

## Chapter 1: Introduction and Problem Statement

Bees are critical to the stability and persistence of many ecosystems, and therefore, must be understood and protected (Allen-Wardell et al., 1998; Kearns, Inouye & Waser, 1998; Michener, 2000; Cane, 2001; Kremen, Williams & Thorp, 2002; LeBuhn, Droege & Carboni, in press). Their pollination services are responsible for global biodiversity and maintenance of human food supplies (Allen-Wardell et al., 1998; Kearns et al., 1998; Michener, 2000; Kremen et al., 2002). Over the past two decades, bees have received increased attention by the scientific community because of population declines (Allen-Wardell et al., 1998; Kearns et al., 1998). Scientific research has focused primarily on honey bee (*Apis mellifera*) declines because this species is the most commonly used pollinator in United States agriculture, but significant declines have also occurred in native bees (Kevan and Phillips, 2001; Allen-Wardell et al., 1998). The United States Department of Agriculture (USDA) Bee Research Laboratory has charted a 25% decline in managed honey bee colonies since the 1980s (Greer, 1999). Estimates on native bee declines, on the other hand, are disputed and vary (Williams, Minckley & Silveira, 2001). Nonetheless, increased anthropogenic effects and exotic pests are impacting global bee populations (Kim, Williams & Kremen, 2006).

The specific consequences of the bee population decline on our food supply and global biodiversity remain to be seen, but the effects will inevitably be negative (Allen-Wardell et al., 1998). Fears of food, economic and biological losses have provoked a surge of scientific literature that examines the associated problems. Recent advancements in geography and landscape ecology suggest that landscape composition and pattern are critical to population dynamics (Turner, Gardner & O'Neill, 2001). Work

by entomologists and agriculturalists reveal links between the landscape matrix and bee populations, however, these landscape and regional scale links are not yet fully understood (Kremen et al., 2004; Steffan-Dewenter et al., 2002a; Dauber et al., 2003)

This thesis explores the spatial components of native bee habitat in Montgomery County, Virginia, by means of spatial analysis informed by a synthesis of interdisciplinary research findings, field data and statistical analysis. The goal of this study is to examine landscape scale components (topography, soils, and land cover) of native bee habitat in Montgomery County, Virginia for the purpose of assessing: 1) the usability of geographic information systems (GIS) analysis in bee research, 2) landscape scale variables important to native bee populations in the region, and 3) the impact of local site influence on bee populations. Specific objectives of this thesis are to:

1. Identify important spatial variables of bee habitat through an extensive literature review.
2. Build and validate a GIS model that generates a landscape scale bee habitat suitability index for Montgomery County, Virginia.
3. Evaluate the use of geographic methods in assessing the relationship between bee population and habitat.

I correlate landscape variables and relate them to nesting and foraging requirements to create a GIS habitat suitability index for native bees. The index, created by incorporating findings from scientific literature, represents a quantitative estimate of bee diversity and abundance at a given location. The index enables a landscape scale

assessment of variation in bee habitat, and therefore, fills an important gap in bee research that can serve to inform land management practices by providing critical coarse scale information on pollinators.

A key distinction between this research and the work of others is that it relies heavily on Geographic Information Systems (GIS) to aid in the research on bees. GIS has become a term that is intertwined with geography and can allow for flexibility and error assessment in modeling, allowing for innovative and creative methods that incorporate decision support, spatial statistic, and relational databases that can be very useful in identifying scales appropriate for analysis (Turner et al., 2001).

### **1.1: Significance of Research**

The importance of pollination services to ecosystem and economic health has been a major concern of many scholars. As a result, honey bee pollination is widely used and documented; pollination services by native bees, on the other hand, are less prevalent and less understood. However, recent research claims some native bees, such as bumblebees, are better than honey bees as pollinators, and this claim is driving new research (Thomson & Goodell, 2001). In addition, bee researchers are expanding and seeking out new methods for pollination because the current honey bee declines have presented needs for alternative pollinators in agriculture.

Strong efforts are being taken to ensure continued pollination by bees, especially in Europe where bee declines and extinctions predate North American declines. One stumbling block in the research efforts for North American bees is that there have been no spatially large, systematic surveys of pollinators and no long term datasets compiled

(Cane, 2001). This has led to criticism of prior studies on population declines and is a strong indication of a need for more research (Cane, 2001; LeBuhn et al., in press). My work contributes to this need by adding to the North American literature on bees which traditionally has been an area dominated by European research.

The need to quantify the temporal and spatial aspects of North America's native bees, demands an accurate means of conducting landscape scale bee population analyses (Cane, 2001; LeBuhn et al., in press). This study will be one of the first of its kind focusing on this, incorporating GIS and suitability indexing methods. It will fill an important gap in bee research by studying native bee populations from a multiple scale and geographic perspective, with a focus on GIS modeling.

This research also contributes to the North American Pollinator Protection Campaign (NAPPC), designed to map and identify all pollinators in North America (LeBuhn et al., in press). By addressing the campaign's specific call for a landscape scale analysis method for assessing pollinator populations this thesis further contributes to bee population research. I focus on building a model that can potentially be used to assess temporal change in pollinator populations, identify current population dynamics and as a quantitative link between landscape pattern and biodiversity.

## Chapter 2: Literature Review

The literature review is separated into two main sections to reflect the major focus areas of this study. The first section, *Pollination and Ecosystem Services*, reviews background on pollination services, and the biogeography of honey bees, native bees and individual bee species. The purpose of this section is to provide important background information on the species modeled in this research. The second section, *Spatial Components and Geographic Concepts*, contextualizes the spatial components of native bee habitat used in the GIS model, with emphasis on theory from landscape ecology and geography. When the model is referred to in the literature review it relates to the GIS model I build for bee habitat suitability which uses landscape variables as a predictor of bee species abundance and diversity. The development of the model is explained in *Chapter 3: Methods*.

### 2.1: Pollination and Ecosystem Services

Honey bees are recognized as contributors to the majority of pollination services because current agricultural practices in North America and most of the world are dependent on managed colonies of honey bees (Kevan & Phillips, 2001). However, declining populations of honey bees has decreased their reliability as pollinators (Greer, 1999). New research is proving that native bees such as bumblebees (*Bombus*), digger bees (*Andrena*, *Colletes*) and mason bees (*Osmia*) are more important than honey bees for pollination (Chambers, 1946; Klein et al., 2003; Kremen et al., 2002).

Using native bees for agriculture is still rare and adoption of new pollination techniques has been slow. Michener (2000) estimates that only 20% of cultivated plants

are pollinated by native bees. Lack of even a simple species list for most geographic regions makes a change in managed pollinators even more difficult for farmers. If honey bee populations don't stabilize, there will be many hurdles to overcome in order to maintain the current level of agricultural production.

The benefits from pollination are most notably important to crop production. Klein et al., (2003) successfully correlated increased yields of fruit with increased diversity and abundance of pollinators. Estimates in the 1980's on the value of insect crop pollination are as high as 18.9 billion dollars (Michener, 2000). Pollination not only increases the number of seeds and size of fruit, it is also an important genetic provider, needed to improve cultivated strains (Fell, 2005; Michener, 2000). O'Toole (1993) reviews usage and trends of native bees and insect pollinated crops.

Pollinators' essential role is to spread genetic information. At the most basic level it is the transfer of pollen grains (male gametes) to the plant carpel, the structure that contains the ovule (female gamete; Fell, 2005). This task produces ecosystem services providing honey for food, improving crop production and improving biodiversity in ecosystems (MEA, 2005). Ecosystem services are those that the natural environment produces, from which humans benefit (Kremen et al., 2004).

Fruit crops are especially susceptible to the decline of pollinators (Fell, 2005). Without pollinators, 110-150 crop species, such as apples, peaches, blueberries, cranberries, squash, pumpkins, melons, strawberries, and almonds will be at risk with limited gene pools, reduced seed quantities and reduced yields (Allen-Wardell et al., 1998). Therefore, preservation of bees is critical to efficient, continued agriculture, and biodiversity (Kremen et al., 2002).

## 2.2: Biogeography of the Honey Bee (*Apis mellifera*)

Honeybees belong to the old world genus *Apis*, of which no species are native to the Americas (Milner, 1996). There are four species of honeybees, but *Apis mellifera*, the domesticated or Western Honeybee (Figure 2.1) was the species introduced to North America and used for agriculture (Milner, 1996). The domesticated honeybee is native to Europe, Africa and western Asia. The Giant Honeybee (*Apis dorsata*) is native to Southeast Asia. The Eastern Honeybee (*Apis cerana*) is native to eastern Asia, Korea & Japan and the Little Honeybee (*Apis florea*) is native to Southeast Asia (Winston, 1987).



Figure 2.1 Honey bee (Jerry A. Payne, USDA Agricultural Research Service, Bugwood.org)

As opposed to the many annual species of native bees, the species of *Apis* have perennially social colonies persisting over the winter from one season to the next for periods of three or four years (Mitchell et al., 1985). There is no interaction between the queen and the worker bees. Queens never engage in foraging activities or build nests (Michener, 2000). Honey bees collect large amounts of honey used for overwintering, which can also be used for economic benefit (Milner, 1996).

### *Honey Bee Decline*

In the late 1980's honeybee feral populations began disappearing and commercial colonies in production dropped drastically due to the varroa mite (*Varroa jacobsoni*), an invasive exotic pest from Indonesia (Sanford, 1987). In addition, Old World parasites,

larval diseases and the red imported fire ant have all weakened honeybee colonies (Allen-Wardell et al., 1998). Furthermore, a new phenomenon labeled Colony Collapse Disorder (CCD) has emerged that resulted in the disappearance of Western honey bee colonies (Engelsdorp et al., 2006).

The exotic varroa mite (Figure 2.2) is considered to be the biggest threat to the honeybee. It was hypothesized that the introduction of the exotic pest resulted from shipping bio-contaminated material or illegal cargo containing infected honeybees into the U.S. (Sanford, 1987). The varroa mite was first identified in Java in 1904. For roughly 40 years, it was not reported in many places other than Indonesian neighboring islands.



Figure 2.2 Varroa mite (Scott Bauer, USDA Agricultural Research Service, Bugwood.org)

Around 1960 there was a marked increase in the range of the varroa habitat moving to Africa, Asia, Europe, South America and then finally North America in 1988 (Rademacher, 1991).

Varroa mites are estimated to have caused a 50-75% loss in commercial honey bee populations, almost entirely destroying feral honey bee colonies (Allen-Wardell et al., 1998; Gegner, 2003). All policies and eradication plans failed at containing the pest (Sanford, 1989). The varroa mite is most destructive to the European honey bee because of an undeveloped host parasite relationship. In developed host parasite relationships the parasite typically does not kill the host. The introduction has been called a “nightmare come true” (Sanford, 2003). Several states have already associated the honeybee decline



with reduced crop yields. For example, the California Almond has suffered decreased yields and prices increases (Morse, 2002).

### **2.3: Biogeography of Native Bees**

North America is home to more than 3500 species of native bees, which are also referred to as pollen bees (Greer, 1999). Most native bees are different from social bees because they don't form large colonies like honeybees, although some solitary species may form small colonies (Michener, 2000). For example, the bumblebee is considered solitary, but exhibits social characteristics and nests in small colonies of up to 500 individuals. Solitary bees are also annual species that die out each year, unlike honeybees (Greer, 1999).

Native bee species can be divided between wood dwellers and soil dwellers. Soil dwellers include bumblebees, sweat-bees, digger-bees, squash-bees, alkali-bees, polyester-bees and others (Greer, 1999). Soil dwelling bees prefer south facing dry soils for nesting (Michener et al., 1958; Wuellner, 1999). Wood dwelling species include the orchard mason bee, hornfaced bees, leafcutter bees and carpenter bees. They prefer dead wood or brush and seem to be attracted to holes of a specific shape and size (Greer, 1999).

Native bees are often mentioned in the literature with the domesticated honey bee decline because they are not susceptible to the varroa mite, which makes them excellent candidates to act as alternative pollinators if the honeybee shortage can not be alleviated (Greer, 1999; Michener, 2000). In some instances, native bees even appear to have benefits over honey bees (Thomas & Goodell, 2001). For instance, bumblebees will fly

and forage in a broad range of weather conditions (Gathmann & Tscharnkte, 2002), whereas, honeybees only perform pollination in a narrow weather conditions: sunny with low winds and high temperatures (Gegner, 2003). Other species, such as digger-bees or the blue orchard bee seem to be more effective at successfully transferring pollen grains, which is critical for fertilization. For example, an acre of apples can be successfully pollinated using a small percentage of blue orchard bees compared to the honeybees needed to cover the same area (Wolf et al., 2002).

### *Native Bee Decline*

Though resistant to the varroa mite, native bee populations have also been declining, likely due to the combined influences of habitat fragmentation, urbanization and pesticides (Aizen & Feinsinger, 1994; Cane, 2001; Roubik, 2001). However, a lack of systematic large scale bee sampling and conflicting research results confound the truth on native bee declines (Cane, 2001; Lebuhn et al., in press). For example, Packer (2001) suggests that bees flourish in fragmented and disturbed habitats, even though the negative effect of habitat fragmentation on species abundance and diversity of pollinators has been well documented. To further complicate explanations, solitary bee populations can be dynamic, exhibiting temporal and seasonal variability (Roubik, 2001). One potential reason for confounded explanations is the use of simple linear regression and correlation estimates to build models in many of these studies. Biological data is rarely linear and transformations can change data, making the use of all linear modeling concerning and possibly even explaining the drastic variations (Agresti, 1996).

