CAN PESTICIDE USE BE REDUCED BY MANAGING LANDSCAPE COMPLEXITY?

by

ERIN FROETSCHEL JAY

(Under the Direction of Elizabeth Kramer)

ABSTRACT

Pesticide use reduces crop losses but can result in significant negative externalities. To reduce pesticide use, farmers might take advantage of ecosystem services like pest suppression provided by agricultural landscape complexity. I hypothesize that temporal and spatial landscape complexity will reduce pest pressure, lowering pesticide application rates. I develop measures of landscape complexity using primary productivity calculated from remotely sensed data to detect patterns of vegetation diversity from 2008 - 2012. I incorporate this information and important covariates in an econometric model describing pesticide use in Midwestern and Southeastern United States. Results indicate that landscape pattern metrics reflecting composition, configuration, and connectivity influence application rates at various points during the growing season. Inclusion of these metrics strengthens model function significantly, increasing adjusted R2 from 0.66 to 0.79. Additional information regarding landscape effects could improve farmers' ability to reduce risk by controlling harmful pests while reducing the need for pesticide application.

INDEX WORDS: Pesticide Use, Biological Control, Ecosystem Services, Sustainable Agriculture, Pest Suppression, Landscape Complexity

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DEDICATION

This work is dedicated to my Dad, Dr. Mark Froetschel. His support and inspiration for my academic ideas and career have greatly contributed to this work in particular, as well as all of my academic work.

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CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

Chemical pesticides are a ubiquitous and important element of modern agriculture. The United States Department of Agriculture (USDA) estimates that 877 million pounds of active ingredient was applied to US fields in 2007, costing about $7.9 billion (Pesticide Use and Markets, 2012). However, continued widespread use of chemicals for insect pest control is not cost-effective or sustainable for society as a whole. While chemical pest control is cost-effective for farmers in order to reduce immediate crop losses to pests, the costs to society and the environment are significant, and not taken into account by farmers in their decision making process. Concern is growing over broader environmental impacts like water contamination, risk to human health, and damages to native ecological systems (Sexton, Lei, & Zilberman, 2007; Soares & de Souza Porto, 2009). Additionally, pesticide use has spurred rising pest resistance, limiting our ability to use chemical controls. These harmful effects extend to the farmer – from health concerns to economic considerations involving increasing costs of pest control due to resistance and to decreases in economically important crop pollinator populations (Waterfield & Zilberman, 2012).

While technological advancements, including the introduction of genetically modified organisms and precision agriculture, have greatly reduced chemical pesticide applications, farmers are still operating with imperfect information and vast uncertainties concerning drivers of pest populations. Importantly, croplands exist within a landscape context which can have significant impacts on agricultural production. The area surrounding croplands influence production processes in a myriad of ways, including regulation of population dynamics for economically important species of insects such as pollinators, pests, and predatory insects.

Insect individuals and populations rely on habitat, food resources, protection, and mechanisms for dispersal which are provided by various characteristics of the landscape as these mobile organisms move and relocate in pursuit of food, protection, and reproduction (Vasseur, et al., 2013). Recent studies have examined the dynamics of agricultural landscapes, investigating the role of the landscape for pest insect and pest predator movement and population dynamics in terms of connectivity, diversity, and ecosystem service provision. Theoretically, landscapes which contain more semi-natural areas of habitat, such as minimally-disturbed riparian areas, forested land, and wetlands could provide more pest suppression by harboring predators of pests. Semi-natural habitat generally maintains a certain level of vegetation throughout the year – a stark contrast to the high disturbance characteristics of many agricultural fields which are transformed rapidly from tilled earth to full productivity and then stripped of vegetation during harvest. Landscapes containing greater amounts of natural or semi-natural vegetation are commonly referred to in the literature as being more complex, while landscapes consisting almost entirely of cropland have been described as simplified landscapes. These landscapes interact with pest insects and beneficial insects predating these pests, as mobile species move across the landscape utilizing resources provided by various assemblages of vegetation.

Numerous studies of landscape and vegetative complexity under different cropping systems at varying spatial scales show that certain types of diversity within landscapes can have a net positive effect on pest control (Chaplin-Kramer, O'Rourke, Blitzer, & Kremen, 2011; Veres, Petit, Conord, & Lavigne, 2012; Bianchi, Booij, & Tscharntke, 2006). Many of these studies find that field-level management practices incorporating semi-natural habitat such as incorporating hedgerows, proximity of fields to non-crop habitat, and natural borders around fields promotes diversity in species and enhances predator and beneficial insect abundance and diversity. This evidence supports the theory that the landscape surrounding agricultural production could be utilized to the benefit of the farmer in order to mitigate risk from pests and potentially reduce pesticide use. The interaction between landscape complexity and pest population dynamics must be better understood if farmers are to make optimal and sustainable pest control decisions, maintaining high yields and profits while reducing costs of pest control.

Recent meta-analyses and reviews consolidating the literature to date on this interaction between landscape complexity and pest suppression indicate that landscape complexity does have a measurable effect on predator insect populations, and theoretically therefore pest suppression (Chaplin-Kramer, O'Rourke, Blitzer, & Kremen, 2011; Shackelford, et al., 2013). These analyses find that beneficial insect populations are routinely bolstered by increased landscape complexity, but for pest insects the results are often mixed or inconclusive. Fewer studies have been conducted focusing on pests as opposed to beneficial insects, and even fewer have looked specifically at crop damage caused by pests as it relates to landscape dynamics (Chaplin-Kramer, O'Rourke, Blitzer, & Kremen, 2011). The relative lack of studies focusing on pest insects is likely contributing to the lack of consensus as to how landscape dynamics impact pest populations, however an additional concern is the lack of a consistent definition of landscape complexity. The most common measure of complexity is amount or percentage of non-cropped land in a defined area, a measure which ignores key elements of landscape diversity (Bianchi, Booij, & Tscharntke, 2006; Veres, Petit, Conord, & Lavigne, 2012; Chaplin-Kramer, O'Rourke, Blitzer, & Kremen, 2011; Shackelford, et al., 2013). Crop type, planting times, weed dynamics, and native vegetation management all lead to various habitat assemblages with implications for pest suppression. Furthermore, the spatial and temporal complexities of different agricultural systems are not easily comparable, limiting our ability to understand the landscape context of pest regulation more broadly.

Previous studies largely rely on land cover classification methods to inform their analyses of landscape complexity. Land cover classification involves categorizing the "biophysical cover of the Earth's surface" into a predetermined classification system in order to depict characteristics of the landscape. However, these classification maps can be biased and arbitrary due to the lack of a formal and flexible classification scheme (Di Gregorio & Jansen, 2005). Land cover classification maps are lacking important information on the true dynamics of agricultural landscapes because these systems are only capable of capturing the dominant vegetation type at a snapshot in time. In agricultural landscapes, a snapshot does not provide an adequate depiction of the actual resources that are available to organisms as time progresses and fields are cultivated, irrigated, and harvested in the typical disturbance regime of conventional agriculture. Therefore, these measures of dominant vegetation classes do not truly represent availability of habitat and food for insects at various critical stages in their life cycles.

Additionally, the dichotomous view of a landscape as crop or non-crop may not be a useful description for pest and predator insect species of interest. There is extensive heterogeneity across the agricultural landscape stemming from the variety of common agricultural practices available to farmers, the varieties of crops planted, the organization of crops across time and space, and the timing of plantings, crop rotations, and harvesting. This heterogeneity is driven by farmers' decisions made based on multiple factors including environmental conditions, crop uses and expected price outcomes, and logistical constraints.

Insects of economic importance utilize aspects of this landscape, moving from less suitable habitat to more suitable habitat. The frequent disturbances that routine in agricultural production alter this quality of habitat underlying insect movement, driving movement to and away from fields and field borders. Pests and predators are not confined to a certain crop or non-crop habitat type, instead these species are mobile and colonize patches as they become available, accessible, and suitable for the species needs. Insects colonize habitat patches based on various characteristics which could include factors such as plant type, plant height, density of vegetation, protection provided from predators, and nutritional value of plant matter to name a few (Schellhorn, Bianchi, & Hsu, 2014; Vasseur, et al., 2013). In order to capture the interaction of the landscape with pest and predator dynamics, this high disturbance character and temporal change integral to the agricultural system must be taken into account. High temporal frequency satellite data provides an alternative measure of habitat availability and landscape complexity which can outperform static measurements of landscape composition.

Vegetation is inherently important in the life cycle of economically important insect species; crop pests are herbivores, relying on plant productivity for food resources. Additionally, vegetation alters the environmental conditions in which pests and insect predators exist by providing shelter from predators and the elements and facilitating (or disrupting) movement and the finding of mates. Crops often provide ideal habitat, but this habitat is unstable over time, forcing insects to rely on other varieties of vegetation for life support in order to persist year-round (Schellhorn, Bianchi, & Hsu, 2014). This evidence indicates that measuring the actual amount of vegetation across the landscape could be more informative than differentiating by vegetation type or between crop and non-crop habitat. Primary productivity describes the lowest trophic, or energetic, level in an ecosystem – the original capture of energy from the sun in the form of photosynthesizing plant matter. Productivity measures derived from satellite data describe a gradient of vegetative density, capturing the resources actually available to insects spatially and temporally.

Pest suppressive capabilities of surrounding landscapes, such as habitat fostering predators of pests or alternative habitat other than crops which appeal to pests, could serve as a new tool for farmers to control pest damage, reducing their risk and maintaining high yields. Farmers already utilize an extensive toolset of high-tech and high-cost solutions to reduce pest damage. The advent and widespread adoption of genetically modified organisms (GMO's) has transformed the farmscape and significantly influenced pesticide applications (Fernandez-Cornejo & Wechsler, 2015). In the case of insecticides and insect control, engineered crops such as the widely used Bt crops significantly reduce the need for chemical insecticide applications. Adoption rates of these technologies have increased rapidly over the past decade, which has likely contributed to changing patterns of pesticide use, as well as altered pest population dynamics.

With additional information on the landscape drivers for pest suppression such as diversity of habitat throughout the landscape or the existence of more or less semi-natural habitat, farmers can utilize crop and non-crop resources to provide more sustainable pest control. This could result in fewer pesticide applications and reduced active ingredient entering the environment. This is essential for the sustainability of agricultural production because while pest control measures have direct costs, chemical pesticides are associated with many costs external to the market, not often accounted for by farmers making management decisions. These negative externalities impact native systems as well as agricultural systems. Water contamination poses risks to many species of native flora and fauna due to generalized toxins but even very specific pesticides damage native insect populations (Sexton, Lei, & Zilberman, 2007; Soares & de Souza Porto, 2009; Bunzel, Liess, & Kattwinkel, 2014). These include important pollinators and predators of pest insects which are extremely valuable to agriculture.

Additionally, widespread application of pesticides creates negative externalities impacting farm systems, farmers, and farmworkers. While pest control is necessary for a farm's economic viability and ability to reduce risk, there are powerful human health concerns for farmers regularly handling and applying chemical pesticides containing persistent carcinogens and toxins which can accumulate over time; while small amounts of pesticide may have negligible health effects, build-up of toxins can seriously compromise farmer health (Waterfield & Zilberman, 2012).

Pesticide contamination of water supply is a major concern for agricultural communities as pesticide residues last for decades in groundwater and aquifers (Bunzel, Liess, & Kattwinkel, 2014; Katz, Berndt, & Crandall, 2013). Reducing externalities of chemical pest control by eliminating some of the need for chemical pesticides will create more sustainable long-term environmental and economic conditions. Management can be tailored to foster ecosystem services provided by the landscape, while maintenance of a more diverse landscape enhances environmental quality by making better use of natural biological controls. The resulting reduction in chemical pesticides preserves valuable resources and ecosystem services.

Economically, reduction of chemical pesticide required to maintain predictable and profitable yields also reduces costs of inputs to the system. Pesticides are expensive inputs to the production process, and as insecticides become more targeted and precise the cost increases as well. Additionally, pest resistance has important economic implications for farmers: development of resistance to insecticides could result in significantly greater expenses due to the need to purchase additional or more powerful chemical pesticides, as well as potentially unavoidable damages to yields due to an uncontrollable pest outbreak (Waterfield & Zilberman, 2012). Landscape function could contribute to improving conditions on farms by reducing overall pest pressure and diversifying insect populations, thus diminishing development of resistance.

Incorporating landscape considerations into management decisions will encourage better stewardship of native systems. Collaboration with the landscape will result in the more effective use of resources, natural biological cycles and controls, and enhanced environmental quality while maintaining yields and reducing costs, thus sustaining economic viability.

1.2 Literature Review

A large body of research exists which examines, theoretically as well as empirically, the relationship between the surrounding landscape and pest suppression or presence of natural enemies of agricultural pests. However, many results are inconclusive or vary from study to study. Additionally, while the literature to date measures spatial landscape complexity and dynamics, there is very little attention to the temporal change and disturbance regime occurring within the agricultural landscape which significantly impacts the life cycle and population dynamics of agricultural pests.

