MONTE CARLO ANALYSIS OF REFUGE SITE SELECTION: STATISTICAL PROPERTIES AND AN EMPIRICAL EXAMPLE

by

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ABSTRACT

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The Monte Carlo method can be a useful technique providing information on central tendencies and tolerance for selection data. There are many statistical hypothesis tests that are employed in selection studies, but most require the data to be normally distributed in order to adhere to the assumption of normality. Monte Carlo methods build a null distribution to test hypotheses based on available conditions and therefore do not require distributions of data to be normal. A Monte Carlo is also an extremely flexible technique and can be designed to test hypotheses for any particular experimental design.

I designed a Monte Carlo method that uses use/availability data to detect patterns of selection in a species population. The Monte Carlo randomly re-samples from an available distribution a sample size equal to the sample size of the data making

the used distribution with 1,000 permutations. For each re-sample, two statistics (mean and standard deviation) are calculated and compared to the statistics of the used distribution. A tail probability is then calculated. Because this method is not common among selection studies and each Monte Carlo design potentially behaves with different dynamics when considering sample size and Type I and II error rates, I performed randomization tests on simulated datasets to evaluate Type I and II error rates for sample sizes from 2 to 50.

Datasets were generated by drawing data points (samples) from a Gaussian distribution (i.e., hypothetical species response curve) of specified parameters and compared to conditions associated with an available distribution. The change in error rates as a function of species selection away from mean available distribution as well as differences in standard deviations were assessed using randomization procedures (number of significant results). Type I error was generally low at all samples and parameters of available distributions examined while power increased as a function of sample size and divergence away from the mean of the available conditions. Power in the standard deviation statistic of each hypothetical used distribution was more influenced by the standard deviations associated with the available distributions. Power in the mean statistic was unaffected by the standard deviation of the available distributions. Power in the mean statistic also produced lower Type II error rates at lower sample sizes than the standard deviation statistic and at smaller differences between each hypothetical used distribution and the simulated available distributions.

In a case study using the Monte Carlo method designed to evaluate refuge site selection, I sampled abiotic variables including temperature, moisture, and rock size related to potential refuge rocks in the Smoky and Flint Hills of Kansas. I collected data associated with refuge sites for 9 species and large amounts of abiotic data from haphazardly chosen rocks adjacent to the observed or used sites. Only five species were abundant enough for analysis, *Diadophis punctatus* being the most abundant. I found that thermal properties, humidity, and rock size varied in their importance among species and between locations. I predict that along with thermal properties, a major factor in selection of a particular refuge habitat is the refuge site's humidity properties and the relative homogeneity of thermal and humidity properties under refuge rocks determined by rock size.

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CHAPTER 1

INTRODUCTION

1.1 Resources and Habitat Use

Resources, biotic and abiotic, are items used by species to meet their needs for survival. Resources may include such categories as land, water, air, sunlight, food and other aspects of habitat. Habitat is the subsection of the physical environment that surrounds a species population and in which the species population lives. Each species population requires a particular combination and varying amount of resources within its habitat. Biologists document the use and availability of resources for species populations to better understand which resources are selected more with respect to other resources and to understand how species use and partition available resources.

Most resources are limited in local environments; thus, the potential for competitive interactions is high. When more than one species occupies the same niche, sympatric populations may respond in one of two ways to the limited supply or quality of resources. Either the more competitive species drives the less competitive species to extirpation or one species evolves a different set of resource requirements or resource quality requirements for survival. This second scenario is resource partitioning and allows species populations occupying similar niches to coexist with a limited amount of resources (Rosenzweig 1981). Disproportionate resource use by a species as compared to the availability of the resource is resource selection (Johnson 1980).

Habitats are characteristically heterogenous and can be described on many different scales ranging from the entire geographic range of a species, to regional macrohabitat to microhabitat patches of varying spatial extents. Macrohabitat variables include major vegetation, soil type, rock type, sources of water, precipitation, and physiographic features of the landscape. Habitat variables include general features of an individual home range. Microhabitat variables include amount of shading, sunlight intensity, temperature, moisture, particular vegetation associations within the microhabitat, and spatial extent. Microhabitat can be split further into particular subclasses based on temporal use; such as, mating, nesting, gestation, and refuge sites.

Refuge sites are a particular subclass of microhabitat that serve as refugia or protection for an individual in a species population from the surrounding stochastic environment, and may aid in thermoregulation and in encountering prey items (Downes 1999, Beck and Jennings 2003, Howes and Lougheed 2004). Refuge sites can play an important role in the survival of species populations with respect to the degree of 'harshness' or stochasticity in the environment by providing a buffering mechanism from environmental extremes. The more stochastic the environment, the more important the selection of the appropriate site becomes, because switching to a new site during adverse conditions would be too costly. For ectotherms, refuge site selection may be an especially important task. Ectotherms are dependent on their immediate environment and are highly vulnerable due to their physiological need to thermoregulate, conserve energy and avoid dehydration. In addition, many temperate-zoned reptiles spend most of their day sequestered under rocks or in burrows, only emerging above ground during favorable conditions (Avery 1976; Huey 1982; Rutherford and Gregory 2003). The amount of time spent in refuge sites then emphasizes the importance of refuge site selection; some ectotherms spend over 99% of their total time in refuge sites (Beck 1990).

In a study on the refuge site selection of Gila Monsters, *Heloderma suspectum*, Beck and Jennings (2003) investigated shelter use in a strongly seasonal desert environment. They found Gila Monsters do not use shelters randomly, but use shelters based on availability and quality of shelter, and that Gila Monsters show strong fidelity to shelters. This indicates high variability in environmental parameters within shelters and suggests that shelters of high quality are limited. Furthermore, adequate conditions must be recognized by Gila Monsters; otherwise, shelters would (or would appear) to be used randomly and Gila Monsters would not show strong site fidelity. On the contrary, Garter Snakes (*Thamnophis elegans*) in northern California typically switch retreat sites during the night showing low site fidelity (Huey et al. 1989). Huey et al. (1989) suggest the switch could serve to find better refuge conditions for thermoregulatory purposes, or to escape predators. Regardless, for this to be an effective strategy there must be suitable alternative refuge sites available within the area for the reptiles to relocate. In a mark recapture study describing characteristics of summer and hibernation sites for Northern Alligator Lizards, *Elgaria coerulea*, and Western Skinks, *Eumeces* (*Plestiodon*) *skiltonianus*, Rutherford and Gregory (2003) note that individuals were recaptured on average within 10m of a previous capture site and individuals did not travel long-distances. Although these reptiles along with the Garter snakes might switch amongst rocks in a local site, the relative area selected provides adequate amounts of refuge sites with conditions flexible enough for species population survival.

Huey et al. (1989) emphasized the importance of refuge sites and highlighted the lack of refuge site selection studies with respect to behavioral thermoregulation, with notable exceptions (e.g. citations within). Since his review, there has been an increase in studies on refuge sites demonstrating their importance in the thermal biology, water regulation, dispersion patterns, disturbance patterns, and other biological aspects of ectotherms (e.g., Schlesinger and Shine 1994; Web and Shine 1998; Goldingay and Newell 2000; Whitaker and Shine 2002; Beck and Jennings 2003; Kerr et al. 2003; Rutherford and Gregory 2003; Howes and Lougheed 2004; Kerr and Bull 2004; Webb et al. 2004).

1.2 Methods for Analyzing Microhabitat Use

Analyzing microhabitat selection is crucial to understanding the types, quantities, and qualities of resources that species populations need for survival. There are many methods for analyzing microhabitat use and the particular method a researcher uses depends on many different aspects of the study. Particular consideration is given to data types, study techniques, experimental designs, and particular questions of interest.

1.2.1 Data Types

Generally, there are two types of variables associated with microhabitat selection studies. Discrete variables consist of categorical data, presence/absence data, or count data; such as, cover rock, woody shrub, open field, or forest, shade or presence/absence. Continuous variables consist of measurements, such as percent cover, measured rock or shrub size, moisture level, or temperature. Microhabitat selection studies utilize both types of variables and often consist of a combination of both. There exists a surplus of methods to analyze qualitative observations from microhabitats and to extract quantitative data from biotic and abiotic factors associated with microhabitats or refuge sites. For example, the availability of habitat can be quantified by using aerial photography, maps, or visiting and sampling the sites. In sampling sites, one could take random samples of the site, or divide the site into quadrants and systematically sample all representative areas in the site. In most cases the objective is to better understand proximate and/or ultimate factors involved in microhabitat selection.

1.2.2 Study Techniques

The use of a microhabitat can be evaluated several ways. Mark-recapture studies, radio-telemetry studies, and snap shot studies all use different techniques to quantify habitat selection. Mark-recapture studies consist of the researcher capturing an organism, recording variables associated with that organism, marking the organism, releasing the organism, and later having the possibility of recapturing the organism and recording biotic and abiotic variables associated with its new capture. Mark-recapture studies are preferable when the capture number and recapture number are both high due to high site fidelity and/or observations are easily made and when the organisms are too small to implant radio tracking devices. Radio-telemetry studies consist of the researcher capturing an organism, recording variables associated with that organism, implanting a tracking device inside the organism, and having the ability to relocate and record microhabitat variables associated with the same individual at will. This type of study would be preferable when the organism is large enough to implant the radio tracking device, when captured population size is low, and when the cost of finding individual organisms is high. Snapshot studies consist of capturing many organisms in one period (e.g. a day, a weekend, a week), as long as there is no re-sampling, and recording the associated habitat variables. In essence, snapshot studies are replicated in space as opposed to telemetric studies, which are replicated in time (Diamond 1986). Snapshot studies are preferred when the captured population size is abundant, the researcher is interested in the short term, and many independent samples are needed.

1.2.3 Sampling Designs

There are three identifiable sampling designs associated with microhabitat selection described by Thomas and Taylor (1990) and outlined by Manly et al. (1993). In design 1, measurements are taken at the level of the population. Individuals are not identified; therefore, units of microhabitats that are used by a particular species population and units of microhabitats that are available to the species population for use (but are not necessarily being used during the sampling period) are pooled across all samples taken. This design fits well with snapshot studies. Hereafter, units of microhabitat that are used by a species population and data or distributions associated with that microhabitat are referred to used, selected, or observed. Units of microhabitat that are used or can potentially be used by a species population are referred to as available. Design 2 takes into account specific individuals and the resources used by each, but the availability data are pooled across the population level. This design fits with both the mark recapture study and the radio telemetry study. If a design 2 study were to have only one observation for each individual, it would be equivalent to a design 1 study. In design 3, individuals are identified, their resource use quantified, and the availability in the surrounding habitat that is associated with each individual is quantified. This design works well with radio telemetry studies. In both design 2 and 3 individuals are identified and inferences are extended to the species population level as well as the individual level. In this case an assumption has to be made when inferring habitat choice on a species population level that the individuals are sampled at random from their species population.

1.2.4 Analytical methods

Two types of analytical methods exist for selection studies; indices of selection and hypothesis testing. Indices of selection quantify selectivity. Early researchers attempted to quantify selectivity using an index ratio percentage of a resource used compared to the percentage of the resource available (e.g., within Manly et at. 1993; Scott 1920; Savage 1931; Hess and Swartz 1940). Statistical methods test hypotheses and set confidence intervals that assist in evaluating if resources are being used selectively and compare the strength of the selectivity. The number of statistical methods that can be used in evaluating habitat selection is extremely large and researchers often use several combinations of methods to infer species population choices based on the type of data collected and the sampling design. Table 1.1 is updated from Manly et al. (1993) and comprises a number of different statistical methods and example references for each.

Recently, both indices of selection and hypothesis testing have been commonly used in concert for evaluating habitat selection. For example McLoughlin et al. (2004) evaluated hierarchical habitat selection by tundra wolves and used a resource selection index proposed by Manly et al. (1993) and Friedman's nonparametric 2-way ANOVA. Meik et al. (2002) also used a combination of indices of selection and hypothesis testing. These analyses consisted of a chi-squared test, a stepwise regression, and the resource selection index to evaluate the effects of bush encroachment on an assemblage of diurnal lizard species. They used the chi-square test of independence to test the homogeneity of species assemblages between two habitat types, for each species a stepwise regression to quantify the associated macrohabitat, and an index of selection to quantify preferences.

The use of a statistical test and/or selection index depends on many factors. Is the intention of the test to describe, compare, quantify, or predict variables? Do the variables come from a Gaussian population distribution, a binomial population distribution, a uniform population distribution, or any other type of distribution? Table 1.2 describes the types of statistical tests suggested for use under specific conditions. This table does not include all the statistical tests available for use, but it includes commonly represented statistical tests in the literature.

In statistical testing, the null hypothesis is assumed to be true until statistical evidence indicates otherwise. In habitat selection studies, the null hypothesis is typically based on species populations utilizing habitat randomly. Although this is an appropriate statistical hypothesis, most researchers would not expect organisms to use habitat in proportion to its availability. Thus, many researchers have abandoned hypothesis tests focused on this question and have instead concentrated efforts on how populations use habitat differentially (Cherry 1998). Of course, analyses designed to determine which habitat variables are selected for would still require hypothesis testing or model fitting approaches. I incorporate a Monte Carlo method to evaluate habitat selection, an approach seldom used in microhabitat selection studies to determine which habitat variables are selected.

1.3 Monte Carlo Analysis to Evaluate Refuge Site Selection

A Monte Carlo analysis is a powerful and extremely flexible statistical technique that utilizes high numbers of permutations of randomized or reshuffled data to build a distribution as a null reference for evaluating values of interest. These simulations allow a researcher to create a statistical test to address a certain experiment or specific question and data type rather than having to construct the experiment around conventional statistical tests. The most powerful advantage of this method over parametric methods is that it does not require data to be sampled from a specified distribution. The Monte Carlo builds the null distribution from the actual used data making clear the underlying assumptions of the test. This method is computationally challenging, but, with today's computer speed, easily tractable.