Finally, the current state of native bee populations is largely unknown in North America (Cane, 2001; Lebuhn et al., in press). Cane (2001) concluded that while populations might be declining there was not strong enough evidence to support such claims and that a better approach to understanding changes in bee populations might be assessing habitat change. This approach may be facilitated with geographic methods incorporating spatial analysis and GIS modeling, as spatial and temporal habitat change is commonly modeled by geographers.

#### 2.4: Biogeography of Bees Species of Interest

A major objective of this thesis was to develop a bee habitat suitability model using the currently available research. This model was developed for solitary, soil dwelling species such as digger bees, bumblebees, and sweat bees. Scale limitations in the available GIS and remote sensing data meant that wood dwelling bees were omitted from the model because of their fine scaled habitat requirements, which are identified through wood debris composition and nesting hole diameter (Greer, 1999; Wolf et al., 2002). It is difficult or impossible to detect these requirements with available resolution imagery. Described below are the major groups of bees to which the literature refers that could be used in a GIS.

Digger bee is the common name for a group of fast-flying, ground-nesting bees with velvety fur (Figure 2.3). These bees are a cosmopolitan species, meaning they are located throughout the world



**Figure 2.3** Digger bee (*Andrena wollastoni* Cockerell, Scott Bauer, USDA Agricultural Research Service, Bugwood.org)

(Michener, 2000). Several thousand species exist, of which more than 900 occur in the United States and Canada. Digger bees are generalists, visiting a wide variety of flowers (Greer, 1999). They form their nests in the ground, leaving small mounds of soils behind (Wuellner, 1999). Although digger bees are solitary they sometimes nest together in dense patches (Michener et al., 1958). Their size can vary considerably. Rarely noticed digger bees are often the most abundant pollinator in the agricultural fields (Greer, 1999).

Bumblebee is the common name for a group of large, hairy, black and yellow, social bees ranging in size from 9 - 22 mm long (Figure 2.4, Michener, 2000). They are found in temperate regions of the northern hemisphere, including alpine environments (Michener, 2000). Bumblebees' large size and ability to regulate their own body temperature allow the bees to live in a wide range of habitats (Michener, 2000). This unique characteristic also allows them to fly and forage in harsh weather conditions. They are important pollinators that visit a wide variety of floral hosts (Greer, 1999). The bumblebee pollinates important agricultural crops such as tomatoes, eggplants, pepper, melons, raspberries, strawberries, blueberries, cranberries, apples, etc (Smith-Heavenrich, 1998). They are also the only pollinators of the potato flower (Reickenberg, 1994).



**Figure 2.4** Bumble bee (*Bombus fervidus* Fabricus, David Cappaert, Michigan State University, Bugwood.org)

North America is home to fifty species of bumblebees (Michener, 2000). The common bumble bee on the eastern landscape is *Bombus impatiens*. They form nests much like honeybees except colony sizes are small and underground. Bumblebees often

use tunnels previously made by other animals and prefer to nest in undisturbed meadows (Byczynski, 1998).

Sweat bee is the common name for a large family of bees characterized by an attraction to salts in human perspiration. These bees have a broad range of nesting habitats, with some forming small clusters of nests and others being completely solitary (Michener, 2000). All species nest in the ground. Sweat bees are small to medium-sized ranging from 3 -10 mm long (Figure 2.5, Greer, 1999). Sweat bees are abundant on all continents except



Figure 2.5 Sweat bee (*Halictidae*, David Cappaert, Michigan State University, Bugwood.org)

Australia and Antarctica. There are 1000 species of sweat bees in the Americas (Michener, 2000). They are considered to be good general pollinators and are abundant in many agricultural fields (Greer, 1999).

## 2.5: Spatial Components of Bee Habitat

Nesting and foraging requirements are the critical factors limiting the spatial extent of bee habitat (Ulbrich and Seidelmann, 2001). A great deal of work has been done to determine the habitat constraints of native bees; the majority of this work has been conducted in Europe (refer to Williams et al., 2001). Anthropogenic effects, such as urbanization have impacted the European landscape for much longer than they have in North America. Consequently, pollination shortages and bee extinctions have been researched and reported much more intensively in European literature. Recently, work

has been conducted in the U.S., but fewer publications exist, possibly because bee declines are a newer phenomenon in the U.S. One U.S. example is the Kremen et al. (2004) study that quantified the area requirements for pollination services in California based on native bee habitat. They determined that pollination services increased with an increase in natural habitat area.

Most bee research, however, lacks complex geospatial modeling and rigorous statistical analysis. Kremen et al. (2004), Steffan-Dewenter et al. (2002) and Dauber et al. (2003) all explored bee habitat at a landscape scale, but had conflicting results. They also all use simple linear statistical analysis methods and simple mapping techniques, which could potentially explain the variations because statistical transformations typically are needed.

Data exist on flight range, land cover/land use types, boundaries, soils, topography, area and connectivity of habitats, but have never been combined at regional or broad scales. These data are valuable for understanding spatial limiting factors of bees, especially when incorporated into a GIS. The following sections highlight the spatial components of bee habitat and address how the variables can be incorporated into a GIS for modeling purposes.

### *Flight and Habitat Range*

Bees are foremost limited in habitat by their flight and foraging ranges. It is widely documented that honey bees have a flight range of 2.5 km (Gegner, 2003). Native bees' ranges, however, vary based on species and size of the bee. Typically, a larger

body size is indicative of a greater potential foraging distance (Gathmann and Tscharnkte, 2002).

Results on flight and foraging ranges of solitary bees are conflicting. For example, the bumblebee has been observed to fly distances of up to 5 km, but Walter-Hellwig and Frankl (2000) claim bumblebees forage at distances reaching only 600 m. Westrich (1989) estimated that the average flight range of European wild bees was 50 m. In contrast, Gathmann and Tscharnkte (2000) indicate foraging distance ranging from 150-600 m for solitary bees in Germany. Further research by Steffan-Dewenter et al. (2002b) aimed at determining the scale dependent effects of landscape context on pollinators and found the strongest correlations between landscape variables, bee abundance and diversity at 250m. This finding suggests that that a 250 m scale is appropriate for landscape variable analysis of bees. Morandin and Winston (2006), on the other hand, suggested a 750m buffer zone and Kremen et al. (2004) found that providing 30% uncultivated land in a 750m buffer improved agricultural profits. Such conflicting claims complicate modeling endeavors of bee habitat, and are likely a product of studying a small species and insufficient statistical analysis. Improvements may be made by using GIS and geostatistical tools along with rigorous statistical analysis.

### *Land Cover Categories*

Landscape composition, symbolized by land cover classification has been a common variable in habitat studies on bees and used frequently in habitat modeling (Turner et al., 2001). For this study land cover is defined as the natural landscape recorded as surface components, for example forest, water, grass, soils, rocks, and urban

infrastructure. Land cover interpretations are made by analyzing satellite and aerial imagery and are based on spectral signatures.

Variability in bee species and populations exists between different land cover types (Steffan-Dewenter, 2001). Therefore, a discussion of land cover categories associated with bees must be discussed. Skovgaard (1936) concluded that in agricultural landscapes of Denmark, the abundance of nest-seeking queen bees was influenced by landscape character, vegetation and other species-specific characteristics. Svensson et al. (2000) also compared bumble bee abundance in different landscapes. They confirmed Skovgaard (1936) findings and concluded that nest-seeking bees were most abundant in forest boundaries, then open unmanaged land and field boundaries. Road boundaries also had slightly higher frequencies of encounters than forests and pastures, as well as the highest species diversity (Skovgaard, 1936). Wuellner (1999) also concluded that solitary ground nesting bees prefer to nest in relatively open landscapes with landmarks in close proximity.

Bees are highly susceptible to human disturbances, indicating that natural habitats with minimal anthropogenic disturbance are the most beneficial (Kremen et al., 2002). Bee abundance and diversity is frequently higher in natural areas (Greer, 1999; Kremen et al., 2004; Kim et al., 2006). Disturbed areas are unsuitable for native bees. For example, a construction site would likely be of little value for ground nesting bees because digging can disturb nests. Cultivated land used annually for agriculture is of little value to ground nesting bees in relation to nesting habitat, because it is regularly tilled and sprayed with pesticides (O'Toole, 1993).



### *Habitat Fragmentation*

Habitat fragmentation is a reduction in area and connectivity of an organism's preferred habitat, creating discontinuous patches of habitat (Turner et al., 2001). Strong negative effects on bees result from habitat fragmentation caused by urbanization, expanding agriculture, deforestation and other geologic processes (Steffan-Dewenter & Tschardt, 1999; Aizen & Feinsinger, 1994; Powell & Powell, 1987). Powell and Powell (1987) concluded that most euglossine bee species' visitation rates declined with fragment size. In addition, Aizen and Feinsinger (1994) also claim that frequency and taxon richness of native pollinators declined with decreasing forest-fragment size. Furthermore, Steffan-Dewenter and Tschardt (1999) concluded habitat connectivity was essential to maintain abundant and diverse bee communities.

Despite the scientific findings that habitat fragmentation is deleterious to bee species, others have concluded differently. For example, Cane (2001) brings to light the negations and importance of incorporating spatial and temporal scale into studies of habitat fragmentation. Cane agrees that detrimental effects of fragmentation to bees are scalar and species-specific. The challenge lies in determine the appropriate scale for these type of analyses.

Though there are complications with determining the appropriate scale to measure connectivity for a measure of fragmentation, predicting bee abundance and diversity is less debated. Area of natural habitat appears to be the best predictor of pollinator populations (Steffan-Dewenter, 2003). Increasing the area of natural habitat and floral resources will increase bee abundance and diversity (Steffan-Dewenter, 2003; Kremen et al., 2004; Kim et al., 2006).

### *Topography & Soils*

Most native bees thrive in sun and dry soils, preferring south facing slopes to slopes of other aspects (Greer, 1999). Dauber et al. (2003) also concluded that bees preferred dry south facing slopes, but this preference was attributed to an increase in floral resources in areas with more sunlight. Michener et al. (1958) provides specific details on aspect and bee nesting abundance with statistical evidence. No research has examined the influence of elevation gradients on changes in bee population variability.

Most species of native bees nest in the ground, but few studies aim at determining the factors specific to soils that are most important for nesting habitat. Species richness of wild bees was more abundant on dry soils than moist soils (Dauber et al., 2003). Sandy soils are the preferred substrate because adequate drainage is necessary for bees (Cane, 1991; Cross & Bohart, 1960). In a study of eight nests in Utah, U.S.A., Cross and Bohart (1960) found bees to nest in sandy loam, silt loam, clay loam and other sandy soils. Cane (1991) also found bee species to have a preference for sandy soils.

## **2.6: Concepts from Geography and Landscape Ecology**

Geography and landscape ecology are both concerned with understanding spatial patterns to understand process, and process to understand pattern. Geography and landscape ecology introduce fundamental questions on the concepts of scale, space and place (Turner et al., 2001). The major difference between the two disciplines is that landscape ecology is focused solely on ecological processes, whereas geography encompasses all systems, including human, ecological, biological, and physical. Ultimately, geography and landscape ecology are concerned with broad-scale

environmental issues and help provide insight on studies of ecological systems that operate over various scales.

The systems provided and maintained by bees are inherently related to geography and landscape ecology because of the importance of spatial scale and spatial pattern in bee habitat. Bee distribution is geographic in nature because it is limited by climate, topography, soils, and vegetation types (Michener, 2000). Thousands of species of bees exist on our planet; their distributions limited by spatial variables, create great regional diversity in bee populations.

Geography has also been on the forefront of GIS development, which may prove to be an important data management solution for these spatial variables that effect bee populations. It allows for many spatial variables to be modeled and statistically analyzed. The benefits of using a GIS for modeling are that you can use large data sets and it is easy to conduct multiple scale and temporal analysis. Vast quantities of historical data exist that can be incorporated in models. Change detection algorithms and methods have also been present in GIS analysis for a long time. GIS provides a prefect opportunity to incorporate geography into modeling bee habitat at a landscape scale.

The most notable contribution of geography to research on bees was by Michener (1979), in which he covered the distributional history of bees throughout the world. This major biogeographic work encompassed the distribution of major groups of bees, and speculated as to the historical and ecological explanations of such distributions. Technological limitations at the time of publishing made it difficult for Michener to quantify, and accurately map, bee populations. Additionally, in 2000 Michener authored *The Bees of the World*, an update to his previous work. Other research is beginning to

incorporate GIS into bee research, primarily for the purpose of simple mapping and linear-based modeling (Kremen et al., 2004; Dauber et al., 2003; Steffan-Dewenter et al., 2004). Shortcomings of these approaches are the use of simple models to represent complex systems that are rarely linear and can produce erroneous results; this topic is discussed further in Agresti (1996).

Most research on bees has also neglected other key geography concepts such as spatial autocorrelation. Spatial autocorrelation is foremost important in bee habitat research because biological, ecological and landscape variables are most often spatially autocorrelated. Bees are also small and dynamic, which complicates sampling measures and statistical analysis. When spatial correlation is not accounted for, the results of statistical tests can be inflated, increasing the chances of type I errors in hypothesis testing (Davis, 1986). This can be misleading and makes standard significance test inaccurate. There are techniques to work around this problem, but when possible it is best to sample so that spatial autocorrelation is minimized. .