The larger landscape surrounding an agricultural operation influences pest pressure by directly interacting with pest movement and resource availability or by interacting with the movement of and resource availability to pest predators (Veres, Petit, Conord, & Lavigne, 2012). Enhanced habitat for pest predators will support predator populations, which will in turn reduce pest pressure on agricultural fields, but there has been little indication that increased predator populations actually decreases pest pressure (Chaplin-Kramer, O'Rourke, Blitzer, & Kremen, 2011; Bianchi, Booij, & Tscharntke, 2006; Veres, Petit, Conord, & Lavigne, 2012).

Multiple studies have been conducted at field and landscape levels in order to determine the relationship between landscape complexity and pest pressure, density, or abundance. There are various methods and metrics employed to measure and quantify landscape complexity, many of which describe three important characteristics of the landscape: composition, configuration, and connectivity. Examples of methods for measuring these three landscape characteristics and their use in the literature on pest suppression are presented in Table 1. The majority of studies use a single measure of landscape composition such as amount or type of crop contained within the area of study.

Table 1: Landscape Characteristics Contributing to Landscape Complexity and Methods of Measurement

Landscape Characteristic	Description	Example Measures	Citations from the Literature
Composition	What types of landscape elements (i.e. patches or habitat types) exist in the landscape extent, and how much of the landscape is occupied by each different element	• Percent of area in crop • Percent of area in specific crop or habitat type • Diversity Indices (Measure of diversity of patch types based on proportion and abundance) • Evenness Indices (Measure of how evenly distributed a patch type is across the landscape) • Land cover classification	(Larsen, 2013); (Meehan, Werling, Landis, & Gratton, 2011); (Laterra, Orue, & Booman, 2012); (Concepciòn, et al., 2012); (Zhao, et al., 2013); (Costamagna, Venables, & Schellhorn, 2015)
Configuration	The spatial arrangement of landscape elements	• Field size • Number of patches • Patch shape	(Laterra, Orue, & Booman, 2012); (Concepciòn, et al., 2012)
Connectivity	Ease of movement across the landscape to and from similar landscape elements	• Edge length • Isolation of patches • Length of boundaries • Distance between patch centroids • Ratio of edge length to number of patches	(Concepciòn, et al., 2012); (Margosian, Garrett, Hutchinson, & With, 2009)

Several reviews and meta-analyses illuminate prevailing results from the numerous studies examining field and landscape level effects of complexity on pests and pest predators. In a 2006 review, Bianchi and colleagues found in 74% of studies that predator populations were higher in more complex landscapes. However, the relationship between pests and the landscape was less clear, with far fewer studies and only 45% of these reporting a relationship between landscape complexity and pest populations (Bianchi, Booij, & Tscharntke, 2006). A more recent review by Veres and colleagues reveals that in the majority of studies examined, the presence of semi-natural habitat both reduced pest abundance and increased predator abundance. However, when landscape complexity was measured by the amount of cropland in the landscape this suppressive effect is reduced (Veres, Petit, Conord, & Lavigne, 2012). Chaplin-Kramer et al (2011) performed a meta-analysis of 46 landscape studies examining this relationship. Their results demonstrate a strong positive response of predator populations to increased landscape complexity, but an insignificant response of pests themselves. The authors note that there were generally fewer studies directly examining the relationship between pests and landscape complexity, and the relationship between pest predator populations and pest populations is not well understood (Chaplin-Kramer, O'Rourke, Blitzer, & Kremen, 2011).

These reviews and meta-analyses indicate a significant and growing interest in the relationship between agricultural pests and landscape dynamics and lay the groundwork for understanding this relationship. It is clear from these studies that predators of agricultural pests appear to be responding to landscape-level patterns and habitat availability, however pest response is much less apparent, which seems counterintuitive since an increased abundance of predators should dampen pest populations. This unexpected result and the fact that there is less focus in general on pests in the literature implies that the relationship between pest insects and the landscape is not thoroughly understood and begs for more attention.

The studies described previously directly measure insect and predator presence; another method for addressing this question is to examine farmer response to pest pressure in the form of pesticide application. Two studies published in Proceedings of the National Academy of Sciences investigate the relationship between pesticide use and landscape simplification. Timothy Meehan and colleagues published their study in 2011 which used cross-sectional, county-level pesticide use data to show that according to the 2007 USDA Agriculture Census data, insecticide use was being driven by landscape simplification, defined as percent of the landscape in crop (Meehan, Werling, Landis, & Gratton, 2011). Ashley Larsen, however, replicated this study using panel data analysis (including USDA Ag Census data from 1987, 1992, 1997, 2002, and 2007), and demonstrates that insecticide use is not consistently related to landscape simplification (Larsen, 2013). The relationship Larsen finds is positive in some years, negative in some, and insignificant in others. One important weakness of both of these studies is the lack of attention to GMO adoption. Larsen's panel analysis takes place over a time period when GM adoption rates changed from 0% (before the technology existed) to over 70% (Fernandez-Cornejo & Wechsler, 2015). This is a key change which has occurred in agricultural production over the last decade which must be taken into account when considering farmer's responses to insect pests via pesticide use. Leaving this information out of the analysis could result in omitted variable bias, biasing any estimates relating pesticide use to landscape simplification.

As evidenced by these studies, the general trend among the literature to date is the use of percent crop or percent non-crop as the description of landscape complexity or landscape simplification. The majority of the studies in the 2011 meta-analysis by Chaplin-Kramer et al used this metric for describing landscape complexity. Similarly, Meehan and colleagues in 2011 and Larsen in 2013 simply used the inverse (proportion of county in cropland) as their variable of interest representing landscape simplification. This simplified measure of landscape composition may not account for the ecological patterns that are relevant to the movements and life cycles of agricultural pests. In the ecosystem services literature there are various landscape metrics, calculated using GIS technology, which quantify various aspects of the landscape, capturing the characteristics of connectivity and configuration in addition to composition, which could be more descriptive of ecosystem service provision such as biological pest control (Syrbe & Walz, 2012; Bennett, Radford, & Haslem , 2006; Laterra, Orue, & Booman, 2012).

This overly-simplified measure of landscape complexity could be contributing to the mixed results produced so far describing the effects of the landscape on pest suppression; however, an additional and even more important consideration lies in the temporal dynamics of the landscape. The agricultural landscape is characterized by frequent disturbance and changes dramatically and rapidly as fields are managed by farmers to transition from bare ground to full vegetation and subsequent harvest often multiple times per year (Watson, Luck, Spooner, & Watson, 2014; Bennett, Radford, & Haslem , 2006). These temporal changes in the landscape are interacting with and influencing insect and predator life cycles, movement, and resource availability at any given time. While pesticide use has additive effects as more is applied, and can therefore be aggregated to an annual measurement without issue, the impacts of the landscape are more likely to be cyclical or non-linear within the year indicating that more frequent observations are required to capture these dynamics. Watson et al (2014) argue for the need to include historical land use change in current ecological research, because changes over time set the stage for current ecosystems under study. For insect populations, however, the temporal dynamics of resource availability within the landscape are critical throughout the life cycle, providing functional habitat which insects must find and utilize in order to persist in this environment. In the highly managed disturbance systems of agricultural production, insects utilize the cropping system itself as well as non-crop borders and patches to survive the dramatic changes which occur in the cropping system (Schellhorn, Bianchi, & Hsu, 2014). Crops often provide bountiful resources for pests and pest predators, while field turnover forces insect population relocation to different areas in the landscape, therefore insect movement through the landscape is essential to survival (Vasseur, et al., 2013). There is also evidence that the timing of predation is just as important as landscape composition for pest suppression (Schellhorn, Bianchi, & Hsu, 2014). Predator populations build up in crop and non-crop habitats, but the functional connections providing access to pest populations may be critical in facilitating predator movement and timing of predator arrival for pest suppression.

Interest in utilizing landscape data of finer temporal resolution is growing in the field of landscape ecology in general (Watson, Luck, Spooner, & Watson, 2014). Eerens and colleagues (2014) present a software package developed to describe phenological changes (the changes associated with life cycles of plants or animals, such as timing of leaf-out, leaf drop, or dormancy) in a landscape based on a time series of remotely-sensed images (Eerens, et al., 2014). Additionally, techniques such as multivariate landscape trajectory analysis are being developed utilizing the toolsets available in landscape ecology. Landscape trajectory analysis is a technique for tracking change in a landscape over a period of time using fine temporal resolution satellite imagery in which relevant landscape metrics are calculated for each time period, then principal component analysis is employed to examine each time step in relation to all other time periods. This type of analysis can inform researchers as to the rates and patterns of change occurring within that landscape context (Cushman & McGarigal, 2007; Cushman & Wallin, 2000).

Crop species diversity in US agricultural landscapes is generally in decline (Aguilar, et al., 2015). It is important to assess the changes occurring across the agricultural landscape and understand the various ways landscapes provide services to agricultural production. With the changing composition of agricultural crops and especially decreasing crop diversity, it may become essential to carefully plan the spatial layout and timing of crop planting, harvesting, and rotations within the agricultural landscape in order to maximize the ecosystem services which can be provided. An improved understanding of the larger landscape impacts on services such as pest suppression will arm farmers with an additional tool for dealing with pest pressure and risk management.

1.3 Study Objectives

This analysis will contribute knowledge of habitat assemblages, from farm to landscape, capturing pest suppression. The overarching objective of this study is to utilize an increased and improved set of information on agricultural landscape characteristics, including high temporal resolution satellite imagery and GIS technologies, to further explore the relationship between landscape dynamics and pest pressure in agricultural systems. **I hypothesize that landscape complexity, measured by both temporal and spatial dimensions, will result in pest suppressive landscapes.** In order to test this hypothesis, I utilize insecticide applications as a proxy for pest pressure under the assumption that farmers limit insecticide use to actual pest sightings and outbreaks.

The purpose of this project is to understand linkages between spatial and temporal landscape composition, configuration, and connectivity dynamics and insect pest pressure on crops, and develop a methodology for quantifying this relationship that is applicable to a wide variety of systems for development of more sustainable agricultural practices.

Specific objectives include:

1) Identify space and time variation in landscape features that link with habitat functionality for pest suppression
2) Design a measure of landscape complexity that accounts for spatial and temporal changes in both native vegetation and agricultural systems
3) Test the relationship between different landscape configurations and pesticide use as a proxy for pest outbreak risk
4) Examine the economic implications for utilizing landscape complexity as a form of pest control

CHAPTER 2

METHODS

2.1 Study Design and Data

I have selected four EPA level III Ecoregions (Figure 1) to serve as the study area for this project: the western corn belt plains, central corn belt plains, and eastern corn belt plains regions as well as the southeastern plains region (US Environmental Protection Agency, 2003). The Midwestern corn belt regions were selected for comparability to previous literature including research by Meehan et al (2011) and Larsen (2013). For computational purposes of measuring landscape complexity, the large ecoregions were disaggregated to the state level resulting in 22 unique geographic areas. The southeastern region is included because of the increased complexity of the Southeastern agricultural landscape. Most studies have focused on highest-intensity production areas such as the Midwest; the production systems in the Southeast are likely to provide critical information about the interaction of landscape complexity with insect population dynamics and the provision of pest suppression. The landscape in the Midwest is relatively homogeneous (spatially, at least) with a large percentage of the landscape involved in very similar cropping patterns mostly consisting of corn, grains, and soy. The Southeastern landscape, however, is much more diverse spatially with much higher crop diversity than the Midwestern corn belt (Aguilar, et al., 2015).

The analysis is performed with data from a five year period, from 2008 through 2012. This specific time frame was selected for this analysis in order to reduce the potential effects that adoption of genetically modified (GM) organisms could be contributing to the results.

