40-1.93m light gray (10YR 7/2) sand; many coarse distinct very pale brown (10YR 7/4) and common, medium distinct yellowish brown (10YR 5/6) masses of iron accumulation; single grained; loose; very few fine roots; strongly acid; gradual smooth boundary.

Cowarts
Ap 0.00-0.20m dark grayish brown (10YR 4/2) fine sandy loam; weak fine granular structure; very friable; few fine dark concretions; strongly acid; abrupt wavy boundary.
BE 0.20-0.30m yellowish brown (10YR 5/4) fine sandy loam; weak medium granular structure; very friable; strongly acid; clear wavy boundary.
Bt1  0.30-0.48m  yellowish brown (10YR 5/8) sandy clay loam; weak medium subangular blocky structure; friable; few faint clay films on faces of peds; sand grains coated and bridged with clay; strongly acid; gradual wavy boundary.

Bt2  0.48-0.64m  yellowish brown (10YR 5/8) sandy clay loam; many coarse prominent yellowish red (5YR 5/8) and red (2.5YR 4/8) mottles; moderate medium subangular blocky structure; firm; few faint clay films on faces of peds; 3 percent nodules of plinthite; strongly acid; gradual wavy boundary.

C  0.64-1.52m  mottled red (10R 5/6), yellowish brown (10YR 5/6) and light gray (10YR 7/2) sandy clay loam with pockets and strata of coarser and finer textured material; massive; very firm; strongly acid.

Gainesville Series

A11  0.00-0.13m  very dark grayish brown (10YR 3/2) loamy sand; moderate medium granular structure; friable; numerous fine and medium roots; common fine and medium pores; few fine and medium weathered phosphatic and iron pebbles; strongly acid; clear smooth boundary.

A12  0.13-0.25m  brown (7.5YR 4/2) loamy sand; common, medium distinct yellowish brown (10YR 5/4) splotches; weak medium granular structure; friable; numerous fine and medium roots; many coated sand grains; common fine pores; few fine and medium weathered phosphatic and iron pebbles; strongly acid; clear smooth boundary.

C1  0.25-0.58m  brown (7.5YR 5/4) loamy sand; weak medium granular structure; very friable; common fine and medium roots; many coated sand grains; common root channels filled with brown (7.5YR 4/2) material from above horizon; common fine pores; few fine and medium weathered phosphatic and iron pebbles; strongly acid; clear wavy boundary.

C2  0.58-2.10m  strong brown (7.5YR 5/6) loamy sand; moderate, medium granular structure; friable; many coated sand grains; few pores and root channels; few fine and medium weathered phosphatic and iron pebbles; strongly acid; gradual wavy boundary.

Micanopy Series

Ap  0.00-0.13m  very dark gray (N 3/0) fine sand; moderate medium and coarse granular structure; very friable; common fine and few medium roots; strongly acid; abrupt smooth boundary. (4 to 8 m thick)

E  0.13-0.38m  brown (10YR 5/3) loamy fine sand; moderate medium granular structure; very friable; common fine and few medium roots; common medium faint grayish brown (10YR 5/2) bodies of stripped sand grains in upper 2 m; strongly acid; clear wavy boundary.

Bt1  0.38-0.50m  yellowish brown (10YR 5/6) sandy clay loam; weak medium subangular blocky structure; friable; few fine and medium roots; clay bridging between sand grains; strongly acid; clear wavy boundary.

Bt2  0.50-0.65m  yellowish brown (10YR 5/4) sandy clay; common fine distinct gray and few fine prominent yellowish red mottles; moderate medium subangular blocky structure; friable; very few roots;
faint discontinuous clay films on faces of peds; strongly acid; clear wavy boundary.

**Btg1** 0.65-1.13m  
gray (10YR 5/1) sandy clay; many coarse distinct yellowish brown (10YR 5/8) mottles with prominent dark red (2.5YR 3/6) centers; moderate medium subangular blocky and angular blocky structure; firm; slightly sticky and slightly plastic; prominent continuous clay films on faces of peds; strongly acid; clear wavy boundary.

**Btg2** 1.13-1.35m  
gray (10YR 5/1) sandy clay; many medium and coarse prominent dark red (10R 3/6), few fine faint light gray and strong brown mottles; weak medium subangular blocky and angular blocky structure; firm; slightly sticky and slightly plastic; discontinuous faint clay films on faces of peds; few slickensides; strongly acid; clear wavy boundary.

**Btg3** 1.35-1.40m  
gray (10YR 5/1) clay; many coarse faint gray (5Y 6/1) few fine prominent red and strong brown mottles; weak medium subangular blocky structure; extremely firm; sticky and plastic; few clay films; few slickensides; strongly acid; many stripped sand grains on prism faces; clear wavy boundary.

**BCg** 1.40-2.00m  
mixed gray (10YR 5/1; 5Y 6/1) sandy clay; common coarse strong brown (7.5YR 5/6) and common fine prominent dark red mottles; weak fine subangular blocky structure; very firm; slickensides; few small nodules of hard white limestone; common clean sand grains; strongly acid.

**Millhopper Series**

**Ap** 0.00-0.23m  
dark grayish brown (10YR 4/2) sand; weak medium granular structure; very friable; many fine and medium roots; medium acid; clear wavy boundary.

**E1** 0.23-0.53 m  
yellowish brown (10YR 5/6) sand; weak fine granular structure; very friable; few fine roots; slightly acid; clear wavy boundary.

**E2** 0.53-0.66m  
yellowish brown (10YR 5/4) sand; few fine faint brownish yellow mottles; single grained; loose, few fine roots; slightly acid; clear wavy boundary.

**E3** 0.66-1.22m  
light yellowish brown (10YR 6/4) fine sand; few fine distinct pale brown mottles; single grained; loose; few fine roots; slightly acid; clear wavy boundary.

**E4** 1.22-1.47m  
very pale brown (10YR 7/3) sand; few fine and medium distinct strong brown (7.5YR 5/6) and few fine distinct yellowish brown (10YR 5/8) mottles; single grained; loose; few fine roots; moisture content much greater than in horizon above; medium acid; clear wavy boundary.

**Bt** 1.47-1.63m  
yellowish brown (10YR 5/6) loamy sand; common medium distinct light gray (10YR 7/1) and few fine distinct strong brown mottles; weak fine subangular blocky structure; very friable; sand grains are coated and bridged with clay; medium acid; clear wavy boundary.

**Btg** 1.63-2.18m  
light gray (10YR 7/1) sandy clay loam; common medium faint (10YR 7/3) and few fine distinct strong brown mottles; weak medium subangular blocky structure; friable; thin discontinuous clay films on faces of peds; strongly acid; clear wavy boundary.

**BCg** 2.18-2.26m  
light gray (N 7/0) sandy loam; few medium faint light brownish gray (10YR 6/2) and few fine distinct very pale brown mottles; weak fine subangular blocky structure; friable; sand grains are well coated with clay; strongly acid.
Myakka Series

A 0.00-0.15m  black (10YR 2/1) crushed, sand; weak fine granular structure; very friable; matted with many fine and medium roots; strongly acid; clear smooth boundary.

E 0.15-0.50 m  white (10YR 8/2) sand; common fine faint vertical dark grayish brown, dark gray, and gray streaks along root channels; single grained; loose; common fine and medium roots; strongly acid; abrupt wavy boundary.

Bh1 0.50-0.60m  black (N 2/0) sand; weak coarse subangular blocky structure; many fine and medium roots; sand grained coated with organic matter except for common fine pockets of uncoated sand grains; very strongly acid; clear wavy boundary.

Bh2 0.60-0.82m  dark reddish brown (5YR 2/2) sand; common coarse faint vertical tongues of very dark brown (10YR 2/2) weak coarse subangular blocky structure; many fine and medium roots; sand grains coated with organic matter; very strongly acid; clear smooth boundary.

Bh3 0.82-0.90m  dark reddish brown (5YR 2/2) sand; weak fine granular structure; very friable; few fine roots; sand grains coated with organic matter; strongly acid; clear wavy boundary.

C/B 0.90-1.42m  dark brown (7.5YR 4/4) sand (C); weak fine granular structure; very friable; few fine roots; common medium distinct dark reddish brown (5YR 2/2) Bh bodies; strongly acid; clear wavy boundary.

C 1.42-2.13m  dark grayish brown (10YR 4/2) sand; single grained; loose; few fine roots; strongly acid.

Noboco

Ap 0.00-0.20m  dark grayish brown (10YR 4/2) loamy sand; weak fine granular structure; very friable; common fine and medium roots; moderately acid; abrupt smooth boundary.

E 0.20-0.33m  light yellowish brown (10YR 6/4) loamy sand; common coarse distinct dark grayish brown (10YR 4/2) mottles in upper part; weak fine granular structure; very friable; few fine roots; moderately acid; clear wavy boundary.

Bt1 0.33-0.64m  yellowish brown (10YR 5/8) sandy clay loam; moderate medium subangular blocky structure; friable; common distinct clay films on faces of peds; strongly acid; gradual smooth boundary.

Bt2 0.64-1.03m  yellowish brown (10YR 5/6) sandy clay loam; common medium distinct strong brown (7.5YR 5/6) mottles in lower part; weak medium subangular blocky structure; friable; common distinct clay films on faces of peds; very strongly acid; gradual smooth boundary.

Bt3 1.03-1.19m  yellowish brown (10YR 5/6) sandy clay loam; common medium prominent red (2.5Y 4/8), few medium distinct pale brown (10YR 6/3) and few medium distinct light brownish gray (10YR 6/2) mottles; weak medium subangular blocky structure; friable; common distinct clay films on faces of peds; very strongly acid; gradual smooth boundary.

Bt4 1.19-1.47m  yellowish brown (10YR 5/6) sandy clay loam; common medium faint brown (10YR 5/3), few medium prominent red (2.5YR 4/8) and common medium distinct light gray (10YR 7/1) mottles; weak medium subangular blocky structure; friable; few distinct
clay films on faces of peds; very strongly acid; clear wavy boundary.