1.3.1 Designing a Monte Carlo

Gotelli and Ellison (2004) describe four steps in performing a Monte Carlo analysis. First, a test statistic is specified that describes a pattern of interest. For example, if a researcher is interested in a central tendency measure of a population, the test statistic used could be the mean or median. Likewise, if a researcher wanted to describe a distance measure, the test statistic used could be a difference. Next, a null distribution is created by randomly reassigning the treatment groups within the used data many times to form new combinations of the existing data. To do this step a computer is the most useful tool. Each new combination of the data is described by a test statistic and a distribution can be created consisting of these test statistics generated from the randomly reassigned data. Third, the same test statistic is calculated from the original or used data and placed into the distribution of test statistics. Finally, a tail probability is quantified by counting the number of test statistics between the used test statistic and the tail of the distribution and then dividing by the number of test statistics that were used to make the distribution.

Monte Carlo analyses can use categorical or continuous data measurements and can handle multiple variables simultaneously depending on how the test statistic and randomization technique is designed. The assumptions of a Monte Carlo are three fold. First, the used data are independent and randomly sampled. Second, the test statistic chosen for analysis describes the pattern of interest. Third, the null distribution created by the randomization addresses the question of interest. The first two assumptions are the same assumptions followed by all parametric and nonparametric tests. Although normality tends to be an issue in many analyses, it is not an assumption of the Monte Carlo method and therefore does not have to be considered.

1.3.2 Monte Carlo Method for Refuge Site Selection

To evaluate refuge site selection, I designed a Monte Carlo analysis for a snapshot design 1 use/availability study using two test statistics. These statistics describe patterns of species populations of interest, one being a measure of central tendency, the mean, and the other being a measure of variance, the standard deviation. I then designed a simple randomization technique which randomly draws *n* samples 1000 times from a dataset combining both the used and available data, *n* equals the number of samples used in the used dataset. The test statistics are calculated for each randomized dataset and the distribution is compared to the used data test statistic. The *p*-value is calculated by counting all the simulated test statistics between the used test statistic and the end of the tail and then this value is divided by the number of test statistics that are included in the entire distribution. This test can be one or two-tailed depending on whether there are *a priori* assumptions about the directionality of either test statistic.

Measures of central tendency and variation in use/availability data are important in characterizing selectivity. In designing a Monte Carlo test for evaluating refuge site selection, I considered six possible patterns in the distribution of selectivity data (Figure 1.1.1). Throughout the following discussion, ‘availability’ datasets/distributions, etc., refers to all sampled units of data including randomly sampled data plus data associated with any observations of interest. The ‘used’ datasets/distributions etc., refer to the collective observations of interest for any given group or category. Selection is detected if the variance in the used distribution is smaller or the mean diverges from that of the availability distribution. Variance can be a highly explanatory statistic in selection data as it relates the tolerance levels of a species to the particular environmental variable studied. Variance is also important to consider because refuge sites will likely be occupied during periods when mean conditions within refugia tend to be ideal. Thus, regardless of the used mean value, if the variance in the used distribution is smaller than the availability distribution, selection is detected (Figure 1.1: A and B). The mean statistic can also be highly explanatory in selectivity data. When the mean in the used distribution diverges from the mean in the availability distribution, selection is detected (Figure 1.1: C). The variance of the used distribution should not be larger than the variance in the resource availability distribution. This pattern indicates error or high selectivity of extreme conditions (Figure 1.1: D and E). No selection is detected when the used/availability distributions do not differ (Figure 1.1: F).

1.3.3 Objectives

Herein, I examine Type I (detecting a pattern that does not actually exist) and Type II (failure to detect a real pattern) error rates in using Monte Carlo methods for evaluation of refuge site selection. I use a simulation approach to obtain data for plotting power curves based on Type I and Type II error rates. These power curves can be useful when making inferences about selectivity based on variance in the used data and used sample sizes. Next, I present an empirical example using this Monte Carlo method. I collected abiotic data from two geographically disparate, but ecologically similar regions in Kansas that have very similar squamate assemblages and climate. I use the data to make inferences about the selectivity of certain resources in context of the power of the test as obtained from the simulations. I find that the power curves are particularly useful in helping justify inferences made when sample sizes are low and/or when the variance between the used distribution and the resource availability distribution is low.

Table 1.1 Hypothesis tests for categorical and continuous data used to evaluate resource selection updated from Manly et al. (1993).

Statistical test	Example references
Categorical data	
Chi-square goodness-of-fit	Neu et al. (1974), Byers et al. (1984), Blouin-Demers and Weatherhead (2001)
Johnson's prefer method	Johnson (1980)
Friedman's test	Pietz and Tester (1982, 1983)
Chi-squared test of homogeneity	Marcum and Loftsgaarden (1980)
Quade's test	Alldredge and Ratti (1986, 1992)
Log-linear models	Heisey (1985)
G-test	Beck and Jennings (2003)
Wilcoxon's signed rank test	Kohler and Ney (1982), Talent et al. (1982), Schlesinger and Shine (1994), Blouin-Demers and Weatherhead (2001)
Continuous data	
Analysis of Variance	Webb and Shine (1998), Beck and Jennings (2003), Kerr et al. (2003), Kerr and Bull (2004)
Analysis of Covariance	Blouin-Demers and Weatherhead (2001), Beck and Jennings (2003), Webb et al. (2004)
Classification and Regression Tree	Howes and Loughead (2004)
Kolmogorov-Smirnov two-sample test	Raley and Anderson (1990), Petersen (1990)
Kruskal-Wallis test	Beck and Jennings (2003)
Multiple regression	Lagory et al. (1985), Grover and Thompson (1986), Porter and Church (1987), Giroux and Dedard (1988), Beck and Jennings (2003)
Logistic regression	Hudgins et al. (1985), Thomasma et al. (1991)
Discriminant function analysis	Dunn and Braun (1986), Rich (1986), Edge et al. (1987), Dubuc et al. (1990)
Multivariate analysis of variance	Stauffer and Peterson (1985)
Principal components	Edwards and Collopy (1988)
Geometric method	Kincaid and Bryant (1983)
Polytomous logistic regression	Cross and Peterson (2001)
Multiple response permutation procedures	Alldredge et al. (1991)
Mann-Whitney Test	Beck and Jennings (2003)

Table 1.2 Types of statistical tests suggested for use under noted conditions modified from Motulsky (1995).

Purpose	Measurement (from Gaussian Population)	Rank, Score, or Measurement (from Non-Gaussian Population)	Binomial (Two Possible Outcomes)
Describe one group	Mean, SD	Median, interquartile range	Proportion
Compare one group to a hypothetical value	One-sample t test	Wilcoxon test	Chi-squared or Binomial test
Compare two unpaired groups	Unpaired t test	Mann-Whitney test	Fisher's test (chi-square for larger samples)
Compare two paired groups	Paired t test	Wilcoxon test	McNemar's test
Compare three or more unmatched groups	One-way ANOVA	Kruskal-Wallis test	Chi-squared test
Compare three or more matched groups	Repeated-measures ANOVA	Friedman test	Cochrane Q
Quantify association between two variables	Pearson correlation	Spearman correlation	Contingency coefficients
Predict value from another measured variable	Simple linear or nonlinear regression	Nonparametric regression	Simple logistic regression
Predict value from several measured or binomial variables	Multiple linear or nonlinear regression		Multiple logistic regression

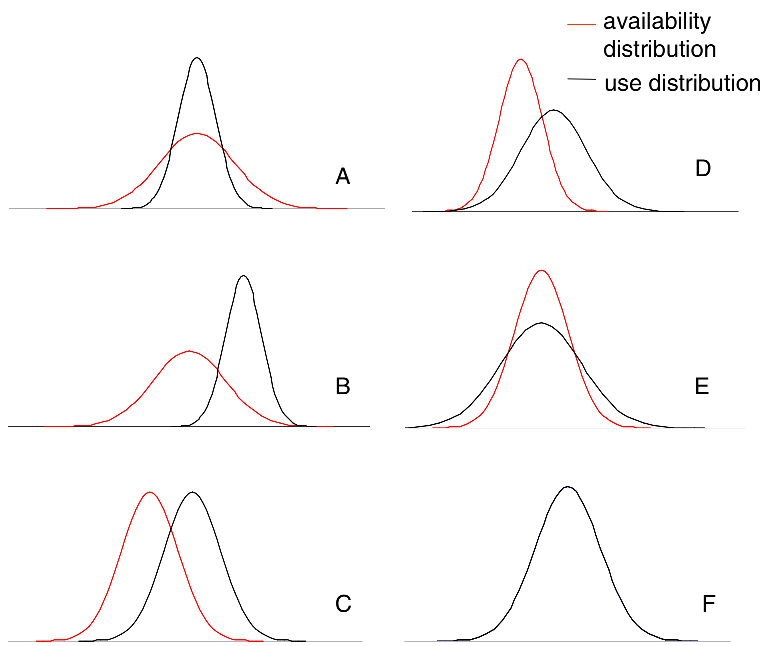

Figure 1.1 Six possible response patterns in resource use/availability data. In patterns similar to A, B and C, selectivity of a resource can be detected because the use distribution has a smaller variance than the availability distribution and/or the mean values of the two distributions are different. D and E represent error, noise in the data, and/or selectivity of extreme conditions. F detects no selectivity because there is no difference in mean or variance of the use and availability distributions.

CHAPTER 2

TYPE I AND TYPE II ERROR RATES IN MONTE CARLO METHODS DESIGNED FOR REFUGE SITE SELECTION STUDIES

2.1 Introduction

In the past several decades, Monte Carlo methods have become increasingly popular in many biological disciplines, although Monte Carlo methods are rarely used in studies evaluating microhabitat selection in populations. One of the reasons for using a Monte Carlo method is it does not require the tested data to have a specific underlying distribution. Typically, the underlying distribution of data associated with a particular species habitat is characterized by a normal curve (Gaussian response curve to environmental gradients: McCrune and Grace 2002). Regardless of the fact that niche data usually conform to normality, there are many other reasons the Monte Carlo is becoming a more popular and applicable technique to use in all scientific disciplines. Computational power is no longer a restriction, and the Monte Carlo approach is flexible and easily applicable to most scenarios.

Gotelli and Ellison (2004) describe 4 steps in designing a Monte Carlo analysis to fit any experimental design for hypothesis testing: describe a test statistic, build null distributions from re-sampling available data, compare the used data distribution to each re-sampled distribution, and calculate a tail probability. The last three of these four steps require computer simulations; however, codes have become increasingly simple, the technique more defined and straight-forward, and an increasing number of programs are becoming available for ease of use when computing a Monte Carlo. Another positive aspect of using a Monte Carlo is that it does not require underlying distribution assumptions of normality; the method builds null distributions from the available data distribution instead of using the normal curve as the null distribution. The characterization of these 4 steps, an increase in computing power, and the generality of the Monte Carlo makes it an appealing technique, and accordingly its popularity has increased in a number of disciplines.

Selectivity is measured by the unequal use of a resource when compared to the availability of that resource (Johnson 1980). Here, I use two test statistics, mean and standard deviation, to describe and compare the resource use distribution and the available distribution of resources in the Monte Carlo analysis I designed to evaluate refuge site selection. Using these two statistics I am able to identify six patterns regarding the use/availability distributions (Figure 1.1). If the distributions resulting from Monte Carlo analyses follow the pattern of any of the distributions in Figure 1.1 A, B, or C, selectivity is detected.

Although the Monte Carlo method has been around for decades, each particular Monte Carlo design possesses unique qualities and has the potential to behave differently when subjected to a power analysis. In order to make accurate and justified inferences with the Monte Carlo analysis for a snapshot, design 1, use/availability study to evaluate refuge site selection, I performed a power analysis to estimate Type I and Type II error rates. I simulated used and available datasets with 'known' distribution parameters and examined error rates associated with varying sample sizes. With this method I am able to determine the sample sizes necessary for the Monte Carlo method to detect selection of particular environmental variables. Type I error occurs when the Monte Carlo returns a significant result when there should not be a significant result. Type II error occurs when the Monte Carlo does not return a significant result when the result should be significant.

2.2 Methods

Using computer simulations, I created known distributions of used (i.e., variables associated with the use of a particular refugium) and available data by drawing from a normal curve. I had five varying parameters; including alpha, sample size, mean and standard deviation of the used distribution (in units away from a 'fixed' available distribution), and the standard deviation of the fixed available distribution. The mean and standard deviation of each used distribution were decreased separately, away from the mean and standard deviation of each available distribution. The units consisted of $1/4^{th}$ of the available condition's standard deviation until the used distribution was 3 standard deviations away from the mean and standard deviation of the available distribution. To calculate the difference in mean between the used distribution and available distribution measured in standard deviations, I used the absolute value of the used mean minus the available mean divided by the available standard deviation. The available data distribution consisted of an infinite number of samples and the samples in the used distribution varied from 2 through 50. These simulated samples were drawn from a normal distribution with specified mean and standard deviation. For judging significance of results, I used three alpha values 0.01, 0.05, and 0.1. The standard deviation of the fixed available distribution varied and had the values of 2, 4, 6, 8, 10, and 12 SDs. For the available distribution standard deviation of 2, the 1/4th standard deviation units ended at 1 3/4th instead of 3 because at this point there are no standard deviations away from the mean left to decrease. For each of the 146,016 simulated datasets, a Monte Carlo analysis was performed with 1,000 permutations. I wrote and implemented all simulations in C Programming Language for all analyses (see Appendix A).