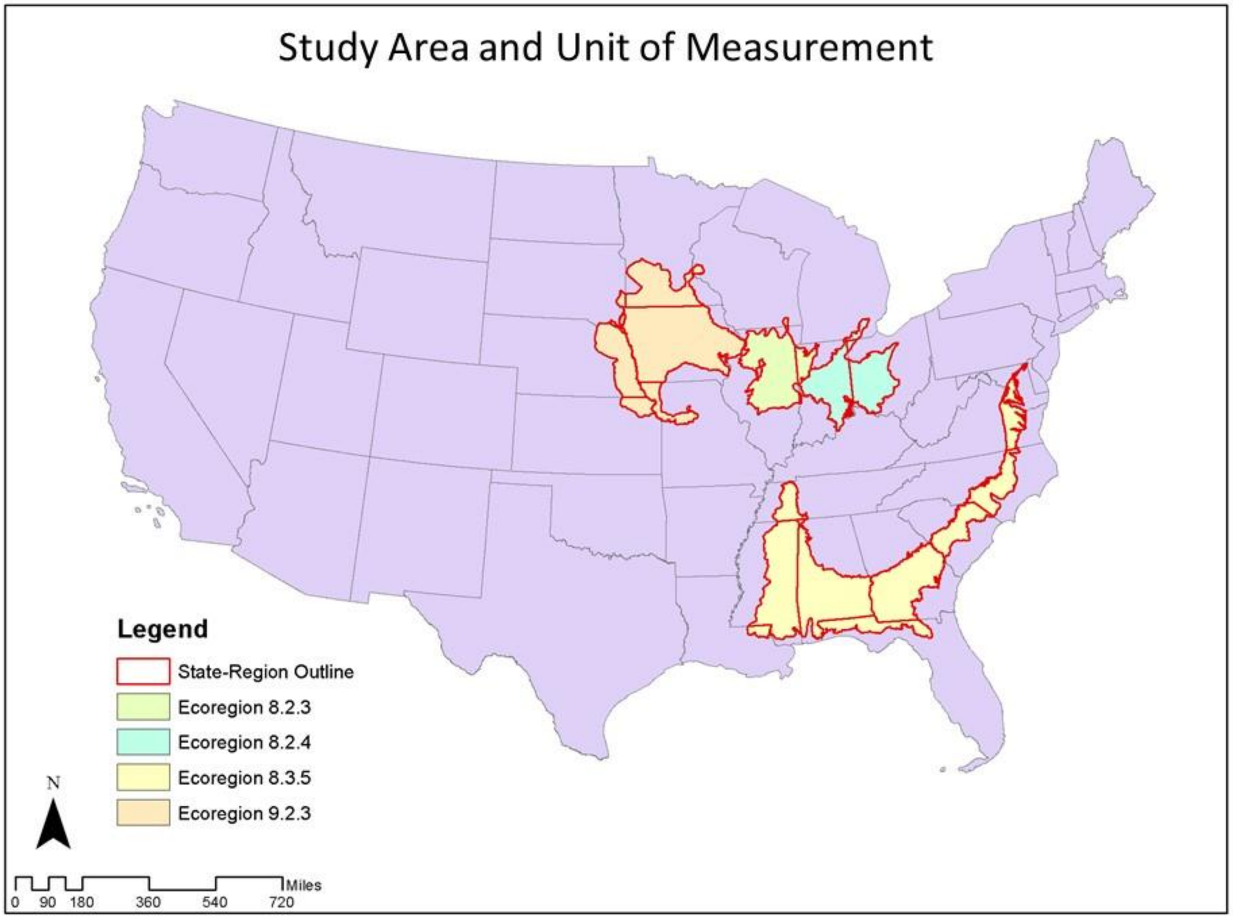

Figure 1: EPA Level III Ecoregions Included in Study Area

Data on GM adoption is limited, but national data provided by USDA (Figure 2) indicate that adoption rates for many GM crops slow dramatically after 2007 as the adoption rates approach full saturation (Fernandez-Cornejo & Wechsler, 2015). By restricting the study to this time period, I intend to mitigate at least some of the variation in our dependent variable which might be driven by GM adoption.

The dependent variable in our analysis is estimated pesticide application rate. This data is provided by United States Geological Survey (USGS) National Water Quality Assessment (NAWQA) Program through the E-Pest database (Baker & Stone, 2015). Annual, county-level estimated applications of multiple pesticide active ingredient compounds are calculated from proprietary surveys conducted within USDA Crop Reporting Regions and compiled by NAWQA. Since the surveys were conducted at the regional level, the disaggregated county-level estimates have a substantial amount of uncertainty, therefore the county-level estimates have been aggregated up to the regional level of the previously described 22 states within the ecoregions of interest. Additionally, the data on specific pesticide compounds was aggregated up to a more universal estimate of insecticide use per harvested hectare in order to capture the overall behavior of pesticide application. For exploration into individual insecticide compounds, refer to Appendix E.

The independent variable of interest is landscape complexity; in order to describe this complexity I explore spatial and temporal dynamics of vegetation density across the landscape using satellite imagery collected by the Moderate Resolution Imaging Spectroradiometer (MODIS), available from United States Geological Survey (USGS), which provides data at high temporal resolution (daily).

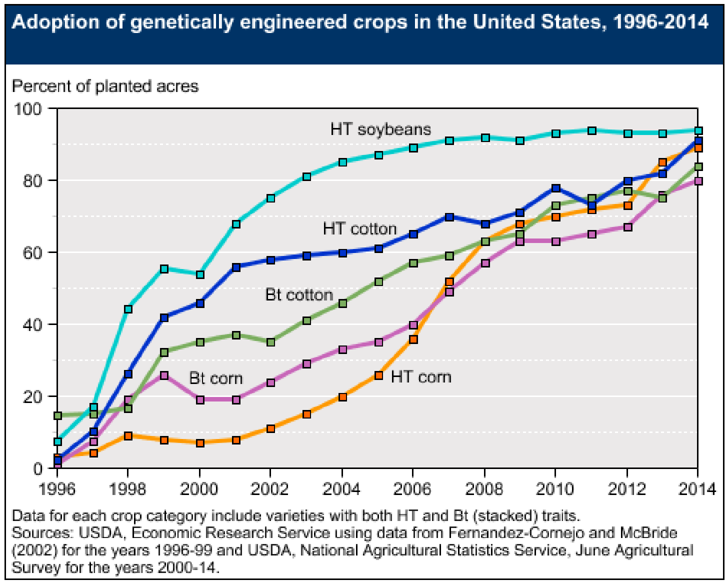

Figure 2: Adoption of Genetically Engineered Crops in the United States, 1996-2014

Important covariates were also included in the study in order to control for variation in the dependent variable not necessarily driven by landscape complexity. These covariates include cropping data, economic information, and weather data.

Cropping data were obtained from USDA's National Agricultural Statistics Survey (NASS) Cropscape database. I calculated hectares of total area, total cultivated area, and area cultivated with certain crop groups of interest from these data. In order to capture the economic factors involved in the farmer's decision to apply pesticide, I included prices of the key crops in our analysis. Additionally, to compare my model with previous studies, I tested the model with net farm income per harvested hectare as an additional covariate which would presumably impact a farmer's economic decisions. Finally, I included the Palmer Drought Severity Index provided by the National Oceanic and Atmospheric Administration (NOAA) for each region in order to account for weather anomalies.

2.2 Analysis of Landscape Complexity

In order to measure landscape complexity, I analyzed high frequency temporal satellite data for spatial patterns. I started with MODIS satellite imagery which provides daily images of large areas of land with each pixel representing an area 250 m^2. I utilize the Normalized Difference Vegetation Index (NDVI) 16-day composite product, provided by USGS from atmospherically corrected and cloud-free reflectance data. A vegetation index is a measure of primary productivity scaled from -1 to 1, with higher values representing higher amounts of productivity or vegetation. Because photosynthesizing plant matter reflects most of the light from the near infrared band of the visible light spectrum, while absorbing much of the red light, the values of these two bands which are detectable by satellite sensors can be exploited to obtain a measure of vegetative density; one such measure is the NDVI. The NDVI is the most commonly used vegetation index, taking advantage of the unique spectral absorption properties of photosynthesizing organisms in the red (R) and near infrared (NIR) regions of the spectrum.

$$NDVI = \frac{(NIR-R)}{(NIR+R)} \tag{1}$$

NDVI data was obtained for every 16 day period for a total of 23 non-overlapping images per year. A value is calculated for each pixel in an NDVI image using this ratio. The values for each image are therefore scaled independently, meaning that the same pixel from two NDVI images taken at two different dates are not directly comparable. Therefore, these data were converted using equation 2, rescaling each pixel across the time period of a year to provide comparability across time, and constraining the dataset between biologically important thresholds. Thus, providing a more meaningful measure of vegetative density and distribution as well as standardizing the data range, resulting in comparable data sets.

$$VEG = 0.95 * \frac{NDVI-NDVImin}{NDVImax-NDVImin} \tag{2}$$

This is a function of the maximum and minimum NDVI values for each pixel over the time series, in which NDVI represents the NDVI value of a pixel, NDVImin the minimum NDVI value of that pixel for that year, and NDVImax the maximum NDVI value of that pixel for the year. The function is multiplied by 0.95, which is established as the maximum range of possible values before the satellite receptors are saturated (Donohue, McVicar, & Roderick, 2008). Standardizing the dataset across the year allowed me to compare vegetative productivity at various dates and track changes in the NDVI over time.

I classified the resulting data into ten classes ranging from bare ground to high density vegetation in order to describe a gradient of vegetative density. This classification scheme allowed me to identify changes in the availability of vegetative habitat for insect utilization. The subdivision of primary productivity into ten classes, with class 1 representing bare ground and class 10 representing high vegetation allows enough detail to differentiate between the many stages of plant growth captured during the growing season. Figure 3 provides a visual demonstration of the changes in primary productivity over the course of a growing season.

These reclassified vegetation data were subsequently analyzed using the spatial pattern analysis program, FRAGSTATS, which computes landscape pattern metrics at several scales (patch, class, and landscape) describing spatial patterns related to composition, configuration and connectivity characteristics of the landscape (Cushman & McGarigal, 2007). Patches are defined as groups of adjacent pixels of the same class. Classes are user-determined categories which are defined by a range of values that each pixel can take, therefore each pixel in the image falls into one of the set of classes. Landscape pattern metrics quantify various characteristics of the landscape based on how these patches are shaped, distributed, and connected throughout the landscape.

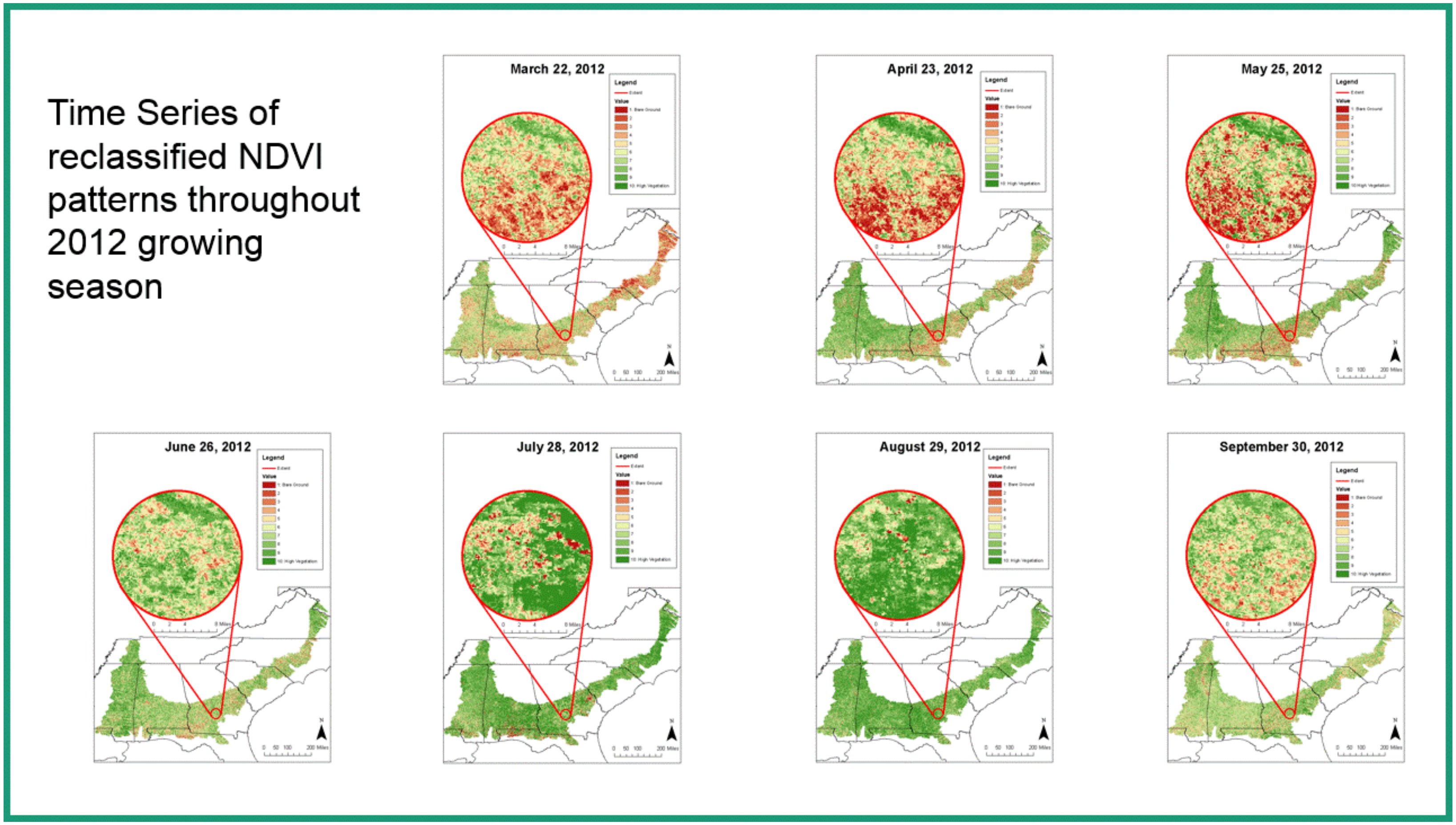

Figure 3: Time Series of Reclassified NDVI Patterns throughout 2012 Growing Season.

Classes range from bare ground (class 1) to high vegetation (class 10).