**Norfolk Series**

<table>
<thead>
<tr>
<th>Layer</th>
<th>Depth</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bt5</td>
<td>1.47-2.00m</td>
<td>Mottled light gray (10YR 7/1), yellowish brown (10YR 5/6), red (10R 4/8), and brown (10YR 5/3) clay loam; moderate medium subangular blocky structure; red part is firm; gray, yellowish brown and brown part is friable; lenses and pockets of loamy sand in lower part; very strongly acid.</td>
</tr>
<tr>
<td>Ap</td>
<td>0.00-0.23m</td>
<td>Grayish brown (10YR 5/2) loamy sand; weak fine and medium granular structure; very friable; few fine and medium roots; some darker-colored material in old root channels; strongly acid; clear smooth boundary</td>
</tr>
<tr>
<td>E</td>
<td>0.23-0.36m</td>
<td>Light yellowish brown (10YR 6/4) loamy sand; weak medium granular structure; very friable; few fine and medium roots; some darker-colored material in old root channels; strongly acid; clear smooth boundary.</td>
</tr>
<tr>
<td>Bt1</td>
<td>0.36-0.43m</td>
<td>Yellowish brown (10YR 5/6) sandy loam; weak medium subangular blocky structure; friable; few fine and medium roots; strongly acid; clear wavy boundary.</td>
</tr>
<tr>
<td>Bt2</td>
<td>0.43-0.95m</td>
<td>Yellowish brown (10YR 5/6) sandy clay loam; weak medium subangular blocky structure; friable; many fine and medium pores; few faint clay films on faces of peds; strongly acid; clear wavy boundary.</td>
</tr>
<tr>
<td>Bt3</td>
<td>0.95-1.47m</td>
<td>Yellowish brown (10YR 5/6) sandy clay loam; few fine faint soft masses of iron accumulation of strong brown, pale brown, and yellowish red; weak medium subangular blocky structure; friable; few faint clay films on faces of peds; strongly acid; clear wavy boundary.</td>
</tr>
<tr>
<td>Bt4</td>
<td>1.47-1.78m</td>
<td>Yellowish brown (10YR 5/6) sandy clay loam; common medium distinct yellowish red (5YR 5/8) soft masses of iron accumulation, pale brown (10YR 6/3) and light brownish gray (10YR 6/2) iron depletions; weak medium subangular blocky structure; friable; few firm yellowish red plinthite nodules; strongly acid; gradual wavy boundary.</td>
</tr>
<tr>
<td>BC</td>
<td>1.78-2.05m</td>
<td>Mottled brownish yellow (10YR 6/6), strong brown (7.5YR 5/6), yellowish red (5YR 5/6) sandy clay loam; weak medium subangular blocky structure; friable; approximately 5 percent firm, brittle nodules of plinthite; strongly acid; gradual wavy boundary. (7 to 15 m thick (2.5YR 4/8), strong brown (7.5YR 5/8), brownish yellow (10YR 6/8), and gray (10YR 5/1) sandy clay loam; massive; friable; strongly acid.</td>
</tr>
</tbody>
</table>

**Osier**

<table>
<thead>
<tr>
<th>Layer</th>
<th>Depth</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>0.00-0.09m</td>
<td>Very dark grayish brown (10YR 3/2) loamy fine sand; moderate fine granular structure; very friable; very strongly acid; abrupt wavy boundary.</td>
</tr>
<tr>
<td>A2</td>
<td>0.09-0.20m</td>
<td>Mixed dark gray (10YR 4/1) and grayish brown (2.5Y 5/2) loamy sand; weak medium granular structure; very friable; common fine and coarse roots; thin strata of sand; very strongly acid; clear wavy boundary.</td>
</tr>
<tr>
<td>Cg1</td>
<td>0.20-0.40m</td>
<td>Dark gray (10YR 4/1) loamy sand; weak fine granular structure; very friable; common fine roots; thin strata of gray (10YR 6/1) sand; very strongly acid; gradual wavy boundary.</td>
</tr>
</tbody>
</table>
Cg2 0.40-0.90m gray (10YR 6/1) sand; single grained; loose; few fine roots; few fine distinct yellowish brown (10YR 5/6) masses of iron accumulation; very strongly acid; gradual wavy boundary.

Cg3 0.90-1.20m light brownish gray (2.5Y 6/2) sand; single grained; loose; few fine roots; common coarse distinct brownish yellow (10YR 6/6) masses of iron accumulation; very strongly acid; gradual wavy boundary.

Cg4 1.20-1.50m light gray (2.5Y 7/2) coarse sand; single grained; loose; few fine distinct yellowish brown (10YR 5/6) masses of iron accumulation; common medium faint light brownish gray (2.5Y 6/2) areas of iron depletions; very strongly acid; gradual wavy boundary.

Cg5 1.50-1.88m dark gray (10YR 4/1) coarse sand; single grained; loose; many coarse faint light brownish gray (10YR 6/2) areas of iron depletions; very strongly acid.

Pickney
A1 0.00-0.25m black (N 2/0) loamy fine sand; weak fine granular structure; very friable; common clean sand grains; many fine and medium roots; few fine pores; extremely acid; clear smooth boundary.

A2 0.25-0.60m black (N 2/0) loamy fine sand; weak fine granular structure; very friable; common clean sand grains; common fine and medium roots; few fine pores; extremely acid; clear smooth boundary.

A3 0.60-0.86m black (10YR 2/1) loamy fine sand; weak fine granular structure; very friable; common clean sand grains; common fine and medium roots; very strongly acid; clear smooth boundary.

Cg1 0.86-1.75m dark gray (10YR 4/1) fine sand; common medium faint white (10YR 8/1) mottles; single grained; loose; few fine roots; strongly acid; clear smooth boundary.

Cg2 1.75-2.00m dark gray (10YR 4/1) fine sand; single grained; loose; moderately acid.

Sparr Series
Ap1 0.00-0.13m dark gray (10YR 5/1) fine sand; moderate medium and coarse crumb structure; very friable; many fine and few medium roots; very strongly acid; clear wavy boundary.

Ap2 0.13-0.20m mixed dark gray (10YR 4/1), grayish brown (10YR 5/2), and pale brown (10YR 6/3) fine sand; weak medium crumb structure; very friable; many fine and few medium roots; strongly acid; clear wavy boundary.

E 0.20-0.98m very pale brown (10YR 7/4) fine sand; common fine distinct light gray (10YR 7/1) mottles; few medium and coarse grayish brown (10YR 5/2) krotovina; single grained; loose; common fine roots; many uncoated sand grains; strongly acid; clear wavy boundary.

EB 0.98-1.22m yellowish brown (10YR 5/4) fine sand; few fine faint yellowish brown and common fine distinct light gray (10YR 7/1) mottles; single grained; loose; few fine roots; strongly acid; clear wavy boundary.

Bt 1.22-1.42m yellowish brown (10YR 5/4) fine sandy loam; few fine distinct gray and common medium prominent yellowish red (5YR 5/8) mottles; weak medium subangular blocky structure; friable; very few roots; few fine pores; clay bridging between sand grains;
about 3 percent plinthite; very strongly acid; clear wavy boundary.

**Btg 1.42-1.80m**

gray (N 5/0) sandy clay; common fine and medium prominent yellowish red (5YR 5/6) mottles; moderate medium subangular blocky structure; friable; very few roots; few fine pores; clay films on faces of peds; about 2 percent plinthite; strongly acid; clear wavy boundary.

**BCg 1.80-2.50m**

gray (N 5/0) sandy clay loam with lenses of sandy loam material; common medium distinct strong brown (7.5YR 5/6) and few fine distinct pale brown mottles; weak medium subangular blocky structure; friable; very strongly acid.

**Tavares Series**

**Ap 0.00-0.18m**

very dark grayish brown (10YR 3/2) sand; weak fine granular structure; friable; many fine and medium roots; common uncoated light gray sand grains; strongly acid; abrupt wavy boundary.

**C1 0.18-0.63m**

very pale brown (10YR 7/3) sand; few fine faint yellowish brown mottles; single grained; loose; common fine roots; common very fine carbon particles; many uncoated sand grains; strongly acid; gradual wavy boundary.

**C2 0.63-0.86m**

light yellowish brown (10YR 6/4) sand; single grained; loose; few fine roots; many uncoated sand grains; strongly acid; gradual wavy boundary.

**C3 0.86-1.53m**

very pale brown (10YR 7/3) sand; few medium faint yellow mottles; single grained; loose; many uncoated sand grains; strongly acid; clear wavy boundary.

**C4 1.53-2.00m**

white (10YR 8/2) sand; common medium faint very pale brown mottles; single grained; loose; many uncoated sand grains; abundance of mottles decreases at lower depths; strongly acid.
### APPENDIX B
### MAGELLAN GPS RECEIVER SETTINGS

<table>
<thead>
<tr>
<th>Setting</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Position</td>
<td>Latitude: 29 55 0.0000</td>
</tr>
<tr>
<td></td>
<td>Longitude: 82 29 0.0000</td>
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<tr>
<td>Solve for Altitude</td>
<td>3D</td>
</tr>
<tr>
<td>Time and Date</td>
<td>UT</td>
</tr>
<tr>
<td>Mask Angle</td>
<td>$15^\circ$</td>
</tr>
<tr>
<td>Data Sample Rate</td>
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</tr>
<tr>
<td>Position Data</td>
<td>1 (every fix)</td>
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<tr>
<td>Raw Data</td>
<td>1 (every fix)</td>
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<tr>
<td>Timer</td>
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<tr>
<td>Data Ports</td>
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</tr>
<tr>
<td>Coordinate System</td>
<td>Latitude/Longitude, Degree Minutes Seconds (0.0001)</td>
</tr>
<tr>
<td>Map Datum</td>
<td>WGS84</td>
</tr>
<tr>
<td>Altitude Reference</td>
<td>HAE (Height Above Ellipsoid)</td>
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<tr>
<td>Altitude Units</td>
<td>meters</td>
</tr>
<tr>
<td>Magnetic Variation</td>
<td>Automatic</td>
</tr>
<tr>
<td>Distance, Speed</td>
<td>km, km hr$^{-1}$</td>
</tr>
<tr>
<td>Route Mode</td>
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<tr>
<td>Velocity Average</td>
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APPENDIX C
ALBERS CONIC EQUAL AREA PROJECTION

Projection Albers
Units Meters
Datum NAD27
Spheroid Clarke1866
1st standard parallel (DMS) 24 0 0.0000
2nd standard parallel (DMS) 31 30 0.0000
Central Meridian (DMS) -84 0 0.0000
Latitude of projection’s origin (DMS) 24 0 0.0000
False easting (m) 400000.0000
False northing (m) 0.0000

DMS = Degrees Minutes Seconds
APPENDIX D
SOIL PEDON DESCRIPTIONS

This appendix contains the soil profile descriptions for the sample locations at the Santa Fe Beef Unit test site (Franz, 1997). Descriptions are from samples taken with the bucket auger.