The Monte Carlo analysis used the simulated data from each parameter combination. For every used distribution, a random sample was drawn without replacement within each sample size, starting at 2 and increasing in units of 1 sample until a sample size of 50 was reached. The samples drawn from the used distribution were replaced after all samples were drawn for a single sample size. With 1,000 permutations, each of the samples drawn from the available distribution had both test statistics calculated and a frequency of number of test statistics greater than or equal to the test statistics calculated for the used distribution. This frequency was used to generate p-values at each of the three alpha levels considered.

Each distribution of available conditions was simulated with respect to distributions A, B, C, and F (Figure 1.1). I neglect to simulate distributions D and E because they represent excessive noise in data collection or selection of extreme conditions. Selection of extrema is unlikely unless there is disruptive selection and can be tested by evaluating the fit of the data to a bimodal distribution; however, this procedure is beyond the scope of this study.

2.3 Results

An alpha equal to 0.01, 0.05, and 0.10 in the Monte Carlo simulations produces Type I error rates approximately equal to 1%, 5%, and 10% as expected, regardless of sample size and amount of variance in resource availability distributions (Table 2.1). Figure 2.1 displays Type I error for both test statistics with alpha equal to 0.10 for sample sizes 2 through 10. The number of significant results, which theoretically should be zero, tends to oscillate around 100 out of 1000 possible significant results, making the Type I error rate approximately 0.10. The Type I error rate remains approximately 0.10 for all sample sizes up to 50 (data not shown).

Type II error decreases as a function of increasing sample size (Figure 2.2 and Figure 2.3): as the mean of the used distribution increases away from the mean of the available distribution (Figure 2.2), and as the standard deviation of the used distribution decreases away from the standard deviation of the available distribution (Figure 2.3). The standard deviation of the available distribution does not have a noticeable effect on the power dynamics of the mean statistic (Figure 2.2). Type II error rates, with respect to the mean statistic, begin decreasing toward zero when sample size is greater than or equal to 4 and the difference in the mean test statistic between the two distributions increases above 1 standard deviation. However, the standard deviation of the available distribution has a large effect on the power dynamics of the decreased standard deviation in the used distribution (Figure 2.3). Type II error rates, with respect to the standard deviation statistic, require samples greater than 10 to approach an error rate close to zero. For low sample sizes ($2 \leq n \leq 10$), statistical power adequate to detect selection in the standard deviation statistic alone is only achievable at very low standard deviations for the available distributions ($\sigma \leq 2$). Type II errors are high when the mean and standard deviation statistics in the used distribution differ little from the available distribution.

The mean statistic, rather than the SD statistic, has more power associated with it as both the mean and SD in the used distributions deviates away from the available distributions (Figure 2.4). There is little detectable interaction between the two test statistics as they both decrease away from the conditions in the available distribution, as indicated by the extremely vertical and extremely horizontal patterns in Figure 2.4.

As expected, the power increases for the Monte Carlo designed for refuge site selection as a function of sample size for both the mean and SD test statistics. In Table 2.2, the sample size required for adequate power (80%, sensu Cohen 1977) to detect a pattern that is actually present in the data is listed with respect to amount of deviation required amongst the used and available distributions, the initial available conditions, and the alpha value.

2.4 Discussion

Sample size effects in analysis of refuge site selection data can present difficulties. Tables 2.2 can be used both for evaluating whether meaningful inferences can be made from an assembled dataset, or in the design phase of a project to determine sample sizes required for adequate power. Obtaining a greater number of samples to avoid power loss in various statistical methods may require more time, money, and/or researcher assistance. Some research questions are time/money sensitive or research efforts don’t provide high samples of individuals being studied and researchers have to either analyze and interpret data or neglect data with smaller sample sizes. For example, Butler et al. (2000) studied relationships between sexual size dimorphism and habitat use in many *Anolis* lizards species and excludes several species due to limited sample sizes $n<15$.

For any sample size, detecting a pattern that is not present is, as expected, approximately equal to the alpha value (Type I error) used in the Monte Carlo analyses. Type II error decreases with increased sample size and as the use distribution parameters deviate from those of the available distributions. Careful consideration should be given to the standard deviation of the available conditions and the amount of deviation in the statistic that is required to detect selection with respect to sample size. For example, if the standard deviation in a used/observed variable ($\sigma = 1$) deviates from available conditions ($\sigma = 4$) by 3 standard deviations and the mean does not deviate, the minimum sample size required to obtain results with at least 80% statistical power (a commonly accepted level; see Cohen 1977) is 7 when $\alpha = 0.01$, 5 when $\alpha = 0.05$, and 4 when $\alpha = 0.1$. If the available distribution has a larger standard deviation ($\sigma = 8$), then the sample size of 4 would yield a result with a power of 10% or less. The minimum sample size required to obtain 80% power would be 26 when $\alpha = 0.01$, 24 when $\alpha = 0.05$, and 17 when $\alpha = 0.1$.

Figures 2.3 and 2.4 show the dynamics of the power analyses and can be used to identify the amount of deviation required in the species use distribution and the available distribution to avoid encountering Type II errors. In Figure 2.2, effects of the

SD in the available distributions seem nonexistent. This can be expected and is a useful property. The units increased in the use distribution are measured by 1/4th a standard deviation which is directly proportional to the available distribution by the total amount increased. This feature gives a researcher the ability to interpolate between and beyond the 6 availability distributions analyzed with 6 different standard deviations because the dynamics remain the same between the different available distributions for the mean statistic.

Two steps are used in the interpolation process. First, divide the difference between the standard deviation of the used and available distributions by three. Three is the largest difference in the used standard deviation from the available standard deviation calculated in Table 2.2. Second, the standard deviation in the available distribution is then divided by the value obtained from the first step and the result is the new standard deviation value that is used for the standard deviation of the available distribution. The difference used to calculate the necessary sample size is three. If the new standard deviation is not equal or less than 12 (the maximum available distribution's standard deviation that I calculated), another division is appropriate. Divide both the new difference value and the new available standard deviation by a value that will allow the available standard deviation to be reduced to a value of 12 or less. The results are used to calculate the necessary sample size for adequate statistical power.

In Figure 2.3, the decreasing standard deviation in the used distribution does not decrease in large enough increments to have high power for detecting selectivity of a resource, except in the available distribution with a standard deviation of 2. This is an intuitive outcome in that the higher the standard deviation in available resources, the smaller in standard deviation the selection data has to be to detect patterns. The mean statistic is more powerful in small sample sizes and a better predictor of real patterns when the divergence between a used distribution and the mean in the available distribution differ by more than 1 standard deviation.

Although the standard deviation statistic is not as powerful as the mean statistic in the Monte Carlo methods presented, it provides useful information in the evaluation of tolerance levels in resource selection at which individual species or populations reside. The mean statistic is more powerful at lower sample sizes, but when the mean of the available distribution is selected for, the standard deviation statistic can provide further insight into the selection tolerance of a species population. Combing both statistics and looking at the patterns of the use distributions compared to the available distributions is the most insightful approach, as it incorporates more information. If there is a significant result in the mean or the standard deviation statistic and the patterns between the two distributions follow Figure 1.1 A, B, or C, then selection is detected.

The Monte Carlo methods presented can be highly useful when exploring patterns in refuge-site selection. Animals often do not reside in refuge-sites year around and may only seek refuge in particular refugia when the likelihood of the mean available conditions present converge to that of the preference for the animal's physiology; therefore, a prediction of seasonal refugia use would be that a population use mean would be very similar to the available mean conditions but would likely have a lower standard deviation. This might present additions to Johnson's (1980) definition of selection; in that, selectivity is a not only a function of disproportionate use versus availability of a resource, but also a function of species tolerance and seasonality. The next chapter includes analysis of refuge-site selection with use/availability data where I use the Monte Carlo analysis presented in Chapter 1 and, adhering to the power analyses presented in this chapter, I make inferences on refuge site selection in correlated multiple response variables.

Table 2.1 Averages of Type I error rates for n = 2–10 for test statistics mean and standard deviation. The error rates were calculated for three alpha values.

	SD of Simulated Available Distribution					
	2	4	6	8	10	12
α						
Mean						
0.01	0.0100	0.0112	0.0103	0.0080	0.0126	0.0122
0.05	0.0542	0.0503	0.0503	0.0539	0.0487	0.0459
0.1	0.1041	0.1076	0.1027	0.1210	0.1002	0.1071
SD						
0.01	0.0138	0.0109	0.0114	0.0084	0.0102	0.0118
0.05	0.0497	0.0560	0.0544	0.0442	0.0468	0.0476
0.1	0.0987	0.1136	0.0997	0.1077	0.0980	0.0946

Table 2.2 Sample size required for adequate power to detect patterns in each available distribution's standard deviation equaling σ. The difference in mean (Δ Mean) and the difference in standard deviation (Δ SD) are calculated between the used and available distributions and are measured in standard deviations. Alpha (α) is the level of Type I error the allowed in the analysis.

			Δ Mean												
σ	α	Δ SD	0	1/4	1/2	3/4	1	1 1/4	1 1/2	1 3/4	2	2 1/4	2 1/2	2 3/4	3
2															
	0.01	0	-	>50	47	20	12	8	6	4	3	3	2	2	2
		1/4	>50	>50	43	20	11	7	5	4	3	3	2	2	2
		1/2	>50	>50	42	19	11	7	5	4	3	3	2	2	2
		3/4	37	37	36	17	11	7	5	4	3	2	2	2	2
		1	16	16	16	16	11	7	5	4	3	2	2	2	2
		1 1/4	11	11	10	10	9	6	4	3	2	2	2	2	2
		1 1/2	7	7	7	7	7	6	4	3	3	2	2	2	2
		1 3/4	5	5	5	5	5	4	3	3	2	2	2	2	2
	0.05	0	-	>50	28	12	8	5	4	3	2	2	2	2	2
		1/4	>50	>50	28	12	7	5	4	3	2	2	2	2	2
		1/2	>50	>50	28	11	7	5	3	2	2	2	2	2	2
		3/4	21	20	20	11	7	5	3	3	2	2	2	2	2
		1	14	14	14	10	6	4	3	2	2	2	2	2	2
		1 1/4	8	8	8	8	6	4	3	2	2	2	2	2	2
		1 1/2	5	5	5	5	5	3	3	2	2	2	2	2	2
		1 3/4	4	4	4	4	4	3	2	2	2	2	2	2	2
	0.1	0	-	>50	23	11	6	4	3	2	2	2	2	2	2
		1/4	>50	>50	23	11	6	4	3	2	2	2	2	2	2
		1/2	46	46	21	10	6	4	3	2	2	2	2	2	2
		3/4	19	18	18	9	5	3	3	2	2	2	2	2	2
		1	10	10	10	8	5	3	2	2	2	2	2	2	2
		1 1/4	6	6	6	6	4	3	2	2	2	2	2	2	2
		1 1/2	4	4	4	4	4	3	2	2	2	2	2	2	2
		1 3/4	3	3	3	3	3	3	2	2	2	2	2	2	2

Table 2.2 – *continued*

σ	α	Δ SD	Δ Mean 0	1/4	1/2	3/4	1	1 1/4	1 1/2	1 3/4	2	2 1/4	2 1/2	2 3/4	3
4															
	0.01	0	-	>50	>50	24	13	9	6	5	4	3	3	2	2
		1/4	>50	>50	46	21	12	8	5	4	3	3	2	2	2
		1/2	>50	>50	46	20	11	8	5	4	3	3	2	2	2
		3/4	>50	>50	42	19	11	8	5	4	3	2	2	2	2
		1	>50	>50	42	19	11	8	5	4	3	3	2	2	2
		1 1/4	>50	>50	39	19	11	8	5	4	3	2	2	2	2
		1 1/2	31	31	31	19	11	8	5	4	3	2	2	2	2
		1 3/4	22	22	21	18	10	7	5	4	3	2	2	2	2
		2	21	21	21	17	10	7	5	4	3	2	2	2	2
		2 1/4	14	14	14	14	10	7	4	3	3	2	2	2	2
		2 1/2	11	11	11	11	8	6	4	3	3	2	2	2	2
		2 3/4	8	8	8	8	8	6	4	3	3	2	2	2	2
		3	7	7	7	7	7	6	4	3	2	2	2	2	2
	0.05	0	-	>50	30	15	9	6	4	3	3	2	2	2	2
		1/4	>50	>50	30	14	9	5	4	3	2	2	2	2	2
		1/2	>50	>50	30	14	9	5	4	3	2	2	2	2	2
		3/4	>50	>50	26	14	7	5	4	3	2	2	2	2	2
		1	>50	>50	26	11	7	5	3	3	2	2	2	2	2
		1 1/4	33	32	26	11	7	4	3	2	2	2	2	2	2
		1 1/2	20	20	20	11	7	4	3	2	2	2	2	2	2
		1 3/4	17	16	16	11	7	4	3	2	2	2	2	2	2
		2	12	12	11	10	6	4	3	2	2	2	2	2	2
		2 1/4	9	9	9	9	6	4	3	2	2	2	2	2	2
		2 1/2	7	7	7	7	6	4	3	2	2	2	2	2	2
		2 3/4	6	6	6	6	6	4	3	2	2	2	2	2	2
		3	5	5	5	5	5	4	3	2	2	2	2	2	2
	0.1	0	-	>50	26	12	7	4	3	3	2	2	2	2	2
		1/4	>50	>50	26	12	7	4	3	3	2	2	2	2	2
		1/2	>50	>50	26	10	6	4	3	2	2	2	2	2	2
		3/4	>50	>50	22	9	5	4	3	2	2	2	2	2	2
		1	40	40	18	9	5	4	3	2	2	2	2	2	2
		1 1/4	34	34	18	9	5	4	3	2	2	2	2	2	2
		1 1/2	21	20	17	8	5	3	2	2	2	2	2	2	2
		1 3/4	13	12	12	8	4	3	2	2	2	2	2	2	2
		2	10	10	10	8	4	3	2	2	2	2	2	2	2
		2 1/4	8	7	7	7	4	3	2	2	2	2	2	2	2
		2 1/2	7	6	6	6	4	3	2	2	2	2	2	2	2
		2 3/4	5	5	5	5	4	3	2	2	2	2	2	2	2
		3	4	4	4	4	4	3	2	2	2	2	2	2	2