I selected a suite of metrics which have been frequently utilized in the literature to describe landscape patterns and which capture the various attributes of complexity, connectivity, and configuration (Macfadyen, Kramer, Parry, & Schellhorn, 2015). These metrics included: number of patches, total edge, area, gyrate, fractal, contiguity, core area, Euclidean nearest-neighbor distance, contrast-weighted edge density, contagion, percentage of like adjacencies, cohesion, division, Shannon Diversity Index, and the aggregation index (For a full description of all of these metrics as well as descriptive statistics, please refer to Appendix A). I ran principal component analysis on these results to observe which of the spatial pattern metrics were contributing most strongly to temporal variation in the landscape areas under study. Based on the results of the principal component analysis, I selected eight landscape pattern metrics which contributed most strongly to the variation in the temporal data, these metrics are described in greater detail in Table 2. These eight metrics were explored more thoroughly by including them as independent variables in my econometric model in order to understand how they might be contributing to pesticide use.

Table 2: Selected Landscape Pattern Metrics and Descriptions

Landscape Metric, Abbreviation	Full Name	Description	Units
AREA	Patch Area Distribution	The distribution of the area of each patch	Hectares
CONTAG	Contagion	Describes how patches of the same type are dispersed and how connected these patches are; this measure increases with greater connection between patches of the same type	Percent
GYRATE	Patch Radius of Gyration	Describes the ease of movement across the landscape by an organism which must remain in the same patch type; a measure of continuity across the landscape	Meters
CONNECT	Connectance	The number of connections between patches of the same type throughout the landscape (reported as a percentage of the maximum possible number of connections)	Percent

Landscape Metric, Abbreviation	Full Name	Description	Units
TE	Total Edge	Total edge length of patches within the landscape	Kilometers
DIVISION	Landscape Division Index	Probability that two pixels randomly chosen from the landscape will occur in two different patches	Proportion
CWED	Contrast-Weighted Edge Density	Edge length is standardized to per-unit area, and weighted according to the contrast between adjoining patches, includes information on both edge density and edge contrast	Meters per hectare
SHDI	Shannon's Diversity Index	Measure of diversity of patches in the landscape, utilizing the distribution and proportion of the landscape occupied by that patch type	None
PLADJ	Percentage of Like Adjacencies	The proportion of adjacent cells of the same type out of all possible cell adjacencies	Percent
NP	Number of Patches	Total number of patches in the landscape	None
CONTIG	Contiguity Index	Patch boundary configuration including the size and shape of each patch	None
AI	Aggregation Index	Ratio of like adjacencies to the maximum possible number of like adjacencies	Percent

2.3 Econometric Modeling

Our model is built upon those established by Meehan et al (2011) and Larsen (2013), expanding upon these studies by including additional information on and utilizing more descriptive measurements of landscape complexity, incorporating temporal as well as spatial dynamics. I obtained data that is comparable to the data used by the authors, but performed a more detailed analysis in several ways: including covariates which were not included previously and taking advantage of annual observations as opposed to data from the Agricultural Census which is only provided every five years. Most importantly, however, I have improved upon the variable which represents landscape complexity to include more information about the spatial context of the landscape as well as capture the disturbance regime which is an essential temporal component of the agricultural landscape.

The basic model presented by Meehan et al (2011) and Larsen (2013) included proportion of county treated with insecticides as their measure of insecticide use for the dependent variable. The independent variable of interest was proportion of county in cropland which represented a measure of landscape simplification (the inverse of landscape complexity) and covariates, including net farm income as an economic determinant, and proportion of harvested area in the county which was cropped in each category of corn, soy and small grains, and fruit and vegetables as controlling factors. Meehan and colleagues examined a cross-sectional dataset, while Larsen employed a fixed effects model which included data from five Ag Census years (each spaced five years apart).

I employ a fixed effects model using panel data. I improve upon the previous models by including covariates such as the Palmer Drought Severity Index to capture weather anomalies during our time period in each region. I include crop price data because the value of the crop in question is likely to drive farmer's decisions for pesticide use. I include the same cropping data that have been included in the previous studies, measuring the proportion of harvested land under each major crop type of corn, soy and small grains, and fruit and vegetables, however I add in cotton as well since my analysis includes the southeastern plains and cotton is a major crop for this region.

Finally, the measure I employ to capture landscape complexity is more appropriate than the previous estimates of proportion crop or proportion non-crop. I include the previously described landscape metrics over a series of months throughout the growing season in order to capture the very rapidly changing agricultural landscape over the course of each year. The model contains monthly observations from seven different dates of each landscape metric included, allowing me to see at approximately which dates in the growing season each metric is contributing to pesticide application rates.

Econometric Model:

$A_{T,S} = \beta_0 + \beta_{1i}LM(081)_{i,T,S} + \beta_{2i}LM(113)_{i,T,S} + \beta_{3i}LM(145)_{i,T,S} + \beta_{4i}LM(177)_{i,T,S} + \beta_{5i}LM(209)_{i,T,S} + \beta_{6i}LM(241)_{i,T,S} + \beta_{7i}LM(273)_{i,T,S} + \beta_8 NC_{T,S} + \beta_9 C_{T,S} + \beta_{10} QT_{,S} + \beta_{11} Y_{T,S} + \beta_{12} F_{T,S} + \beta_{13} D_{T,S} + \beta_{14} OC_T + \beta_{15} OQ_T + \beta_{16} OY_T + \beta_{17} S + \beta_{18} T + e$

A: Aggregated insecticide compounds, units are KG applied per hectare, varies across time and state-region

LM: Landscape Metric, i

Model includes metric value for seven dates throughout growing season: Julian dates 081, 113, 145, 177, 209, 241, and 273 which correspond to monthly observations from late March through late September, see Table 3 below for conversion from Julian dates.

NC: Proportion of non-crop habitat

C: Proportion of cultivated area under Corn

Q: Proportion of cultivated area under Cotton

Y: Proportion of cultivated area under Soybeans and small grains

F: Proportion of cultivated area under Fruit and Vegetables

D: Drought severity index

OC: Output crop price, Corn

OQ: Output crop price, Cotton

OY: Output crop price, Soybeans

S: State

T: Year

Table 3: Julian Date Conversion

Julian Date	Calendar Date
81	March 21
113	April 22
145	May 24
177	June 25
209	July 27
241	August 28
273	September 30

Additionally, our dataset includes information from the southeastern plains region, an agricultural region with a far more diverse landscape structure in general than that of the Midwest. Previous studies have focused solely on the Midwestern US, however the rich diversity of agricultural production in the Southeast is likely to provide unique information to this analysis of landscape complexity and its relationship to pest suppression.

CHAPTER 3

RESULTS

3.1 Principal Component Analysis

Principal component analysis (PCA) informed our decision as to which variables to include in the econometric model to describe landscape complexity. PCA reduces the dimensionality of the data, and the resulting scores describe how each variable contributes to the total variability in the data. Landscape pattern metrics are often correlated, making it difficult to include all of the metrics of interest. PCA allows us to visualize which variables are contributing the most information to our analysis.

I performed PCA over each year for each separate state-region. The averages of the PCA scores for each landscape metric are displayed in Table 4. I calculated average PCA scores for the total dataset including all 22 regions as well as individually for the Midwestern region and the Southeastern region, to check for regional variation in the importance of metrics. There is regional variation, with a different set of metrics contributing the most variation to the dataset for each region. I selected the eight metrics which contributed the most information for the total dataset, as well as for each of the Southeastern and Midwestern datasets to explore further as independent variables in the fixed effects model. I selected eight metrics because I needed to narrow the total set of metrics down a manageable number of variables which could be explored given the data limitations of my dataset.

Table 4: PCA Results

Total Dataset		Midwestern data		Southeastern Data	
VARIABLE	**PC1**	**VARIABLE**	**PC1**	**VARIABLE**	**PC1**
AREA_AM	-0.398213815	**TE**	-0.37661	**CONTAG**	-0.97998709
CONTAG	-0.39788502	**NP**	-0.35041	**CONTIG_AM**	-0.9691505
GYRATE_AM	-0.388740426	**DIVISION**	-0.31779	**PLADJ**	-0.96559234
CONNECT	-0.386541204	**SHDI**	-0.3121	**AI**	-0.96494777
CONTIG_AM	-0.382342521	**CWED**	-0.30817	**GYRATE_CV**	-0.96023513
PLADJ	-0.382161249	**FRAC_MN**	-0.24394	**GYRATE_AM**	-0.95088861
CORE_AM	-0.381950679	**FRAC_CV**	-0.17469	**AREA_AM**	-0.94560648
AI	-0.381938958	**CONTIG_MN**	-0.09828	**CORE_AM**	-0.92261057
GYRATE_CV	-0.371942763	**ENN_AM**	-0.01574	**ENN_MN**	-0.9063406
ENN_MN	-0.363357465	**CONNECT**	0.059553	**CORE_MN**	-0.82710986
CORE_MN	-0.306087567	**ENN_CV**	0.290779	**CONNECT**	-0.74077205
ENN_CV	-0.285980254	**AREA_AM**	0.317655	**ENN_CV**	-0.72260187
COHESION	-0.238201965	**CORE_AM**	0.325714	**COHESION**	-0.70095606
CONTIG_MN	0.187195724	**ENN_MN**	0.339716	**CONTIG_MN**	0.39493739
ENN_AM	0.26645418	**GYRATE_AM**	0.341419	**ENN_AM**	0.45780411
FRAC_CV	0.326891128	**COHESION**	0.35167	**FRAC_CV**	0.69072293
FRAC_MN	0.341043435	**CONTAG**	0.359245	**FRAC_MN**	0.77551918
NP	0.34500791	**CORE_MN**	0.365185	**NP**	0.88102307
TE	0.382161221	**AI**	0.376375	**CWED**	0.94432591
DIVISION	0.398157204	**PLADJ**	0.376614	**DIVISION**	0.9456073
CWED	0.399887992	**CONTIG_AM**	0.380669	**SHDI**	0.95439484
SHDI	0.404808785	**GYRATE_CV**	0.391709	**TE**	0.96559234

Notes: Averages of PCA scores are displayed in this table, in the leftmost panel these are averaged across the entire dataset. In the center panel, scores are averaged only for the Midwestern US region. In the rightmost panel, scores are averaged only for the Southeastern US region. The four metrics which average highest scores across each region in both the positive and negative directions of the principal component axes are highlighted in green.

3.2 Fixed Effects Model

I estimated several different specifications of the general fixed effects econometric model described previously. First I estimated the model including only one landscape metric at a time along with all other covariates using the total dataset as well as using data from the Midwest and Southeast separately. I observed which metric and date combinations arose as significant (results listed in Table 5). I also estimated the model including all of the dates and all of the eight variables of interest included as independent variables. Then, I included variables at the dates which appeared to be significant in either the models including individual metrics or the model including all of the metrics. Finally, I included just the metric-date combinations which were significant in this smaller model. The results from these three iterations of the model including the landscape metrics are listed in Table 6.

In order to compare these results with those from previous studies, I performed this analysis using my dataset but including comparable data and variables to those used by Meehan et al (2011) and Larsen (2013). Table 6 displays the comparison of results from the various models performed. The baseline model, Model 1, includes only similar covariates to those used by Meehan and Larsen, with proportion non-crop the only measure of landscape complexity. I subsequently added proportion of harvested land in cotton (Model 2) as a major agricultural product of the Southeast, and then a drought index (Model 3) to account for extraordinary weather anomalies. Finally, I included our new measures of landscape complexity (Models 4, 5, and 6 described in Table 7).

Table 5: Coefficients for Selected Metrics in Individual Metric Models

Total Dataset								
Landscape Metric	TE	AREA_AM	CONTAG	GYRATAE_AM	CONNECT	DIVISION	CWED	SHDI
Julian Date								
81	-0.002	-0.00006	0.7	0.27	-2450	63	9.61	-1.35
113	-0.003	0.00001	3.68	0.79	4991	216	-29.4	-51.69
145	0.003	-0.00004	-13.99*	-3.29	-8419	1053	62.9*	427.58
177	-0.002	0.00019	-4.89	1.48	-1535	422	5.49	317.81
209	0.001	0.00002	-5.88	1.81	-2863	450*	34.97	170.98
241	0.001**	0.00014	-1.75	-1.17	-29.83	49	-55.35	127.57
273	0.005***	-0.00127	-12.51*	-19.18	-12696*	1307	112.4***	402.79
Midwest								
Landscape Metric	CONTAG	CONTIG_AM	PLADJ	AI	CWED	DIVISION	SHDI	TE
Julian Date								
81	-.0000019	-0.082	-0.00084	-0.00084	0.00435	0.013117	-0.005	-2.3E-07
113	0.00159**	0.071	0.000737	0.000735	-0.0039	0.027373	-0.053**	-3.3E-07
145	-0.00157*	0.032	0.000347	0.000349	0.0005	-0.2904	0.057*	1.9E-07
177	0.000205	-0.021	-0.00021	-0.00021	-0.00023	0.001167	0.001	-1.2E-07
209	-0.00067*	-0.056	-0.00057	-0.00057	0.0065*	0.018177	0.039***	1.1E-07
241	0.000339	0.043	0.000407	0.000408	-0.0039	-0.03784	-0.011	1.2E-07
273	-0.00044	-0.060	-0.00061	-0.0006	0.0033	0.171697	0.017	3.2E-07**
Adjusted R^2	0.819	0.790	0.789	0.788	0.811	0.774	0.823	0.778
Southeast								
Landscape Metric	TE	NP	DIVISION	SHDI	AI	PLADJ	CONTIG_AM	GYRATE_CV
Julian Date								
81	-1.9E-06	-3.2E-07	0.540726	0.231	-0.01127	-0.011	-1.12946	-3.05*
113	-2.1E-06	-9.2E-07	-4.91856	-0.098	-0.00413	-0.004	-0.44062	-0.64
145	1.59E-06	4.6E-07	0.207633	0.220	0.003098	0.003	0.273306	-1.17
177	-1.3E-06	-6.3E-07	-1.39357	-0.289	0.009384	0.009	0.979442	3.82**
209	-3.8E-07	-5.2E-07	-0.16963	0.0116	0.001125	0.001	0.101029	0.005
241	-6.8E-07	-4E-07	1.385559	0.033	-0.00143	-0.001	-0.15587	-0.66
273	1.1E-07	2.7E-07	0.745432	0.274	0.005126	0.005	0.456663	0.147
Adjusted R^2	0.719	0.683	0.692	0.705	0.732	0.732	0.729	0.727

Notes: * $p < 0.1$, ** $p< 0.05$, ***$p<0.01$
This table displays results of interest from a total of 24 regressions, each regression includes the seven monthly observations (corresponding to the Julian Dates listed in the far left column) of the eight most important metrics for each of three areas – the total area under study, just the Midwest and just the Southeast. Each regression includes only observations of one individual metric, therefore each column containing a different metric represents the results from one regression.