<table>
<thead>
<tr>
<th>Site</th>
<th>Layer</th>
<th>Depth (m)</th>
<th>Color (Munsell)</th>
<th>Texture</th>
<th>Structure</th>
<th>Rooting</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>001 Gainesville</td>
<td>Ap</td>
<td>0.00-0.17m</td>
<td>10YR 2/1</td>
<td>loamy fine sand, weak fine subangular blocky structure, very friable, common fine roots.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ap/Bw</td>
<td>0.17-0.40m</td>
<td>10YR 2/1 and 4/4, loamy fine sand, weak fine subangular blocky structure, very friable, very few fine roots.</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>Bwl</td>
<td>0.49-0.88m</td>
<td>10YR 4/4</td>
<td>loamy sand, very weak fine subangular blocky structure, very friable, very few fine roots.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bw2</td>
<td>0.88-1.39m</td>
<td>10YR 4/6</td>
<td>loamy sand, weak fine subangular blocky structure, very friable, very few 7.5YR 4/6 and 1 or 3/3 iron stone 6m diameter.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bw3</td>
<td>1.39-1.60m</td>
<td>10YR 5/6</td>
<td>loamy sand, weak fine subangular blocky structure, very few fine roots.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bw4</td>
<td>1.60-2.00m</td>
<td>10YR 6/4</td>
<td>loamy sand, very weak fine subangular blocky structure, few 7.5YR 416 and 10R 3/3 nodules.</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Site</th>
<th>Layer</th>
<th>Depth (m)</th>
<th>Color (Munsell)</th>
<th>Texture</th>
<th>Structure</th>
<th>Rooting</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>002 Gainesville</td>
<td>Ap</td>
<td>0.00-0.12m</td>
<td>10YR 2/1</td>
<td>loamy fine sand, very weak fine subangular blocky, very friable, common fine roots.</td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>Ap/Bw</td>
<td>0.12-0.25m</td>
<td>10YR 2/1 and 4/3, loamy fine sand, very weak fine subangular blocky, very friable, few fine roots.</td>
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<tr>
<td></td>
<td>Bwl</td>
<td>0.25-0.50m</td>
<td>10YR 4/3</td>
<td>loamy fine sand, very weak fine subangular blocky, very friable, few fine roots.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bw2</td>
<td>0.50-1.29m</td>
<td>10YR 4/4</td>
<td>loamy fine sand, very weak fine subangular blocky, very friable, few fine roots.</td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>Bw3</td>
<td>1.29-1.85m</td>
<td>10YR 5/6</td>
<td>loamy fine sand, very weak fine subangular blocky, very friable, few coarse 7.5 YR 5/8 and 5YR 3/3 concretions, few fine roots.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bw4</td>
<td>1.85-2.00m</td>
<td>10YR 5/4</td>
<td>loamy fine sand, very weak fine subangular blocky, very friable, substantial pick-up in moisture at 1.85m.</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Site</th>
<th>Layer</th>
<th>Depth (m)</th>
<th>Color (Munsell)</th>
<th>Texture</th>
<th>Structure</th>
<th>Rooting</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>003 Gainesville</td>
<td>Apl</td>
<td>0.00-0.13m</td>
<td>10YR 3/1</td>
<td>loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.</td>
<td></td>
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<tr>
<td></td>
<td>Ap2</td>
<td>0.13-0.30m</td>
<td>10YR 3/3 and 2/1, loamy fine sand, very weak fine subangular blocky structure, very friable, few fine roots.</td>
<td></td>
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<tr>
<td></td>
<td>Bwl</td>
<td>0.30-0.92m</td>
<td>10YR 4/4</td>
<td>loamy sand, very weak fine subangular blocky structure, very friable, few fine roots.</td>
<td></td>
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<tr>
<td></td>
<td>Bw2</td>
<td>0.92-1.81m</td>
<td>10YR 5/6</td>
<td>loamy sand, very weak fine subangular blocky structure, very</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Bw3 1.81-2.00m 10YR 6/6, loamy sand, very weak fine subangular blocky structure, very friable, roots.

004 Gainesville
Ap 0.00-0.14m 10YR 2/1, loamy fine sand, very weak fine subangular blocky, very friable, common fine roots.
Ap/Bw 0.14-0.30m 10YR 2/1 and 4/4, loamy fine sand, very weak fine subangular blocky, very friable, few fine roots.
Bw 0.30-1.31m 10YR 4/4, loamy fine sand, very weak fine subangular blocky, very friable, few fine roots.
Bw2 1.31-1.71m 10YR 5/6, loamy fine sand, very weak fine subangular blocky, very friable, pick-up in moisture at 1.71 m.
Bw3 1.71-2.00m 10YR 5/4, loamy fine sand, very weak fine subangular blocky, very friable.

005 Gainesville
Ap 0.00-0.22m 10YR 3/2, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.
Ap/Bw 0.22-0.28m 10YR 3/2 and 3/4, loamy sand, very weak fine subangular blocky structure, very friable, few fine roots.
Bw 0.28-0.94m 10YR 4/4, loamy sand, very weak fine subangular blocky structure, very friable, few fine roots.
Bw2 0.47-1.00m 10YR 4/4, loamy sand, very weak fine subangular blocky structure, very friable, very few fine roots.
Bw3 1.00-2.00m 10YR 5/6, loamy sand, very weak fine subangular blocky structure, very friable, iron stone at 1.70m, very few fine 10YR 3/2 organic stains, pick up in moisture at 1.95m.

006 Bonneau
Ap 0.00-0.14m 10YR 2/1, loamy fine sand, very weak fine subangular blocky, very friable, common fine roots.
Ap/Bw 0.14-0.29m 10YR 2/1 and 4/4, loamy fine sand, very weak fine subangular blocky, very friable, few fine roots.
Bw 0.29-0.94m 10YR 4/4, loamy fine sand, very weak fine subangular blocky, very friable, few fine roots.
Bt 0.94-1.10m 10YR 5/4, sandy loam, weak fine subangular blocky, friable, few fine roots.
Bt2 1.10-1.18m 10YR 5/3, sandy clay loam, weak fine subangular blocky, common fine faint 10YR 5/8 redox concentrations and few fine faint 10YR 5/1 redox depletions, friable.
Bt3 1.18-1.34m Common medium distinct 10YR 5/6 redox accumulations (50% of matrix color) and common medium distinct 10YR 6/1 redox depletions (50% of matrix color), sandy clay loam, moderate fine subangular blocky, common fine-medium 10YR 8/1 nodules, friable.
Bt4 1.34-1.43m Common fine-medium distinct 10YR 5/6 and 7.5YR 5/8 redox accumulations (50% of matrix color) and common fine distinct 10YR 7/1 redox depletions (50% of matrix color), sandy clay loam, moderate fine subangular blocky, friable.
Bt5 1.43-2.00m 10YR 7/1, sandy clay loam, moderate medium subangular blocky, common medium distinct 7.5YR 4/6 redox accumulations, friable.
007 Norfolk
Ap  0.00-0.14m  10YR 3/1, loamy fine sand, very weak very fine subangular blocky structure, very friable, common fine roots.
Ap/Bw 0.14-0.30 m  10YR 3/1 and 4/4, loamy sand, moderate fine subangular blocky structure, friable, few fine roots.
Bti  0.30-0.92m  10YR 4/4, sandy clay loam, moderate fine subangular blocky structure, friable, 10YR 8/1 nodules.
Bt2  0.92-1.02m  10YR 5/4 and 10YR 5/8 redox accumulations and depletions, sandy clay loam, strong fine subangular blocky, friable.
Bt3  1.02-1.38m  10YR 5/4 and 7.5YR 5/8 redox accumulations and depletions, sandy clay loam, strong fine subangular blocky, friable.
Bt4  1.38-2.00m  10YR 7/8 and 10YR 8/2 redox accumulations and depletions, sandy clay loam, strong fine subangular blocky, friable.

008 Cowarts
Ap  0.00-0.15m  10YR 2/1, loamy fine sand, very weak fine subangular blocky, very friable, common medium and fine roots.
Bw  0.15-0.29m  10YR 4/3, loamy fine sand, very weak fine subangular blocky, very friable, common fine to medium iron stone concretions.
Btl  0.29-0.86m  10YR 4/4, sandy clay loam, moderate fine subangular blocky, friable.
Bt2  0.86-0.95m  10YR 5/6 sandy clay loam, moderate fine subangular blocky, common fine to medium 7.5YR 4/6 redox accumulations, at 0.95m few coarse 10YR 8/1 nodules.
2Bt3  0.95-2.00m  10YR 7/4, sandy clay, strong medium subangular blocky, many medium prominent 7YR 5/8 redox accumulations, plastic.

009 Norfolk
Apl  0.00-0.10m  10YR 3/2, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.
Ap2  0.10-0.15m  10YR 3/3, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.
Bw  0.15-0.40m  10YR 4/4, loamy sand, very weak fine subangular blocky structure, very friable, very few fine roots.
Bti  0.40-1.00m  10YR 4/4, sandy clay loam, moderate fine subangular blocky structure, friable, very few 7.5YR 516 redox accumulations at 100m.
Bt2  1.00-2.00m  7.5YR 5/1 and 5/8 and 7.5YR 8/1 redox accumulations and depletions, sandy clay loam, moderate fine subangular blocky, friable.

010 Millhopper
Ap  0.00-0.19m  10YR 2/1, loamy sand, very weak fine granular structure, very friable.
Bw  0.19-125m  10YR 5/4, loamy sand, very weak fine subangular blocky structure, very friable.
El  1.25-1.70m  10YR 6/3, sand, very weak fine subangular blocky structure, very friable.
E2  1.70-1.90m  10YR 6/1, sand, very weak fine subangular blocky structure, very friable.
Bt  1.90-2.00m  10YR 7/1, sandy clay loam, moderate fine subangular blocky structure, friable, common medium prominent 7YR 5/8 redox accumulations, common fine phosphate nodules.
011 Millhopper
Ap  0.00-0.13m  10YR 3/1, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.
Ap/Bw 0.13-0.53m  10YR 4/4 and 3/1, loamy sand, very weak fine subangular blocky structure, very friable, few fine roots.
Bwl 0.53-1.23m  10YR 4/4, loamy sand, very weak fine subangular blocky structure, very friable, very few fine roots.
Bw2 1.23-1.71m  10YR 5/4, loamy sand, very weak fine subangular blocky structure, very friable, very few fine roots.
Btl 1.71-1.91m  10YR 6/1 and 10YR 6/4 redox accumulations and depletions, sandy loam, moderate fine subangular blocky structure, friable.
Bt2 1.91-2.00m  10YR 5/8 and 10YR 6/1 redox accumulations and depletions, sandy loam, moderate fine subangular blocky, friable.

012 Gainesville
Ap  0.00-0.13m  10YR 2/2, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
Ap/Bw 0.13-0.27m  10YR 2/2 and 4/3, loamy fine sand, very weak fine granular structure, very friable, few fine roots.
Bwl 0.27-0.72m  10YR 4/4, loamy fine sand, very weak fine subangular blocky structure, very friable, few fine roots.
Bw2 0.72-1.88m  10YR 4/6, loamy fine sand, very weak fine subangular blocky structure, very friable, very few fine roots.
Bw3 1.88-2.00m  10YR 5/4, loamy fine sand, very weak fine subangular blocky structure, very friable.

013 Gainesville
Ap  0.00-0.14m  10YR 3/2, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.
Bw/Ap 0.14-0.29m  10YR 4/4 and 3/2, loamy sand, very weak fine subangular blocky structure, very friable, few fine roots.
Bwl 0.29-0.72m  10YR 4/4, loamy sand, very weak fine subangular blocky structure, very friable, very few fine roots.
Bw2 0.72-1.15m  10YR 4/6, loamy sand, very weak fine subangular blocky structure, very friable, very few fine roots.
Bw3 1.15-2.00m  10YR 5/6, loamy sand, very weak fine subangular blocky structure, very friable.

014 Millhopper
Ap  0.00-0.15m  10YR 2/2, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
Ap/Bw 0.15-0.29m  10YR 2/2 and 4/3, loamy fine sand, very weak fine subangular blocky structure, very friable, few fine roots.
Bwl 0.29-1.52m  10YR 4/6, loamy fine sand, very weak fine subangular blocky structure, very friable, few fine roots.
Bw2 1.52-2.00m  10YR 5/4, loamy fine sand, very weak fine subangular blocky structure, very friable.