Table 2.2 – *continued*

σ	α	Δ SD	Δ Mean 0	1/4	1/2	3/4	1	1 1/4	1 1/2	1 3/4	2	2 1/4	2 1/2	2 3/4	3
6															
	0.01	0	-	>50	>50	26	13	8	6	4	4	3	2	2	2
		1/4	>50	>50	>50	26	13	8	6	4	3	3	2	2	2
		1/2	>50	>50	47	23	12	8	6	4	3	3	2	2	2
		3/4	>50	>50	47	23	11	8	6	4	3	3	2	2	2
		1	>50	>50	41	21	11	8	6	4	3	3	2	2	2
		1 1/4	>50	>50	41	19	11	7	5	4	3	3	2	2	2
		1 1/2	>50	>50	41	19	11	7	5	4	3	3	2	2	2
		1 3/4	>50	>50	41	19	11	7	5	4	3	2	2	2	2
		2	41	41	41	19	11	7	5	4	3	2	2	2	2
		2 1/4	35	35	34	17	9	6	5	3	3	2	2	2	2
		2 1/2	23	23	23	17	9	6	5	3	3	2	2	2	2
		2 3/4	21	21	21	17	9	6	5	3	3	2	2	2	2
		3	17	17	17	17	9	6	5	3	3	2	2	2	2
	0.05	0	-	>50	34	18	9	6	4	3	3	2	2	2	2
		1/4	>50	>50	30	15	9	6	4	3	3	2	2	2	2
		1/2	>50	>50	30	14	8	5	4	3	2	2	2	2	2
		3/4	>50	>50	30	12	7	5	4	3	2	2	2	2	2
		1	>50	>50	30	12	7	5	4	3	2	2	2	2	2
		1 1/4	>50	>50	30	11	7	5	3	3	2	2	2	2	2
		1 1/2	>50	>50	30	11	7	5	3	3	2	2	2	2	2
		1 3/4	31	31	30	11	7	4	3	2	2	2	2	2	2
		2	27	27	24	11	7	4	3	2	2	2	2	2	2
		2 1/4	27	27	22	11	6	4	3	2	2	2	2	2	2
		2 1/2	18	18	18	10	6	4	3	2	2	2	2	2	2
		2 3/4	15	15	14	10	6	4	3	2	2	2	2	2	2
		3	12	12	12	10	6	4	3	2	2	2	2	2	2
	0.1	0	-	>50	24	13	7	5	3	2	2	2	2	2	2
		1/4	>50	>50	23	13	7	5	3	2	2	2	2	2	2
		1/2	>50	>50	23	12	7	5	3	3	2	2	2	2	2
		3/4	>50	>50	21	11	6	4	3	2	2	2	2	2	2
		1	>50	>50	21	11	6	4	3	2	2	2	2	2	2
		1 1/4	>50	>50	21	10	6	4	3	2	2	2	2	2	2
		1 1/2	49	49	21	10	6	4	3	2	2	2	2	2	2
		1 3/4	28	28	20	9	6	4	3	2	2	2	2	2	2
		2	22	20	19	9	5	4	3	2	2	2	2	2	2
		2 1/4	19	19	19	9	5	4	3	2	2	2	2	2	2
		2 1/2	14	14	13	9	5	4	3	2	2	2	2	2	2
		2 3/4	11	11	11	8	5	4	2	2	2	2	2	2	2
		3	8	8	8	8	5	4	2	2	2	2	2	2	2

Table 2.2 – *continued*

			Δ Mean												
σ	α	Δ SD	0	1/4	1/2	3/4	1	1 1/4	1 1/2	1 3/4	2	2 1/4	2 1/2	2 3/4	3
8															
	0.01	0	-	>50	>50	25	14	9	6	5	4	3	3	2	2
		1/4	>50	>50	44	24	14	9	5	5	4	3	3	2	2
		1/2	>50	>50	44	24	14	9	5	5	4	3	3	2	2
		3/4	>50	>50	44	21	11	8	5	4	3	3	2	2	2
		1	>50	>50	44	21	11	8	5	4	3	3	2	2	2
		1 1/4	>50	>50	42	20	11	8	5	4	3	3	2	2	2
		1 1/2	>50	>50	42	20	11	8	5	4	3	3	2	2	2
		1 3/4	>50	>50	42	19	11	7	5	4	3	3	2	2	2
		2	>50	>50	42	19	11	7	5	4	3	3	2	2	2
		2 1/4	>50	>50	42	17	10	7	5	4	3	3	2	2	2
		2 1/2	>50	>50	42	17	10	7	5	4	3	3	2	2	2
		2 3/4	33	33	32	16	10	6	5	3	3	3	2	2	2
		3	26	26	26	16	10	6	5	3	3	3	2	2	2
	0.05	0	-	>50	37	16	9	6	4	3	3	2	2	2	2
		1/4	>50	>50	37	16	9	6	4	3	3	2	2	2	2
		1/2	>50	>50	32	14	8	5	4	3	2	2	2	2	2
		3/4	>50	>50	32	14	8	5	4	3	2	2	2	2	2
		1	>50	>50	31	14	8	5	4	3	2	2	2	2	2
		1 1/4	>50	>50	30	14	8	5	4	3	2	2	2	2	2
		1 1/2	>50	>50	29	14	8	5	4	3	2	2	2	2	2
		1 3/4	>50	>50	29	14	8	5	4	3	2	2	2	2	2
		2	>50	>50	29	13	7	5	4	3	2	2	2	2	2
		2 1/4	44	44	29	13	7	5	4	3	2	2	2	2	2
		2 1/2	32	32	27	12	7	5	3	3	2	2	2	2	2
		2 3/4	26	26	25	12	7	5	3	3	2	2	2	2	2
		3	24	24	24	12	7	5	3	2	2	2	2	2	2
	0.1	0	-	>50	25	12	7	4	3	2	2	2	2	2	2
		1/4	>50	>50	25	11	7	4	3	2	2	2	2	2	2
		1/2	>50	>50	25	11	7	4	3	2	2	2	2	2	2
		3/4	>50	>50	24	11	7	4	3	2	2	2	2	2	2
		1	>50	>50	24	11	7	4	3	3	2	2	2	2	2
		1 1/4	>50	>50	21	11	6	4	3	2	2	2	2	2	2
		1 1/2	>50	>50	21	11	6	4	3	2	2	2	2	2	2
		1 3/4	36	34	21	11	6	4	3	2	2	2	2	2	2
		2	29	29	21	9	6	4	3	2	2	2	2	2	2
		2 1/4	30	29	21	9	5	4	3	2	2	2	2	2	2
		2 1/2	25	25	21	9	5	4	3	2	2	2	2	2	2
		2 3/4	21	21	19	9	5	3	3	2	2	2	2	2	2
		3	17	17	17	9	5	3	3	2	2	2	2	2	2

Table 2.2 – *continued*

σ	α	Δ SD	Δ Mean: 0	1/4	1/2	3/4	1	1 1/4	1 1/2	1 3/4	2	2 1/4	2 1/2	2 3/4	3
10															
	0.01	0	-	>50	47	22	13	8	6	5	4	3	2	2	2
		1/4	>50	>50	47	22	13	8	6	5	4	3	2	2	2
		1/2	>50	>50	44	22	12	8	6	4	3	3	2	2	2
		3/4	>50	>50	44	22	12	8	6	4	3	3	2	2	2
		1	>50	>50	43	22	12	8	6	4	3	3	2	2	2
		1 1/4	>50	>50	43	21	11	7	6	4	3	3	2	2	2
		1 1/2	>50	>50	43	21	11	7	6	4	3	3	2	2	2
		1 3/4	>50	>50	43	20	11	7	5	4	3	3	2	2	2
		2	>50	>50	43	20	11	7	5	4	3	3	2	2	2
		2 1/4	>50	>50	43	20	11	7	5	4	3	3	2	2	2
		2 1/2	>50	>50	38	20	11	7	5	4	3	3	2	2	2
		2 3/4	>50	>50	38	20	11	7	5	4	3	2	2	2	2
		3	>50	>50	37	20	11	7	5	4	3	2	2	2	2
	0.05	0	-	>50	39	17	10	6	4	3	3	2	2	2	2
		1/4	>50	>50	39	15	8	6	4	3	2	2	2	2	2
		1/2	>50	>50	34	15	8	5	4	3	2	2	2	2	2
		3/4	>50	>50	34	15	8	5	4	3	2	2	2	2	2
		1	>50	>50	34	15	8	5	4	3	2	2	2	2	2
		1 1/4	>50	>50	34	13	7	5	4	3	2	2	2	2	2
		1 1/2	>50	>50	34	12	7	5	4	3	2	2	2	2	2
		1 3/4	>50	>50	29	12	7	5	4	3	2	2	2	2	2
		2	>50	>50	29	12	7	5	4	3	2	2	2	2	2
		2 1/4	>50	>50	29	12	7	5	4	3	2	2	2	2	2
		2 1/2	>50	>50	28	11	6	5	4	3	2	2	2	2	2
		2 3/4	39	37	28	11	6	5	3	3	2	2	2	2	2
		3	39	37	23	11	6	5	3	3	2	2	2	2	2
	0.1	0	-	>50	26	12	7	4	3	2	2	2	2	2	2
		1/4	>50	>50	26	12	7	4	3	2	2	2	2	2	2
		1/2	>50	>50	25	12	7	4	3	2	2	2	2	2	2
		3/4	>50	>50	25	12	7	4	3	2	2	2	2	2	2
		1	>50	>50	24	11	7	4	3	2	2	2	2	2	2
		1 1/4	>50	>50	24	11	7	4	3	2	2	2	2	2	2
		1 1/2	>50	>50	23	11	6	4	3	2	2	2	2	2	2
		1 3/4	>50	>50	21	11	6	4	3	2	2	2	2	2	2
		2	>50	>50	21	10	6	4	3	2	2	2	2	2	2
		2 1/4	>50	>50	21	10	6	4	3	2	2	2	2	2	2
		2 1/2	42	40	21	10	6	4	3	2	2	2	2	2	2
		2 3/4	-	>50	47	22	13	8	6	5	4	3	2	2	2
		3	>50	>50	47	22	13	8	6	5	4	3	2	2	2

Table 2.2 – *continued*

σ	α	Δ SD	Δ Mean 0	1/4	1/2	3/4	1	1 1/4	1 1/2	1 3/4	2	2 1/4	2 1/2	2 3/4	3
12															
	0.01	0	-	>50	>50	24	14	8	6	4	3	3	2	2	2
		1/4	>50	>50	>50	22	13	8	6	4	3	3	2	2	2
		1/2	>50	>50	47	22	13	8	6	4	3	3	2	2	2
		3/4	>50	>50	47	22	13	8	6	4	3	3	2	2	2
		1	>50	>50	46	21	13	8	6	4	3	3	2	2	2
		1 1/4	>50	>50	46	21	12	8	6	4	3	3	2	2	2
		1 1/2	>50	>50	43	21	12	8	6	4	3	3	2	2	2
		1 3/4	>50	>50	43	20	12	8	6	4	3	3	2	2	2
		2	>50	>50	39	19	11	8	6	4	3	3	2	2	2
		2 1/4	>50	>50	39	19	11	8	6	4	3	3	2	2	2
		2 1/2	>50	>50	38	18	11	7	6	4	3	3	2	2	2
		2 3/4	>50	>50	38	18	11	7	5	4	3	2	2	2	2
		3	>50	>50	38	18	10	7	5	4	3	3	2	2	2
	0.05	0	-	>50	39	16	9	6	4	3	3	2	2	2	2
		1/4	>50	>50	31	16	9	6	4	3	3	2	2	2	2
		1/2	>50	>50	30	14	9	6	4	3	3	2	2	2	2
		3/4	>50	>50	30	14	9	6	4	3	3	2	2	2	2
		1	>50	>50	30	14	9	6	4	3	3	2	2	2	2
		1 1/4	>50	>50	30	14	8	6	4	3	3	2	2	2	2
		1 1/2	>50	>50	29	13	8	5	4	3	2	2	2	2	2
		1 3/4	>50	>50	29	13	8	5	4	3	2	2	2	2	2
		2	>50	>50	29	13	8	5	4	3	2	2	2	2	2
		2 1/4	>50	>50	29	13	8	5	4	3	2	2	2	2	2
		2 1/2	>50	>50	29	13	8	5	4	3	2	2	2	2	2
		2 3/4	>50	>50	29	13	8	5	4	3	2	2	2	2	2
		3	47	44	23	12	8	5	4	3	2	2	2	2	2
	0.1	0	-	>50	26	12	9	7	3	3	2	2	2	2	2
		1/4	>50	>50	26	12	9	7	3	3	2	2	2	2	2
		1/2	>50	>50	26	12	9	7	3	3	2	2	2	2	2
		3/4	>50	>50	23	11	7	4	3	3	2	2	2	2	2
		1	>50	>50	23	11	7	4	3	3	2	2	2	2	2
		1 1/4	>50	>50	23	11	7	4	3	3	2	2	2	2	2
		1 1/2	>50	>50	23	10	7	4	3	2	2	2	2	2	2
		1 3/4	>50	>50	22	10	7	4	3	2	2	2	2	2	2
		2	>50	>50	22	10	6	4	3	2	2	2	2	2	2
		2 1/4	-	>50	>50	24	14	8	6	4	3	3	2	2	2
		2 1/2	>50	>50	>50	22	13	8	6	4	3	3	2	2	2
		2 3/4	>50	>50	47	22	13	8	6	4	3	3	2	2	2
		3	>50	>50	47	22	13	8	6	4	3	3	2	2	2