Table 6: Fixed Effects Model Results

	Model 1: Baseline Model All Regions	Model 2: Baseline including Cotton	Model 3: Baseline including PDSI and Cotton	Model 4: All dates of chosen landscape metrics	Model 5: All significant dates of landscape metrics included	Model 6: Significant dates of chosen landscape metrics
Proportion Non-crop	375726	390949	385137	1342847***	731000**	544000*
Proportion Soy and Small Grains	-1105***	-1088***	-1057***	-1599***	-1870***	-1870***
Proportion Corn	3204***	3231***	3273***	4003***	3490***	3440***
Proportion Fruit and Vegetable	-1104***	-2304	-2823	-249	-419	-1110
Proportion Cotton	--	-498	-174	881	-169	-28
Drought Severity	--	--	48*	111**	27.1	33
TE (81)	--	--	--	0.008*	0.0009	--
TE (113)	--	--	--	-0.004	-0.002	--
TE (177)	--	--	--	-0.013**	-0.001	--
TE (273)	--	--	--	0.0091	0.004*	0.002*
CONTAG (81)	--	--	--	152***	63.39***	55**
CONTAG (145)	--	--	--	-121**	-68.99***	-59***
CONTAG (209)	--	--	--	-109.14**	-18.81	--
CONTAG (241)	--	--	--	-110**	-57.83**	-16**
CONTAG (273)	--	--	--	81.77	6.77	--
SHDI (81)	--	--	--	4950***	1838.5**	1730**
SHDI (145)	--	--	--	-3587*	-2243.04***	-2010***
SHDI (209)	--	--	--	-3697.8**	-692.89	--
SHDI (241)	--	--	--	-2896.7**	-1224.39	--
SHDI (273)	--	--	--	2944.6*	733.77	--
CWED (241)	--	--	--	-303***	-209.85***	-127**
AREA_AM (113)	--	--	--	0.0038*	0.00006	--
DIVISION (177)	--	--	--	-4764.6***	-502.98	--
DIVISION (209)	--	--	--	-8.70	-19.99	--
CONNECT (81)	--	--	--	-16459**	-6757***	-6740***
CONNECT (273)	--	--	--	-3020	-12900***	-11000**
R^2	0.745	0.759	0.747	0.894	0.870	0.866
Adjusted R^2	0.657	0.655	0.667	0.852	0.804	0.791
Number of observations	110	110	110	110	110	110
Degrees of freedom	81	80	79	23	59	70

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Model 1 contains only the covariates comparable to those utilized in previous studies by Meehan et al (2011) and Larsen (2013). Model 2 includes the covariate of proportion of harvested area under cotton, since cotton is a major Southeastern crop. Model 3 includes the Palmer Drought Severity Index. Model 4 includes all metric-date combinations of the eight metrics most important for the total dataset. Model 5 includes the metric-date combinations which were significant in Model 4, as well as in the individual metric models depicted in Table 5. Finally, Model 6 includes just the significant metric-date combinations from Model 5.
For full model results, please refer to Appendix C.

Based on changes in the adjusted R^2, the model performance improves slightly as covariates are added, and improves substantially when the landscape metrics are included. The model including all dates of all important variables has the highest adjusted R^2. In order to test whether the added covariates were statistically important for model function, I performed F-tests comparing the baseline model with each of the subsequent models, and then comparing the several specifications of the model containing landscape metrics. The results of the F-tests are reported in Table 7.

Table 7: Fixed Effects Model, F-Tests Results

Total				
Unrestricted	Restricted	F statistic	F critical value	Reject H0?
Model 2	Model 1	0.156126	2.49	No
Model 3	Model 1	0.906224	2.33	No
Model 4	Model 1	2.587011	1.89	Yes
Model 5	Model 1	3.400312	1.7	Yes
Model 6	Model 1	5.818182	1.97	Yes
Model 5	Model 6	1.187635	1.87	No
Model 4	Model 6	1.463846	1.91	No
Model 6	Model 3	9.422222	2.14	Yes
Model 5	Model 3	3.888834	1.75	Yes
Model 4	Model 3	2.641712	1.89	Yes

Notes: F tests were performed to determine if the models compared in Table 6 actually differ. The cases in which the null hypothesis, H_0: $\beta_i = \beta_j = \beta_k = 0$, was rejected are highlighted in green demonstrating that the models are statistically different from each other and that the additional covariates included in these models are contributing to improved model function.

From this suite of F-tests, we can see that Model 1, the baseline model, does not differ statistically from Models 2 or 3, therefore adding in the additional covariates of proportion of harvested land planted in cotton and the drought index are not contributing significantly to overall model function. However, Models 4, 5, and 6 are all statistically different both from Model 1 (baseline) and Model 3 (baseline with cotton and PDSI included). In these cases, we are able to reject the null hypothesis of the F-test which states that the coefficients of the additional variables included in Models 4, 5, and 6 are jointly equal to zero – at least one of these additional variables is contributing to the model significantly. These results indicate that the landscape variables are indeed important in describing pesticide application rates in this system.

In order to examine whether I have been able to capture the temporal dynamics of the landscape by including monthly observations of each metric in the model, I ran the same model but with the means and standard deviations of each of the eight important metrics included as the covariates representing landscape complexity, instead of including the seven monthly observations. The results of these models are displayed in Table 8.

Table 8: Regressions including Mean and Standard Deviation of Metrics

	Means and Standard Deviations	Means	Standard Deviations
Proportion Non-crop	-1950.51	-828.61	-1110.11
Proportion Soy and Small Grains	-1526.6***	-1461.88***	-1305.46***
Proportion Corn	3384***	3390.55***	3210***
Proportion Fruit and Vegetable	-3410.33	-1323.10	-6144.09
Proportion Cotton	-8.4	-135.62	-13.52
Price Corn	-20.28	37.91	-32.25
Price Soy	4.80	-41.57	10.53
Price Cotton	104.72	-72.53	1.41
Drought Severity	63.69**	53.69**	60.77**
TE Mean	0.0028*	0.003***	--
TE Std. Dev.	-0.0037	--	-0.005
CONTAG Mean	-12.49	-30.57	--
CONTAG Std. Dev.	29.90	--	48.53
SHDI Mean	-600.53	-1016.91	--
SHDI Std. Dev	-686.20	--	-1895.45
CONNECT Mean	-5090.86	942.65	--
CONNECT Std. Dev	2822.55	--	1254.52
CWED Mean	-11.77	9.81	--
CWED Std. Dev.	78.53	--	227.87
AREA_AM Mean	0.0006	0.0001	--
AREA_AM Std. Dev	-0.0002	--	0.0002
DIVISION Mean	2284.50	2401.23	--
DIVISION Std. Dev.	-950.69	--	-3803.80***
GYRATE Mean	-4.07	17.44	--
GYRATE Std. Dev	13.30	--	21.70**
R^2	0.833	0.820	0.810
Adjusted R^2	0.719	0.729	0.715
Number of observations	110	110	110

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Results are displayed for three separate regressions: the first includes the means and standard deviations of each of the eight most important metrics for the total dataset. The second includes only the means of those metric values, and the third includes only standard deviations.

While I cannot directly compare the results of these models with the previous models using F-tests due to the entirely different nature of the independent variables included, we can examine the R^2 and adjusted R^2 values for the different specifications: both R^2 and adjusted R^2 values are substantially higher in the specifications containing observations at multiple dates throughout the growing season than in the regression containing the means and standard deviations of these metrics. This is an indication that collapsing the distribution of metric values observed throughout the year down to its mean and standard deviation may not provide enough information on the temporal dynamics taking place in the landscape. Including the limited time series of observations, as in the previous models, appears to better describe pesticide application rates. This result lends credence to the theory that temporal dynamics occurring with high frequency in the agricultural landscape are impacting pest insect population dynamics, and thus the response by farmers to apply insecticides. This is also an indication that the temporal data cannot simply be aggregated up to a longer time span, such as a year, without losing important information describing the impacts of the landscape on pest insects.

3.3 Regional Comparison of Models

The studies by Meehan et al (2011) and Larsen (2013) only examine data from the Midwestern United States, focusing on the region due to its intensity of agricultural production and extensive amount of land devoted to cropland. Therefore, in order to compare my results to those described by these authors, I estimated my model with data just from the Midwestern United States region and then with data just from the Southeastern plains region, allowing me separate out the effects of sample selection bias from my results and allow for more direct comparability with the results found by Larsen and Meehan et al. As before, for each region I estimated the model including just the variables included in previous studies by Larsen (2013) and Meehan et al (2011) in a baseline model, then added additional covariates, and finally added the new measurements for landscape complexity to examine how the results change with the addition of these new variables. Results for the Midwestern data are reported in Table 9, followed by results of F-tests comparing these Midwestern models reported in Table 10. Table 11 contains results from the models including just Southeastern data, followed by the results of F-tests comparing the models from the Southeast in Table 12.

Table 9: Fixed Effects Model Results, Midwestern Region

Midwest	Midwest Model 1: Baseline Model just Midwest	Midwest Model 2: Baseline including PDSI	Midwest Model 3: Significant Dates from Midwest data
Proportion Non-crop	-14.541	-25.133*	-10.374
Proportion Soy and Small Grains	0.161*	0.167**	-0.068
Proportion Corn	0.149*	0.139*	0.114
Proportion Fruit and Vegetable	-2.384	-3.017	-1.773
Drought Severity	--	0.024***	0.005
TE (273)	--	--	1.5E-7**
CONTAG (113)	--	--	0.001
CONTAG (145)	--	--	-0.00195**
CONTAG (209)	--	--	0.0017
SHDI (113)	--	--	-0.034
SHDI (145)	--	--	-0.00804
SHDI (209)	--	--	0.0957
CWED (241)	--	--	-0.0002
R^2	0.813	0.854	0.930
Adjusted R^2	0.723	0.778	0.860
Number of observations	43	43	43

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01
Model 1 is the baseline model, very similar to models used in previous literature. Model 2 includes the Palmer Drought Severity Index. Model 3 includes the metric date combinations which were significant in the individual metric regressions, results of which are reported in Table 5. Proportion of harvested area planted in cotton was not included in the Midwestern regression because of missing observations, as cotton is not a major crop in the Midwestern US.

Table 10: Fixed Effects Model, F-Tests Results, Midwestern Region

Midwest				
Unrestricted	Restricted	F statistic	F critical value	Reject H0?
Model 2	Model 1	2.901826	2.92	No
Model 3	Model 1	3.064286	2.24	Yes
Model 3	Model 2	4.085714	2.65	Yes

Notes: F tests were performed to determine if the models compared in Table 9 actually differ. The cases in which the null hypothesis, H_0: $\beta_i = \beta_j = \beta_k = 0$, was rejected are highlighted in green demonstrating that the models are statistically different from each other and that the additional covariates included in these models are contributing to improved model function.

From the results displayed in Table 9 reflecting my econometric model estimated with data from just the Midwestern corn belt region of the U.S., and the results of F-tests reported in Table 10, it is clear that in the Midwest the addition of the more descriptive variables for landscape complexity improves the model function. The F-tests demonstrate that the additional variables included in Model 3, which includes the significant landscape metrics from the regression results displayed Table 5, are jointly significant compared with the baseline Model 1 as well as Model 2 which includes the Palmer Drought Severity Index as a covariate.