015 Millhopper
Ap  0.00-0.14m  10YR 2/2, loamy fine sand, very weak fine subangular blocky, very friable, common fine roots.
<table>
<thead>
<tr>
<th>Depth (m)</th>
<th>Color</th>
<th>Texture</th>
<th>Structure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00-0.12m</td>
<td>10YR 2/2</td>
<td>loamy fine sand</td>
<td>very weak fine granular structure, very friable, common fine roots.</td>
<td></td>
</tr>
<tr>
<td>0.12-0.30m</td>
<td>10YR 2/2 and 4/3</td>
<td>loamy fine sand</td>
<td>very weak fine subangular blocky structure, very friable, common fine roots.</td>
<td></td>
</tr>
<tr>
<td>0.30-0.63m</td>
<td>10YR 4/4</td>
<td>loamy fine sand</td>
<td>very weak fine subangular blocky structure, very friable, common fine roots.</td>
<td></td>
</tr>
<tr>
<td>0.63-0.81m</td>
<td>10YR 4/4</td>
<td>sandy loam</td>
<td>weak fine subangular blocky structure, very friable.</td>
<td></td>
</tr>
<tr>
<td>0.81-1.75m</td>
<td>10YR 4/3</td>
<td>sandy clay loam</td>
<td>moderate medium subangular blocky structure, friable.</td>
<td></td>
</tr>
<tr>
<td>1.75-2.00m</td>
<td>10YR 4/3</td>
<td>loamy fine sand</td>
<td>very weak fine subangular blocky structure, very friable.</td>
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</tr>
<tr>
<td>0.00-0.20m</td>
<td>10YR 2/2</td>
<td>sand</td>
<td>single grained structure, loose consistency.</td>
<td></td>
</tr>
<tr>
<td>0.20-0.81m</td>
<td>10YR 4/6</td>
<td>sand</td>
<td>very weak fine granular structure, very friable.</td>
<td></td>
</tr>
<tr>
<td>0.81-1.00m</td>
<td>10YR 4/4</td>
<td>sandy loam</td>
<td>very weak fine subangular blocky structure, very friable.</td>
<td></td>
</tr>
<tr>
<td>1.00-1.48m</td>
<td>10YR 3/4</td>
<td>sandy clay loam</td>
<td>moderate medium subangular blocky structure, friable.</td>
<td></td>
</tr>
<tr>
<td>1.48-2.00m</td>
<td>10YR 3/3</td>
<td>sandy loam</td>
<td>weak fine subangular blocky structure, friable.</td>
<td></td>
</tr>
<tr>
<td>0.00-0.12m</td>
<td>10YR 2/2</td>
<td>loamy fine sand</td>
<td>very weak fine subangular blocky structure, very friable, common fine roots.</td>
<td></td>
</tr>
<tr>
<td>0.12-0.28m</td>
<td>10YR 2/2 and 4/3</td>
<td>loamy fine sand</td>
<td>very weak fine subangular blocky structure, very friable, common fine roots.</td>
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</tr>
<tr>
<td>0.28-0.85m</td>
<td>10YR 4/4</td>
<td>loamy fine sand</td>
<td>very weak fine subangular blocky structure, very friable.</td>
<td></td>
</tr>
<tr>
<td>0.85-1.90m</td>
<td>10YR 4/4</td>
<td>sandy clay loam</td>
<td>moderate fine subangular blocky structure, friable.</td>
<td></td>
</tr>
<tr>
<td>1.90-2.00m</td>
<td>10YR 4/4</td>
<td>sandy loam</td>
<td>weak fine subangular blocky structure, very friable.</td>
<td></td>
</tr>
<tr>
<td>Location</td>
<td>Depth Range</td>
<td>Color</td>
<td>Texture/Structure Description</td>
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</tr>
<tr>
<td>-------------</td>
<td>-------------</td>
<td>-------</td>
<td>------------------------------</td>
<td></td>
</tr>
<tr>
<td><strong>019 Gainesville</strong></td>
<td>Ap 0.00-0.18m</td>
<td>10YR 2/1, sand, single grained structure, loose consistency.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bw1 0.18-0.48m</td>
<td>10YR 4/3, sand, very weak fine granular structure, very friable.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bw2 0.48-1.60m</td>
<td>10YR 4/6, loamy sand, very weak fine granular structure, very friable.</td>
<td></td>
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<td>Bw3 1.60-2.00m</td>
<td>10YR 5/4, loamy sand, very weak fine subangular blocky structure, very friable.</td>
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<td><strong>020 Millhopper</strong></td>
<td>Ap 0.00-0.15m</td>
<td>10YR 3/3, loamy fine sand, very weak fine subangular blocky structure, very friable, few fine roots.</td>
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<td>Bw1 0.15-0.37m</td>
<td>10YR 4/4, loamy fine sand, very weak fine subangular blocky structure, very friable, few fine roots.</td>
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<td>Bw2 0.37-1.48</td>
<td>10YR 4/6, loamy fine sand, very weak fine subangular blocky structure, very friable, few fine roots.</td>
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<td>Bw3 1.48-1.88</td>
<td>10YR 5/4, loamy fine sand, very weak fine subangular blocky structure, very friable, very few fine faint 5Y 4/6 redox accumulations at approximately 180m.</td>
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<td>Btg 1.88-2.00m</td>
<td>10YR 5/1(50% of matrix) and 5YR 4/6 (50% of matrix), sandy clay loam, moderate fine to medium subangular blocky structure, friable.</td>
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<td><strong>021 Gainesville</strong></td>
<td>Ap 0.00-0.13m</td>
<td>10YR 2/1, loamy fine sand, very weak fine granular structure, very friable, common fine roots.</td>
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<td>AB 0.13-0.23m</td>
<td>10YR 2/1 and 4/3, loamy fine sand, very weak fine granular structure, very friable, common fine and medium roots.</td>
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<td>Bw1 0.23-1.30m</td>
<td>10YR 4/4, loamy fine sand, very weak fine subangular blocky structure, very friable, few fine roots.</td>
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<td>Bw2 1.30-2.00m</td>
<td>10YR 4/6, loamy fine sand, very weak fine subangular blocky structure, very friable, very few very fine roots.</td>
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<td><strong>022 Millhopper</strong></td>
<td>Ap 0.00-0.06m</td>
<td>10YR 3/2, loamy fine sand, very weak fine granular structure, very friable, common fine roots.</td>
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<td>AB 0.06-0.16m</td>
<td>10YR 3/2 and 2.5Y 5/4, loamy fine sand, very weak fine granular structure, very friable, common fine roots.</td>
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<td>Bw 0.16-0.70m</td>
<td>10YR 2.5Y 5/4, loamy fine sand, very weak fine granular structure, very friable, common fine roots.</td>
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<td>B/E 0.70-1.21m</td>
<td>10YR 2.5Y 4/1 and 10YR 7/1, loamy fine sand, very weak fine granular structure, very friable, common fine roots.</td>
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<td>Btl 1.21-1.80m</td>
<td>10YR 5/4, sandy clay loam, moderate fine subangular blocky structure, friable, very few medium distinct 10 YR 7/1 nodules.</td>
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<td>Bt2 1.80-2.00m</td>
<td>10YR 5/4, sandy clay loam, moderate fine subangular blocky structure, friable, few very fine distinct 7.5YR 5/8 redox accumulations, very few fine distinct 10YR 6/1 redox depletions.</td>
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<tr>
<td><strong>023 Millhopper</strong></td>
<td>Ap 0.00-0.21m</td>
<td>10YR 2/1, loamy fine sand, very weak fine granular structure, very friable, common fine roots.</td>
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<td>Bw 0.21-0.90m</td>
<td>10YR 5/4, loamy fine sand, very weak fine granular structure, very friable.</td>
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<td>B/E 0.90-1.10m</td>
<td>10YR 5/4 and 7/3, loamy fine sand, very weak fine granular structure, very friable.</td>
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</table>
structure, very friable.

E/B 1.10-1.39m 10YR 7/3 and 5/4, fine sand, very weak fine granular structure, very friable.

Btl 1.39-1.70m 10YR 5/4, sandy clay loam, moderate fine subangular blocky structure, friable, common medium distinct 10YR 5/8 and 7.5 YR 5/6 redox accumulations, few fine distinct 10 YR 5/1 redox depletions.

Bt2 1.70-2.00m 10YR 6/1, sandy clay loam, moderate fine to medium subangular blocky structure, common medium distinct 7.5YR 5/8 redox accumulations.

024 Millhopper
Ap 0.00-0.13m 10YR 2/2, loamy fine sand, very weak fine granular structure, very friable, common fine roots.

Ap/Bw 0.13-0.19m 10YR 2/2 and 5/4, loamy fine sand, very weak fine granular structure, very friable, common fine roots.

Bw 0.19-0.42m 10YR 5/4, loamy fine sand, very weak fine granular structure, very friable.

E 0.42-1.00m 10YR 7/3, loamy fine sand, weak fine granular structure, very friable, few fine roots, few fine distinct 10YR 7/1 sand grain stripping.

Bt 1.00-1.51m 10YR 4/6, sandy loam weak fine subangular blocky structure, friable, common fine roots.

B’w 1.51-1.89m 10YR 4/4, loamy fine sand, very weak fine subangular blocky structure, very friable, very few fine roots.

B’t 1.89-2.00m 10YR 4/3, sandy loam, weak fine subangular blocky structure, very friable.

025 Bonneau
Ap 0.00-0.10m 10YR 3/2, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.

Bw/Ap 0.10-0.30m 10YR 4/6 and 3/2, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.

Bw 0.30-0.55m 10YR 4/6, loamy fine sand, very weak fine subangular blocky structure, very friable, few fine roots.

Btl 0.55-1.00m 10YR 4/4, sandy loam, weak fine subangular blocky structure, friable, common fine roots.

Bt2 1.00-2.00m 10YR 4/3, sandy loam, weak fine subangular blocky structure, friable, few fine roots.

026 Millhopper
Ap 0.00-0.15m 10YR 2/2, sand, very weak fine granular structure, very friable.

Bwl 0.15-0.92m 10YR 4/4, loamy sand, very weak fine granular structure, very friable.

Bw2 0.92-1.20m 10YR 4/3, very weak fine subangular blocky structure, very friable.

Bt 1.20-1.50m 10YR 5/2, sandy loam, weak fine subangular blocky structure, friable, common medium distinct 10YR 3/3 clay concentrations.

Btg 1.50-2.00m 10YR 5/1, sandy loam, weak fine subangular blocky structure, friable, common medium distinct 10YR 4/3 redox accumulations.

027 Bonneau
Ap 0.00-0.13m 10YR 3/2, loamy fine sand, very weak fine granular structure, very friable, common fine roots.

A 0.13-0.48m 10YR 3/3, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.
028 Bonneau
Ap  0.00-0.16m  10YR 2/1, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
AB  0.16-0.20m  10YR 2/1 and 4/4, very weak medium granular structure, very friable, few fine roots.
Bw  0.20-0.70m  10YR 4/4, loamy fine sand, very weak fine subangular blocky structure, very friable.
Bt  0.70-1.30m  10YR 4/4, sandy clay loam, weak fine subangular blocky structure, friable, common medium distinct 2.5YR 4/6 redox accumulations.
Bt2 1.30-1.60m  10YR 4/2, sandy clay loam, moderate fine subangular blocky structure, friable, common medium 10YR 5/1 redox depletions.
Btg 1.60-2.00m  10YR 6/1, sandy clay loam, moderate fine subangular blocky structure, common medium prominent 5YR 3/4 redox accumulations and nodules, few coarse medium 10YR 8/1 nodules.