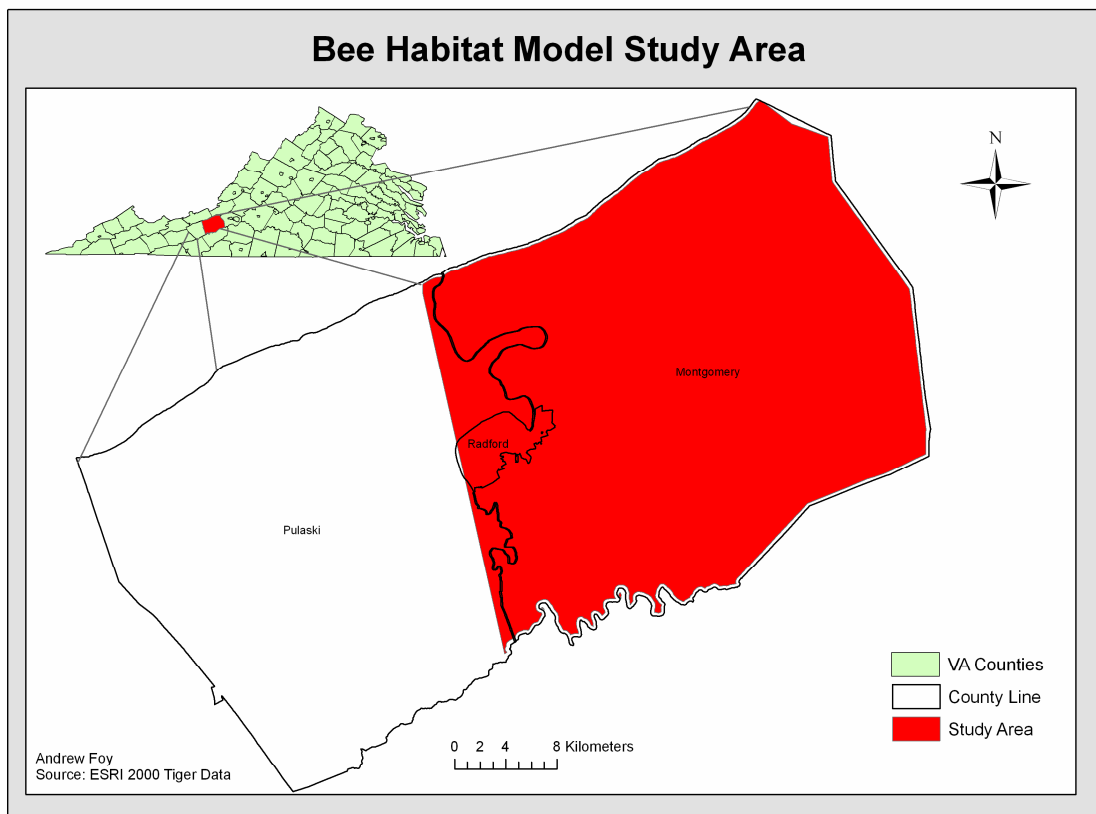
Spatial autocorrelation is defined as an assessment of the correlation of a variable in reference to the spatial location of the variable (Turner et al., 2001). It tests for whether a value of a variable at one locality is independent of the values of that variable at neighboring localities. For example, the presence of some quantity of a given variable in a county makes its presence in a neighboring counties more or less likely (Cliff and Ord, 1973). In geographic applications there is most always positive spatial autocorrelation, which suggests clustering of like values or variables. The spatial autocorrelation association is always affected by scale, making it important to this study and bee habitat research.

Landscape ecology is also important for understanding bee populations because of the discipline's focus on broad spatial scales and the ecological effects of the spatial patterning of ecosystems (Turner et al., 2001). One theory common to landscape ecology and important in the conceptualization of this research was percolation theory, which addresses spatial pattern in random assembly. Applications of percolation theory have brought to light questions of size, shape and connectivity of habitats (Turner et al., 2001). Percolation theory has offered much insight into the nature of connectivity or inversely fragmentation of landscapes (Gardner et al., 1992).

## Chapter 3: Methods and Procedures

### 3.1: Study Area

The area of interest was Montgomery County, Virginia and a small section of eastern Pulaski County, Virginia (Figure 3.1). For this study I had originally constructed the GIS model with data sets available at the county level, but because of the logistical problems associated with sampling a large area, the sampling area was restricted to that within 300 m of the road, public land and land that I was granted permission to enter. Research was facilitated by familiarity with the area, access to property, and reduced financial costs.



**Figure 3.1** Map of the study area for the bee habitat model

Montgomery County is located in the southwestern part of Virginia in the New River Valley region, and has a land area of 1018 km<sup>2</sup>. It lies between the Appalachian Plateau and the Blue Ridge Mountains with topography varying from gently rolling to steep mountainous terrain. Elevation varies from 397 - 822 m above sea level with the majority of the county at 600 m. Climate data for the county is presented in Table 3.1.

**Table 3.1** Climate statistics for Montgomery County, VA (Montgomery County, VA Government, 2007)

<b>Climate Characteristic</b>	<b>Statistic</b>
Average Winter temperature	mid 40s (high) / mid 20s (low)
Average Summer temperature	low 80s (high) / high 50s (low)
Average annual rainfall	40 inches
Average annual snowfall	28 inches (varies greatly)
Average growing season	161 days
Average relative humidity	66 percent (mid-afternoon)
Prevailing wind	West

### **3.2: Digital Data Collection and Preparation**

In this thesis, a top-down approach was adopted for developing the GIS model because a sufficient amount of information had previously been collected and described in the literature on bee habitat. I also apply and evaluate the use of large scale GIS modeling by using local data obtained by other findings to determine if the literature that exists accurately predicts bee habitat. The literature reveals conclusive evidence on landscape variables that are important to bees, but there is disagreement on the correct scale for analysis. My GIS model will provide further quantitative estimates on the

validity of the current bee research and it will investigate the uncertainties in spatial scale by using complex GIS modeling, decision support, and rigorous statistical analysis.

The literature review revealed that land cover, soils, and aspect are important geographic variables for bees. These data are described as landscape variables for the development of this GIS model, which maps bee habitat suitability. Model creation was done with a Multiple Criterion Evaluation (MCE) of land cover, soils, and aspect in IDRISI. The data for this evaluation were collected from three main sources: United States Geologic Survey (USGS) seamless data server, Virginia Department of Forestry (VDOF) 2005 edition of the Virginia Forest Cover Map (VFCM 2005), and the United States Department of Agriculture (USDA) National Resource Conservation Service (NRCS) Soil Mart server. The data types, scales and sources are given in Table 3.2.

**Table 3.2** Original data type, scale and source

<b>Data Set</b>	<b>Data Type</b>	<b>Data Scale/Resolution</b>	<b>Source</b>
Land Use (VFCM 2005)	Raster	15 m	VDOF
Elevation (DEM)	Raster	10 m	USGS
Topography	Raster	15 m	USGS
Roads	Line	1:24000	USGS
Soils	Polygon/Tabular	1:24000	NRCS
Agriculture Areas	Polygon	1:24000	Montgomery County, VA Web Server

The USGS seamless data server was used to collect a National Elevation Dataset (NED) 1/3 Arc Second digital elevation model (DEM) and a roads shapefile. The NED 1/3 Arc Second (10 m resolution) is a raster product assembled by the USGS. These data



were designed to provide national elevation data in a seamless form with a consistent datum, elevation unit, and projection. There are corrections made to minimize artifacts, perform edge matching, and fill sliver areas of missing data. The USGS roads were obtained from the Bureau of Transportation Statistics (BTS) published in 2002. They cover the 50 states, scaled 1:100,000.

The VDOF VFCM 2005 data was downloaded off the VDOF GIS web site. It was developed to identify forests in Virginia as defined by the United States Forest Service (USFS) Forest Inventory and Analysis (FIA) Program. VFCM 2005 was developed through segment based classification of Landsat imagery spanning March 10, 2002 to May 8, 2005. An accuracy assessment of water, forest, and non-forest land cover classes was conducted by the USFS using over 120,000 points, which resulted in an overall accuracy of 88.24%.

The NRCS Soil Mart server was used to download the soils data. This USDA maintained site is an extensive data base with 1:12,000 soils maps and tabular data. One additional data set produced by Montgomery County, VA was used obtained to error check agricultural areas in the study site.

Preprocessing involving standardization of data was necessary before incorporation into the model. Files were projected to the local UTM coordinate system, and clipped to the same spatial extent to allow for proper spatial analysis. The VFCM data classes were classified into similar classes used in research described in the literature to ensure proper comparisons (Kremen et al., 2004; Dauber et al., 2003; Steffan-Dewenter et al., 2004). The hardwood forest, pine forest and mixed forest classes were reclassified to one class named forest, because forest type delineations have not been

made in previous research. Rooftops and pavement classes were also merged since they represent impervious surfaces, which are equally detrimental to bees digging and habitat. There were also very few rooftops pixels in the study area, making them statistically insignificant. The USGS roads line file was rasterized and then overlaid with the pavement raster class. A cross-tab calculation was done to determine the overlapping, misclassified, or omitted roads and revealed the VFCM 2005 data mainly misclassified small rural roads. Because these roads impact bee habitat the misclassified pixels were corrected to represent pavement (Steffan-Dewenter et al., 2004).

An additional cross-tab calculation was conducted with the crops VFCM 2005 data and the grass/pasture class from the 2000 National Land Cover data set because I suspected that the VFCM 2005 crops classification was misrepresenting crops as pastures, grass, or land left fallow. The cross-tab revealed misrepresentation was the case, indicating that the VFCM 2005 data poorly distinguishes between pastures/grass and agriculture. For this reason, an agricultural districts polygon shapefile was obtained from Montgomery County for the study area. This polygon was rasterized and overlaid with the VFCM 2005 data. All pixels in the agricultural district and labeled as crop in the VFCM 2005 data set were reclassified to agriculture. All other pixels were considered to be pasture/grass. The study area contained no pixels classified as bare soil, salt marsh, natural barren or mine.

Finally, a boundary detection algorithm in the FILTER module in IDRISI was used to delineate forest, road and field boundaries because these edges have a significant impact on bee habitat, as described in the literature review. The final result of numerous cross-tab calculations and overlays was a land cover classification named VLC 2005

(Appendix A) that contained the following classes: water, pavement, residential/industrial, forest, agriculture, pasture/grasses, forest boundary, field boundary and road boundary (Table 3.3). The definitions other than the boundary classes are analogous to the USGS land cover class definitions (Anderson et al., 1976).

**Table 3.3** VLC 2005 class names and definitions

<b>Class Name</b>	<b>Class Name Definition</b>
Water	All areas of open water
Pavement	> 75% asphalt, concrete, buildings and roads
Residential/Industrial	Urban residential/Industrial areas 25-75 % asphalt, concrete, buildings, etc. with some vegetation, and areas of recent disturbance
Forest	Areas dominated by trees where 75 % or more of the tree area is tree cover
Agriculture	Areas used for the production of annual row and cover crops or used intensively for livestock grazing
Pastures/Grass	Areas characterized by natural or semi-natural herbaceous vegetation; herbaceous vegetation accounts for 75-100 % of the cover
Forest Boundary	Filter module output, area bordering forests
Field Boundary	Filter module output, area bordering fields
Road Boundary	Filter module output, area bordering roads

The NED 10 m DEM was resampled to 15 m resolution to allow for proper overlays and to derive an aspect map (Appendix A), following the protocol outlined by IDRISI. Aspect was separated into the five classes referred to in the literature and are defined in Table 3.4 (Michener et al., 1958; Wuellner, 1999)

**Table 3.4** Aspect derived from NED 10 m DEM

<b>Class Name</b>	<b>Class Definition</b>
North East	0-90 degrees
South East	90-180 degrees
South West	180-270 degrees
North West	270-360 degrees
Flat	-1 value

The soils spatial data set, a polygon shapefile, was joined with the soils tabular data to attach more information to the spatial data. The soils polygons were merged with the soil polygons that had the same hydrologic group classification. This process produced polygons with values referencing the four hydrologic groups. Hydrologic groups were used because they best represented characteristics such as water retention, drainage and parent material, all important variables to bee habitat (Wuellner, 1999). A hydrologic group represents soils with the similar runoff potential and drainage (USDA, 2002). The groups are derived from properties such as parent material, depth to water table, intake rate, permeability after prolonged wetting, and depth to slowly permeable layers (USDA, 2002). For analysis the soils data was converted to raster format (Appendix A). The class names and definitions of the hydrologic groups were defined following USDA (2002) (Table 3.5).

**Table 3.5** Hydrologic group class names and definitions

<b>Class Name</b>	<b>Class Definition</b>
A	Low runoff potential, high infiltration rate, Deep, well drained to excessively drained sands or gravels
B	Moderate infiltration, moderately deep to deep, moderately well drained to well drained soils, moderately fine to moderately coarse textures
C	Slow infiltration rate, have a layer that impedes downward movement of water or have moderately fine to fine texture
D	High runoff potential very slow infiltration, clay soils that have a high swelling potential, soils that have a permanent high water table, soils that have a claypan or clay layer at or near the surface, and shallow soils over nearly impervious material

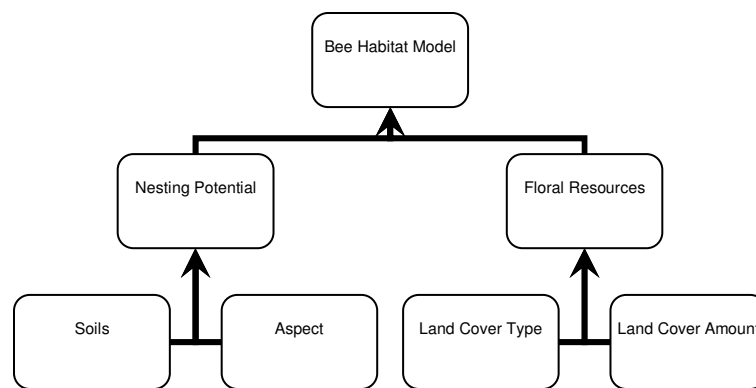
Outcomes of the data preprocessing were three raster files to be used in the GIS model development: land cover, aspect and soils. The resolution of all data files was 15 m. Data type scale and source are outlined in Table 3.6.