Table 11: Fixed Effects Model Results, Southeastern Region

Southeast	Southeast Model 1: Baseline Model	Southeast Model 2: Baseline including Cotton	Southeast Model 3: Significant dates of landscape metrics
Proportion Non-crop	418.01	380.82	415.38
Proportion Soy and Small Grains	-0.0579	-0.089	-0.193
Proportion Corn	0.326	0.046	-0.052
Proportion Fruit and Vegetable	-2.066	-1.73	-1.03
Proportion Cotton	--	0.668***	0.415
TE (81)	--	--	-1.3E-6
SHDI (145)	--	--	0.052
R^2	0.762	0.847	.0864
Adjusted R^2	0.657	0.736	0.735
Number of observations	56	52	52

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01
Model 1 is the baseline model, very similar to models used in previous literature. Model 2 includes the proportion of cultivated area planted in cotton. Model 3 includes all of the variables from Model 2 as well as the metric date combinations which were significant in the individual metric regressions, results of which are reported in Table 5. The Drought Severity Index could not be included because of perfect collinearity.

Table 12: Fixed Effects Model, F-Tests Results, Southeastern Region

Southeast				
Unrestricted	Restricted	F statistic	F critical value	Reject H0?
Model 2	Model 1	4.259259	3.03	Yes
Model 3	Model 1	2.5	2.6	No
Model 3	Model 2	5	3.09	Yes

Notes: F tests were performed to determine if the models compared in Table 11 actually differ. The cases in which the null hypothesis, H_0: $\beta_i = \beta_j = \beta_k = 0$, was rejected are highlighted in green demonstrating that the models are statistically different from each other and that the additional covariates included in these models are contributing to improved model function.

The story is similar in the Southeastern plains, where we once again see an increase in adjusted R^2 and improvement in model function. The results of the F-tests from the Southeastern models are not as clear cut as those for the Midwestern models, however, likely due to the small number of observations. Model 3, which includes the significant landscape variables from the regression results displayed in Table 5, is significantly different from Model 2 but not significantly different from the baseline model, Model 1. However, Model 2 is different from Model 1 based on the F-test results. The fact that I am able to reject the null hypothesis that the additional variables included in Model 3 compared to Model 2 are not jointly equal to zero, and with the increase we see in the adjusted R^2, we can conclude even with the limited dataset that the additional landscape variables included in Model 3 are contributing valuable information as to pesticide use patterns.

3.4 Testing Sensitivity to Inclusion of Income

One important difference between the model I have specified and the models estimated by Meehan et al (2011) and Larsen (2013) is the variables included which account for farmers' economic decisions. The previous studies include net farm income per harvested hectare to account for variation in farmers' economic positions. I have instead included crop prices. I have chosen to include crop price because net farm income is a broadly defined economic measurement that includes farm types other than those of interest to this study: farms involved in animal production as well as those involved in crop production. However, crop price could be an indicator of the value of certain crops, and the more valuable the crop is, the more likely the farmer is to apply an expensive input to protect that crop. There could arguably be other measures of economic factors involved in farmers' decisions to apply insecticides as well.

In order to compare my results and model with those estimated by Meehan et al and Larsen, I have estimated the models as previously described but including net farm income per harvested hectare as an additional covariate. The results are displayed in Table 13.

Table 13: Comparison of Models for Total Area with Farm Income Included

	Model 1: Baseline Model All Regions	Model 2: Baseline Model With Crop Price	Model 3: Baseline including Cotton	Model 4: Baseline including PDSI and Cotton	Model 5: All dates of chosen landscape metrics	Model 6: All significant dates of landscape metrics included	Model 7: Significant dates of chosen landscape metrics
Proportion Non-crop	154714	136934	147565	148737	727634***	158951	94297
Proportion Soy and Small Grains	254	268	276	269	-489*	-219	-126
Proportion Corn	1978***	2001***	2021***	2041***	2518***	2249***	2216***
Proportion Fruit and Vegetable	2445	2137	1912	1651	4177	2375	2249
Proportion Cotton	--	--	-331	-207	150	-236	-293
Income per Harvested Hectare	-0.607***	-0.60***	-0.60***	-0.59***	-.42***	-0.51***	-0.53***
Price Corn	--	66.97	82.7	52.8	389	88.92	140.6
Price Soy	--	-54.54	-65.56	-35.2	-308	-71.7	-108.1
Price Cotton	--	--	-237.1	-54.8	61.63	-123	-296
Drought Severity	--	--	--	18.7	45*	25*	21*
TE (177)	--	--	--	--	-0.008***	-0.002**	-0.002**
TE (273)	--	--	--	--	0.007*	0.0024**	0.002***
CONTAG (145)	--	--	--	--	-89.1***	-25.15*	-13.39*
CONTAG (177)	--	--	--	--	-60.4***	-4.75*	-3.65*
CONTAG (273)	--	--	--	--	83.8***	16.18	--
SHDI (145)	--	--	--	--	-2646***	-855*	-402
SHDI (273)	--	--	--	--	2680***	480	--
CWED (145)	--	--	--	--	-90.0*	-6.38	--
CWED (273)	--				74.2	0.34	--
AREA_AM (113)	--	--	--	--	0.002**	0.00003	--
DIVISION (81)	--	--	--	--	-1022.4*	-98.5	--
DIVISION (273)	--	--	--	--	-90.2	102.7	--
CONNECT (81)	--	--	--	--	-9950.8***	-1994.8	--
CONNECT (113)	--	--	--	--	-14755.7*	952.6	--
CONNECT (273)	--	--	--	--	-6355.9	-7546.7*	-3987**
GYRATE (113)	--	--	--	--	-51.4**	1.14	--
GYRATE (209)	--	--	--	--	-.47	0.65	--
GYRATE (241)	--	--	--	--	-9.0	0.004	--
GYRATE (273)	--	--	--	--	-64.4**	-5.46	--
R^2	0.944	0.946	0.947	0.948	0.992	0.97	0.966
Adjusted R^2	0.927	0.926	0.927	0.928	0.962	0.946	0.949
Number of observations	110	110	110	110	110	110	110

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01
Model 1 contains only the covariates comparable to those utilized in previous studies by Meehan et al (2011) and Larsen (2013), with income as the variable capturing farmers' economic decisions. Model 2 includes the covariates from the baseline model, adding in crop prices as well. Model 3 adds the covariate of proportion of harvested area under cotton, since cotton is a major Southeastern crop. Model 4 includes the Palmer Drought Severity Index. Model 5 includes all metric-date combinations of the eight metrics most important for the total dataset. Model 6 includes the metric-date combinations which were significant in Model 5, as well as in the individual metric models depicted in Table 5. Finally, Model 7 includes just the significant metric-date combinations from Model 6. For full model results, please refer to Appendix C.

Including net farm income per harvested hectare results in extraordinarily high R^2 and adjusted R^2 values across the board, for all model specifications which include this covariate. However, there are still important differences between the baseline model and the models which include the more descriptive measures of landscape complexity. F-tests were once again conducted to establish whether the additional variables are important, and results of these tests are displayed in Table 14.

Table 14: F-tests Comparing Models Including Income as a Covariate

Unrestricted	Restricted	F statistic	F critical value	Reject H0?
Model 2	Model 1	0.987654	2.72	No
Model 3	Model 1	1.117925	2.49	No
Model 4	Model 1	1.2	2.33	No
Model 5	Model 1	2.163934	1.89	Yes
Model 6	Model 1	2.288793	1.7	Yes
Model 7	Model 1	4.235294	1.97	Yes
Model 6	Model 7	0.782493	1.87	No
Model 5	Model 7	1.43	1.91	No
Model 7	Model 4	5.747899	2.14	Yes
Model 6	Model 4	2.441379	1.75	Yes
Model 5	Model 4	2.171053	1.89	Yes

Notes: F tests were performed to determine if the models compared in Table 13 actually differ. The cases in which the null hypothesis, H_0: $\beta_i = \beta_j = \beta_k = 0$, was rejected are highlighted in green demonstrating that the models are statistically different from each other and that the additional covariates included in these models are contributing to improved model function.

Once again, it is shown that Models 5, 6, and 7 which include the landscape metrics over the course of the growing season are contributing important information to the model. I am able to reject the null hypothesis that each of these models is different both from the baseline model used in the previous studies, as well as Model 4 which included additional covariates such as crop prices, drought severity, and proportion of harvested area planted in cotton. This strengthens the previous assertion that the landscape metrics are contributing important information about pesticide application rates.

I once again examine whether the temporal frequency of the data included in the models displayed in Table 13 is important by estimating the model including just the means and standard deviations of the metrics – results are displayed in Table 15.

Table 15: Testing Inclusion of Income with Mean and Standard Deviation of Landscape Metrics

	Means and Standard Deviations	Mean	Standard Deviations
Proportion Non-crop	-998.47	-399.90	-940.08
Proportion Soy and Small Grains	-72	-40.89	106.20
Proportion Corn	2188***	2189***	2083***
Proportion Fruit and Vegetable	512.92	1941.43	-962.84
Proportion Cotton	-218.86	-225.13	-187.15
Income per Harvested Hectare	-0.53***	-0.54***	-0.55***
Price Corn	106.57	110.25	33.97
Price Soy	-74.73	-82.42	-22.32
Price Cotton	-127.6	-222.25	-8.32
Drought Severity	30.55**	20.82*	31.34***
TE Mean	0.0011	0.0012**	--
TE Std. Dev.	-0.0038	--	-0.005
CONTAG Mean	-40.27	-47.16*	--
CONTAG Std. Dev.	-0.31	--	9.93
SHDI Mean	-1201.33	-1366.33	--
SHDI Std. Dev	413.37	--	-193.42
CONNECT Mean	-2517.58	1082.87	--
CONNECT Std. Dev	1856.35	--	594.92
CWED Mean	-39.99	-19.03	--
CWED Std. Dev.	57.52	--	143.51**
AREA_AM Mean	0.0000	0.0000	--
AREA_AM Std. Dev	0.0001	--	0.0002
DIVISION Mean	418.67	672.03	--
DIVISION Std. Dev.	-876.29	--	-1974.7***
GYRATE Mean	2.69	12.05	--
GYRATE Std. Dev	6.31	--	10.80**
R^2	0.965	0.963	0.959
Adjusted R^2	0.942	0.943	0.938
Number of observations	110	110	110

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Results are displayed for three separate regressions: the first includes the means and standard deviations of each of the eight most important metrics for the total dataset. The second includes only the means of those metric values, and the third includes only standard deviations.

Similar to the previous iterations of this model, I cannot directly compare these results with those of the regressions in Table 13 by means of an F-test, however once again I observe that the R^2 and adjusted R^2 values are higher for the regressions which include the temporal observations of the landscape metrics than those in which the metrics are reduced to mean and standard deviation. Again, this result supports the idea that temporal information on the landscape is important for understanding landscape interactions with pesticide application (and thus presumably pest pressure).

For comparability to the previous studies, I once again estimated the regression including income as a covariate for just the Midwestern region as well as the Southeastern region individually. The results for the Midwestern data are displayed in Table 16, with results of F-tests conducted to compare the several model specifications displayed in Table 17. Results from regressions including only Southeastern data are displayed in Table 18, with the related F-tests in Table 19.

These results once again reinforce my previous findings that additional information regarding landscape complexity is important in describing pesticide application rates. Not only to we once again observe increases in R^2 and adjusted R^2 when we add in the landscape metrics, but F-tests also demonstrate that the additional variables in both the Midwest and the Southeast are contributing valuable information, and we are able to reject the null hypothesis that the coefficients of these additional variables are jointly equal to zero.

This analysis including net farm income provides additional evidence that the models estimated in the previous literature do not include enough landscape information to adequately describe landscape complexity, and thus do not accurately depict the interactions between the landscape and pesticide use.

Table 16: Fixed Effects Model Results, Midwestern Data with Income Included

	Midwest Model 1: Baseline Model just Midwest	Midwest Model 2: Baseline including Crop Prices	Midwest Model 3: Baseline including PDSI	Midwest Model 4: Significant Dates from Midwest data
Proportion Non-crop	19.25	0.397	-15.26	-31.5
Proportion Soy and Small Grains	0.108	0.174*	0.177**	-0.032
Proportion Corn	0.136	0.177**	0.162*	0.116
Proportion Fruit and Vegetable	-2.384	-1.05	-1.99	-1.09
Income Per Cultivated Hectare	-0.0089	-0.010	-0.006	0.013
Price Corn	--	-0.006	-0.039**	-0.031*
Price Soy	--	0.010	0.047***	0.025
Drought Severity	--	--	0.020**	-7.8E-05
TE (273)	--	--	--	1.4E-07**
CONTAG (113)	--	--	--	0.001137
CONTAG (145)	--	--	--	-0.00159
CONTAG (209)	--	--	--	0.002282
SHDI (113)	--	--	--	-0.03872
SHDI (145)	--	--	--	0.00653
SHDI (209)	--	--	--	0.112192
CWED (241)	--	--	--	0.001082
R^2	0.714	0.818	0.846	0.929
Adjusted R^2	0.588	0.722	0.757	0.849
Number of observations	50	50	50	50

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Model 1 is the baseline model, very similar to models used in previous literature. Model 2 adds crop prices. Model 3 includes the Palmer Drought Severity Index. Model 4 includes the metric date combinations which were significant in the individual metric regressions, results of which are reported in Table 5. Proportion of harvested area planted in cotton was not included in the Midwestern regression because of missing observations, as cotton is not a major crop in the Midwestern US.