029 Millhopper
Ap  0.00-0.16m  10YR 3/2, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
Ap/Bw 0.16-0.40m  10YR 3/2 and 4/4, loamy fine sand, weak fine granular structure, very friable, few fine roots.
Bw  0.40-0.97m  10YR 5/6, loamy fine sand, very weak fine granular structure, very friable.
B/E  0.97-1.25m  10YR 5/6 and 7/1, loamy fine sand, very weak fine granular structure, very friable.
E/B  1.25-1.60m  10YR 7/1 and 5/6, sand, very weak fine granular structure, very friable.
Bt  1.60-1.70m  10YR 4/4, sandy loam, weak fine subangular blocky structure, very friable.
Bt2 1.70-1.90m  10YR 4/4, sandy clay loam, moderate fine subangular blocky structure, friable, common medium distinct 5YR 4/6 redox accumulations.
Btg 1.90-2.00m  10YR 6/1, sandy clay loam, moderate fine subangular blocky structure, friable, common medium prominent 5YR 4/6 and few medium distinct 7.5YR 5/8 redox accumulations.

030 Millhopper
Ap  0.00-0.06m  10YR 3/2, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
Ap/Bw 0.06-0.16m  10YR 3/2 and 2.5Y 5/4, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
Bw  0.16-0.70m  10YR 2.5Y 5/4, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
B/E  0.70-1.21m  10YR 2.5Y 5/4 and 10YR 7/1, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
structure, very friable, common fine roots.

Btl 1.21-1.80m 10YR 5/4, sandy clay loam, moderate fine subangular blocky structure, friable, very few medium distinct 10YR 7/1 nodules.

Bt2 1.80-2.00m 10YR 5/4, sandy clay loam, moderate fine subangular blocky structure, friable, few very fine distinct 7.5YR 5/8 redox accumulations, very few fine distinct 10YR 6/1 redox depletions.

031 Millhopper
Ap 0.00-0.29m 10YR 3/3, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
Bw/Ap 0.29-0.41m 2.5Y 5/4 and 10YR 3/3, loamy fine sand, very weak fine granular structure, very friable common fine roots.
Bw 0.41-0.90m 2.5Y 5/4, loamy fine sand, very weak fine granular structure, very friable, few fine roots.
B/E 0.90-1.39m 2.5Y 5/4 and 10YR 7/2, loamy fine sand, very weak fine subangular blocky structure, very friable, few fine roots.
E/B 1.39-1.80m 10YR 7/2 and 2.5Y 5/4, sand, very weak fine subangular blocky structure (due to moisture), very friable.
Bt 1.80-2.00m 10YR 6/1, sandy clay loam, moderate medium subangular blocky structure, friable, common medium prominent 7.5YR 5/8 redox accumulations.

032 Millhopper
Ap 0.00-0.09m 10YR 2/1, sand, single grain structure, loose consistence.
Ci 0.09-0.80m 10YR 8/1, fine sand, single grain structure, loose consistence.
C2 0.80-0.90m 10YR 7/1, fine sand, single grain structure, loose consistence.
Bwbd1 0.90-1.30m 10YR 5/2, loamy sand, weak fine granular structure, very friable.
Bwbd2 1.30-2.00m 10YR 5/2, loamy sand, weak fine granular structure, very friable, occasional 7.5YR 5/8 mottles throughout horizon.

033 Millhopper
Ap 0.00-0.20m 10YR 2/2, sand, single grain structure, loose consistence.
Bw1 0.20-0.68m 10YR 4/3, loamy fine sand, single grain structure, loose consistence, few fine to medium faint 10YR 5/8 mottles.
Bw2 0.68-200m 10YR 5/4, loamy fine sand, single grain structure, loose consistence, common medium to coarse distinct 7.5YR 4/6 mottles.

034 Chipley
Ap 0.00-0.20m 10YR 2/2, sand, single grain structure, loose consistence
Bw1 0.20-0.69m 10YR 4/4, loamy fine sand, single grain structure, loose consistence.
Bw2 0.69-1.20m 10YR 412, loamy fine sand, single grain structure, loose consistence.
Bw3 1.20-1.70m 10YR 4/2, loamy fine sand, single grain structure, loose consistence, common medium faint 10YR 6/8 mottles.
Bw4 1.70-2.00m 10YR 4/2, loamy fine sand, single grain structure, loose consistence, common medium to coarse distinct 7.5YR 4/6 mottles.

035
Unable to sample due to flooded conditions.
036 Bibb
Al 0.00-0.12m 10YR 3/2 and 6/2 (50/50), sand, very weak medium granular structure, very friable.
A2 0.12-0.46m 10YR 2/1, loam, moderate medium to coarse granular structure, friable, common fine and medium roots.
A3 0.46-0.77m 10YR 3/1, sand, weak fine to medium granular structure, very friable.
Bw 0.77-1.03m 10YR 5/2, sand weak fine granular structure, very friable.
Ab 1.03-1.60m 10YR 3/1, sand, moderate fine granular structure, very friable.
B’wb 1.60-2.00m 10YR 4/3, sand, weak fine to medium granular structure, very friable.

037 Bonneau
Ap 0.00-0.17m 10YR 3/3, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
AB 0.17-0.24m 2.5YR 5/4, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
Bw 0.24-0.62m 2.5Y 5/4, loamy fine sand, very weak fine granular structure, very friable, few fine roots.
B/E 0.62-0.70m 2.5Y 5/4 and 10YR 7/2, loamy fine sand with pockets of sand, very weak fine granular structure, very friable, very few fine distinct 7.5YR 5/8 redox accumulations.
Btl 0.70-1.25m 2.5Y 5/4, sandy loam, weak fine granular structure, very friable, common fine distinct 7.5YR 5/8 redox accumulations.
Bt2 1.25-1.42m 2.5Y 5/4, sandy loam, weak fine to medium subangular blocky structure, friable, common medium distinct 10YR 5/1 redox depletions.
Btgl 1.42-1.60m 10YR 5/4, sandy loam, weak fine to medium subangular blocky structure, friable, common medium distinct 7.5YR 5/8 redox accumulations, few fine distinct 2.5Y 3/3 nodules.
Btg2 1.60-2.00m 10YR 5/1, sandy clay loam, moderate medium subangular blocky structure, friable, common medium distinct 5YR 3/4 redox accumulations, common very fine distinct 10YR 8/2 phosphate nodules surrounding redox accumulations.

038 Millhopper
Ap 0.00-0.14m 10YR 2/2, sand, single grained structure, loose consistency.
Bw 0.14-0.92m 10YR 4/4, loamy sand, very weak fine granular structure, very friable.
E 0.92-1.30m 10YR 7/2, sand, very weak fine granular structure, very friable.
E/B 1.30-1.52m 10YR 7/2 and 5/4, sand, very weak fine granular structure, very friable.
Btl 1.52-1.66m 10YR 5/4, sandy loam, moderate fine to medium subangular blocky structure, friable, common medium distinct 7.5YR 5/8 redox accumulations.
Bt2 1.66-1.90m 10YR 4/4, sandy clay loam, moderate fine to medium subangular blocky structure, friable.
Bt3 1.90-2.00m 10YR 4/4, sandy clay loam, moderate fine to medium subangular blocky structure, friable, very few fine distinct 7.5 YR 5/8 redox accumulations, very few fine faint 10YR 6/1 redox depletions.

039 Osier
Ap 0.00-0.15m 10YR 2/1, sand, single grain structure, loose consistence.
C1 0.15-0.30m 10YR 6/1, sand, single grain structure, loose consistence, common medium distinct 10YR 3/1 streaks in matrix.
C2 0.30-2.00m 10YR 6/2, sand, single grain structure, loose consistence.
040 Bibb
AI  0.00-0.07m  10YR 5/3, very fine sand, single grain structure, loose consistence.
A2  0.07-0.14m  10YR 3/2, sand, single grain structure, loose consistence.
Bwdl 0.14-0.70m  10YR 6/3, sandy loam, single grain structure, loose consistence.
Bwd2 0.70-0.85m  7.5YR 4/6, sandy loam, moderate medium to coarse granular structure, friable.
Bwd3 0.85-1.10m  10YR 5/3, loamy sand, weak fine granular structure, very friable.
Bwl  1.10-1.20m  10YR 5/3, loamy sand, weak fine granular structure, very friable, common medium distinct 7.5YR 4/6 mottles.
Bw2  1.20-2.00m  10YR 5/3, loamy sand, weak fine granular structure, very friable.

041 Bibb
Ap  0.00-0.20m  10YR 2/1, loam, moderate fine granular structure, very friable.
C   0.20-0.50m  10YR 6/2, sand, single grain structure, loose consistence.
Bwbd 0.50-1.00m  10YR 4/2, loamy sand, weak fine granular structure, very friable.
Bwbd2 1.00-1.40m  10YR 5/2, loamy sand, weak fine granular structure, very friable.
Bwb  1.40-2.00m  10YR 5/2, loamy sand, very weak fine granular structure, very friable, occasional 5YR 4/6 mottles throughout horizon.

042 Bibb
Ap  0.00-0.25m  10YR 2/1, loam, moderate fine granular structure, very friable.
C   0.25-0.50m  10YR 6/2, sand, single grain structure, loose consistence.
Bwbd 0.50-1.02m  10YR 4/2, loamy sand, weak fine granular structure, very friable.
Bwbd2 1.02-1.38m  10YR 5/2, loamy sand, weak fine granular structure, very friable.
Bwb  1.38-2.00m  10YR 5/2, loamy sand, very weak fine granular structure, very friable, occasional 5YR 4/6 mottles throughout horizon.

043 Bibb
Ap  0.00-0.19m  10YR 2/1, loam, moderate fine granular structure, very friable.
C1  0.19-0.90m  10YR 8/1, fine sand, single grain structure, loose consistence.
C2  0.90-1.04m  10YR 7/2, fine sand, single grain structure, loose consistence.
Bwbd 1.04-2.00m  10YR 4/1, loamy sand, weak fine granular structure, very friable.

044 Water
Not sampled due to flooded conditions.

045 Bibb
Ap  0.00-0.48m  10YR 2/1, loam, moderate fine granular structure, very friable.
C   0.48-0.85m  10YR 6/2, sand, single grain structure, loose consistence.
Abd 0.85-1.30m  10YR 3/2, loamy sand, single grain structure, loose consistence, difficulty augering.
Bwb  1.30-1.43m  10YR 4/1, loamy sand, moderate medium subangular blocky structure, very friable.
Bwbd 1.43-2.00m  10YR 5/1, loamy sand, moderate medium subangular blocky structure, firm but friable, common 5YR 4/6 mottles.

046 Osier
AI  0.00-0.13m  10YR 2/1, sand, single grain structure, loose consistence.
A2  0.13-0.30m  10YR 3/2, sand, single grain structure, loose consistence.
Bw  0.30-0.69m  10YR 4/2, sand, single grain structure, loose consistence.
C1  0.69-1.40m  10YR 7/1, sand, single grain structure, loose consistence.
C2  1.40-1.69m  10YR 7/1, sand, single grain structure, loose consistence, common fine to medium distinct 10YR 4/3 nodules.
2Bw  1.69-2.00m  10YR 5/3, loamy sand, very weak medium to coarse granular, very friable, common medium to coarse distinct 7.5YR 4/4 mottles.