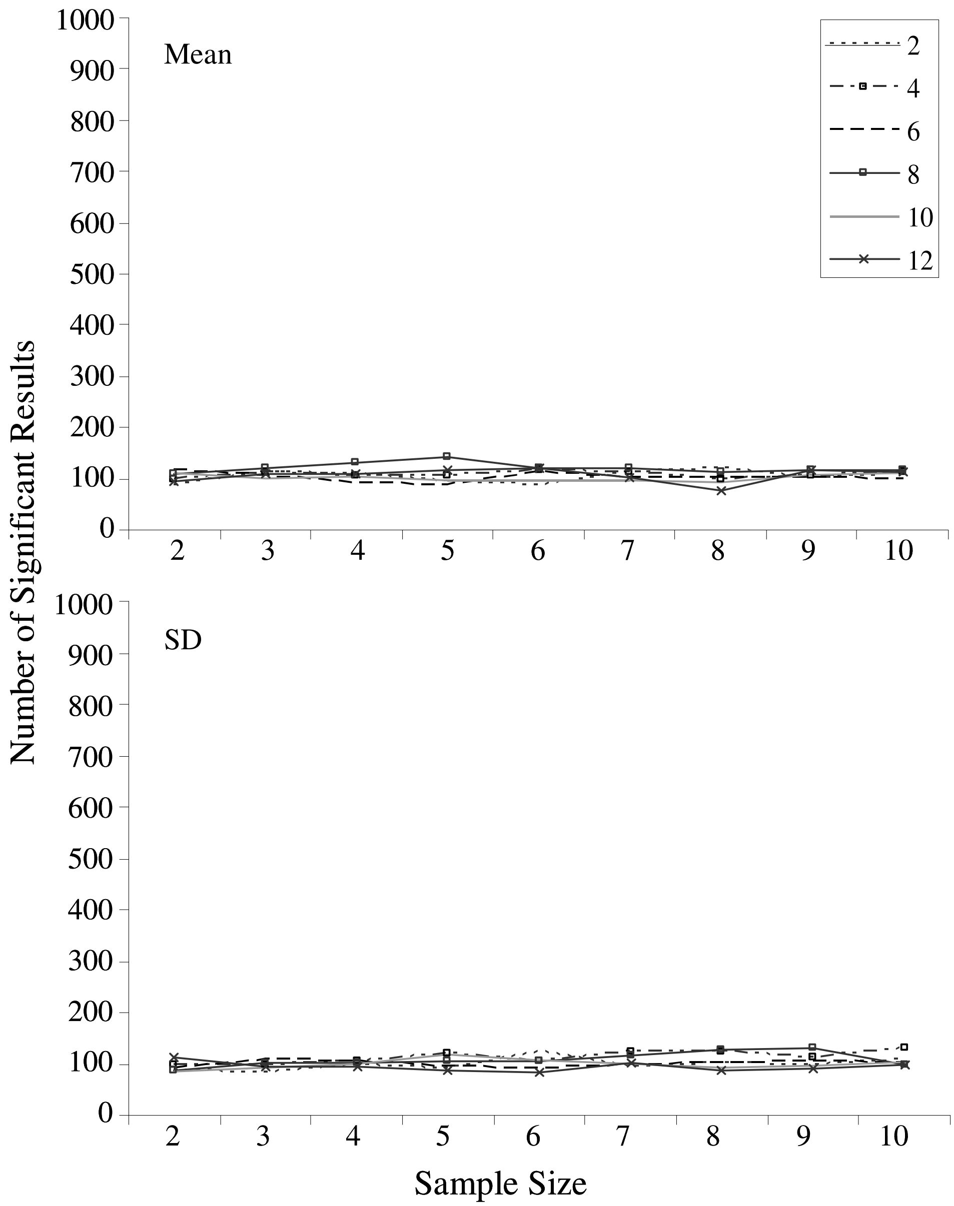

Figure 2.1 Type I error for each sample size 2 through 10 from a Monte Carlo randomization procedure, with 1,000 iterations and alpha = 0.1. The availability distribution's standard deviations are represented in the key.

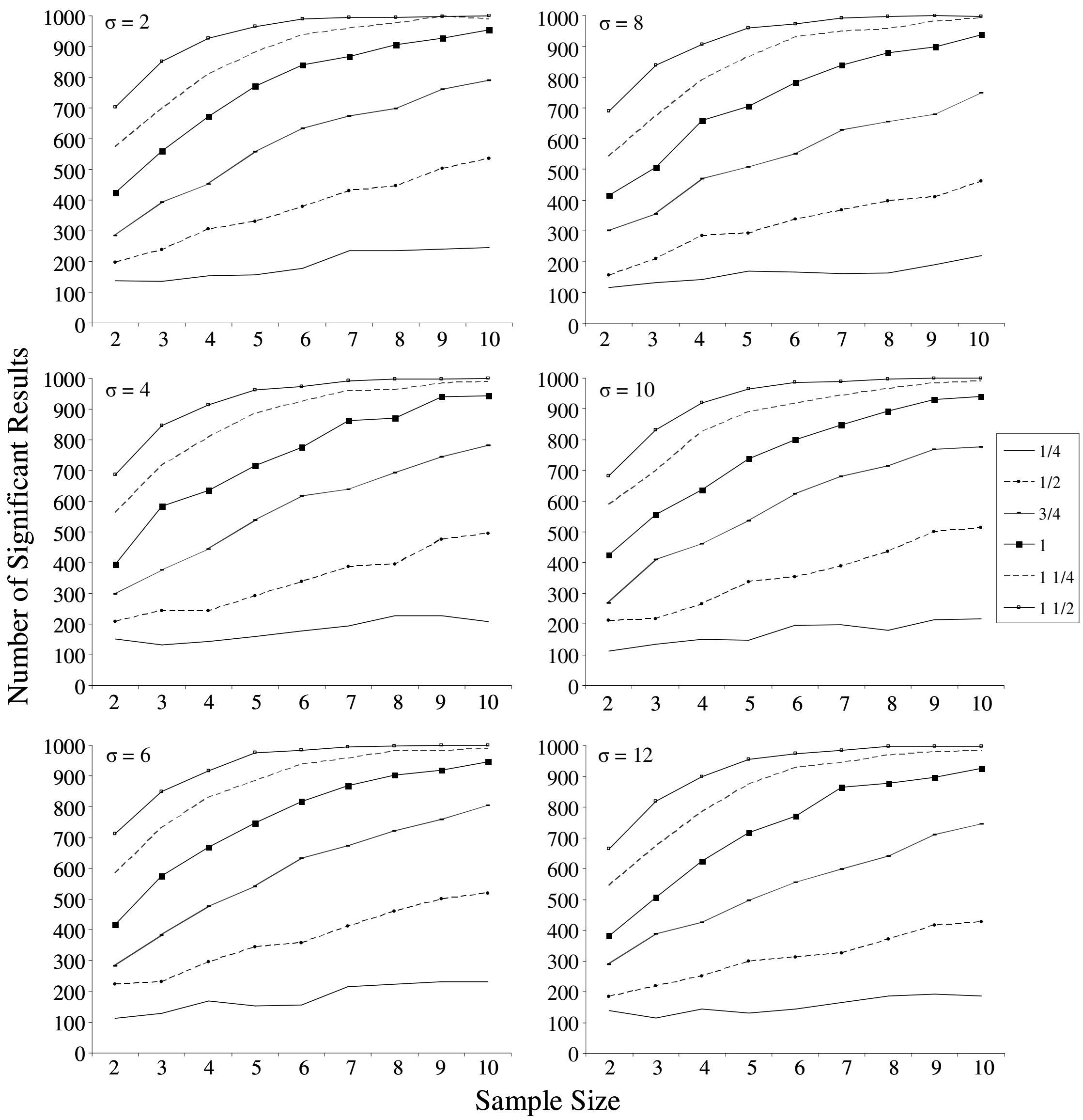

Figure 2.2 Power curves for the mean test statistic resulting from a Monte Carlo randomization procedure, with 1,000 iterations and an alpha value of 0.1. Each line represents 1/4th of a unit away from the mean of the available distribution. Sigma is the standard deviation of the available distribution.

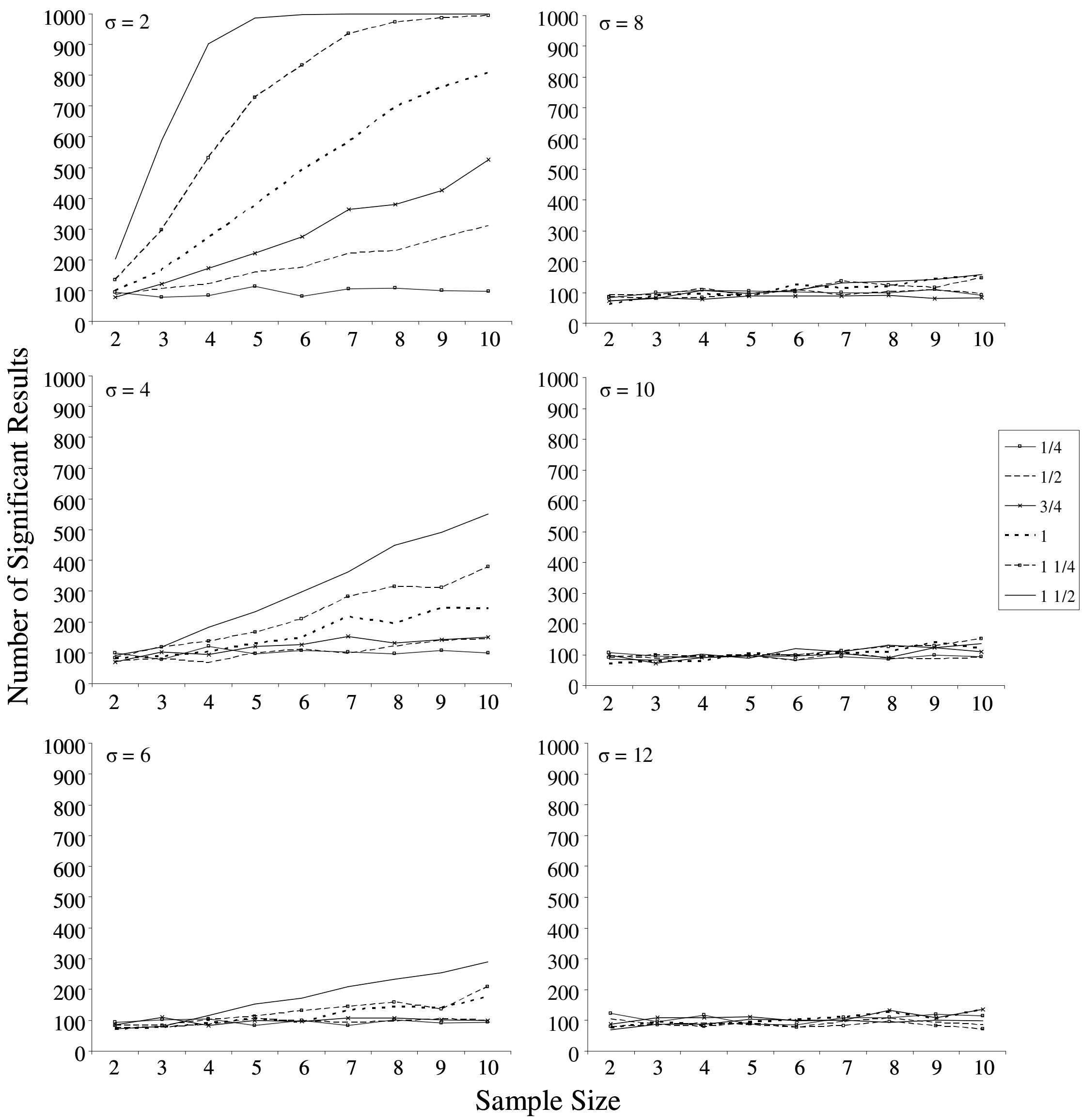

Figure 2.3 Power curves for the SD test statistic resulting from a Monte Carlo randomization procedure, with 1,000 iterations and an alpha value of 0.1. Each line represents 1/4th of a unit from the SD of the available distribution. Sigma is the standard deviation of the available distribution.