Table 17: F-tests Comparing Models from Midwest, Income Included

Midwest				
Unrestricted	Restricted	F statistic	F critical value	Reject H0?
Model 2	Model 1	9.142857	3.32	Yes
Model 3	Model 1	8.857143	2.92	Yes
Model 4	Model 1	1.869356	2.24	No
Model 4	Model 3	2.570364	2.37	Yes

Notes: F tests were performed to determine if the models compared in Table 16 actually differ. The cases in which the null hypothesis, H0: $\beta i = \beta j = \beta k = 0$, was rejected are highlighted in green demonstrating that the models are statistically different from each other and that the additional covariates included in these models are contributing to improved model function.

Table 18: Fixed Effects Model Results, Southeastern Data with Income Included

	Southeast Model 1: Baseline Model	Southeast Model 2: Baseline including crop price	Southeast Model 3: Baseline including Cotton	Southeast Model 4: Significant dates of chosen landscape metrics
Proportion Non-crop	340.7	206.2	379.8	576.5
Proportion Soy and Small Grains	-0.094	-0.13	-0.221	-0.321
Proportion Corn	0.069	0.024	-0.048	-0.162
Proportion Fruit and Vegetable	-0.801	-0.988	-0.99	-0.153
Income Per Cultivated Hectare	0.069***	0.067**	0.041	0.059
Price Corn	--	-0.01	-0.13	-0.306
Price Soy	--	0.02	0.103	0.254
Price Cotton	--	--	0.077	0.283
Proportion Cotton	--	--	0.483	0.499*
GYRATE_CV (81)	--	--	--	-2.20
GYRATE_CV (177)	--	--	--	2.667**
R^2	0.831	0.836	0.855	0.894
Adjusted R^2	0.746	0.737	0.729	0.782
Number of observations	56	56	52	52

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Model 1 is the baseline model, very similar to models used in previous literature. Model 2 includes crop prices. Model 3 adds the proportion of cultivated area planted in cotton. Model 3 includes all of the variables from Model 2 as well as the metric date combinations which were significant in the individual metric regressions, results of which are reported in Table 5. The Drought Severity Index could not be included because of perfect collinearity.

Table 19: F-tests Comparing Models from Southeast, Income Included

Southeast				
Unrestricted	Restricted	F statistic	F critical value	Reject H0?
Model 2	Model 1	0.426829	3.32	No
Model 3	Model 1	1.268966	3.03	No
Model 4	Model 1	1.981132	2.6	No
Model 4	Model 3	3.962264	3.09	Yes

Notes: F tests were performed to determine if the models compared in Table 18 actually differ. The cases in which the null hypothesis, H_0: $\beta_i = \beta_j = \beta_k = 0$, was rejected are highlighted in green demonstrating that the models are statistically different from each other and that the additional covariates included in these models are contributing to improved model function.

CHAPTER 4

DISCUSSION

4.1 Landscape Interactions

Previous studies have attempted to establish a link between landscape complexity and natural pest suppression provided by the landscape with mixed results. This study demonstrates that the metrics which are often relied upon for measuring and quantifying landscape complexity are too simplified. Our results indicate that additional information is required to actually capture the landscape effects; richer spatial data on connectivity, landscape configuration, and patch diversity as well as temporal information conveying landscape structure over the course of time are required for this type of landscape analysis.

The metric used in many previous studies to describe landscape complexity is percent non-crop, or the inverse of this measure, percent of area in cropland. This measure of landscape simplification was used by both Meehan (2011) and Larsen (2013) to determine whether landscape simplification is a driver for pesticide use. Using similar techniques and data, our results show that percent non-crop is not an adequate measure of landscape simplification in order to answer this type of question. Our models clearly demonstrate that other descriptors of the landscape are also significant and important for understanding the relationship between the landscape and the provision of ecosystem services such as pest suppression. Larsen found that the proportion of the landscape in cropland did not consistently increase insecticide use. I am able to demonstrate via improved model function as well as F-testing that including richer and more descriptive information about landscape configuration, connectivity, and diversity over time adds important information to the model.

The metrics which are revealed as important for the total dataset include Total Edge, Contagion, Shannon Diversity Index, Contrast-Weighted Edge Density, and Connectance. Each of these five metrics quantify a different aspect of the landscape including length and contrast of edges between distinct patches, the distribution of and connectivity between patches of the same type, and the diversity of patch types as well as evenness of patch type distribution across the landscape. These metrics are far more descriptive of spatial landscape patterns than those used in the previous literature to measure landscape complexity: this combination of metrics provides information about landscape connectivity and configuration as well as composition.

Our results indicate that temporal dynamics are important to consider when examining agricultural landscapes. Our metrics are significant for certain dates during the growing season, indicating that the structure of the landscape at certain times in the year has a more powerful impact on pest suppression than at other times in the year. A static classification of the landscape does little to capture the high frequency disturbance regime of agricultural production, or the availability of resources which is actually facing pest and predatory insects at any given time during the growing season. Additionally, the model appears to perform better when observations of metrics at multiple dates throughout the growing season are included, as opposed to collapsing the measures of landscape complexity down to mean or standard deviation of the metric values. This is another indication that the richer temporal information is contributing to the model and should be included.

It is interesting to note that for several of the metrics, the sign of the coefficient reverses at certain dates in the growing season. Both Contagion and the Shannon Diversity Index have a positive impact on pesticide application rates earlier in the year, but later in the year show a negative impact. The landscape likely looks very different to an insect at these two dates, because vegetative structure changes rapidly with the growth of crops as well as peak foliage of natural and semi-natural vegetation resulting in increased availability of resources for insects. Pests are likely motivated to move and cultivate new areas (potentially crops) based on different criteria at different times during the season. High diversity early in the season when fields are being tilled and planted is likely to indicate greater amounts of semi-natural habitat, or a greater interspersion of a variety of crop types, since a large area of monoculture under a single crop would likely result in lower diversity. High diversity later in the season might indicate areas of no vegetation, such as urban areas, since both native vegetation as well as crops will be at peak production mid to late season. It may be that these non-vegetative areas are serving as barriers to pest movement through the landscape, reducing pesticide use, resulting in the negative impact of increased diversity captured by our model in mid growing season.

Edge also arises as an important measure for understanding the effect of the landscape on insecticide application rates: while total edge (in Kilometers) has a very small but significant impact, the Contrast-Weighted Edge Density has a much larger impact, which could partially be due to a scaling effect. Both of these edge characteristics arise as significant only late in the growing season – Julian dates 241 and 273 (August 28 and September 30) – around the time of harvest, possibly because at this time the edge between cultivated land and natural vegetation may be more distinct than when crops and natural areas are both in full foliage. Contrast-Weighted Edge Density has a negative impact on pesticide application rates at this time, indicating that relatively more edge per total area and the increasingly stark differences between neighboring patches reduces pesticide application rates. This could be driven by patches of native vegetation bordering fields which are being harvested at these dates (and thus classified as minimum vegetation or even bare ground).

Connectance has the largest impact on pesticide application rates, and is significant both early in the season and very late in the season. The elasticity calculated at the mean for this coefficient is 3.36 early in the season and 5.48 at the end of the season. This indicates that a 1% increase in connectivity early in the season could result in a 3.36% decrease in insecticide application rates, while a 1% increase in connectivity later in the season could result in a 5.48% decrease in pesticide application rates. This could be a significant difference in the amount of pesticide applied. Connectivity is important for both pest and predatory insects moving through a landscape and utilizing resources and refuges. Increased connectance in this case results in a reduction in pesticide application rates, which could indicate that connectivity of vegetation across the landscape, during planting and harvesting times when crops are not available as vegetative resources, may provide predatory insects the resources and refuge to safely disperse and suppress pest populations, reducing the need for pesticide application.

The Southeast is generally considered to be a more spatially complex landscape than that of the Midwest. The results comparing the two regions are therefore of interest: the marginal effect of proportion of non-crop area in the landscape is positive for the Southeastern region, indicating that increasing proportion of non-crop land is contributing to increased insecticide use, whereas this effect is negative in the Midwestern region. Additionally, the landscape metrics appear to be more important in the Midwest than they are in the Southeast (while still improving model function in the Southeast), indicating that the landscape may have a greater impact in more intensely cultivated landscapes. Insecticide use rates are higher overall in the Southeast compared to the Midwestern region (see Appendix B for descriptive statistics of the full dataset as well as those specifically for the Southeastern and Midwestern regions). This could be driven by several factors including the climate of the Southeast fostering more pests and more continuous pest pressure compared to the Midwest, as well as more diverse cropping systems associated with the Southeastern plains regions. These crops include cotton, a non-food crop, as well as many fruits and vegetables which are higher-value crops and may require more interventions to maintain high yields.

This model was specifically designed to be comparable to those of Meehan et al (2011) and Larsen (2013). My results provide strong support that the measures used in these previous studies are not capable of accurately describing the landscape and its interaction with pest control measures. Including the net farm income variable in the regression yielded similar results as when this variable was excluded. This result lends additional comparability to the studies conducted by Meehan et al and Larsen. I also compared the function of their dependent variable in my model specification with my own dependent variable, and am able to demonstrate that the choice of dependent variable does not significantly change the results of the analysis given the independent variables I have included. For the full details of model results comparing dependent variables, please refer to Appendix D.

4.2 Implications

Armed with a better understanding of the landscape context for pest suppression, farmers can optimize their management decisions and better understand their risk of damage caused by pests. This richness of information could have a powerful economic impact for producers. Insecticides are expensive inputs and are also associated with significant negative externalities, often found unfavorable by consumers. Farmers could potentially use greater information about the landscape in which their fields are positioned to mitigate and reduce risk from pest pressure without applying additional pesticides. For instance, being aware that edge contrast can significantly reduce pesticide use, a farmer could spatially optimize where to locate crops which may be particularly sensitive to pest pressure or particularly responsive to these edge dynamics. Farmers could adapt the shape and size of their fields to support and maintain contrasting edges in order to reduce the need for pesticide applications, creating long fields bordering areas of continuous vegetation (areas not tilled or harvested) to increase the total amount of edge and intensify edge contrast. Additionally, farmers could utilize different crops planted in adjacent fields to achieve greater edge length, density, and contrast. The spatial arrangement and shape of fields could reflect a landscape which is planned strategically to reduce pest pressure on crops.

Additionally, a farmer could gain insight into their production process by taking the larger landscape context in which his or her operation exists into account, especially for long-run decision making processes. For instance, if a farmer is considering changing their planting regime or growing a new type of crop, they could better understand the risk they might face from pest pressure for each decision based on the characteristics of the surrounding landscape. The landscape context could inform a farmer's long run cropping choices to more accurately reflect the risk of pest damage. This could also impact a farmer's decision as to whether or not to bring marginal lands under cultivation or to remove marginally productive lands from cultivation to be set aside as semi-natural habitat. These marginal areas, if left as natural or semi-natural vegetation could contribute to the overall landscape dynamics for pest suppression, therefore, if a farmer is considering setting aside marginal lands or bringing marginal land under cultivation, the pest control aspect of that land should be taken into account for the farmer to accurately estimate the costs and benefits of altering production practices on that particular land.

Alternatively, farmers could utilize the information on the temporal effects of the landscape to time the planting and harvesting of neighboring fields, for instance maintaining additional connectivity across their production area instead of harvesting all of their fields at the same time. By planting different crops in adjacent fields which will be harvested at different times, or by staggering plantings and harvesting of crops across the landscape, the temporal component of landscape complexity could be harnessed in order to maintain connectivity across the landscape and encourage pest suppression via landscape-scale processes.

Almost 2 billion dollars were spent in the US on insecticides in 2007 (Pesticide Use and Markets, 2012). Leveraging landscape dynamics to reduce risk from pest outbreaks and the need for pesticide application would not only strengthen the resiliency of our food system, but also reduce the amount of money farmers must invest in expensive inputs. The reduction of pesticide use also reduces the associated negative externalities on native flora and fauna, pollinators, and people. One important result of pesticide application and widespread GMO adoption is pest resistance to insecticides and GM strategies for pest control. Fostering desirable insect movement and population dynamics through the landscape to maximize pest suppression would greatly reduce risk of pests developing pesticide resistance; by utilizing ecosystem services to the fullest extent for pest suppression, farmers can reduce losses due to pest damage while retaining the powerful advantages that chemical pesticides provide over pest insect populations for use in extreme or necessary cases. If farmers can reduce pesticide use to a minimal amount of application only applied when controlling a particularly persistent outbreak and otherwise employ mechanisms provided by cropping system and non-crop landscape dynamics, the total cost of pest control to the farmer would be reduced as well as the negative externalities caused by higher insecticide application rates which impact farmer health, pest resistance to insecticide, native ecosystem health, water quality, and public health.

The benefits of utilizing landscape factors for pest suppression could be significant. These benefits include additional information and support for potential risk reduction associated with important decisions that farmers regularly make regarding cropping and cultivation practices. Additionally, farmers could potentially reduce private costs of insecticide inputs to their system. Benefits of utilizing landscape characteristics for pest suppression extend beyond the private interests of the farmer as well: reduction in pesticide applications results in reduced externalities associated with the application of chemical pesticides which cause significant harm to people and natural systems in the vicinity of agricultural production. Additional benefits of a landscape which specifically harbors certain types of insects and suppresses others could result in reduced likelihood of pests developing resistance to pesticides, which benefits both farmers and society since resistance usually implies additional and more potent chemicals necessary to control pest outbreaks. Other benefits could include increased habitat not only for pest predators, but for economically important pollinator species which contribute to other ecosystem services aside from pest suppression. There are multiple private and social benefits involved if landscape scale processes could be better understood and harnessed for the ecosystem service of pest suppression.