**Table 3.6** Preprocessed data for use in the GIS model development

<b>Data Set</b>	<b>Data Type</b>	<b>Data Scale</b>	<b>Source</b>
Land Cover	Raster	15 m	Modified VFCM (2005)
Aspect	Raster	15 m	Derived USGS
Soils	Raster	15 m	Derived NRCS

### 3.3 Bee Habitat GIS Model Development

Once the necessary data were collected and preprocessed, I was able to develop the GIS model's conceptual framework (Figure 3.2) to meet Objective 2. According to Cane (2001), bee habitat is dependent on two variables, nesting potential and floral resources. Influences on nesting potential are soil type, aspect, drainage and water availability (Cane, 2001). Factors affecting floral resources are vegetation type and percentage of vegetative cover (Kremen et al., 2004).



**Figure 3.2** The conceptual framework for the development of the bee habitat model

Decision support modeling was chosen for this GIS model development because of its flexibility in modeling parameters and because it provided a framework for scoring and standardizing variables. Decision theory, the root of decision support modeling, is concerned with how one arrives at a decision (House, 1983). Decision support is a useful form of modeling for problems that involve multiple objectives, large data sets, multiple iterations and uncertainties because the user can set rules and assign weight to variables (Pearlstine, 2006). In recent years, GIS has been viewed as a decision support system and efforts to guide decision making and uncertainty have been developed in IDRISI. Decision support systems are already commonplace in business and resource allocation

and are becoming increasingly popular in GIS and in habitat modeling (Armstrong & Densham, 1990).

The three files were analyzed using a Weighted Linear Combination technique. The MCE module in IDRISI allows for WLCs that produce one raster file with a score for each cell. In this model the score signifies the suitability of that cell for native bees in relation to land cover, soils, and aspect. This process involved separating the spatial factors (land cover, soils, and aspect) into zero and one, using the BREAKOUT module in IDRISI. The factors were then used in a pairwise comparison matrix to assign weights for each factor. These comparisons were then implemented with WEIGHT, the IDRISI module, which sets relative weights for a group of factors in the multi-criterion evaluation. This is a scientific method for reclassing data from multiple sources, types and scales.

Three separate comparisons were done for each group of factors because the comparison matrix in IDRISI was too small to fit all of the combined factors. The factor weights are developed by providing a series of pairwise comparisons of the relative importance of factors to the suitability of pixels for the activity being evaluated, in this case bee habitat suitability. These pairwise comparisons produce a set of weights that sum to one. Comparisons were made based on the weight, importance and frequency of the factors found in the literature. The weight and consistency ratios are provided in Table 3.7.

**Table 3.7** Weight for aspect (consistency ratio = .04), land cover (consistency ratio = .07), soils (consistency ratio = .02), derived from a pairwise comparison. Consistency ratios all are acceptable.

<b>Variable</b>	<b>Weight</b>
<b>Aspect</b>	
Flat	0.0316
NW	0.0776
NE	0.1166
SW	0.2773
SE	0.4969
<b>Land Cover</b>	
Forest Boundary	0.2788
Field Boundary	0.2449
Road Boundary	0.1661
Grass	0.1113
Forest	0.0803
Residential/Industrial	0.0547
Agriculture	0.0340
Water	0.0149
<b>Soils</b>	
D	0.0618
C	0.2295
B	0.5825
A	0.1262

Once factor weights were determined they were used in the Multiple Criterion Evaluation (MCE) module that provides a platform to perform the WLC. The method of running the WLC in this study is different than a standard WLC because the factors are weighted twice. Typically, a WLC works by multiplying each factor by its factor weight and then adding the results. I used this technique, but in a hierarchical fashion, applying



weights to my factors listed in table 3.7, and then applying a second set of factor weights to the groups of factors (i.e. land cover, aspect and soils) because the literature revealed different weights for two habitat components. Most of the literature refers to land cover and vegetation, and land cover relates specifically to floral resources, one of two components critical to bee habitat. Thus, it was assigned a weight of 0.5. Aspect was assigned a weight of 0.3 and soils 0.2 because they make up the nesting requirements. Aspect was weighted higher than soils because more evidence supported the role of aspect in bee habitat. In addition, there is more uncertainty in a soils map than in a topographic map. This weighting assured that both floral resources and nesting substrates were accounted for in the model, while still addressing uncertainty.

After the WLC was completed, the neighborhood averages of all the resulting cells in a 250 m, 500 m, 750 m and 1000 m radius were computed to account for and investigate the effects of scale. Bee habitat can not be defined by a single score of one 15 x 15 m cell because it is dependent on the surround landscape matrix (Steffan-Dewenter et al., 2002b). The strongest correlation between landscape metrics and bee populations was at 250 m, with correlations existing up to 1000 m for native bees (Steffan-Dewenter et al., 2002b). Taking the neighborhood averages allowed for area and type of the land cover to be part of the model. The MCE GIS model produced four raster files with pixel values that represented the neighborhood averages of the landscape's bee habitat suitability. This score was used as the independent variable in subsequent modeling to predict bee abundance and diversity.

### 3.4: Field Sampling

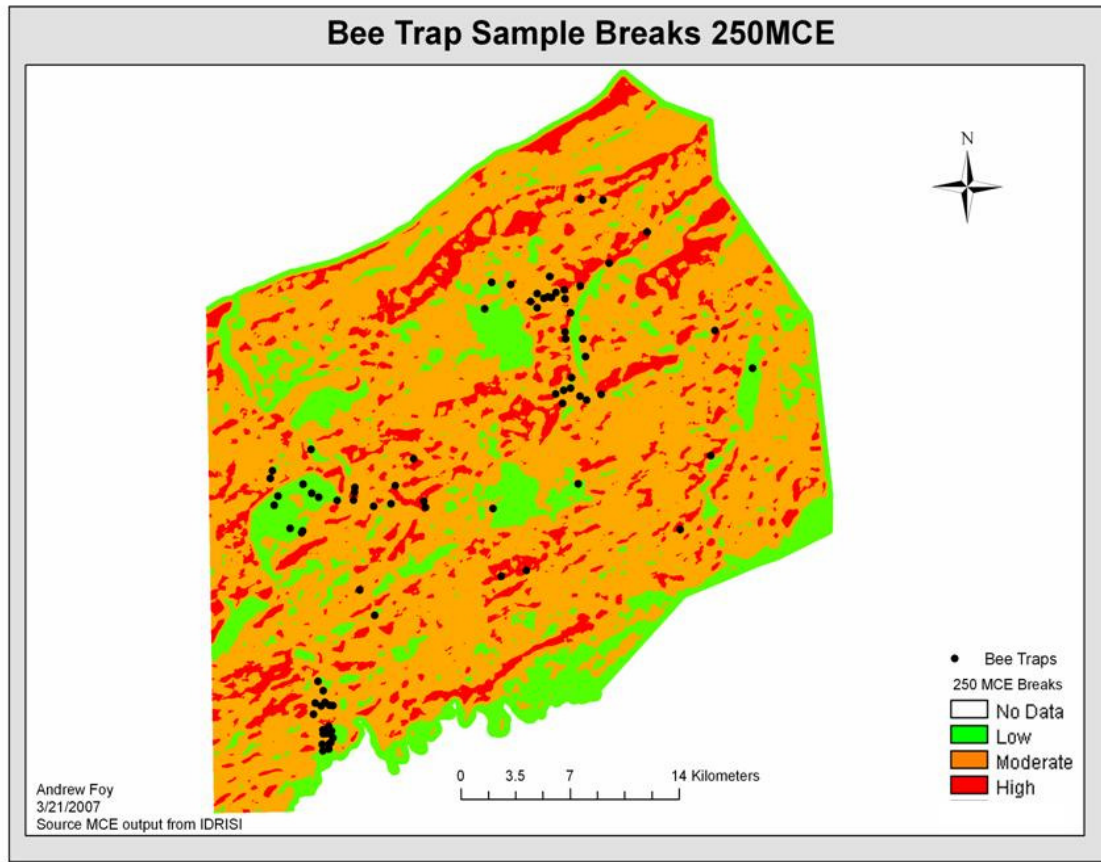
Bee abundance and diversity data were collected in the field to validate the bee habitat suitability model. The field samples were taken to allow for statistical analysis and model validation. The 250 m index was used to select locations for bee traps because it had shown the strongest correlation with bee abundance and diversity in the literature and could allow for a systematic means of obtaining equal samples in MCE class breaks (Steffan-Dewenter, 2004).

The MCE map was broken into three classes: High Suitability, Moderate Suitability and Low Suitability (Figure 3.3). Class breaks were determined by using the histogram of the model outputs. Breaks were set using standard deviations from the mean. One standard deviation from the mean was used to represent Moderate Suitability. Two standard deviations above the mean was High Suitability and two standard deviations below the mean was Low Suitability. The 250 m MCE data  $\bar{x} = 0.558$  and  $\sigma = 0.094$ ; physical breaks of the data are in Table 3.8.

**Table 3.8** Statistical breaks for 250 m MCE data

<b>Class Break</b>	<b>MCE Range</b>
Low	0.001-0.464
Moderate	0.464-0.652
High	0.652-1

To ensure all the MCE classes were represented in the field samples, thirty randomly located samples from within each of the three classes were collected. To verify that a sample of 90 was significant, a post-hock power analysis was run to determine the degree of detection ( $\alpha = 0.05$  &  $\sigma = 0.094$ ). A default power of 0.90 was used. A sample size of 90 allowed for a degree of detection of 0.03 indicating that with 90 samples I could detect a 3% difference in score with a high degree of certainty.



**Figure 3.3** The breaks used to stratify the sampling and bee traps

Bee trapping methods followed in this study were in accordance with the North American Bee Sampling Protocol (Lebuhn et al., in press), a method shown to be the least biased with the lowest material costs. To avoid spatial autocorrelation, traps were not placed if the random geographic locations were within 90 m of each other. This distance was calculated from recommendations in Lebuhn et al. (in press), which outlined methods for sampling a smaller area. Minimizing spatial autocorrelation was important because I wanted to have independent samples. After the field data was collected, spatial autocorrelation was tested in ArcInfo 9.2.

The material used for field sampling included 6.5 oz solo brand cups painted with florescent yellow, blue and white krylon brand paint as suggested in the protocol. The

cups were filled with a solution of blue Dawn brand soap and water at a ratio of one tablespoon of soap to one gallon of water. The color of the cups attracts the bees and when they hit the water they sink and drown because the soap reduces the surface tension of the water.

Traps were set out before 9:00 am in the morning and collected after 3:00 pm in the evening, the time period when bees are most active (Lebuhn et al., in press). They were placed in random locations 90 m apart, within the selected location and stratified classes (Figure 3.3.). These locations were selected using the RANDOM module in IDRISI, on the area of interest. A GPS was used to navigate to the locations, set and retrieve the traps. Location, time, date and temperature were recorded at trap setting. Cup color was randomly chosen for a trap location within each class. This ensured that there was equal representation of cup color within each bee habitat class.

Upon collection of the traps the water was drained and the bees were placed in an alcohol solution and labeled based on the site number. Differences between bee species were determined using a microscope, the *Discover Life Identification Guide* (<<http://www.discoverlife.org/20/q>>) and Michener's (2000) book *Bees of the World*. Distinctions among bees that indicated a different species were easier to detect than actual species, because of complexities in bee species identification. For this reason the number of species present was recorded to use in statistical analysis. Bees in this thesis are referred to at the genera level.

### 3.5: Statistical Analysis

Statistical analysis was conducted with the Fit Model Platform in JMP 6.0.2. To achieve objective 2 of this study, the MCE GIS model was statistically validated. I used three independent variables: 1) MCE score at 4 distance intervals, 2) color of bee traps and 3) presence of flowers. The MCE score was used as a landscape variable because it represented the combined suitability of land cover, soils and topography. The color of bee traps and the presence of flowers were used as local site variables because these characteristics were not part of the landscape matrix. The MCE sampling was conducted with groups of the scored data explained in the methods. Analysis was conducted on the raw neighborhood averaged MCE scores, scored between zero and one. Two independent variables, bee abundance and bee species diversity, were fit to models because bee abundance and diversity are related and are the most important indicators of bee populations. The model variables are defined in Table 3.9.

**Table 3.9:** Statistical analysis variables

<b>Variable</b>	<b>Definition</b>
Y1	Number of bee caught in a trap (Bee abundance)
Y2	Number of species identified in a trap (Species diversity)
X1	250 m neighborhood average of MCE (250 MCE)
X2	500 m neighborhood average of MCE (500 MCE)
X3	750 m neighborhood average of MCE (750 MCE)
X4	1000 m neighborhood average of MCE (1000 MCE)
X5	Color of bee cups (Color)
X6	Presence of flowers (Flowers)

A generalized linear model (GLM) was chosen for this work because a GLM provides a way to fit responses that don't fit the usual requirements of least-squares fits. Similarly to traditional linear models, fitted generalized linear models can be summarized through statistics such as parameter estimates, standard errors, and goodness-of-fit statistics. In addition, one can make statistical inference about the parameters using confidence intervals and hypothesis testing.

Bee abundance data gathered in the field was grouped into classes to avoid potential violation of the large sample chi-square theory because the data had excessive zeros and counts less than five (Agresti, 1996). Data was grouped into 6 categories following Agresti (1996) guidelines. The categories were separated by a difference of two bees with the bottom class  $< 2$  and the top class  $> 10$ . The grouped bee abundance distribution was tested for fit to a Poisson distribution using the Pearson's goodness of fit test. The tests indicated that the data fit a Poisson distribution ( $\chi^2 = 15.46$ ,  $p = 0.28$ ). The bee diversity data was not grouped because the structure of the data didn't allow for enough groups or counts in groups following Agresti (1996). The bee diversity count data still fit a Poisson distribution indicated by the goodness of fit test ( $\chi^2 = 4.16$ ,  $p = 0.9$ ).