047 Osier
Ap  0.00-0.14m  10YR 2/1, sand, very weak fine granular structure, very friable.
Bwl  0.14-0.30m  10YR 5/3, sand, very weak fine granular structure, very friable.
E  0.30-0.65m  10YR 6/3, sand, very weak fine granular, very friable,
B’w2  0.65-2.00m  10YR 5/2, loamy sand, very weak fine granular structure, very friable, few fine distinct 7.5 YR 3/4 iron nodules, common medium distinct 7.5 YR 5/8 concretions.

048 Osier
Ap  0.00-0.19m  10YR 2/2, sand, single grained structure, loose consistency.
Bwl  0.19-0.49m  10YR 4/3, sand, very weak fine granular structure, very friable.
Bw2  0.49-0.77m  10YR 4/2, sand, very weak fine granular structure, very friable.
Bw3  0.77-2.00m  10YR 5/3, loamy sand, very weak fine subangular blocky structure, very friable, common fine to medium 7.5 YR 3/4 accumulations.

049 Bigbee
Ap  0.00-0.17m  10YR 2/2, sand, single grained structure, loose consistency.
Bwl  0.17-0.90m  10YR 5/4, sand, very weak fine granular structure, very friable.
Bw2  0.90-2.00m  10YR 5/3, loamy sand, very weak fine subangular blocky structure, very friable.

050 Bigbee
Ap  0.00-0.19m  10YR 2/2, sand, very weak fine granular structure, very friable.
Bwl  0.19-1.20m  10YR 5/4, sand, very weak fine granular structure, very friable.
Bw2  1.20-2.00m  10YR 5/3, loamy sand, very weak fine subangular blocky structure, very friable.

051 Bigbee
Ap  0.00-0.10m  10YR 3/2, sand, single grained, loose consistency.
Bwl  0.10-0.42m  10YR 3/3, sand, very weak fine granular structure, very friable.
Bw2  0.42-0.85m  10YR 4/3, sand, very weak fine granular structure, very friable.
C1  0.85-126m  10YR 5/4 and 5/8 (approx. 50/50), sand, no structure, loose.
C2  1.26-2.00m  mottled with 10YR 6/4, 5/8 and 6/3, sand, not structure, loose.

052 Bigbee
Ap  0.00-0.21 m  10YR 2/2, sand, single grained structure, loose consistency.
Bwl  0.21-0.33m  10YR 4/4, sand, very weak fine granular structure, very friable.
Bw2  0.33-0.80m  10YR 5/4, sand, very weak fine granular structure, very friable.
Bw3  0.80-2.00m  10YR 5/3, loamy sand, very weak fine subangular blocky structure, very friable.

053 Bigbee
Ap  0.00-0.19m  10YR 2/2, sand, single grained structure, loose consistency.
Bwl  0.19-0.35m  10YR 4/4, sand, very weak fine granular structure, very friable.
Bw2  0.35-0.74m  10YR 5/4, sand, very weak fine granular structure, very friable.
Bw3  0.74-2.00m  10YR 5/3, loamy sand, very weak fine subangular blocky structure, very friable.

054 Bigbee
Ap   0.00-0.15m  10YR 2/2, sand, single grained, loose consistency.
Bwl  0.15-1.00m  10YR 5/4, sand, very weak fine granular structure, very friable.
Bw2  1.00-2.00m  10YR 5/3, loamy sand, very weak fine subangular blocky structure, very friable.

055 Bigbee
Ap   0.00-0.13m  10YR 4/2, sand, single grained structure, loose consistency.
Bwl  0.13-0.28m  10YR 4/3, sand, very weak fine granular structure, very friable.
Bw2  0.28-0.43m  10YR 5/3, sand, very weak fine subangular blocky structure, very friable.
Bw3  0.43-0.82m  10YR 6/3, sand, very weak fine subangular blocky structure, very friable.
C1   0.82-1.20m  10YR 6/2, sand, very weak fine subangular blocky structure, very friable, few 5YR 5/6 nodules.
C2   1.20-1.62m  10YR 6/2, sand, very weak fine subangular blocky structure, very friable, few 5YR 5/6 nodules, common medium distinct, 10YR 4/4 mottles.
Ab   1.62-2.00m  10YR 4/4, sand, very weak fine subangular blocky structure, very friable.

056 Bigbee
Ap   0.00-0.10m  10YR 2/2, sand, single grained structure, loose consistency.
Bwl  0.10-1.40m  10YR 5/4, sand, very weak fine granular structure, very friable.
Bw2  1.40-1.90m  10YR 5/3, sand, very weak fine subangular blocky structure, very friable.
2Bt  1.90-2.00m  10YR 5/2, sandy loam, weak fine subangular blocky structure, very friable.

057 Bigbee
Ap   0.00-0.15m  10YR 2/1, sand, single grained, loose consistency.
Bwl  0.15-0.54m  10YR 4/2, sand, single grained, loose consistency.
Bw2  0.54-1.55m  10YR 5/4, sand, very weak fine granular structure, very friable.
2Bt  1.55-2.00m  10YR 5/3, sandy loam, weak fine granular, very friable.

058 Bigbee
Ap   0.00-0.16m  10YR 3/2, sand, single grain structure, loose consistency.
Bw   0.16-0.70m  10YR 5/4, sand, very weak fine granular structure, very friable.
El   0.70-1.20m  10YR 5/2, sand, very weak fine subangular blocky structure, very friable.
E2   1.20-1.40m  10YR 6/3, sand, very weak fine subangular blocky structure, very friable.
2Btl 1.40-1.65m  10YR 4/4, sandy loam, very weak fine subangular blocky structure, very friable.
2Bt2 1.65-2.00m  10YR 5/3, sandy loam, very weak fine subangular blocky structure, very friable.
<table>
<thead>
<tr>
<th>Layer</th>
<th>Depth (m)</th>
<th>Color</th>
<th>Consistency</th>
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<tbody>
<tr>
<td>Ap</td>
<td>0.00-0.17</td>
<td>10YR 3/2, sand, single grained structure, loose consistency.</td>
<td></td>
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<tr>
<td>Bwl</td>
<td>0.17-0.60</td>
<td>10YR 4/4, loamy fine sand, very weak fine granular structure, very friable.</td>
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<td>Bw2</td>
<td>0.60-1.40</td>
<td>10YR 5/4, sand, very weak fine subangular blocky structure, very friable.</td>
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<td>Bw3</td>
<td>1.40-2.00</td>
<td>10YR 5/3, sand, very weak fine subangular blocky structure, very friable.</td>
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<td>Ap</td>
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<td>10YR 3/3, sand, single grain structure, loose consistency.</td>
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<td>Bwl</td>
<td>0.07-0.60</td>
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<tr>
<td>E</td>
<td>0.60-0.70</td>
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<td>Bw2</td>
<td>0.70-1.10</td>
<td>10YR 5/4, sand, very weak fine granular structure, very friable.</td>
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<tr>
<td>Btl</td>
<td>1.10-1.44</td>
<td>10YR 4/4, sandy loam, weak fine subangular blocky structure, very friable, few fine faint 7.5YR 4/6 redox accumulations.</td>
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<tr>
<td>Bt2</td>
<td>1.44-1.85</td>
<td>10YR 4/3, sandy loam, weak fine subangular blocky structure, friable.</td>
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<tr>
<td>Ab</td>
<td>1.85-2.00</td>
<td>10YR 3/2, loamy sand, weak fine subangular blocky structure, very friable.</td>
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<tr>
<td>Ap</td>
<td>0.00-0.12</td>
<td>10YR 3/3, sand, single grained structure, loose consistency.</td>
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<tr>
<td>Bwl</td>
<td>0.12-0.54</td>
<td>10YR 4/4, loamy fine sand, very weak fine granular structure, very friable.</td>
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<tr>
<td>Bw2</td>
<td>0.54-0.80</td>
<td>10YR 5/4, sand, very weak fine granular structure, very friable.</td>
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<td>0.80-1.40</td>
<td>10YR 4/3, sandy loam, weak fine subangular blocky structure, friable.</td>
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<td>Abl</td>
<td>1.40-1.65</td>
<td>10YR 3/3, sandy loam, weak fine subangular blocky structure, friable.</td>
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<td>Ab2</td>
<td>1.65-2.00</td>
<td>10YR 3/2, loamy sand, weak fine subangular blocky structure, very friable.</td>
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<td>0.09-0.54</td>
<td>10YR 4/4, loamy fine sand, very weak fine granular structure, very friable.</td>
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<td>Bw2</td>
<td>0.54-0.80</td>
<td>10YR 5/4, sand, very weak fine granular structure, very friable.</td>
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<tr>
<td>Btl</td>
<td>0.80-1.42</td>
<td>10YR 4/3, sandy loam, weak fine subangular blocky structure, friable.</td>
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<tr>
<td>Abl</td>
<td>1.42-1.70</td>
<td>10YR 3/3, sandy loam, weak fine subangular blocky structure, friable.</td>
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<td>Ab2</td>
<td>1.70-2.00</td>
<td>10YR 3/2, loamy sand, very weak fine subangular blocky structure, very friable.</td>
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</tbody>
</table>
064 Bonneau

Ap 0.00-0.10m 10YR 3/2, sand, no structure, loose consistence.
Bwl 0.10-0.29m 10YR 5/4, sand, weak fine granular structure, very friable.
Bw2 0.29-0.59m 10YR 4/4, loamy sand, weak fine granular structure, very friable.
Bw3 0.59-0.98m 10YR 5/4, sand, weak fine granular structure, very friable.
Btl 0.98-1.30m 10YR 4/3, sandy clay loam, moderate fine subangular blocky structure, friable, common fine distinct 7.5 YR 4/6 redox accumulations.
Bt2 1.30-1.45m 10YR 4/3, sandy loam, moderate fine subangular blocky structure, friable, common fine distinct 7.5YR 4/6 redox accumulations, common fine distinct 10YR 6/1 redox depletions.
Bt3 1.45-1.74m 10YR 5/1, sandy loam, moderate fine subangular blocky structure, friable, common medium distinct 7.5YR 5/6 redox accumulations.
B'w 1.74-2.00m 10YR 4/3, loamy sand, moderate fine subangular blocky structure, very friable.

065 Bonneau

Ap 0.00-0.12m 10YR 4/2, sand, single grain structure, loose consistence.
Bwl 0.12-0.30m 10YR 4/4, sand, single grain structure, loose consistence.
Bw2 0.30-0.48m 10YR 5/4, sand, single grain structure, loose consistence.
Bw3 0.48-0.70m 10YR 5/4, sand, single grain structure, loose consistence, 10YR 6/3 mottles.
Btl 0.70-1.25m 10YR 4/6, sandy loam, weak moderate subangular blocky structure, very friable, few fine distinct 5YR 5/6 iron nodules and 10YR phosphate nodules.
Bt2 1.25-1.70m 10YR 5/4, sandy loam, weak moderate subangular blocky structure, very friable, few fine distinct 5YR 5/6 iron nodules and 10YR phosphate nodules, few fine faint 10YR 7/1 depletions.
Bt3 1.70-2.00m 10YR 5/4, sandy clay loam, moderate medium subangular blocky structure, friable, common fine to medium distinct mottles of 10YR 4/4, 512, and 2.5YR 4/4.