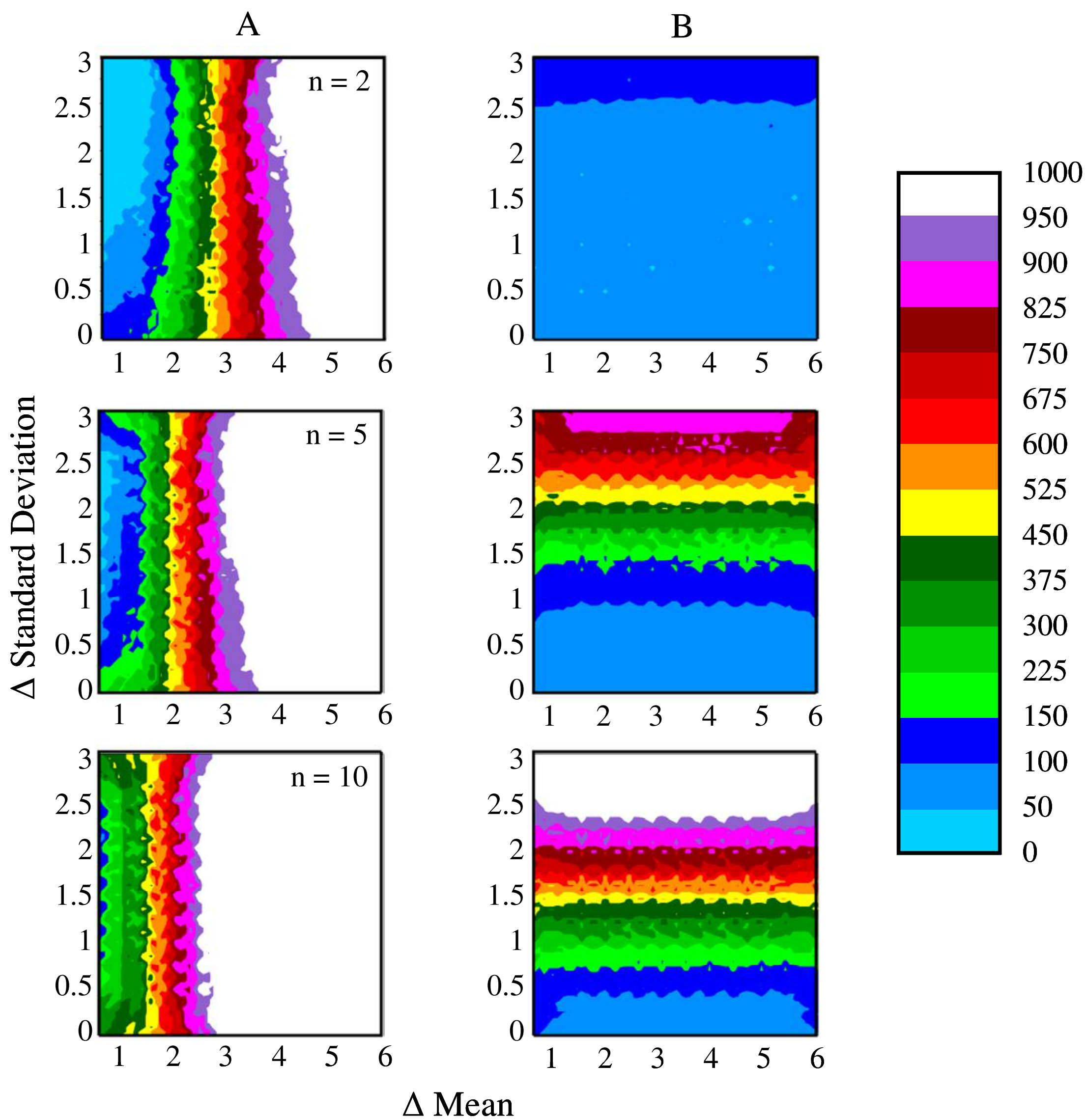

Figure 2.4 Dynamics between the change in mean and the change in standard deviation of each used distribution. Number of significant results using the mean statistic, column A, and the standard deviation statistic, column B, using the availability distribution of σ = 4 and an alpha value of 0.1. White coloration on the graph represents significant results greater than or equal to 95%.

CHAPTER 3

REFUGE SITE SELECTION IN TWO KANSAS SQUAMATE ASSEMBLAGES

3.1 Introduction

For ectothermic vertebrates, the importance of microhabitat features that provide refugia from environmental periodicity, predation, extreme temperatures, etc., is well known (Blouin-Demers and Weatherhead 2001, Beck and Jennings 2003, Howes and Lougheed 2004). In addition to providing a buffer from harsh and often stochastic environmental conditions, refuge sites are also of fundamental importance to thermoregulation and maintaining water balance (Huey et al. 1989, Adolf 1990, Webb and Shine 1998). Refuge site selection is likely influenced by multiple ecological parameters (Kerr and Feldman 2003), and the potential costs of making poor refuge site decisions are often context dependent (Huey et al 1989, Orians and Wittenberg 1991). For example, reptiles inhabiting temperate climates may be particularly vulnerable to mortality resulting from poor selection of either over-wintering sites or temporary refuge sites selected during active periods (e.g., temperature under cover rocks may reach lethal maximum limits during the day or lethal minimum limits during the night). As a result, while refuge site selection is often vital for achieving and maintaining the most advantageous physiological states, while poor refuge site selection can be fatal.

In the central and southern Great Plains region various squamate reptile species are seasonally associated with rock fields and utilize rocks extensively as refuge sites.

Particularly in spring and early summer, individuals of many nocturnal snake and diurnal lizard species remain sequestered under cover rocks for extended periods. Abiotic parameters associated with cover rocks often vary dramatically within a given rock field, and individuals have the opportunity to select the sites that are most suitable for their physiological requirements. Herein, I report the results of a snapshot field study designed to evaluate the relative importance of various abiotic factors in cover rock selection by squamate reptile species in two regions: the Smoky Hills of central Kansas and the Flint Hills of eastern Kansas.

3.2 Methods

3.2.1 Study Sites

The three study sites were located at two distinct areas in Kansas; 1 site in the western portion of the Smoky Hills (site 1: 39.420 N, 96.470 W, altitude 384) and 2 proximal sites in the north central region of the Flint Hills (site 2: 38.765 N, 98.843 W, altitude 562 m; site 3: 39.067 N, 96.539 W, altitude 439). The Smoky Hills are located in the north-central part of Kansas and are delineated by outcrops of Cretaceous-age limestone (Buchanan and McCauley 1987). Site 1 was located within the Greenhorn Limestone outcrop belt in the west Smoky Hills. The chalky limestone beds are mostly made up of large and fragmented thin sheets of limestone. The vegetation consisted of mixed prairie grasslands. The Flint Hills are located to the east of the Smoky Hills and run from the northern border of Kansas beyond the southern border into northern Oklahoma. Sites 2 and 3 were within outcrops of Permian-age limestone and shale. Site 2 was partially burned, with no overstory and sparse to moderate grass cover. Site 3 had open canopy Konza prairie with moderate to dense ground cover. For the purposes of this study, I pooled the data from sites 2 and 3 based on their close proximity (hereafter referred to as Flint Hills).

3.2.2 Data Collection

I collected data during daylight hours on 16−17 April 2005, spending a day at each study site. For both study sites, potential cover rocks were haphazardly selected, and measurements were taken for the following variables: rock dimensions in millimeters (length, width, and depth), soil moisture beneath the rock, and surface temperature beneath the rock. Rock length and width were measured with metric tape, and rock depth was obtained with a metric tree caliper. I used a MiniiiIR Traceable Thermometer (±1°C accuracy between 15°−40°C) for measuring ground temperature and a Portable Soil Moisture Meter (PSMM) for measuring soil moisture. The PSMM records the amount of soil moisture on a 0−10 scale (0 = completely dry, 10 = saturated). I locally calibrated the PSMM to adjust for between-site variation in soil composition. At each site, I attempted to select a representative profile of available rock sizes, ranging from approximately 200 mm in diameter to larger rocks that could be lifted by two individuals. I also attempted to select rocks from various slope aspects. I excluded potential cover rocks that had rock substrata, and rocks for which I could not obtain moisture measurements.

In addition to measuring abiotic variables, I also documented which surface rocks were actually used as cover rocks by snakes or lizards. For each cover rock, I recorded the species and number of individuals encountered. Photographs were taken of representative species and deposited as voucher transparencies at the University of Texas at Arlington Amphibian and Reptile Diversity Research Center.

3.2.3 Data Analysis

I reduced rock length and rock width to a single variable (rock area) for all analyses. I examined distributions of variables for normality prior to inclusion in parametric analyses (only rock area deviated from assumptions of normality and this problem was ameliorated by log-transformation). I evaluated relationships among abiotic variables using a Pearson correlation matrix. Variables were compared between the Smoky and Flint Hills using two-sample t-tests ($\alpha = 0.05$). All parametric analyses were performed using Systat 8.0 (SPSS Inc., 1998).

Most studies of habitat selection incorporate indices and/or conventional hypothesis tests to evaluate specific habitat use proportional to habitat availability. For this study, I used a Monte Carlo approach to determine if species' selection of variables deviated significantly from random based on the range of available values from both potential and actual cover rocks. For each study site, I compared the used means and standard deviation (SD) of variables from cover rocks used by each species to a simulated (null) distribution generated from 1000 permutations of the entire site-specific dataset. Sample statistics from the randomized data were based on the number of observations from each used dataset (e.g., if the used dataset was based on 10 individuals, the randomized datasets were also based on groups of $n = 10$). Although I performed analyses on all species with sample size ≥ 2, I only made inferences where appropriate on the basis of the power analyses presented in the previous chapter.

Since cover rocks are used seasonally, it may be expected that particular species will utilize cover rocks during times when the mean values of parameters in a rock field are most suitable. Under such conditions, the Monte Carlo test alone may fail to detect selection. For this reason, comparisons from multiple sites that vary in available mean values (e.g., both disparate regions in Kansas), as well as testing for variation around the mean (in this case using SD) may strengthen the interpretation of results. Because of the exploratory nature of my study I used a two-tailed test with $\alpha = 0.10$ for all comparisons. This choice was made for two reasons: (1) I had no *a priori* reason to hypothesize on the direction of deviation from the mean (in variable measurements, mean, and SD) and (2) to reduce the likelihood of type II errors in exploratory analysis (Jaeger and Halliday 1998). All Monte Carlo analyses were performed using a program written in C Programming Language (see previous chapters and Appendix B).

3.3 Results

I recorded data for abiotic variables from 409 surface rocks (n = 200 for Smoky Hills, n = 209 for Flint Hills). A Pearson correlation matrix revealed relatively weak ($r \leq 0.36$), but expected, relationships among variables (Table 3.1), For example, rock depth was positively associated with rock area but negatively associated with surface temperature. The relatively low correlation coefficients were likely the result of noise created by variability in topography and different slope aspects at the study sites. The Smoky Hills and Flint Hills differed significantly in all abiotic variables except for rock depth (Table 3.1). In general, surface rocks from the Smoky Hills had lower temperatures, higher soil moisture, and more rocks with greater rock area than did surface rocks from the Flint Hills.

A total of 91 individuals from 9 species were found using cover rocks (n = 52 for Smoky Hills, n = 39 for Flint Hills; Table 3.2). The sample sizes required for sufficient inferential power at alpha = 0.10 are listed in Table 3.3 and 3.4. Species were excluded from analyses when sample size was ≤ 2. I included all other species in analyses but did not make inference in instances when sample sizes were insufficient based on the power analyses from simulations (see Chapter 2 and discussion). The ringneck snake (*Diadophis punctatus*) was the most commonly encountered species and comprised over half of the total observations. In addition to *D. punctatus*, four other species encountered were included in the analysis: the common collared lizard (*Crotaphytus collaris*) from the Smoky Hills, the lined snake (*Tropidoclonion lineatum)* from the Flint Hills, the milksnake (*Lampropeltis triangulum*), and the great plains skink (*P. obsoletus*) from both locales. For *C. collaris*, *D. punctatus*, and *L. triangulum* at least one of the variables had a large enough sample size to detect patterns of selection.

Results from Monte Carlo analyses revealed that the importance of abiotic variables potentially associated with cover rock selection differed among species (Tables 3.5 and 3.6). Overall patterns in cover rock selection among species were generally congruent when differences in abiotic parameters between sites were considered concomitantly. One lizard species was evaluated using Monte Carlo simulations (*Crotaphytus collaris* in the Smoky Hills) and it selected cover rocks with less mean soil moisture than expected from random permutations of the data. However, the variance of the used distribution is significantly larger than the variance of the available distribution, which indicates the data collected are either not a true representation of the population variance or the population is selecting extreme conditions (refer to Figure 1.1 D). Temperature and measures of rock depth and area did not appear to be selected by this species; however, sample sizes were below the accepted level for sufficient power, thus insignificant results may represent Type II errors.

The influence of variables on cover rock selection differed for each of the two snake species analyzed (*Lampropeltis triangulum and Diadophis punctatus*). In the Smoky Hills, *L. triangulum* selected the largest rocks available and the pattern of selection followed Figure 1.1C, but *L. triangulum* had no other significant selected variables. For moisture and rock depth, this may be a result of Type II error; *L. triangulum* did not have a sufficient sample size to detect selection. Alternatively, *L. triangulum* may select for these variables but with less strength than rock size. I did have an adequate sample size to detect selection for temperature by *L. triangulum*, but selection was not detected. The pattern of distribution in this variable resembles Figure 1.1 F. At this time of year, surface temperature itself does not seem to be selected by *L. triangulum*, because this species had an adequate sample size to detect selection in the Flint Hills as well, but selection was not detected.

I found relatively large numbers of *Diadophis puncatus* sheltering under rocks in both the Smoky and Flint Hills. Despite geographic variation in temperature and moisture, *D. punctatus* were consistently found selecting moisture levels with less variation than available at both sites. In the Flint Hills, *D. punctatus* also selected for a higher moisture level of 7.92, rather than the available mean moisture level of 6.89, following a distribution pattern similar to Figure 1.1A. This is consistent with the level of moisture selected in the Smoky hills, which was not significantly different from the mean conditions of 8.06, following the distribution pattern similar to Figure 1.1 B. The moisture levels selected from these two distinct populations of *D. punctatus* converge to a value approximately equal to 8.

Temperature effects on *Diadophis punctatus* are significant in both geographic regions, but do not converge on the same value. In the Smoky Hills, the temperature variable's distribution followed pattern B in Figure 1.1 and the mean temperature selected was higher than that of the available temperature distribution (mean selected = 24.85; mean available = 23.27). In the Flint Hills, the used mean temperature was significantly less than the mean available temperature and the temperature distribution follows pattern C in Figure 1.1 (mean selected = 22.70; mean available = 24.58). However, power was less than 80% for the temperature analysis of *D. punctatus* from the Flint Hills. Detecting selection in such a variable would likely require very strong selective forces.