A GLM with a Poisson distribution was determined to be an appropriate model because both data distributions had Poisson distributions and were rare count data (Agresti, 1996; Shaw & Wheeler, 1985). The assumptions of using this model are 1) the data have a Poisson distribution, 2) the data are count data and 3) the data has a standard deviation close to the mean. To properly conduct a GLM analysis multiple tests are needed to confirm significance. For this statistical analysis I used the tests available in

JMP. A whole model test, goodness of fit test, effects test and parameter estimated test were used. The null hypotheses and specifics of the tests are outlined below.

The whole model test determines if the model fits better than constant response probabilities. It is a specific likelihood-ratio chi-square test that evaluates how well the GLM fits the data using a likelihood-ratio statistic. Larger  $\chi^2$  and smaller p values indicate more significance. It tests the null hypothesis that a reduced model without any effects except the intercepts is better than the full model.

The goodness of fit test is analogous to a lack of fit test and tests for two things: 1) are the variables in the model accurate to describe the situation and 2) does the model have the right form? A Pearson's chi-square statistic ( $\chi^2$ ), a deviance statistic, and an overdispersion parameter indicate adequacy of the GLM. The null hypothesis was that the model fits the data; it is good to not reject the null hypothesis in this case.

The effects test determines if the effects of a variable on the response were zero. The null hypothesis is that variable has no effect as a predictor. The effects test uses joint tests to determine if all the parameters for an individual effect are zero. If an effect has only one parameter, for example, with simple regressors, then the tests are no different from the tests in the parameter estimates. Large  $\chi^2$  and small p values indicate larger effects.

The parameter estimates test gives estimates on standard errors,  $\chi^2$  and p values analogous to the Wald statistic described in Agresti (1996). A Wald statistic is a parameter estimate divided by its standard error and then squared. Larger  $\chi^2$  and small p values are more significant.

## Chapter 4: Results and Discussion

This section reviews the results from the field trapping, the MCE model and the combined GLM model. First, I outline the bee trap data, discussing the basic descriptive statistics on the abundance and diversity of bees. Then, the results of the landscape variables and bee abundance fit to a GLM Poisson are given. Local site variable results are also outlined, computed by adding the additional variables individually to the model. Finally, the results for bee diversity are presented in the same order as bee abundance results. The GLMs that incorporate only the landscape variables address the GIS MCE model. The local site variables were added to the GLM to assess their impact on bee populations and the appropriateness of using only landscape variables to model bees

### 4.1: Results

#### *Bee Trap Results*

A total of 98 bee traps were set in the field, and 81 were collected (Appendix B). The loss was due to spilled, damaged, and lost traps. There were 25 samples collected for MCE class Low, 31 for Moderate and 25 for High. The bee abundance count data before grouping had a range of 0 - 29,  $\bar{x} = 4.20$  and  $\sigma = 4.24$ .

A total of 339 native bees were collected from the 81 traps, which represented 19 different species. Bees were separated by species and grouped by genera. The Halictid bees and *Lassioglossum* spp. were the most abundant bees caught in the traps. The *Bombus* genera were the most diverse followed by *Halictus*, *Andrena* and *Lassioglossum*. The least abundant bee was *Colletess* spp.



No significant spatial autocorrelation was found for bee abundance or bee diversity (Figure 4.1), as shown by the Moran's I Index = -0.01 for bee abundance, and Moran's I Index = -0.03 for bee diversity. The scores indicate that the data is neither clustered nor dispersed and suggest that field sampling was done in a way to reduce the effect of spatial autocorrelation. This is an important finding because I was able to collect independent samples at 90 m.

#### *Bee Abundance and MCE (landscape variable) Results*

To meet Objective 2 and determine if landscape scale factors influenced bee population dynamics, the MCE score was first fitted to the data on bee abundance with a Poisson GLM. The results of the whole model test on MCE score (Table 4.1) show all four spatial scales of MCE scores to have significant prediction capabilities with the 250 MCE score reaching the highest significance level indicated by the chi-square statistic.

**Table 4.1** Whole model test results on MCE (landscape variables) and bee abundance.

<b>Spatial Scale (m)</b>	<b>Model</b>	<b>Log-Likelihood</b>	<b>Chi-Square</b>	<b>DF</b>	<b>Prob&gt;Chisq</b>
<b>250</b>	Difference	21.9436	43.8872	1	< 0.0001
	Full	276.5826			
	Reduced	298.5262			
<b>500</b>	Difference	18.0727	36.1454	1	< 0.0001
	Full	261.3386			
	Reduced	279.4113			
<b>750</b>	Difference	10.1812	20.3623	1	< 0.0001
	Full	228.5783			
	Reduced	238.7595			
<b>1000</b>	Difference	7.1129	14.2258	1	0.0002
	Full	215.0205			
	Reduced	222.1334			

The results of the goodness of fit test were all insignificant indicating that the model fits for all variables (Table 4.2). Insignificant chi-square results suggest that the variables in the model adequately describe the data and that the form of the model is correct. In addition to the chi-square results, overdispersion estimates are provided. Lower overdispersion also suggests that the 250 MCE fits the best.

**Table 4.2** Goodness of fit results on MCE

Spatial Scale (m)	Goodness Of Fit Statistic	Chi-Square	DF	Prob>Chisq	Overdispersion
<b>250</b>	Pearson	37.2858	79	0.9999	0.4720
	Deviance	37.7228	79	0.9999	
<b>500</b>	Pearson	39.8365	79	0.9999	0.5043
	Deviance	40.2096	79	0.9999	
<b>750</b>	Pearson	46.6192	79	0.9986	0.5901
	Deviance	46.4201	79	0.9987	
<b>1000</b>	Pearson	50.1085	79	0.9954	0.6343
	Deviance	49.4131	79	0.9963	

The results of the parameter estimates test in Table 4.3 support the test results of the two previous tests. The results are based off the Log of the predictor variable. The standard error, chi-square results and confidence limits all indicate suitable models, but the evidence is strongest for 250 MCE, as indicated by the lowest standard error.

**Table 4.3** Parameter estimates test results on MCE, analogous to a Wald statistic in JMP

Spatial Scale (m)	Term	Estimate	Std Error	Chi-Square	Prob>Chisq	Lower CL	Upper CL
<b>250</b>	Intercept	-0.6516	0.2647	6.3190	0.0119	-1.1791	-0.1412
	MCE	2.8328	0.4392	43.8872	< 0.0001	1.9795	3.7017
<b>500</b>	Intercept	-1.3037	0.4123	10.8403	0.0010	-2.1317	-0.5149
	MCE	4.0862	0.7191	36.1454	< 0.0001	2.7032	5.5231
<b>750</b>	Intercept	-1.0887	0.4895	5.2524	0.0219	-2.0732	-0.1536
	MCE	3.7408	0.8680	20.3623	< 0.0001	2.0739	5.4781
<b>1000</b>	Intercept	-0.9989	0.5557	3.3994	0.0652	-2.1184	0.0613
	MCE	3.5864	0.9915	14.2258	0.0002	1.6856	5.5744

*Bee Abundance and Color (local variable) Results*

To assess the potential of the GIS model, the impact of local site variables needed to be determined. The color of bee traps was added as a variable to the Poisson GLM. Subsequently, the presence of flowers was added and another GLM computed. The results of the whole model test on color of bee traps and MCE are similar to the results of the MCE only GLM (Table 4.1). The chi-square results still suggest that the model is significantly better at predicting bee abundance than a random model, with 250 MCE yielding the most significant values.

**Table 4.4** Whole model test results on color of bee traps and MCE

<b>Spatial Scale (m)</b>	<b>Model</b>	<b>Log-Likelihood</b>	<b>Chi-Square</b>	<b>DF</b>	<b>Prob&gt;Chisq</b>
<b>250</b>	Difference	23.4966	46.9931	2	< 0.0001
	Full	280.4725			
	Reduced	303.9691			
<b>500</b>	Difference	18.8248	37.6497	2	< 0.0001
	Full	262.7705			
	Reduced	281.5953			
<b>750</b>	Difference	10.6212	21.2425	2	< 0.0001
	Full	228.7904			
	Reduced	239.4116			
<b>1000</b>	Difference	7.5385	15.0769	2	0.0005
	Full	215.3461			
	Reduced	222.8846			

The results of the goodness of fit test are all insignificant suggesting that there is no lack of fit (Table 4.5). The deviance is slightly lower than in the MCE GLM, the model with only landscape variables. A large change in deviance would suggest that the color of bee traps had an effect on bee abundance; however, that failed to happen meaning color of the cups is of little predictive value. The chi-square results and the overdispersion estimates are all more significant for the 250 MCE.

**Table 4.5** Goodness of fit test result on color of bee traps and MCE

<b>Spatial Scale (m)</b>	<b>Goodness Of Fit Statistic</b>	<b>Chi-Square</b>	<b>DF</b>	<b>Prob&gt;Chisq</b>	<b>Overdispersion</b>
<b>250</b>	Pearson	36.1546	78	1.0000	0.4635
	Deviance	36.6540	78	1.0000	
<b>500</b>	Pearson	39.0272	78	0.9999	0.5003
	Deviance	39.5983	78	0.9999	
<b>750</b>	Pearson	45.9037	78	0.9986	0.5885
	Deviance	45.9349	78	0.9986	
<b>1000</b>	Pearson	49.3075	78	0.9954	0.6321
	Deviance	48.9055	78	0.9960	

The results of the effects test confirm the results from the goodness of fit test (Table 4.6). Cup color has no significant impact on bee abundance, as identified by insignificant chi-square values, resulting in a failure to reject the null hypothesis.

**Table 4.6** Effects test results on color of bee traps and MCE

<b>Spatial Scale (m)</b>	<b>Source</b>	<b>DF</b>	<b>Chi-Square</b>	<b>P</b>
<b>250</b>	MCE	1	45.8067	< 0.0001
	Color	1	2.3057	0.1289
<b>500</b>	MCE	1	36.5506	< 0.0001
	Color	1	1.2218	0.2690
<b>750</b>	MCE	1	20.3080	< 0.0001
	Color	1	0.8245	0.3639
<b>1000</b>	MCE	1	14.2070	< 0.0001
	Color	1	0.8031	0.3702

The results of the parameter estimates test also confirm that color is insignificant (Table 4.7). The chi-square results and Wald statistics are poor, the confidence limits are negative and do not span one.

**Table 4.7** Parameter estimates test for color of bee traps and MCE

<b>Spatial Scale (m)</b>	<b>Term</b>	<b>Estimate</b>	<b>Std Error</b>	<b>Chi-Square</b>	<b>Prob&gt;Chisq</b>	<b>Lower CL</b>	<b>Upper CL</b>
<b>250</b>	Intercept	-0.9233	0.3208	8.7070	0.0032	-1.5627	-0.3049
	MCE	2.8772	0.4369	45.8067	< 0.0001	2.0283	3.7415
	Color	0.1111	0.0734	2.3057	0.1289	-0.0322	0.2557
<b>500</b>	Intercept	-1.4868	0.4437	12.0662	0.0005	-2.3742	-0.6346
	MCE	4.0928	0.7158	36.5506	< 0.0001	2.7158	5.5226
	Color	0.0810	0.0735	1.2218	0.2690	-0.0624	0.2257
<b>750</b>	Intercept	-1.2404	0.5170	6.0852	0.0136	-2.2765	-0.2492
	MCE	3.7282	0.8658	20.3080	< 0.0001	2.0652	5.4608
	Color	0.0716	0.0791	0.8245	0.3639	-0.0826	0.2274
<b>1000</b>	Intercept	-1.1529	0.5808	4.1358	0.0420	-2.3186	-0.0408
	MCE	3.5740	0.9885	14.2070	0.0002	1.6787	5.5557
	Color	0.0727	0.0813	0.8031	0.3702	-0.0859	0.2329

*Bee Abundance and Flowers (local variable) Results*

The presence of flowers was next added to the Poisson GLM. The whole model test results for presence of flowers and MCE suggest that these variables are significantly better predictors than only the intercepts (Table 4.8). The addition of this local site variable improves the chi-square results, meaning there is evidence that this is a better model than MCE alone.

**Table 4.8** Whole model test results on presence of flowers and MCE

<b>Spatial Scale (m)</b>	<b>Model</b>	<b>Log-Likelihood</b>	<b>Chi-Square</b>	<b>DF</b>	<b>Prob&gt;Chisq</b>
<b>250</b>	Difference	49.7351	99.4703	2	< 0.0001
	Full	379.8505			
	Reduced	429.5857			
<b>500</b>	Difference	43.8594	87.7188	2	< 0.0001
	Full	353.1977			
	Reduced	397.0571			
<b>750</b>	Difference	34.3628	68.7256	2	< 0.0001
	Full	311.8185			
	Reduced	346.1813			
<b>1000</b>	Difference	30.9076	61.8153	2	< 0.0001
	Full	297.2556			
	Reduced	328.1633			

The goodness of fit test on presence of flowers and MCE provided further evidence that flowers were an important variable in the model (Table 4.9), as noted by the change in deviance. A larger change in deviance means the new variable had a greater impact on the model. All other chi-square results were significant and the overdispersion parameter went down, also suggesting a better fit.