066 Millhopper

Ap 0.00-0.15m 10YR 2/1, sand, no structure, loose consistence.
Bw 0.15-0.74m 10YR 5/4, sand, very weak fine granular structure, very friable.
E 0.74-1.50m 10YR 7/2, sand, very weak fine granular structure, very friable.
Btl 1.50-1.66m 10YR 5/4, sandy loam, weak fine subangular blocky structure, very friable.
Bt2 1.66-1.71m 10YR 5/4, sandy loam, weak fine subangular blocky structure, very friable, few fine faint 10YR 6/2 redox depletions.
Bt3 1.71-1.94m 10YR 4/4, sandy loam, moderate fine subangular blocky structure, friable.
Bt4 1.94-2.00m 10YR 4/4, sandy loam, moderate fine subangular blocky structure, friable, common fine distinct 7.5YR 5/8 redox accumulations, few fine distinct 10YR 6/1 redox depletions.

067 Millhopper

Ap 0.00-0.16m 10YR 2/1, sand, no structure, loose consistence.
Bw 0.16-0.66m 10YR 5/4, sand, very weak fine granular structure, very friable.
E 0.66-1.50m 10YR 7/2, sand, very weak fine granular structure, very friable.
Btl 1.50-1.72m 10YR 4/4, sandy loam, weak fine subangular blocky structure, friable, common fine faint 10YR 6/2 redox depletions.
Bt2 1.72-2.00m 10YR 4/3, sandy loam, weak fine subangular blocky structure, friable, common fine distinct 7.5YR 5/8 redox accumulations, common fine to medium 10YR 6/1 redox depletions.
068 Bonneau

Ap 0.00-0.15m 10YR 2/2, sand, single grain structure, loose consistence.
Bw 0.15-0.50m 10YR 5/4, sand, very weak fine granular structure, very friable.
E 0.50-0.88m 10YR 6/2, sand, very weak fine granular structure, very friable.
Bt 0.88-1.10m 10YR 6/3, sandy clay loam, moderate fine subangular blocky structure, friable, common medium distinct 7.5YR 5/8 redox accumulations.
2Btg 1.10-2.00m 10YR 6/1, sandy clay loam, moderate fine to medium subangular blocky structure, common medium distinct 7.5YR 5/8 redox accumulations, common fine phosphate nodules.

069 Noboco

Ap 0.00-0.10m 10YR 3/2, sand, single grain structure, loose consistence.
Bwl 0.10-0.20m 10YR 4/4, sand, single grain structure, loose consistence.
Bw2 0.20-0.40m 10YR 5/4, sand, single grain structure, loose consistence.
Bt 0.40-0.83m 10YR 5/4, sandy clay loam, moderate medium subangular blocky structure, friable.
2Bt 0.83-2.00m 10YR 5/4, sandy clay, moderate medium subangular blocky structure, firm, common medium distinct 7.5YR 5/6 redox accumulations, common medium distinct 10YR 6/1 redox depletions, few medium phosphate nodules.

070 Bonneau

Ap 0.00-0.20m 10YR 3/2, loamy sand, very weak fine granular structure, very friable.
Bw 0.20-0.60m 10YR 4/4, loamy sand, very weak fine subangular blocky structure, very friable.
Btl 0.60-0.72m 10YR 4/4, sandy clay loam, moderate fine subangular blocky structure, friable.
Bt2 0.72-0.84m 10YR 5/3, sandy clay loam, moderate medium subangular blocky structure, friable, common fine faint 7.5 YR 5/8 redox accumulations, few very fine faint 10YR 6/1 redox depletions.
Bt3 0.84-1.20m 10YR 5/4, sandy clay loam, moderate fine subangular blocky structure, friable, common fine distinct 7.5YR 5/8 redox accumulations.
2Btg 1.20-2.00m 10YR 6/1, sandy clay loam, moderate medium subangular blocky structure, friable, common medium distinct 7.5YR 5/8 redox accumulations, common medium phosphate nodules.

071 Bonneau

Ap 0.00-0.13m 10YR 3/2, sand, no structure, loose consistence, common fine roots.
Bw 0.13-0.54m 10YR 4/4, sand, very weak fine granular structure, very friable.
Btl 0.54-0.60m 10YR 5/2, sandy clay loam, moderate fine subangular blocky structure, friable, common fine faint 7.5 YR 5/8 redox accumulations, very few fine faint 10YR 6/1 redox depletions.
Bt2 0.60-1.19m 10YR 4/4, sandy clay loam, moderate fine subangular blocky structure, friable.
Bt3 1.19-1.30m 10YR 5/4, sandy clay loam, moderate fine subangular blocky structure, friable, common fine distinct 7.5YR 4/6 redox accumulations, few fine distinct 10YR 6/1 redox depletions.
Bt4 1.30-1.45m 10YR 6/2, sandy clay loam, moderate fine subangular blocky structure, friable, common fine very faint 10YR 6/6 redox accumulations.
2Btg 1.45-2.00m 10YR 6/1, sandy clay loam, moderate medium subangular blocky structure, friable common medium distinct 7.5YR 5/8 redox accumulations, common fine phosphate nodules.
072 Bonneau
Ap   0.00-0.13m  10YR 2/2, sand, single grain structure, loose consistence.
Bwl  0.13-0.30m  10YR 4/4, sand, single grain structure, loose consistence.
Bw2  0.30-0.60m  10YR 5/4, sand, single grain structure, loose consistence.
Btl  0.60-0.85m  10YR 4/4, sandy clay loam, moderate medium subangular blocky structure, friable.
Bt2  0.85-1.42m  10YR 4/4, sandy loam, moderate medium subangular blocky structure, very friable.
Bt3  1.42-2.00m  10YR 5/2, sandy loam, common fine to medium distinct 7.5YR 4/4 redox accumulations.

073 Noboco
Ap   0.00-0.05m  10YR 2/1, loamy fine sand, very weak fine granular structure, very friable, common fine roots.
AB   0.05-0.13m  10YR 3/2 and 2/1, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.
Bw   0.13-0.22m  10YR 3/2, loamy fine sand, very weak fine subangular blocky structure, very friable, few medium distinct 5YR 4/6 and 7.5 YR 5/8 concretions.
Btl  0.22-0.47m  10YR 3/3, sandy clay loam, moderate fine subangular blocky structure, friable.
Bt2  0.47-0.73m  10YR 4/3, sandy clay loam, moderate fine subangular blocky structure, friable.
Bt3  0.73-0.95m  10YR 5/4, sandy clay loam, moderate fine subangular blocky structure, common fine faint 10YR 4/2 clay concentrations in root channels, very few fine distinct 10YR 5/1 and very few fine-medium 10YR 8/4 redox depletions, few coarse distinct 10YR 3/4 and 7.5 YR 5/8 concretions.
Bt4  0.95-1.14m  10YR 5/4, sandy clay loam, moderate medium subangular blocky structure, friable, common medium distinct 10YR 5/1 redox depletions, common medium distinct 7.5YR 5/8 and few coarse distinct 10YR 7/18 redox accumulations.
Bt5  1.14-1.22m  10YR 5/4, sandy clay loam, moderate medium subangular blocky structure, friable, common fine to medium distinct 10YR 5/1 redox depletions, very few fine distinct 10YR 5/8 redox accumulations, common very fine distinct 10YR 8/1 nodules.
Bt6  1.22-1.65m  10YR 5/1, sandy clay loam, moderate medium subangular blocky structure, common fine to medium 10YR 4/3 redox accumulations, common medium to coarse 10YR 5/1 nodules, peds marbled with few very fine 5/GY 8/3 depletions.
Bt7  1.65-1.73m  10YR 4/1, sandy clay loam, moderate medium subangular blocky structure, friable, peds marbled with common fine distinct 10YR 5/1 and common fine distinct 10YR 7/2 redox depletions and common fine distinct 10YR 6/4 redox accumulations.
Btg  1.73-2.00m  5YR 8/3, sandy clay loam, friable, peds marbled with few fine distinct 10YR 5/1 redox depletions and few medium distinct 10YR 6/4 redox accumulations.

074 Noboco
Ap   0.00-0.15m  10YR 2/1, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.
AB   0.15-0.24m  10YR 2/1 and 4/4, loamy fine sand, very weak fine subangular blocky structure, very friable, common fine roots.
Bw   0.24-0.47m  10YR 4/4, loamy fine sand, very weak fine subangular blocky structure, very friable.
<table>
<thead>
<tr>
<th>Layer</th>
<th>Depth (m)</th>
<th>Color</th>
<th>Texture</th>
<th>Structure</th>
<th>Fertility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bt1</td>
<td>0.47-1.17m</td>
<td>10YR 4/4, sandy clay loam, moderate fine subangular blocky structure, friable.</td>
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<tr>
<td>Bt2</td>
<td>1.17-1.44m</td>
<td>10YR 4/4, sandy clay loam, moderate fine subangular blocky structure, very friable, few medium distinct 5YR 4/6 and 7.5 YR 5/8 redox accumulations, few medium distinct 2.5YR 3/6 nodules.</td>
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<tr>
<td>Bt3</td>
<td>1.44-1.53m</td>
<td>10YR 5/3, sandy clay loam, moderate fine subangular blocky structure, friable, very few fine distinct 10YR 5/1 redox depletions.</td>
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<tr>
<td>Bt4</td>
<td>1.53-2.00m</td>
<td>10YR 5/3, sandy clay loam, moderate fine subangular blocky structure, common medium distinct 10YR 6/1 and 7/3 redox depletions, common fine to medium distinct 5YR 4/6 and 7.5 YR 5/8 redox accumulations.</td>
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**075 Bonneau**

<table>
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<th>Texture</th>
<th>Structure</th>
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<tbody>
<tr>
<td>Ap</td>
<td>0.00-0.15m</td>
<td>10YR 2/1, sand, no structure, loose consistence.</td>
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<tr>
<td>Bw</td>
<td>0.15-0.30m</td>
<td>10YR 5/4, loamy sand, very weak fine granular structure, very friable.</td>
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<td>E</td>
<td>0.30-0.66m</td>
<td>10YR 6/4, sand, very weak fine granular structure, very friable.</td>
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<tr>
<td>Et</td>
<td>0.66-1.00</td>
<td>10YR 6/2, sandy clay loam, moderate fine to medium subangular blocky structure, friable, common fine to medium faint 7.5YR 5/8 redox accumulations.</td>
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<tr>
<td>2Btg</td>
<td>1.00-2.00m</td>
<td>10YR 6/1, sandy clay loam, moderate medium subangular blocky structure, friable, common medium distinct 7.5YR 5/8 redox accumulations.</td>
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**076 Bonneau**

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<th>Structure</th>
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<tr>
<td>Ap</td>
<td>0.00-0.30m</td>
<td>10YR 2/1, sand, very weak fine granular structure, very friable.</td>
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<td>E</td>
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<td>Et</td>
<td>0.60-2.00m</td>
<td>10YR 6/2, sandy clay loam, moderate medium subangular blocky structure, friable, common medium distinct 7.5YR 5/8 redox accumulations, common fine phosphate nodules.</td>
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**077 Norfolk**

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Ap</td>
<td>0.00-0.12m</td>
<td>10YR 3/1, sand, no structure, loose consistence.</td>
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<tr>
<td>Bwl</td>
<td>0.12-0.37m</td>
<td>10YR 3/4, loamy sand, loose structure.</td>
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<tr>
<td>Bw2</td>
<td>0.37-1.08m</td>
<td>10YR 5/4, loamy sand, very weak fine granular structure, very friable.</td>
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<tr>
<td>E</td>
<td>1.08-1.90m</td>
<td>10YR 6/4, sand, very weak fine subangular blocky structure (due to moisture), very friable.</td>
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<tr>
<td>Btg</td>
<td>1.90-2.00m</td>
<td>10YR 6/2, loamy sand, weak fine subangular blocky structure, very friable, common medium distinct 7.5YR 5/8 redox accumulations, common fine phosphate nodules.</td>
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</table>