Refuge site selection in *Diadophis punctatus* is also related to rock depth and area at both sites. Rocks selected were approximately 60-70mm in depth. The mean used distributions for rock depth at both sites did not converge on the same value. For the rock depth variable for *D. punctatus*, Figure 1.1A represents the distribution pattern used from the Smoky Hills while Figure 1.1C more closely reflects the distribution pattern from the Flint Hills. In addition, there is not an adequate sample size of *D. punctatus* to detect selection for available and used distributions of data associated with rock area in the Smoky Hills. In the Flint Hills, rock area was selected for with a pattern of distribution similar to Figure 1.1 C. The mean of the used distribution in the Flint Hills is very similar to the available mean in the Smoky Hills. The fact that selection was not detected in the Smoky Hills is likely a result of favorable conditions mirroring available conditions for *D. punctatus*.

In an analysis combining all lizards found in the Smoky Hills, rock depth and rock area are selected for (Table 3.8). Lizards used the mean available conditions, but with a smaller variance than the available conditions, following pattern A in Figure 1.1. All used snakes in the Smoky Hills selected for the mean available temperature, but for larger rocks than the mean available, following pattern B in Figure 1.1. All used snakes in the Flint Hills apparently selected for a lower mean temperature than the mean available. The mean available temperature in the Smoky Hills was 23.143°C, and snakes showed selection for the mean (as detected through decreased variation). In the Flint Hills the mean available temperature was 24.657°C, and snakes selected for lower temperatures. All squamates at both sites selected larger rock area than the mean available, mean available moisture, and lower temperature than the mean available (Figure 1.1C).

3.4 Discussion

All sample sizes were relatively low (n < 10), except for *Diadophis punctatus* (Table 3.2), in some cases, the differences between the used and available distributions did not differ greatly. The overall result is that power to detect selection was relatively low, even at seemingly adequate sample sizes. Therefore, when making inferences about selectivity careful consideration must be given to sample size, amount of deviation in mean and standard deviation, and the standard deviation in available conditions. There was not adequate power to detect patterns of selection for six of the nine species sampled in both the Smoky and Flint Hills. For the remaining three species, one to several of the variables within each of them also did not have adequate power to detect selection.

Another consideration must be given when interpreting results by considering the way used and available distributions are dispersed with respect each other (e.g., Figure 1.1 D and E). For example, *Crotaphytus collaris* falsely appears to be selecting for moisture in the Smoky Hills (Table 3.5). The variance in the available conditions is higher than the variance in the used conditions. Even though the used statistic is significantly different from the available statistic, I do not suggest that these are the conditions *C. collaris* is selecting based on consideration of both the used and available variances. Several conclusions are possible. The data are best represented by a bimodal distribution, selection of extreme conditions, too much noise in the data, and/or insufficient sample size. It is likely one or a combination of the last two. In the following paragraphs, I discuss biological inferences regarding refuge site selection in the two most commonly encountered species, *Diadophis punctatus* and *Lampropeltis triangulum*.

Diadophis punctatus selected for rock area in the Flint Hills but did not deviate from the mean available rock area in the Smoky Hills. On average, rocks in the Smoky Hills were larger (in terms of area) than in the Flint Hills; thus sufficient-sized rocks appear to be at a premium in the Flint Hills and snakes appeared to congregate under the fewer, suitable rocks. This inference illustrates the value of using multiple sites in a snapshot study using the Monte Carlo approach—it is apparent from the consideration of both sites that rock area is an important variable in refuge site selection for *D. punctatus*. Simply evaluating *D. punctatus* populations from the Smoky Hills may lead to erroneous inference, since selection by a species cannot be detected if selected parameters do not deviate from the mean available parameters. Thus, the ability to make accurate inferences increases when evaluating multiple sites that may differ somewhat in available conditions.

Diadophis punctatus also appeared to select mean available moisture and higher than mean available temperatures in the Smoky Hills. In the Flint Hills, *D. punctatus* selected higher than mean available moisture and lower than average temperatures. Furthermore, rock area seems to have a more important role in refuge site selection in the Flint Hills (see above). Consideration of mean available conditions at both sites provides insight into the proximate factors influencing refuge site selection in this species. With respect to measured variables, conditions in the Flint Hills were both drier and warmer than the Smoky Hills. During the study period, it is probable that *D.*

punctatus refuge site selection was based primarily on thermoregulation in the favorable Smoky Hills. The higher selectivity of variables in the Flint Hills, suggests that conditions in this region appeared to be less favorable, and selection was based more on encountering cooler, wetter conditions (hence the selection for larger rock area in the Flint Hills).

Refuge site selection for *Lampropeltis triangulum* differed considerably from *Diadophis punctatus*. *L. triangulum* selected for the largest cover rocks available in the Smoky Hills, as well as in the analysis combining data from the Smoky and Flint Hills (Table 3.7). On average, *L. triangulum* selected rocks over 2.5 times and nearly 1.8 times the mean available rock area in the Smoky and Flint hills, respectively. Other variables were not selected more frequently than random expectation. Temperature, in particular, did not appear to influence refuge site selection in *L. triangulum,* since variance in this parameter exceeded available variance at both study sites.

The differences in refuge site selection between these two snake species may relate to the temporal properties of the measured variables. Physical properties of rocks (i.e., area, depth, etc.) are static variables, whereas the other variables are highly dynamic. Moisture is a function of season, and especially rainfall. Temperature is exceptionally dynamic, varying on both seasonal and daily scales. The importance of rock area suggests that *Lampropeltis triangulum* may be more sedentary and choose conditions on the basis of relative stability. Larger rocks are expected to provide more stable conditions, with respect to the under-rock environment, regardless of ambient conditions when the refuge site is chosen. Reasons for this expectation are physicsbased. The surface area to volume ratio of a rock dictates the amount of time the rock takes to heat up or cool off. The larger the rock, the slower the heating or cooling rate; thus, larger rocks provide more stable environments. Larger rocks will likely dry at lower rates as well, and will not experience the extreme daily temperature fluctuations that smaller rocks are susceptible to undergo. Thus, I hypothesize that environmental stability of the refugium is more important in selection for *L. triangulum*. This would suggest that it is either less costly for *Diadophis punctatus* to switch refugia, or the physiological requirements of *D. punctatus* are more sensitive to fluctuations in ambient conditions.

Overall, the Monte Carlo analysis appears to provide meaningful insight into differences among species in refuge selection. In this analysis, I inferred species differences in selection without testing them directly; however, such tests could easily be modified to look directly at species differences. For example, rather than compare a species' use distribution to an available distribution, two species' use distributions could be compared. In most cases, it would be of greater interest to dissect variables that are important to individual species since one would not expect two species to overlap in their use of available resources. There are other points to consider when using this test, some of which have already been outlined above. In a snapshot study, stronger inference can be gained by examining multiple, different sites that will most likely differ somewhat in available conditions. Temporal studies may also be amenable to such analyses; however, special consideration of non-independence of samples needs to be made when using this approach. Also, it would generally be difficult to definitively distinguish relative contributions of the multiple variables examined since most are likely interdependent. Finally, potential aggregations of individuals under a single rock may induce a social component to refuge site selection, influencing the distributions of used means and variance and thus lending to Type I error.

Table 3.1 Pearson correlation matrix of abiotic variables from both the Flint and Smoky Hills of Kansas.

	Moisture	Temperature	Rock Depth	Rock Area
Moisture	1.000			
Temperature	-0.141	1.000		
Rock Depth	0.194	-0.350	1.000	
Rock Area	0.187	-0.342	0.356	1.000

Table 3.2 Available distribution means, SDs, and p-values for two-sample t-tests assuming unequal variances.

	Smoky Hills		Flint Hills		
	Mean	SD	Mean	SD	p-value
Moisture	8.015	1.598	6.809	1.839	<0.001
Temperature	23.143	3.528	24.657	3.272	<0.001
Rock Depth	78.085	26.663	75.526	29.409	0.357
Rock Area	303567.3	206229.3	201307.6	165748.8	<0.001

Table 3.3 Observed species from two Kansas squamate assemblages.

	Smoky Hills	Flint Hills
Aspidoscelis sexlineatus	2	-
Crotaphytus collaris	7	1
Coluber constrictor	-	1
Diadophis punctatus	31	17
Lampropeltis getula	2	-
L. triangulum	8	5
Pantherophis emoryi	-	1
Plestiodon obsoletus	2	7
Tropidoclonion lineatum	-	4

Table 3.4 Required sample size for adequate power (>80%) to detect patterns from the Smoky Hills dataset. The differences are measured in SDs. *SD interpolated to obtain required samples for available distributions SDs > 12 and differences > 3.

	n	Used mean	Used SD	Difference in mean	Difference in SD	Required *n*
Smoky Hills						
A. sexlineatus	2					
Moisture		7.25	1.77	0.48	0.17	3
Temperature		23.10	5.66	0.01	2.13	10
Rock Depth		78.40	9.90	0.01	16.76*	17
Rock Area		185472.50	15941.72	0.57	190287.58*	4
C. collaris	7					
Moisture		6.50	2.48	0.95	0.89	5
Temperature		21.97	3.77	0.33	0.24	>50
Rock Depth		77.71	13.85	0.01	12.81*	8
Rock Area		334912.14	88173.24	0.15	118056.06*	8
D. punctatus	31					
Moisture		8.19	0.77	0.11	0.83	10
Temperature		24.85	2.32	0.48	1.20	18
Rock Depth		69.81	17.79	0.31	8.87*	17
Rock Area		299375.4	233076.91	0.02	26847.61*	>50
L. getula	2					
Moisture		6.25	0.35	1.11	1.25	4
Temperature		26.20	4.38	0.87	0.853	5
Rock Depth		66.50	7.78	0.43	18.88*	4
Rock Area		297800.00	17253.41	0.03	188975.89*	4
L. triangulum	8					
Moisture		7.94	1.21	0.05	0.38	46
Temperature		21.09	4.24	1.58	0.71	5
Rock Depth		88.00	37.07	0.37	10.41*	17
Rock Area		766548.1	268407.10	2.25	62177.81*	2
P. obsoletus	2					
Moisture		7.50	0.71	0.32	0.89	10
Temperature		23.20	4.67	0.02	1.14	34
Rock Depth		77.50	16.26	0.02	10.40*	17
Rock Area		306150.00	113066.37	0.01	93162.93*	8

Table 3.5 Required sample size for adequate power (>80%) to detect patterns from the Flint Hills dataset. The differences are measured in SDs. *SD interpolated to obtain required samples for available distributions SDs > 12 and differences > 3.

	n	Used mean	Used SD	Difference in mean	Difference in SD	Required *n*
<u>Flint Hills</u>						
D. punctatus	17					
Moisture		7.82	0.64	0.55	1.20	6
Temperature		22.81	2.30	0.56	0.97	18
Rock Depth		60.18	39.78	0.52	10.37*	17
Rock Area		321504.80	284459.10	0.73	118710.31*	4
L. triangulum	5					
Moisture		7.50	2.06	0.38	0.26	23
Temperature		20.92	3.24	1.14	0.03	4
Rock Depth		82.80	25.48	0.25	3.92*	>50
Rock Area		313069.60	134603.10	0.67	31145.69*	11
P. obsoletus	7					
Moisture		6.7	1.57	0.06	0.27	>50
Temperature		23.5	3.13	0.35	0.14	>50
Rock Depth		71.8	21.37	0.13	8.04*	27
Rock Area		255976.6	132567.90	0.33	33180.89*	>50
T. lineatum	4					
Moisture		5.38	0.48	0.78	1.36	6
Temperature		23.73	1.89	0.28	1.38	20
Rock Depth		73.50	21.61	0.07	7.80*	38
Rock Area		157992.50	82830.71	0.26	82918.08*	8

Table 3.6 Used and available data from a squamate assemblage in the Smoky Hills of Kansas. The simulated datasets are randomly chosen subsets of the available data. Asterisks denote variables that may be subject to Type II error due to low sample sizes.

	Used mean	Available mean	P-value	Used SD	Available SD	P-value
C. collaris						
Moisture	6.50	7.97	0.01	2.48	1.64	0.05
Temperature*	21.97	23.20	0.17	3.77	3.52	0.34
Rock Depth*	77.71	77.96	0.49	13.86	26.87	0.10
Rock Area*	334912.20	304026.20	0.32	88182.38	204427.22	0.06
D. punctatus						
Moisture	8.19	8.06	0.32	0.95	1.55	**0.00**
Temperature	24.85	23.27	**0.00**	1.98	3.48	**0.00**
Rock Depth	69.81	76.28	0.07	19.95	26.65	**0.05**
Rock Area*	299375.40	290661.90	0.40	204413.52	207910.46	0.47
L. triangulum						
Moisture*	7.94	8.06	0.38	1.21	1.57	0.28
Temperature	21.09	23.13	0.06	4.24	3.48	0.12
Rock Depth*	88.00	77.94	0.15	37.07	26.55	0.09
Rock Area	766548.10	304176.26	**0.00**	268445.14	209607.86	0.20
Lizards						
Moisture	6.82	8.01	0.01	2.07	1.61	0.12
Temperature	22.40	23.16	0.22	3.77	3.52	0.31
Rock Depth	77.91	77.45	0.47	12.32	26.74	**0.01**
Rock Area	302511.81	300788.13	0.45	97197.04	204054.67	**0.03**
Snakes						
Moisture	7.94	8.05	0.29	0.92	1.52	**0.00**
Temperature	24.19	23.43	0.06	3.19	3.42	0.80
Rock Depth	70.73	75.89	0.08	23.52	26.52	0.19
Rock Area	421623.20	295814.30	**0.00**	288095.13	213962.48	**0.00**
Squamates						
Moisture	7.78	8.06	0.09	1.30	1.53	0.16
Temperature	23.83	23.35	0.15	3.37	3.42	0.42
Rock Depth	71.68	75.57	0.14	22.82	26.61	0.14
Rock Area	363842.80	282899.00	**0.00**	258910.54	204988.62	**0.03**

Table 3.7 Used and available data from a squamate assemblage in the Flint Hills of Kansas. The simulated datasets are randomly chosen subsets of the available data. Asterisks denote variables that may be subject to Type II error due to low sample sizes.