**Table 4.9** Goodness of fit test results on presence of flowers and MCE

<b>Spatial Scale (m)</b>	<b>Goodness Of Fit Statistic</b>	<b>Chi-Square</b>	<b>DF</b>	<b>Prob&gt;Chisq</b>	<b>Overdispersion</b>
<b>250</b>	Pearson	25.5825	78	1.0000	0.3280
	Deviance	25.8119	78	1.0000	
<b>500</b>	Pearson	27.6783	78	1.0000	0.3549
	Deviance	27.3092	78	1.0000	
<b>750</b>	Pearson	31.7460	78	1.0000	0.4070
	Deviance	30.4650	78	1.0000	
<b>1000</b>	Pearson	33.4891	78	1.0000	0.4293
	Deviance	31.8961	78	1.0000	

The effects test also indicates that the presence of flowers was a significant regressor in the model (Table 4.10). Chi-square results are more significant for flower presence across all scales with the 250 m scale still yielding the most significant results. In addition, at that scale, local and landscape variables have an almost equal effects test result. MCE effects also diminish as scale increases.

**Table 4.10** Effects test results on presence of flowers and MCE

<b>Spatial Scale (m)</b>	<b>Source</b>	<b>DF</b>	<b>Chi-Square</b>	<b>Prob&gt;Chisq</b>
<b>250</b>	MCE	1	37.3108	< 0.0001
	Flower	1	36.3156	< 0.0001
<b>500</b>	MCE	1	30.2661	< 0.0001
	Flower	1	36.3545	< 0.0001
<b>750</b>	MCE	1	18.6344	< 0.0001
	Flower	1	39.2019	< 0.0001
<b>1000</b>	MCE	1	14.3312	0.0002
	Flower	1	40.7992	< 0.0001

The results from the parameter estimates test further prove that the MCE and Flower GLM are significant (Table 4.11). The std. error and chi-square all indicate significance of the model. In addition, the confidence limits are positive and have ranges more appropriate for the data. The 250 m scale again had the most significant results.

**Table 4.11** Parameter estimates test on presence of flowers

<b>Spatial Scale(m)</b>	<b>Term</b>	<b>Estimate</b>	<b>Std Error</b>	<b>Chi- Square</b>	<b>Prob&gt;Chisq</b>	<b>Lower CL</b>	<b>Upper CL</b>
<b>250</b>	Intercept	-0.8344	0.2266	14.3028	0.0002	-1.2850	-0.3964
	MCE	2.2593	0.3771	37.3108	< 0.0001	1.5251	3.0037
	Flower	0.6428	0.1140	36.3156	< 0.0001	0.4245	0.8719
<b>500</b>	Intercept	-1.3327	0.3401	16.6089	< 0.0001	-2.0123	-0.6787
	MCE	3.1887	0.6043	30.2661	< 0.0001	2.0223	4.3921
	Flower	0.6655	0.1182	36.3545	< 0.0001	0.4392	0.9033
<b>750</b>	Intercept	-1.2347	0.4000	10.1653	0.0014	-2.0346	-0.4662
	MCE	2.9607	0.7114	18.6344	< 0.0001	1.5898	4.3795
	Flower	0.7242	0.1252	39.2019	< 0.0001	0.4854	0.9767
<b>1000</b>	Intercept	-1.2378	0.4517	7.9770	0.0047	-2.1422	-0.3709
	MCE	2.9339	0.8025	14.3312	0.0002	1.3895	4.5365
	Flower	0.7512	0.1279	40.7992	< 0.0001	0.5075	1.0095



*Bee Diversity and MCE (landscape variable) Results*

The same statistical tests were conducted on the number of bee species caught in the traps. The results from the whole model test on MCE indicate that landscape variables can predict bee diversity significantly better than no variables (Table 4.12). The chi-square results are not as strong as the model for bee abundance, but 250 m MCE still has the most significant results, suggesting that the 250 m scale yields the most significant results as indicated by the chi-square and p value.

**Table 4.12** Whole model test results on MCE (landscape variables)

<b>Spatial Scale (m)</b>	<b>Model</b>	<b>Log-Likelihood</b>	<b>Chi-Square</b>	<b>DF</b>	<b>Prob&gt;Chisq</b>
<b>250</b>	Difference	8.9096	17.8192	1	< 0.0001
	Full	191.3259			
	Reduced	200.2355			
<b>500</b>	Difference	5.9679	11.9357	1	0.0006
	Full	185.6652			
	Reduced	191.6330			
<b>750</b>	Difference	2.8760	5.7520	1	0.0165
	Full	177.7308			
	Reduced	180.6068			
<b>1000</b>	Difference	2.0609309	4.1218618	1	0.0423
	Full	175.93154			
	Reduced	177.992471			

The goodness of fit test results also show that this model fits and that it has the appropriate form (Table 4.13), indicated by chi-square results. However, the evidence to support this is not as strong as in the bee abundance MCE GLM model, indicated by higher chi-square results and greater overdispersion.

**Table 4.13** Goodness of fit tests results on MCE

Spatial Scale (m)	Goodness Of Fit Statistic	Chi-Square	DF	Prob>Chisq	Overdispersion
250	Pearson	50.0564	79	0.9955	0.6336
	Deviance	59.4573	79	0.9506	
500	Pearson	52.3035	79	0.9911	0.6621
	Deviance	62.8457	79	0.9084	
750	Pearson	55.4967	79	0.9794	0.7025
	Deviance	66.7073	79	0.8365	
1000	Pearson	56.3118	79	0.9749	0.7128
	Deviance	67.8099	79	0.8112	

The parameter estimates test results begin to show the major differences between the models on abundance and diversity. The standard errors are higher in Table 4.14 and the chi-square results have a lower significance level than the results from Table 4.3. In addition, the 1000 MCE score has confidence limits that are negative, indicating a poor model. The evidence in Table 4.14, suggests 250 m is the best scale variable for predicting bee diversity.

**Table 4.14** Parameter estimates results on MCE and bee diversity

Spatial Scale (m)	Term	Estimate	Std Error	Chi-Square	Prob>Chisq	Lower CL	Upper CL
250	Intercept	-0.8281	0.3634	5.4730	0.0193	-1.5568	-0.1314
	MCE	2.5033	0.6065	17.8192	< 0.0001	1.3278	3.7070
500	Intercept	-1.1510	0.5440	4.8119	0.0283	-2.2529	-0.1187
	MCE	3.1624	0.9555	11.9357	< 0.0001	1.3355	5.0839
750	Intercept	-0.7891	0.6109	1.7430	0.1867	-2.0267	0.3702
	MCE	2.5393	1.0915	5.7519	0.0164	0.4528	4.7357
1000	Intercept	-0.7103	0.6767	1.1426	0.2850	-2.0825	0.5727
	MCE	2.3995	1.2148	4.1218	0.0423	0.0809	4.8474

Further statistical analysis to determine if the local site variable, color, was a significant predictor was done by adding it to the Poisson GLM for the bee diversity response variable. The whole model test results in Table 4.15 on the color of bee traps

and MCE for bee diversity produce similar results as the MCE and color GLM for bee abundance. This finding indicates that color has little effect on bee diversity, as it did for bee abundance.

**Table 4.15** Whole model test results on color of bee traps and MCE

<b>Spatial Scale (m)</b>	<b>Model</b>	<b>Log-Likelihood</b>	<b>Chi-Square</b>	<b>DF</b>	<b>Prob&gt;Chisq</b>
<b>250</b>	Difference	8.7968	17.5935	2	0.0002
	Full	188.9026			
	Reduced	197.6994			
<b>500</b>	Difference	5.9062	11.8125	2	0.0027
	Full	183.1245			
	Reduced	189.0307			
<b>750</b>	Difference	2.8668	5.7335	2	0.0569
	Full	175.2888			
	Reduced	178.1556			
<b>1000</b>	Difference	2.0578	4.1157	2	0.1277
	Full	173.4789			
	Reduced	175.5367			

The goodness of fit test results in Table 4.16 further indicate that color is of little impact as a predictor of bee diversity because a very small change in deviance was observed. In addition, the other estimates from the test are similar to the MCE GLM suggesting the models have a similar predictive power.

**4.16** Goodness of fit result on color of bee traps and MCE

<b>Spatial Scale (m)</b>	<b>Goodness Of Fit Statistic</b>	<b>Chi-Square</b>	<b>DF</b>	<b>Prob&gt;Chisq</b>	<b>Overdispersion</b>
<b>250</b>	Pearson	50.0568	78	0.9942	0.6418
	Deviance	59.4573	78	0.9415	
<b>500</b>	Pearson	52.3524	78	0.9887	0.6712
	Deviance	62.8197	78	0.8944	
<b>750</b>	Pearson	55.5481	78	0.9745	0.7122
	Deviance	66.6649	78	0.8164	
<b>1000</b>	Pearson	56.3768	78	0.9692	0.7228
	Deviance	67.7733	78	0.7892	

The effects test results in table 4.17 further prove that the color of the bee trap is not significant. The 250 m scale has the most significant result again, indicated by the highest chi-square and lowest p value. In addition, the effects of the MCE score diminish as scale increases.

**Table 4.17** Effects test results on color of bee traps and MCE

Spatial Scale (m)	Source	DF	Chi-Square	Prob>Chisq
<b>250</b>	MCE	1	17.5464	< 0.0001
	Color	1	0.0000	0.9987
<b>500</b>	MCE	1	11.7674	0.0006
	Color	1	0.0388	0.8438
<b>750</b>	MCE	1	5.6911	0.0171
	Color	1	0.0596	0.8071
<b>1000</b>	MCE	1	4.0738	0.0436
	Color	1	0.0507	0.8219

The parameter estimates test results on bee diversity outlined in Table 4.18 gives more evidence that color is insignificant. There are negative estimates, insignificant chi-square results and confidence limits that span zero.

**Table 4.18** Parameter estimates result on color of bee traps and MCE

Spatial Scale (m)	Term	Estimate	Std Error	Chi-Square	Prob>Chisq	Lower CL	Upper CL
<b>250</b>	Intercept	-0.8277	0.4391	3.7184	0.0538	-1.7087	0.0133
	MCE	2.5033	0.6113	17.5464	< 0.0001	1.3187	3.7165
	Color	-0.0002	0.1023	0.0000	0.9987	-0.1997	0.2015
<b>500</b>	Intercept	-1.1068	0.5916	3.7005	0.0544	-2.2998	0.0203
	MCE	3.1614	0.9621	11.7674	0.0006	1.3223	5.0967
	Color	-0.0199	0.1011	0.0388	0.8438	-0.2172	0.1794
<b>750</b>	Intercept	-0.7363	0.6517	1.3201	0.2506	-2.0514	0.5051
	MCE	2.5440	1.0996	5.6911	0.0171	0.4428	4.7572
	Color	-0.0253	0.1034	0.0596	0.8071	-0.2270	0.1786
<b>1000</b>	Intercept	-0.6611	0.7156	0.8779	0.3488	-2.1061	0.7011
	MCE	2.4031	1.2239	4.0738	0.0436	0.0677	4.8699
	Color	-0.0233	0.1035	0.0507	0.8219	-0.2253	0.1809

The last set of results comes from a Poisson GLM on the presence of flowers and MCE for bee diversity. The whole model test results for this GLM show the most significant results for the bee diversity GLMs (Table 4.19), this was also the case with the GLMs for bee abundance, suggesting that the addition of the flowers variable improves the model. The 250 m MCE has the most significant chi-square results.

**Table 4.19** Whole model test on presence of flowers and MCE

<b>Spatial Scale (m)</b>	<b>Model</b>	<b>Log-Likelihood</b>	<b>Chi-Square</b>	<b>DF</b>	<b>Prob&gt;Chisq</b>
<b>250</b>	Difference	30.2582	60.5165	2	< 0.0001
	Full	233.2831			
	Reduced	263.5413			
<b>500</b>	Difference	27.4735	54.9469	2	< 0.0001
	Full	227.6904			
	Reduced	255.1639			
<b>750</b>	Difference	25.1213	50.2426	2	< 0.0001
	Full	220.5524			
	Reduced	245.6737			
<b>1000</b>	Difference	24.7290	49.4579	2	< 0.0001
	Full	219.0336			
	Reduced	243.7626			

The goodness of fit test results (Table 4.20), indicate this model fits well and is of the right form. The addition of the presence of flowers produces better, more significant chi-square results and it lowered overdispersion. In addition, presence of flowers lowered the deviance more than the color of traps indicating that the presence of flowers is more important than the color of traps.

**Table 4.20** Goodness of fit test results on presence of flowers and MCE

<b>Spatial Scale (m)</b>	<b>Goodness Of Fit Statistic</b>	<b>Chi-Square</b>	<b>DF</b>	<b>Prob&gt;Chisq</b>	<b>Overdispersion</b>
<b>250</b>	Pearson	37.5509	78	1.0000	0.4814
	Deviance	41.6141	78	0.9998	
<b>500</b>	Pearson	38.7837	78	0.9999	0.4972
	Deviance	43.4269	78	0.9995	
<b>750</b>	Pearson	40.2819	78	0.9999	0.5164
	Deviance	44.8010	78	0.9991	
<b>1000</b>	Pearson	40.5977	78	0.9999	0.5205
	Deviance	45.0060	78	0.9990	

The effects test result (Table 4.21) shows that the presence of flowers indeed has a significant effect on the model. In fact, the chi-square results are more significant in this case than with the bee abundance GLM and the values here improve when MCE distance increases. Conversely, the MCE chi-square results go down as distance increases suggesting an inverse relationship.