**078 Millhopper**

<table>
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<tr>
<th>Layer</th>
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<tbody>
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<td>0.00-0.15m</td>
<td>10YR 2/1, sand, very weak fine granular structure, very friable.</td>
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<tr>
<td>Bwl</td>
<td>0.15-1.20m</td>
<td>10YR 4/2, loamy sand, very weak fine granular structure, very friable.</td>
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<tr>
<td>Et</td>
<td>1.20-1.90</td>
<td>10YR 5/4, sandy loam, weak fine subangular blocky structure, very friable, common fine faint 10YR 6/8 redox accumulations.</td>
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<tr>
<td>2Btg</td>
<td>1.90-2.00m</td>
<td>10YR 6/1, sandy clay loam, moderate medium subangular blocky structure, friable, common medium distinct 7.5YR 5/8 redox accumulations.</td>
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<tr>
<td>Location</td>
<td>Depth</td>
<td>Color</td>
<td>Texture</td>
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<tr>
<td>079 Millhopper</td>
<td><strong>Ap</strong></td>
<td>0.00-0.10m</td>
<td>10YR 2/1</td>
<td>sand, very weak fine granular structure, very friable, common fine roots.</td>
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<td><strong>Bw1</strong></td>
<td>0.10-0.32m</td>
<td>10YR 4/2</td>
<td>sand, very weak fine granular structure, very friable.</td>
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<td><strong>Bw2</strong></td>
<td>0.32-0.49m</td>
<td>10YR 3/2</td>
<td>loamy sand, very weak fine granular structure, very friable.</td>
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<td><strong>Bw3</strong></td>
<td>0.49-1.00m</td>
<td>10YR 4/4</td>
<td>loamy sand, weak fine granular structure, very friable.</td>
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<td><strong>Bw4</strong></td>
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<td><strong>Btl</strong></td>
<td>1.49-1.75m</td>
<td>10YR 5/4</td>
<td>sandy loam, weak fine subangular blocky structure, friable, common fine faint 10YR 6/8 redox accumulations.</td>
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<td><strong>Bt2</strong></td>
<td>1.75-1.95m</td>
<td>10YR 6/2</td>
<td>sandy loam, weak fine subangular blocky structure, common medium distinct 10YR 6/6 redox accumulations.</td>
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<tr>
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<td><strong>2Btg</strong></td>
<td>1.95-2.00m</td>
<td>10YR 6/1</td>
<td>sandy clay loam, moderate fine subangular blocky structure, common medium distinct 10YR 6/4 and 7.5 YR 5/8 redox accumulations, common fine phosphate nodules.</td>
<td></td>
</tr>
<tr>
<td>080 Bonneau</td>
<td><strong>Ap</strong></td>
<td>0.00-0.26m</td>
<td>10YR 2/2</td>
<td>sand, very weak fine granular structure, very friable.</td>
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<td><strong>Bw1</strong></td>
<td>0.26-0.60m</td>
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<td>loamy sand, very weak fine subangular blocky structure, very friable.</td>
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<td><strong>Bw2</strong></td>
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<td>weak sandy loam, weak fine subangular blocky structure, very friable.</td>
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<td><strong>Btl</strong></td>
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<td>1.70-2.00m</td>
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<td>081 Millhopper</td>
<td><strong>Ap</strong></td>
<td>0.00-0.20m</td>
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<td><strong>Bw</strong></td>
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<td>10YR 5/3</td>
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<tr>
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<td><strong>E</strong></td>
<td>0.97-1.10m</td>
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<td></td>
<td><strong>Btgl</strong></td>
<td>1.10-1.30m</td>
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<tr>
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<td><strong>Btg2</strong></td>
<td>1.30-1.50m</td>
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<td><strong>Bt</strong></td>
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<td>10YR 3/3</td>
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<td><strong>Btg</strong></td>
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<td>10YR 4/2</td>
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083 Norfolk
Ap 0.00-0.19m 10YR 3/3, loamy fine sand, very weak fine subangular blocky, very friable, common fine roots.
Bt 0.19-0.76m 10YR 3/3, sandy clay loam, moderate fine subangular blocky, friable, very few fine roots.
Btg 0.76-0.93m 10YR 4/2, sandy clay loam, moderate fine subangular blocky, common fine 7.5YR 4/6 redox accumulations, friable, few fine 7.5YR 5/8 nodules.
2Btg 0.93-2.00m 10YR 5/1, sandy clay loam, common fine 7.5YR 5/8 redox accumulations, friable.

084 Millhopper
Ap 0.00-0.20m 10YR 3/3, loamy fine sand, granular, very friable, common fine roots.
Bwl 0.20-0.35m 10YR 4/4, loamy fine sand, very weak fine subangular blocky, very friable, few fine roots.
Bw2 0.35-1.25m 10YR 5/4, loamy fine sand, very weak fine subangular blocky, very friable, few fine faint 10YR 7/4 redox depletions.
Bt 1.25-1.45m 10YR 5/3, sandy clay loam, moderate fine subangular blocky, friable, common medium distinct 10YR 5/6 redox accumulations.
Btg 1.45-2.00m Common medium distinct 7.5YR 4/6 redox accumulations and Common medium distinct 10YR 5/1 redox depletions, sandy clay loam, friable.

085 Millhopper
Ap 0.00-0.11m 10YR 2/2, loamy fine sand, granular, very friable, common fine roots.
A 0.11-0.33m 10YR 3/2, loamy fine sand, granular, very friable, common fine roots.
Bwl 0.33-0.60m 10YR 5/6, loamy fine sand, very weak fine subangular blocky, very friable, few fine roots.
Bw2 0.60-1.20m 10YR 6/4, loamy fine sand, very weak fine subangular blocky, very friable.
E 1.20-1.43m 10YR 6/3, loamy fine sand, very weak fine subangular blocky, very friable, approximately 40 percent of the sand grains stripped.
E/B 1.43-1.53m 10YR 6/3, loamy fine sand, very weak fine subangular blocky, very friable, common fine faint 10YR 5/8 clay accumulations.
Bt 1.53-1.80m 10YR 6/3, sandy loam, weak fine subangular blocky, friable, common fine faint, 10YR 5/8 redox accumulations.
Btg 1.80-200m 10YR 6/2, sandy clay loam, moderate fine subangular blocky, friable, common medium distinct 10YR 5/6 redox accumulations.

086 Norfolk
Ap 0.00-0.20m 10YR 3/2, sand, single grain structure, loose consistence.
Bwl 0.20-1.45m 10YR 4/4, sand, single grain structure, loose consistence.
Bw2 1.45-2.00m 10YR 5/4, sand, single grain structure, loose consistence, few fine to medium distinct 10YR 6/8 redox accumulations.

087 Millhopper
Ap 0.00-0.15m 10YR 2/2, sand, very weak fine granular structure, very friable.
Bwl 0.15-0.83m 10YR 4/4, loamy sand, very weak fine granular structure, very friable.
Bw2 0.83-1.10m 10YR 5/4, loamy sand, very weak fine granular structure, very friable.
Bw3 1.10-1.90m 10YR 6/4, loamy sand, weak fine subangular blocky structure, very friable.
Bt 1.90-2.00m 10YR 6/1, sandy loam, weak fine subangular blocky structure, very friable, common fine distinct 7.5YR 4/4 redox accumulations.
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<th>Layer</th>
<th>Depth (m)</th>
<th>Color (10YR)</th>
<th>Texture</th>
<th>Structure</th>
<th>Friability</th>
<th>Redox Accumulations</th>
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<td>structure, very friable, common fine distinct 7.5YR 4/4 and 5/8 redox accumulations.</td>
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| **089 Millhopper** | | | | | | |
| Ap    | 0.00-0.15m | 10YR 2/2, sand | very weak fine granular structure, very friable. | | | |
| Bwl   | 0.15-1.20m | 10YR 4/4, loamy sand | very weak fine granular structure, very friable. | | | |
| Bw2   | 1.20-1.50m | 10YR 5/4, loamy sand | very weak fine granular structure, very friable. | | | |
| Bw3   | 1.50-1.90m | 10YR 7/4, sand | very weak fine granular structure, very friable. | | | |
| Bt    | 1.90-2.00m | 10YR 6/1, sandy loam | weak fine subangular blocky structure, very friable, common fine distinct 7.5YR 4/4 and 5/8 redox accumulations. |

| **090 Millhopper** | | | | | | |
| Ap    | 0.00-0.19m | 10YR 2/2, sand | very weak fine granular structure, very friable. | | | |
| Bwl   | 0.19-1.16m | 10YR 4/4, loamy sand | very weak fine granular structure, very friable. | | | |
| Bw2   | 1.16-1.51m | 10YR 5/4, loamy sand | very weak fine granular structure, very friable. | | | |
| Bw3   | 1.51-1.93m | 10YR 7/4, sand | very weak fine granular structure, very friable. | | | |
| Bt    | 1.93-2.00m | 10YR 6/1, sandy loam | weak fine subangular blocky structure, very friable, common fine distinct 7.5YR 4/4 and 5/8 redox accumulations. | | |
APPENDIX E
SITE SPECIFIC SOIL PROPERTIES

Table E-1. Listing of selected soil property values that were used for the site-referenced groundwater vulnerability assessment study.

<table>
<thead>
<tr>
<th>Site Number</th>
<th>Organic Carbon (%)</th>
<th>Depth of A Horizon (m)</th>
<th>Rooting Depth (m)</th>
<th>Depth to Argillic Horizon (m)</th>
<th>Damping Depth (m)</th>
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BIOGRAPHICAL SKETCH

Cornelis Gerrit Hoogeweg was born on July 26, 1967 in Bilthoven, The Netherlands. In 1983, he successfully completed the Middelbaar Algemeen Voortgezet Onderwijs (M.A.V.O.) diploma, followed by the Hoger Algemeen Voortgezet Onderwijs (H.A.V.O.) diploma in 1985 and the Voorbereidend Wetenschappelijk Onderwijs (V.W.O.) diploma in 1987, at the Werkplaats Kindergemeenschap in Bilthoven. In the fall of 1987 he started his studies at the Wageningen Agricultural University in Wageningen, The Netherlands. From 1987 to 1992, he was active as a player, trainer, coach and president of the technical committee of the student volleyball club WAHO. In the second half of 1991, he worked on his masters thesis at the Pesticides in Soils Department of the Winand Staring Centre for Integrated Land, Soil and Water Research at Wageningen. In 1992 and 1993, he fulfilled an internship at the Soil and Water Science Department of the University of Florida, Gainesville, FL. In the spring of 1993, he graduated from the Wageningen Agricultural University with the degree of ‘ingenieur’ (Master of Agricultural Sciences) with a major in soil quality and a minor in microbiology.

In the fall of 1993, he started his studies in the Soil and Water Science Department at the University of Florida, Gainesville, FL. to pursue a doctoral degree in the field of soils physics and geographic information systems.