	Used mean	Available mean	P-value	Used SD	Available SD	P-value
D. punctatus						
Moisture	7.92	6.89	**0.00**	0.73	1.83	**0.00**
Temperature*	22.70	24.58	**0.01**	2.28	3.21	0.08
Rock Depth	60.11	74.49	**0.02**	38.59	30.05	0.06
Rock Area	310475.40	202844.20	**0.01**	279893.57	176149.90	0.09
L. triangulum						
Moisture*	7.60	6.84	0.19	1.82	1.81	0.41
Temperature	23.62	24.69	0.23	5.23	3.26	0.05
Rock Depth*	80.40	75.17	0.33	26.99	29.07	0.45
Rock Area*	357837.60	202126.40	**0.04**	355404.30	161761.76	**0.03**
Lizards						
Moisture	6.06	6.85	0.12	2.43	1.82	0.08
Temperature	23.58	24.66	0.17	3.55	3.30	0.35
Rock Depth	63.50	75.01	0.12	25.30	29.28	0.40
Rock Area	221330.25	201413.65	0.30	219338.28	166649.65	0.14
Snakes						
Moisture	7.13	6.96	0.32	1.59	1.83	0.14
Temperature	22.74	24.49	**0.00**	3.82	3.17	0.06
Rock Depth	69.42	73.31	0.21	36.87	29.32	0.03
Rock Area	226563.50	197450.20	0.17	224705.68	169412.27	0.14
Squamates						
Moisture	7.35	6.95	0.14	1.38	1.83	**0.02**
Temperature	22.97	24.58	**0.01**	2.94	3.18	0.31
Rock Depth	73.44	74.35	0.44	29.60	29.26	0.42
Rock Area	269835.10	194555.80	**0.02**	177848.31	162512.46	0.26

Table 3.8 Used and available data from two combined squamate assemblages from Kansas. The simulated datasets are randomly chosen subsets of the available data.

	Used mean	Available mean	P-value	Used SD	Available SD	P-value
C. collaris						
Moisture	6.69	7.42	0.123	2.36	1.84	0.123
Temperature	22.73	23.91	0.177	4.11	3.47	0.198
Rock Depth	73.13	76.87	0.347	18.25	28.03	0.169
Rock Area	311893.80	251286.20	0.182	104422.04	192434.97	0.196
D. punctatus						
Moisture	8.09	7.50	**0.01**	0.88	1.79	**0.00**
Temperature	24.06	23.84	0.32	2.32	3.38	**0.00**
Rock Depth	66.25	75.32	**0.01**	28.26	28.38	0.47
Rock Area	303452.90	243792.70	**0.02**	232141.47	193815.20	0.14
L. triangulum						
Moisture	7.89	7.47	0.199	1.39	1.80	0.16
Temperature	21.91	23.63	**0.03**	4.47	3.60	0.069
Rock Depth	80.86	75.85	0.244	35.03	28.78	0.136
Rock Area	578883.80	254426.50	**0.00**	204114.43	195017.91	**0.01**
P. obseleta						
Moisture	6.17	7.43	**0.02**	2.29	1.82	0.149
Temperature	22.99	23.91	0.215	3.29	3.48	0.43
Rock Depth	69.11	76.27	0.21	23.31	28.11	0.35
Rock Area	248019.70	250190.60	0.469	209923.87	192571.70	0.288
Lizards						
Moisture	6.50	7.45	**0.01**	2.19	1.83	0.11
Temperature	22.90	23.85	0.12	3.63	3.43	0.34
Rock Depth	71.84	76.35	0.24	19.66	27.94	0.07
Rock Area	268330.09	248815.10	0.31	160166.23	192757.06	0.45
Snakes						
Moisture	7.59	7.51	0.34	1.31	1.78	**0.00**
Temperature	23.57	23.86	0.22	3.52	3.32	0.18
Rock Depth	70.17	74.40	0.07	29.78	28.03	0.24
Rock Area	337639.2	244491.7	0.00	278484.81	197011.41	0.00
Squamates						
Moisture	7.62	7.53	0.32	1.34	1.80	**0.00**
Temperature	23.50	23.83	0.19	3.22	3.36	0.31
Rock Depth	72.35	74.84	0.20	25.42	27.84	0.19
Rock Area	328093.31	239656.9	**0.00**	234619.53	192061.04	**0.04**

APPENDIX A

C CODE FOR ERROR ANALYSIS OF MONTE CARLO METHOD

```
#include <stdlib.h>
#include <stdio.h>
#include <math.h>
#include <time.h>

#define DATAFILE "outfile8.1.txt"
#define RECNUM  1000
#define PERMUT  1000   //for the monte carlo
#define availableSD  8.0
#define SS       2      //start sample size
#define TSS      51      //to end sample size
#define ALPHA   50

int sim_cnter, sim_cnter2;
FILE *outfile;

int GetSeed(void);
int Permute(double mean, int n, float obsSD, double *data);
void AvailableData(double *data);
double GetNormal(double mu, double sd);
void Monte(int n,double iave,double ivar, double *data);

int main(void) {
   int k=0, n=0, x=0, s=0, stop=0;
   float q=0, m=0, p=0, obsSD=0;
   double data[RECNUM];
   outfile = fopen(DATAFILE,"w");

   fprintf(outfile,"obsSD\tN\tDmean\tDsd\n");
   for(x=0;x<13;x++)
   {
     for(s=0;s<RECNUM;s++)
        data[s]=0;
     srand48(GetSeed());
     AvailableData(data);
     obsSD=availableSD-p;
     if (obsSD>0)
     {
       for(n=SS;n<TSS;n++)
       {
         q=0;
         stop=0;
           //while(stop==0) {
            for (k=0;k<13;k++)
```

```
          {
            m = availableSD*q;
            stop = Permute((m+100),n,obsSD,data);
            //if(stop==1)
                    //fprintf(outfile,"-\n");
               q += 0.25;
          }
            //}

        }
        p+=0.25;
       }
      printf("%d\n",x);
  }
  fclose(outfile);
  return (0);
}

void AvailableData(double *data)
{
    int x;
    double ranvalue, mean;

    for (x=0;x<RECNUM;x++)
    {
        ranvalue = 0; mean = 100;
        ranvalue = GetNormal(mean, availableSD);
        data[x] = ranvalue;
    }
}

double GetNormal(double mu, double sdin)
{
   double value1, value2, normal;
   value1 = value2 = normal = 0;
   value1 = drand48();
   value2 = drand48();
   normal = mu +

(sqrt(-2*log(value1)))*(sdin*(sin(2*3.141592654*value2)));
   return normal;
}

int Permute(double mean, int n, float obsSD, double *data)
```

```
{
    int x, j, z, temp, temp2;
    double ranvalue=0;
    double values[RECNUM][n];
    double iave, ivar, iave1[RECNUM], ivar1[RECNUM];

    temp = temp2 = 0;
    for (x=0;x<RECNUM;x++)
    {
       iave = ivar = 0;
       for (j=0;j<n;j++)
       {
           ranvalue = GetNormal(mean, obsSD);
           values[x][j] = ranvalue;
           iave += values[x][j];
       }
       iave = iave/n;
       for (j=0;j<n;j++)
          {ivar += pow((values[x][j] - iave),2);}
        ivar = ivar / (n-1);
        iave1[x] = iave; ivar1[x] = ivar;
     }

     for(x=0;x<RECNUM;x++)
     {
       sim_cnter = sim_cnter2 = 0;
       Monte(n, iave1[x], ivar1[x], data);
       if(ALPHA>sim_cnter) temp++;
       if((1000-ALPHA)<sim_cnter) temp++;
       if(ALPHA>sim_cnter2) temp2++;
       if((1000-ALPHA)<sim_cnter2) temp2++;
     }

          fprintf(outfile,"%.2f\t%d\t%d\t%d\n", obsSD, n, temp, temp2);
          if(temp>799) return 0;
          else return 0;
}

void Monte(int n, double iave, double ivar, double *data)
{
    int j, i, x, records;
    double thisval[n];
    double rvar, rave, avar, aave;
```

```
    rvar = rave = avar = aave = 0;

    for (j=0;j<PERMUT;j++)
    {
       records = PERMUT-1;
       rave = rvar = 0;
       for (i=0;i<n;i++)
       {
         x = (int)records*drand48();
         thisval[i] = data[x];
         data[x] = data[records];
         data[records] = thisval[i];
         rave += thisval[i];
         records--;
       }
       rave = rave / n;
       for (i=0;i<n;i++)
       {  rvar += pow((thisval[i] - rave),2); }
       rvar = rvar / (n-1);
       aave += rave;
       avar += rvar;
       if (rave >= iave) sim_cnter++;
       if (rvar >= ivar) sim_cnter2++;
    }
}

int GetSeed()
{
  int seed;
  struct tm *preztime;
  time_t nowtime;

  time(&nowtime);
  preztime = localtime(&nowtime);
  seed = (int)((preztime->tm_sec + 1)*(preztime->tm_min + 1)*
           (preztime->tm_hour + 1)*(preztime->tm_year)*
           (preztime->tm_year));
  if(seed%2==0) seed++;
  return(seed);
}
```

APPENDIX B

C CODE FOR MONTE CARLO ANALYSIS OF REFUGE SITE SELECTION

```
#include <stdlib.h>
#include <stdio.h>
#include <math.h>
#include <time.h>
#define DATA_FILE "D_punctatus.txt"
#define PERMUT  1000
#define RECNUM  1000
struct RockInfo {
      float depth;
      float area;
};
struct RockRecord {
      float moisture;
      float temperature;
      struct RockInfo size;
      float observations;
};
   struct RockRecord rocks[RECNUM];
   int recnum, obs;
   int i, j, x, y, temp;
   float iave, isd, ivar;
   float rave, rsd, rvar, rtotal;
   float aave, asd, avar;
   float   sim_cnter;
void GetObservedVar(int k);
void Permute(int k);
int ReadDataFile();
char *GetType(int k);
float GetData(int k, int x);
int main(void) {
   char *line;
   char *filename;
   int k;
   time_t *thistime;
   recnum = obs = 0;
   x = y = temp = 0;
   srand48(time(thistime));
      recnum = ReadDataFile();
      printf("\nNumber of records read: %d\n\n", recnum);
   for (k=0;k<4;k++) {
       iave = isd = ivar = 0;
       rave = rsd = rvar = rtotal = 0;
       asd = avar = aave = 0;
       sim_cnter = 0;
```

```
      printf("------------------------------------------\nCalculations for %s\n-------------------
          -------------------------\n",GetType(k));
      GetObservedVar(k);
        printf("   Selected Average:\t %.3f\n", iave);
        printf("        Selected SD:\t %.3f\n", isd);
        printf("  Selected Variance:\t %.3f\n", ivar);
      Permute(k);
        printf("            p-value:\t %.3f\n", sim_cnter/PERMUT);
        printf(" Average of Average:\t %.3f\n", aave/PERMUT);
        printf("Average of Variance:\t %.3f\n", avar/PERMUT);
    }
    return (0);
}
char *GetType(int k) {
//    char *type;
//    type = malloc(100);
     if (k == 0)
       return "Moisture";
     else if (k == 1)
       return "Temperature";
     else if (k == 2)
       return "Rock Depth";
     else if (k == 3)
       return "Rock Area";
     return "";
}
float GetData(int k, int x) {
    if (k == 0)
      return rocks[x].moisture;
    if (k == 1)
      return rocks[x].temperature;
    if (k == 2)
      return rocks[x].size.depth;
    if (k == 3)
      return rocks[x].size.area;
    return -1;
}
void GetObservedVar(int k) {
      for (i=0;i<recnum;i++) {
         if (rocks[i].observations) {
           iave += GetData(k, i);
         }
      }
```

```
    iave = iave / obs;
    for (i=0;i<recnum;i++)
        if (rocks[i].observations) {
            ivar += pow((GetData(k, i) - iave),2);
        }
    ivar = ivar / (obs-1);
    isd  += sqrt(ivar);
}
void Permute(int k) {
    float values[recnum];
    float thisval[obs];
    int records;
    for (j=0;j<PERMUT;j++) {
        for (i=0;i<recnum;i++) { values[i] = GetData(k, i); }
        records = recnum-1;
        rvar = rsd = rave = 0;
        for (i=0;i<obs;i++) {
            x = (int)records*drand48();
            thisval[i] = values[x];
            values[x] = values[recnum-1];
            values[records-1] = thisval[i];
            rave += thisval[i];

        }
        rave = rave / obs;
        for (i=0;i<obs;i++)
            rvar += pow((thisval[i] - rave),2);
        rvar = rvar / (obs-1);
        rsd  += sqrt(rvar);
        aave += rave;
        avar += rvar;
        asd  += rsd;
        if (rave >= iave)
            sim_cnter++;
    }
}
int ReadDataFile() {
    FILE *datafile;
    int dindex;
    char *line;
    line = malloc(1000);
    dindex = 0;
    datafile = fopen(DATA_FILE, "r");
```

```
    while (!feof(datafile)) {
        fgets(line, 1000, datafile);
        sscanf(line, "%f,%f,%f,%f,%f", &rocks[dindex].moisture,
                                        &rocks[dindex].temperature,
                                        &rocks[dindex].size.depth,
                                        &rocks[dindex].size.area,
                                        &rocks[dindex].observations);
        if (rocks[dindex].observations) { obs++; }
        dindex++;
    }
    fclose(datafile);
    dindex--;
    return dindex;
}
```

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