**Table 4.21** Effects test results on presence of flowers and MCE

<b>Spatial Scale (m)</b>	<b>Source</b>	<b>DF</b>	<b>Chi-Square</b>	<b>Prob&gt;Chisq</b>
<b>250</b>	MCE	1	9.8597	0.0017
	Flower	1	37.0636	< 0.0001
<b>500</b>	MCE	1	5.9004	0.0151
	Flower	1	39.0542	< 0.0001
<b>750</b>	MCE	1	3.0203	0.0822
	Flower	1	42.4183	< 0.0001
<b>1000</b>	MCE	1	2.6029	0.1067
	Flower	1	43.8130	< 0.0001

The final statistical test, the parameters estimates test (Table 4.22), supports all of the above results on bee diversity. Landscape variables (land cover, topography and soils) included in this model and the presence of flowers can predict bee diversity as

indicated by the chi-square results, standard errors and confidence limits. The 250 m scale of analysis was still the most significant.

**Table 4.22** Parameter estimates results on presence of flowers and MCE

<b>Spatial Scale (m)</b>	<b>Term</b>	<b>Estimate</b>	<b>Std Error</b>	<b>Chi-Square</b>	<b>Prob&gt;Chisq</b>	<b>Lower CL</b>	<b>Upper CL</b>
<b>250</b>	Intercept	-1.1894	0.3354	13.6089	0.0002	1.8614	-0.5459
	MCE	1.6832	0.5434	9.8597	0.0017	0.6275	2.7588
	Flower	1.0134	0.1873	37.0636	< 0.0001	0.6614	1.3981
<b>500</b>	Intercept	-1.3373	0.4688	8.7884	0.0030	2.2803	-0.4417
	MCE	1.9519	0.8230	5.9004	0.0151	0.3699	3.5985
	Flower	1.0481	0.1897	39.0542	< 0.0001	0.6919	1.4381
<b>750</b>	Intercept	-1.1473	0.5208	5.1460	0.0233	2.1950	-0.1521
	MCE	1.5639	0.9167	3.0203	0.0822	0.1958	3.4003
	Flower	1.0914	0.1916	42.4183	< 0.0001	0.7325	1.4861
<b>1000</b>	Intercept	-1.1805	0.5761	4.4442	0.0350	2.3405	-0.0808
	MCE	1.6064	1.0145	2.6029	0.1067	0.3375	3.6421
	Flower	1.1048	0.1916	43.8130	< 0.0001	0.7461	1.5000

## 4.2: Discussion

The results of the analysis on the GIS model and the multiple Poisson GLMs show that landscape composition significantly influences bee abundance and diversity. In addition, the results showed that the presence of flowers within a 15 m radius of the bee traps positively influenced bee abundance and diversity. Another finding was that the color of the bee traps had no influence on bee abundance and diversity. Lastly, the scale at which the landscape variables had the most significant effect on bee abundance and diversity was 250 m.

To help understand these findings and their implications, I discuss the results of the GIS model and statistical analysis reviewing the landscape variables (GIS MCE score) impact on bee abundance, bee diversity and the impacts of adding local site variables (Flowers and Color) to the GLM. My discussion focuses on the best fitting GLM (MCE and Flowers, Table 4.8). The applicability of using GIS for bee habitat modeling is also discussed, along with the effects of scale and biogeographic implications.

Dauber et al. (2003), Steffan-Dewenter et al. (2002), and Kremen et al. 2004 all concluded that landscape composition heavily influences bee populations, which supports the findings from this study that landscape composition has a significant impact on bee abundance and diversity. The previous studies focused on using simple indicators of landscape composition, such as proportion of semi-natural habitats, soils type or aspect. This study, however, combined these indicators to build an index that allowed for many different landscape variables to contribute to a habitat model. This technique allowed for tradeoff between the variables, which meant that land cover, soils and aspect all



contributed to the bee habitat GIS model. I chose this approach because most biological systems are complex and cannot be model through simple indicators; it proved to be a valid and appropriate method.

When the GIS model was analyzed there was a positive association with bee abundance and diversity, suggesting the landscape variables used for this study impact bees. The fact that the GIS model was significant proves there is value in using GIS to model bee habitat and populations. This is important for land management because it is now possible to model and analyze bee habitat on a landscape scale. Cane (2001) and Lebuhn et al. (in press) have expressed the need for a landscape scale analysis method for bee populations and this may be a solution that can facilitate the study and conservation of bees.

The findings on the importance of the landscape composition were not new, but the approach I used can now be replicated for many other areas and regions. By applying geographic theories and methods I was able to confirm the results of many previous works and I was also able to address conflicting research on the appropriate scale in which landscape composition was important. Scalar issues are a major research problem as noted by Schumm (1999), one for which geography could offer.

A review of the conflicting findings on spatial scale revealed that Kremen et al. (2004) found no relationship to exist between the landscape matrix and bee population dynamics under 600 m. Alternatively, Steffan-Dewenter et al. (2002) found the strongest correlation between native bee diversity and abundance to be at 250 m. Dauber et al. (2003) found similar results, noting important spatial scales to be at 50 m and 200 m for bees.

The results of this study suggest that the best scale for using landscape composition to model bee habitat was 250 m, supporting Steffan-Dewenter et al. (2002) results. This finding can be quickly identified from Table 4.1 because 250 MCE had the most significant chi-square result within its model, from Table 4.2, by the least deviance from the “perfect model” and from Table 4.3 because 250 MCE gives the most stable parameter estimates (smallest standard error).

Another interesting finding, important to biogeography and the debates over habitat fragmentation, was that the effects of landscape composition on bee abundance and diversity dropped as spatial scale increased. This means that bees respond to landscape composition on a small scale and that patches of 250 m size or a buffer of 250 m around farms could be adequate to preserve bees. This is opposite to many findings on habitat fragmentation that have found small patches to be detrimental to species abundance and diversity (Stefan-Dewenter & Tschamntke, 1999; Aizen & Feinsinger, 1994; Powell & Powell, 1987). However, the findings on habitat fragmentation are supported by Cane (2001).

The addition of the presence of the flowers variable and the color of the bee traps to the model was done to see if local site variables had an impact on bee abundance and diversity because Williams et al. (2001) suggested that there is large variability between bee populations on sites of a similar composition. To detect importance of these variables they were added to the model and I looked for a large change in the tests results. The addition of the color of bee traps had no impact on bee abundance and diversity at all scales. According to Lebuhn et al. (in press) the developers of the North American bee sampling protocol the color of bee traps is not supposed to effect the results of the

trapping. However, they advocated using colored cups to gather more data so that their finding could be confirmed. The results from my study further proved that color is of little importance in the trapping of bees.

Conversely, the addition of the presence of the flowers variable greatly improved the GLM model. This was expected because flowers are the primary food source for bees. If an area is void of flowering plants, then it is of little value for foraging, one critical component of bee habitat. Another interesting influence of the flowers variable on the model was that as scale increased, so did the importance of flowers for bee diversity and abundance. This means that large areas of flowering plants are more beneficial to bees than small patches of flowers. With this in mind, it would seem that agricultural land has a benefit to bees from a food standpoint. The differences in significance were also larger for the bee diversity GLM, meaning the larger the area of flowering plants, the greater the bee diversity. The combined findings on flowers were opposite of what I had expected; I thought flower presence would affect bee populations at a localized scale.

The findings in this study suggest that bees require a large area of flowers or food and need a small area with a specific landscape composition, which could be advantageous to agriculture because the agricultural landscape is highly managed. By conserving patches or fringes of land for bees and providing floral resources, farmers may be able to increase bee abundance and diversity, which would help with pollination services. The idea of managing fringe agricultural land or patches was similar to Kremen et al. (2002), but they recommended management using a larger area. The bottom line is that the preservation of bees may be facilitated by conserving small areas for bees. Planting dense floral resources could also improve the bee populations and ecosystem functions.

The results of this study show that bee habitat can be modeled with the included landscape variables alone, but the importance and usability of the model drastically improved with the addition of local site variables, such as flowers. The presence of flowers is important to bees at a large scale and landscape composition important at a small scale. However, there are limitations on the use and interpretations of this analysis because of the Poisson tests used. Conducting analysis with data that is not normal requires using the non-parametric alternative tests, which are not as unified, robust and conclusive as parametric tests (Shaw and Wheeler, 1985). There are no meaningful *r*-square values or root mean square errors associated with a Poisson regression, so conclusions need to come from multiple tests (Agresti 1996). However, it was imperative that I used the appropriate statistical test for this study because using statistics that don't meet all the assumptions can lead to improper conclusion and invalid results.

The problems with non-normal data and modeling local site variables create a hurdle for the application of GIS to assessing bee habitat. It will be challenging to incorporate the presence of local flowers into a GIS, unless intensive field research is done. I am unaware of any remote sensing application that can detect flower presence; however it is possible if ground truth information revealed flowering plants this could be added to a GIS.

The problems associated with detecting flower presence should not discredit GIS modeling for bee habitat. The GIS model proved to have an important predictive power, identified by Table 4.1, but as indicated by the addition of flowers presence, there are more variables impacting the bee populations. At this time, it is also difficult to model

pesticide levels, natural disturbances, and very small scale variables that could affect bees.

The GIS model created in this project has several beneficial applications to the study of bees. The spatial characteristics of the model allowed for systematic sampling methods, which could be tailored to conduct bee trapping across larger landscapes. One could insure that they were sampling a broad range of habitat levels to get an accurate cross-section of the bee population. The structure of the model could also allow a user to conduct habitat change analysis by building this model with historical data as opposed to the 2005 data I used.

There are also applications for this model in agriculture and conservation. Land owners could assess their property and farms to determine how many bees they likely have. With further research bee population estimates could be made. Kremen et al. (2004) has already made substantial progress into calculating the area requirement needed for farms to ensure pollination. This model could possibly aid in that model refinement.

### 4.3: Conclusions

The objectives of this research were to identify and use spatial variables important to bee habitat to build a GIS model for bee populations and to evaluate the use of such a model. The results lead to my conclusions that landscape composition is a significant predictor of bee abundance and diversity. The landscape variables used were more significant and a better fitting model for bee abundance than for diversity. The 250 m scale model was the most significant. Cup color has no predictive power on bee abundance and diversity. The presence of flowers, on the other hand, is a significant predictor. The MCE score, the output from the GIS model and the flowers had similar test results for bee abundance and the addition of flowers greatly improve the overall model. Flower presence was more significant as scale increased and MCE score was less significant as scale increased.

GIS modeling has its application for bee research because it provides a landscape scale analysis method, can be used to model temporal change and can aid in systematic sampling. It is always difficult to model complex systems, but this model provides evidence that GIS can be suited to studying the habitat of these fascinating insects. Their conservation is imperative to the continuation of our planets fragile existence. The model and the associated methods have potential to be used in broad range of environments and across large landscape to assist scientists. I hope that it can aid in the understanding of one of Earth's most precious ecosystem resources.

#### **4.4: Future Research**

Although this model proved to be significant there are ways in which it could be improved. Logistical matters made field sampling challenging. With additional funding and time I would like to have sampled every month of the bee season and to have take samples spanning several years. 2007 was also climatically difficult for bees because of a very late frost that could have killed some early risers and destroyed many flowers, potentially causing fluctuations in the bee populations.

An objective of this model was to determine if the current literature allowed for a model to be built. I was able to build a significant model, but if I were to do this research again, I would break up the variables up to see if this model could be improved and if regional differences exist. In addition, something as simple as forest type could be a significant factor, not just forest.

One final hurdle to overcome is finding places to sample. Further research is dependent on a large area to sample. This can be very difficult to find with increasing urbanization and could potential impact future work.

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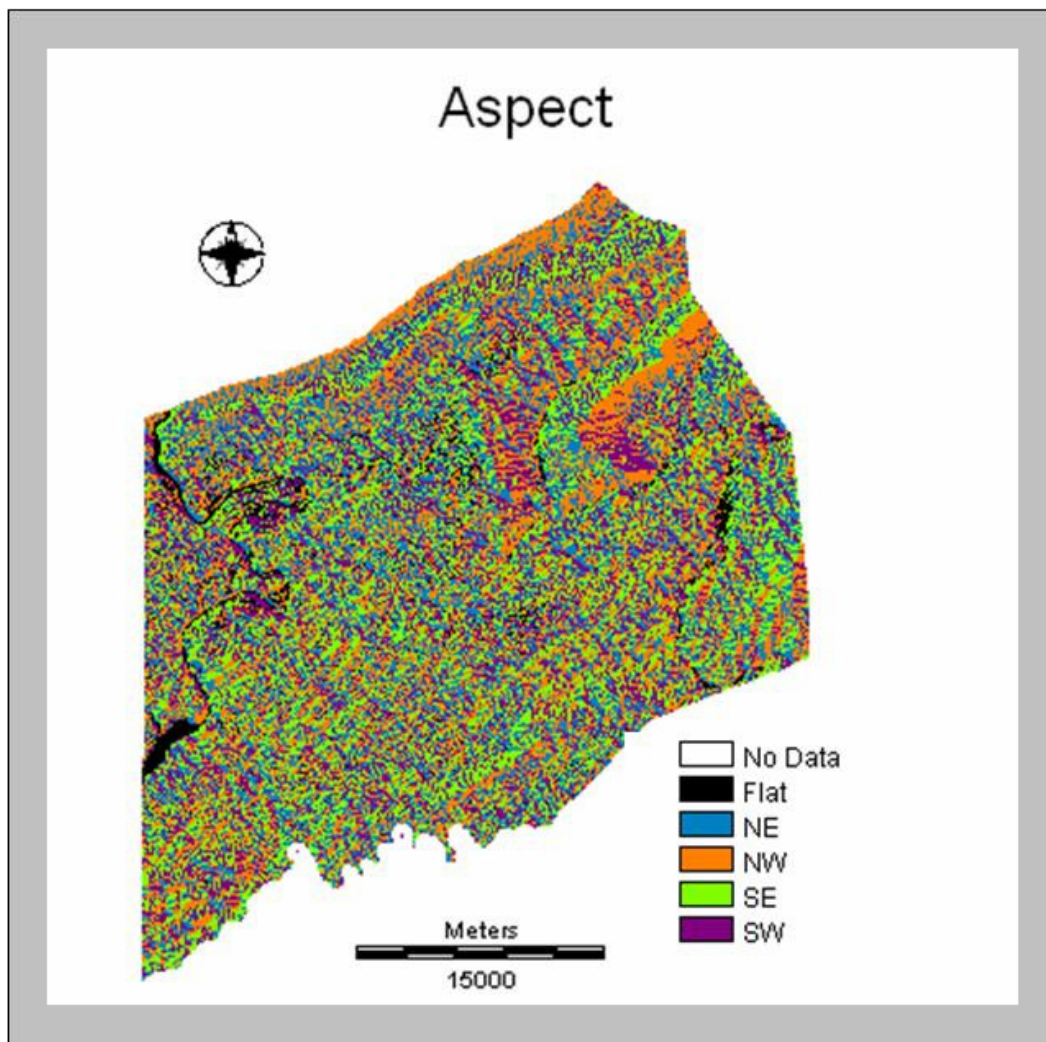
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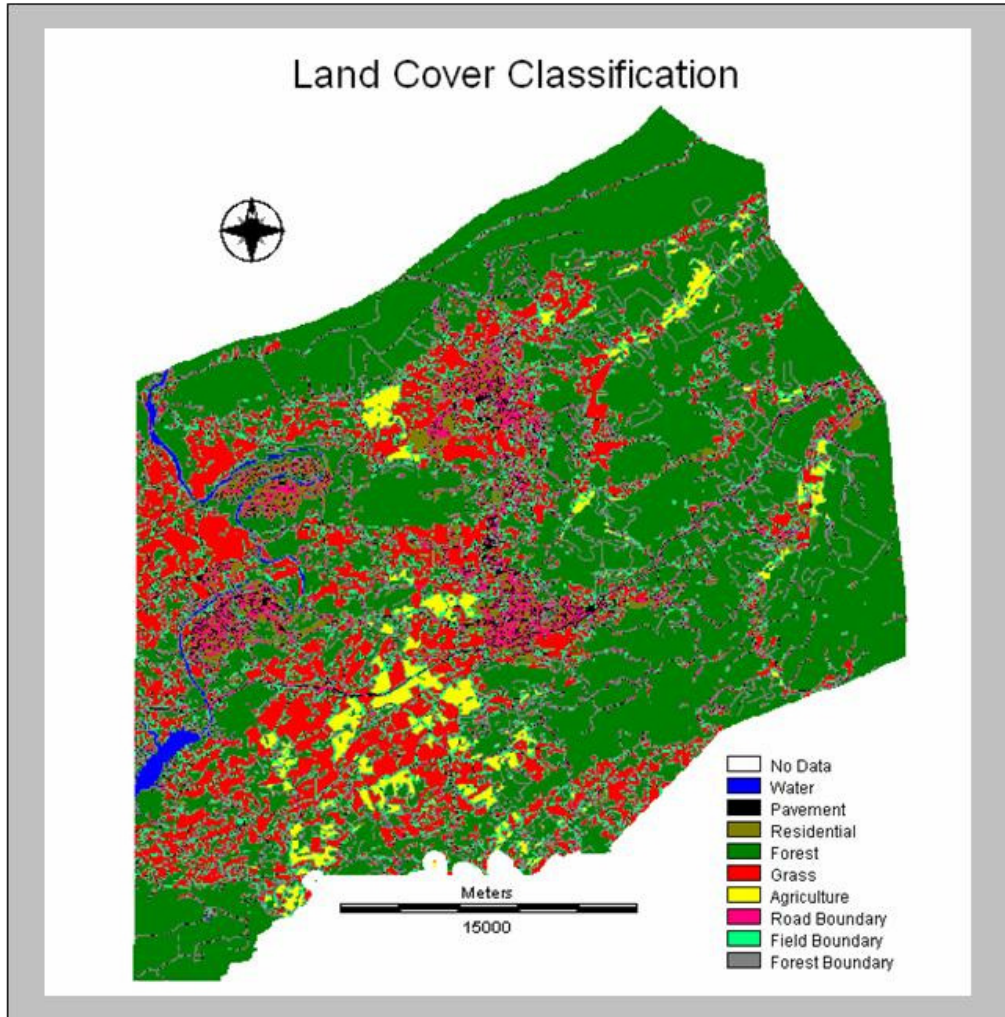
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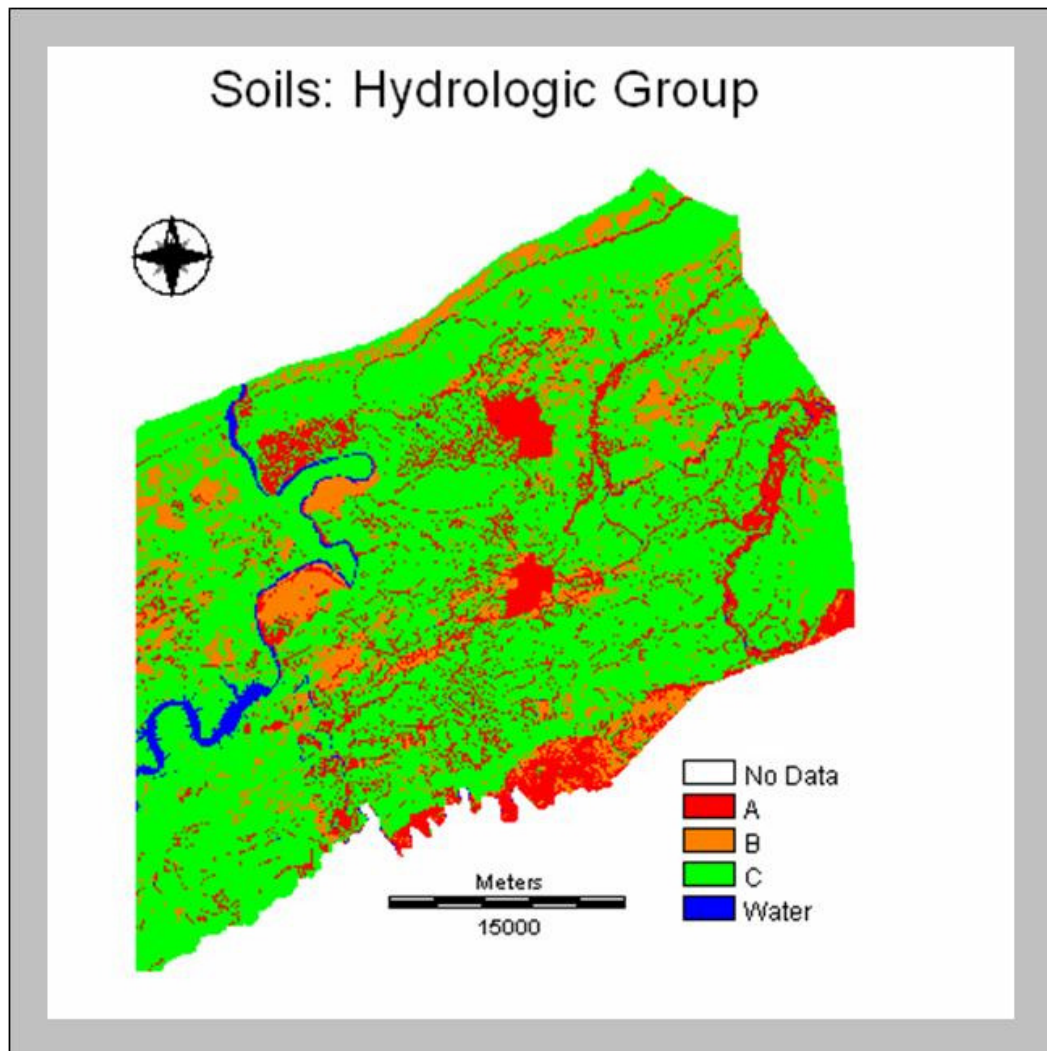
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### Appendix A







## Appendix B

250_MCE	500_MCE	750_MCE	1000_MCE	Flowers	Species Num	Color 2	Bee Abundance Group
0.3	0.331	0.392	0.422	n	1	b	1
0.45	0.502	0.548	0.557	y	2	w	2
0.55	0.553	0.558	0.57	y	1	y	2
0.445	0.501	0.538	0.555	n	0	y	1
0.314	0.342	0.41	0.436	n	1	w	1
0.378	0.369	0.371	0.405	y	3	y	1
0.365	0.401	0.398	0.419	y	2	y	2
0.408	0.471	0.46	0.484	y	1	b	2
0.428	0.46	0.464	0.486	y	2	y	2
0.383	0.479	0.514	0.517	n	0	w	1
0.522	0.511	0.525	0.525	y	2	y	4
0.585	0.542	0.542	0.54	y	3	b	3
0.611	0.569	0.56	0.542	y	2	y	2
0.677	0.615	0.587	0.565	y	1	y	4
0.463	0.449	0.461	0.494	y	2	b	2
0.521	0.523	0.495	0.481	n	2	y	2
0.627	0.55	0.531	0.527	y	3	y	4
0.427	0.465	0.457	0.434	y	2	b	2
0.443	0.465	0.475	0.467	y	1	y	3
0.539	0.559	0.579	0.59	n	2	y	2
0.439	0.532	0.526	0.539	n	0	b	1
0.619	0.599	0.576	0.578	y	2	y	2
0.574	0.534	0.53	0.546	y	2	y	4
0.555	0.59	0.595	0.58	y	2	b	3
0.595	0.575	0.563	0.581	y	2	b	2
0.445	0.563	0.606	0.606	n	0	b	1
0.573	0.561	0.556	0.557	y	3	b	4
0.462	0.559	0.568	0.583	y	1	w	3
0.663	0.59	0.554	0.552	y	5	y	6
0.525	0.57	0.562	0.572	y	3	w	3
0.681	0.648	0.603	0.586	y	3	y	5
0.69	0.636	0.627	0.618	y	1	b	6
0.58	0.575	0.562	0.56	n	1	y	2
0.509	0.537	0.554	0.558	n	1	b	1
0.695	0.577	0.603	0.594	n	1	y	1
0.682	0.615	0.611	0.592	y	1	y	3
0.585	0.561	0.538	0.531	y	1	y	2
0.682	0.601	0.563	0.564	y	3	y	5
0.618	0.573	0.574	0.576	n	0	y	2
0.687	0.632	0.588	0.572	y	3	b	6
0.46	0.52	0.548	0.569	n	0	b	1
0.577	0.578	0.566	0.563	n	2	y	2
0.464	0.509	0.505	0.52	n	1	y	1
0.627	0.549	0.517	0.524	n	0	b	3
0.715	0.598	0.582	0.554	y	3	y	2



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0.671	0.628	0.594	0.577	y	3	b	6
0.661	0.636	0.585	0.577	y	4	w	4
0.553	0.6	0.582	0.588	y	3	w	2
0.565	0.601	0.575	0.581	y	1	w	2
0.518	0.545	0.572	0.564	y	4	y	4
0.572	0.554	0.589	0.601	y	3	y	4
0.678	0.663	0.649	0.617	y	1	y	5
0.665	0.647	0.631	0.611	y	5	b	4
0.383	0.445	0.434	0.418	y	1	b	2
0.654	0.636	0.63	0.626	y	2	b	3
0.621	0.652	0.622	0.609	y	2	b	2
0.662	0.605	0.615	0.613	y	2	w	2
0.795	0.644	0.613	0.592	y	3	y	4
0.445	0.511	0.528	0.53	y	1	b	2
0.676	0.615	0.583	0.565	n	1	y	1
0.735	0.615	0.587	0.572	y	3	y	5
0.442	0.522	0.574	0.601	n	0	b	1
0.608	0.601	0.576	0.561	n	1	w	1
0.68	0.631	0.603	0.603	y	4	b	4
0.628	0.602	0.613	0.618	y	2	y	4
0.395	0.367	0.4	0.441	n	0	y	1
0.419	0.394	0.387	0.394	n	1	w	1
0.399	0.388	0.383	0.377	y	1	y	2
0.434	0.427	0.45	0.475	y	1	b	2
0.653	0.611	0.602	0.599	y	2	y	3
0.736	0.643	0.638	0.643	y	3	y	2
0.68	0.629	0.661	0.645	y	1	y	2
0.387	0.408	0.404	0.398	y	1	b	1
0.542	0.488	0.466	0.49	y	2	w	2
0.696	0.603	0.577	0.558	y	2	y	3
0.453	0.51	0.55	0.578	y	3	b	4
0.69	0.601	0.575	0.572	n	1	y	3
0.611	0.569	0.56	0.542	y	2	y	2
0.585	0.542	0.542	0.54	y	3	b	3
0.555	0.59	0.595	0.58	y	2	b	3
0.657	0.593	0.567	0.554	y	4	y	6

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## Vita

Andrew Scott Foy

Andrew was born in Tacoma, Washington in 1983. He spent a few years there and then his family moved to Massachusetts and finally to Virginia. Much of his interests in science developed while in rural Virginia, with ample room to explore as a kid. After high school, Radford University and then Virginia Tech were his other homes where he studied a variety of disciplines, eventually finding geography. The excellent faculty and resources provided focus and allowed many internship opportunities to arise. The hands-on work coupled with the two university educations was instrumental in his academic development. He has traveled, studied and worked both locally and abroad, for example Dinosaur National Monument and the Galapagos Islands. His broad academic interests focus on using GIS to solve every day, real world problems. Other passions are green development and alternative fuels, but everything biological and new technologies are always interesting. He plans to continue his education by beginning the PhD program in Geospatial and Environmental Analysis at Virginia Tech.