However, there are also private and social costs associated as well. These costs include the steep information costs associated with farmers needing to understand and "read" the overall landscape for information on pest suppression. Additionally, there could be private costs involved in altering production systems to accommodate a particular landscape configuration, or taking marginal lands out of production in order to enhance a certain landscape characteristic.

The costs of maintaining a complex or optimal landscape could be significant for farmers in terms of information, time, and effort required. Social costs could include reduced efficiency gains and reduced economies of scale from production systems altered to accentuate landscape features. Similarly, there is an opportunity cost associated with lost production.

4.3 Future Directions

This study has several limitations which should be addressed by future research and investigation. Primarily, I use estimated pesticide application rates as a proxy for pest pressure. The underlying assumption here is that farmers are applying pesticides directly in response to pest outbreaks. This is not unreasonable, because pesticides are an expensive input and a profit-maximizing producer would try to minimize the use of this input, only applying pesticides when necessary. However, this is not guaranteed to be the case. A study designed specifically to answer this question which collects actual insect and predator data would be more effective for thoroughly understanding the pest suppressive capabilities of the landscape. Studies collecting actual insect data would need to occur over a large area to capture landscape effects, but also with an appropriate duration and frequency of observations to understand the temporal effects. A dependent variable collected with the same frequency as the landscape information is available would begin to truly inform us as to the nature of temporal landscape dynamics.

Scale is important to address in future studies as well, both spatial and temporal resolution could be important to understanding these landscape dynamics. Our landscape data is calculated from high temporal frequency but relatively low spatial resolution satellite data. The scale at which these processes are occurring will be very important to understand if we are to make policy or production suggestions based on these results.

In addition, it will be essential to translate the values of important landscape metrics involved into practical and economically feasible cropping and management decisions which can be reasonably employed by farmers. These quantitative descriptors must become better understood in terms of actual management decisions such as field size, field shape, planting and harvesting times, spatial arrangement of crops, and selection of crop types if farmers are to fully utilize this knowledge to enhance pest control services provided by the landscape.

While insecticide application and pest control is a very important issue to address in our modern agricultural system, this approach for understanding landscape configuration, composition, and connectivity could be useful for assessing many other impactful areas of research in which the landscape plays a key role. This is particularly important when examining ecosystem service provision. While it is often difficult to incorporate fine-resolution temporal data, the nature of change in all ecosystems and across landscapes necessitates this type of analysis and the inclusion of richer temporal information. This study contributes to the methodology for incorporating additional temporal information into ecological research.

There is concern over the general loss of crop diversity in the US, and the impact this loss of diversity will have for ecosystem service provision (Aguilar, et al., 2015). We cannot understand how these ecosystem services are being affected by diversity losses until we are able to accurately describe the spatial and temporal provisioning of these services. Moving forward, we must gain greater insight into the effects of diversity loss, as well as other powerful agents of change such as climate change and increased areas of land coming under agricultural production on the provision of necessary ecosystem services on which we all depend.

CHAPTER 5

CONCLUDING REMARKS

Pest control is an integral part of modern agricultural production. However, there is evidence that farmers could make better use of the landscape surrounding their crops in order to minimize their risk of pest outbreaks and reduce the need for chemical pesticide applications. This reduction of insecticide use has positive economic implications for farmers as well as positive biological implications for pollinators, surrounding ecosystems, and various people involved in the food system, all of which experience negative externalities from the application of pesticides.

Our study demonstrates that the landscape plays an important role in pesticide application rates. While it is difficult to pin down the spatial and temporal dynamics which are driving pest pressure, I have shown that certain landscape attributes at certain times during the growing season have a significant impact on pesticide use. In this study, pesticide application functions as a proxy for pest pressure; this dependent variable could be improved in future research looking at this relationship.

These methods for describing landscape complexity over time are useful not just for pesticide use or pest suppression, but could contribute to a better understanding of overall ecosystem service provisioning by the landscape. All agricultural systems exist within a landscape context, and understanding the fundamental impacts that this context has on agricultural production can inform future production decisions, facilitating an agricultural system which is both more resilient and more sustainable in the long run.

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APPENDIX A

LANDSCAPE METRICS

Here I provide a short description of each landscape metric which was included in the principal component analysis. Additionally, I report the descriptive statistics of each of the landscape metrics over all periods of time and units of area (Table 21).

Table 20: Descriptions of all Metrics Included in PCA

Landscape Metric, Abbreviation	Full Name	Description	Units
AREA	Patch Area Distribution	The distribution of the area of all patches	Hectares
CONTAG	Contagion	Describes how patches of the same type are dispersed and how connected these patches are; this measure increases with greater connection between patches of the same type	Percent
GYRATE	Area-Weighted Mean Patch Radius of Gyration	Describes the ease of movement across the landscape by an organism which must remain in the same patch type; a measure of continuity across the landscape	Meters
CONNECT	Connectance	The number of connections between patches of the same type throughout the landscape (reported as a percentage of the maximum possible number of connections)	Percent
TE	Total Edge	Total edge length of patches within the landscape	Kilometers
DIVISION	Landscape Division Index	Probability that two pixels randomly chosen from the landscape will occur in two different patches	Proportion

CWED	Contrast-Weighted Edge Density	Edge length is standardized to per-unit area, and weighted according to the contrast between adjoining patches, includes information on both edge density and edge contrast	Meters per hectare
SHDI	Shannon's Diversity Index	Measure of diversity of patches in the landscape, utilizing the distribution of and proportion of the landscape occupied by that patch type	None
PLADJ	Percentage of Like Adjacencies	The proportion of adjacent cells of the same type out of all possible cell adjacencies	Percent
NP	Number of Patches	Total number of patches in the landscape	None
CONTIG	Contiguity Index	Patch boundary configuration including the size and shape of each patch	None
AI	Aggregation Index	Ratio of like adjacencies to the maximum possible number of like adjacencies	Percent
FRAC	Fractal Dimension Index	Ratio of patch perimeter to area, adjusted to correct for bias	None
CORE	Core Area	Area internal to a patch, based on a specified distance from edge of patch	Hectares
ENN	Euclidean Nearest Neighbor Distance	Shortest edge to edge distance from a patch to the nearest patch of the same type	Meters
COHESION	Patch Cohesion Index	At the class level, represents physical connectedness of the class in question	None

Table 21: Descriptive Statistics of Landscape Metrics

	Median	Mean	Variance	Std. Deviation
NP	4.459E+04	8.019E+04	8.015E+09	8.953E+04
TE	9.168E+04	1.280E+05	1.622E+10	1.273E+05
AREA_AM	8.379E+03	2.278E+05	6.778E+11	8.233E+05
GYRATE_AM	2.984	10.130	308.320	17.559
GYRATE_CV	0.126	0.143	0.003	0.057
FRAC_MN	1.029	1.030	0.000	0.004
FRAC_CV	4.084	4.081	0.055	0.234
CONTIG_MN	0.144	0.151	0.001	0.032
CONTIG_AM	0.434	0.452	0.016	0.128
CORE_MN	3.628	10.862	372.193	19.292
CORE_AM	1.869E+03	1.227E+05	3.003E+11	5.480E+05
ENN_MN	687.876	706.137	4641.905	68.132
ENN_AM	560.860	559.260	229.204	15.139
ENN_CV	83.661	97.188	2091.189	45.730
CWED	6.784	7.104	8.548	2.924
CONTAG	32.182	35.410	247.975	15.747
PLADJ	45.995	47.386	163.185	12.774
CONNECT	0.008	0.036	0.005	0.073
COHESION	92.672	88.950	122.354	11.061
DIVISION	0.993	0.930	0.019	0.139
SHDI	1.716	1.620	0.156	0.395
AI	46.138	47.660	163.988	12.806

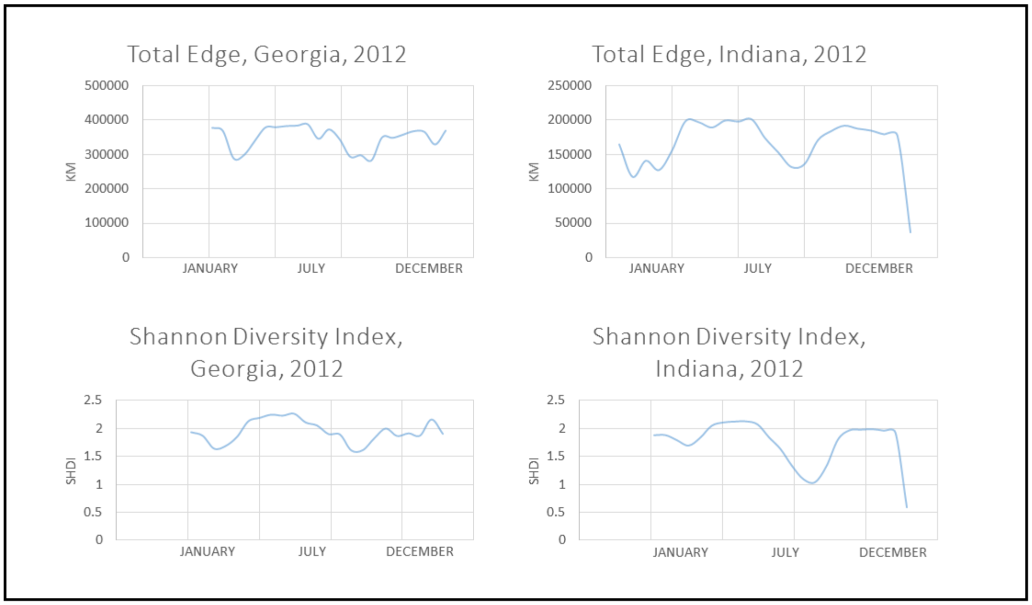

Figure 4: Comparing Metrics between States, 2012

Figure 4 provides a visual comparison of the range of values that two different landscape metrics might take throughout the calendar year, in two very different states. The metrics change in a somewhat similar cyclical pattern in both states, Georgia and Indiana, along with the growing season: in the case of total edge and Shannon's diversity index which are pictured here, dipping into lower values at the peak of the growing season. Values for total edge in Georgia are generally higher than in Indiana, which is expected because total edge is often considered a measure of spatial complexity, and the spatial landscape in Indiana is generally less complex than that of Georgia.

Figure 5 (below) displays several visualizations of the metrics total edge and Shannon's diversity index (SHDI), displaying an example of what maximum and minimum values for these metrics might look like in one particular landscape (south Georgia in this case). We can generally see a greater diversity of patch types across the landscape in both cases at the maximum values of total edge and SHDI.

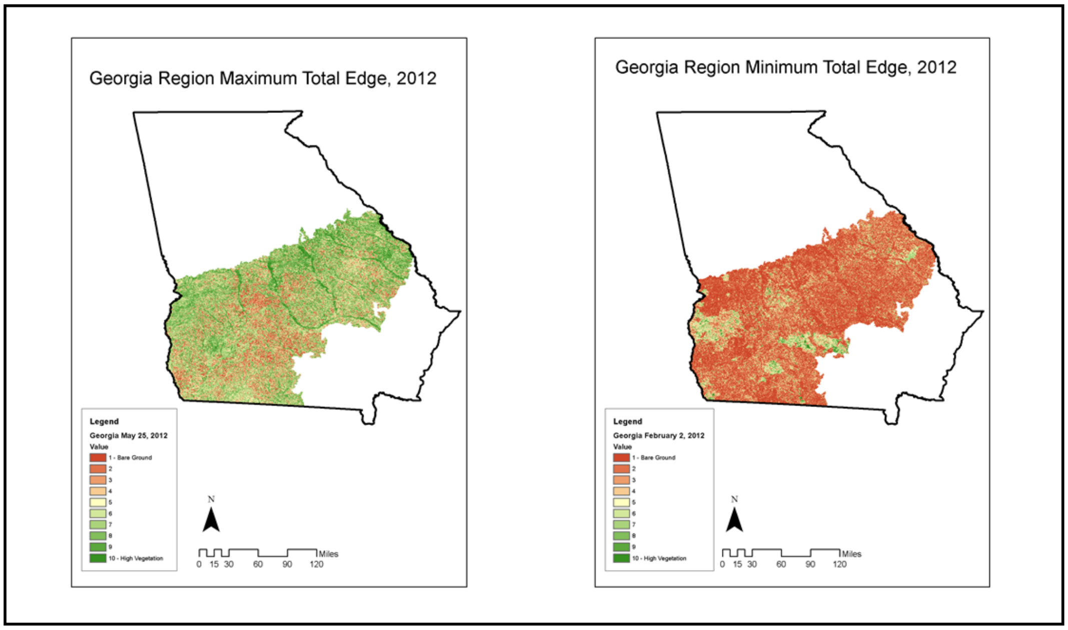

Figure 5: Total Edge Maximum and Minimum in Georgia, 2012

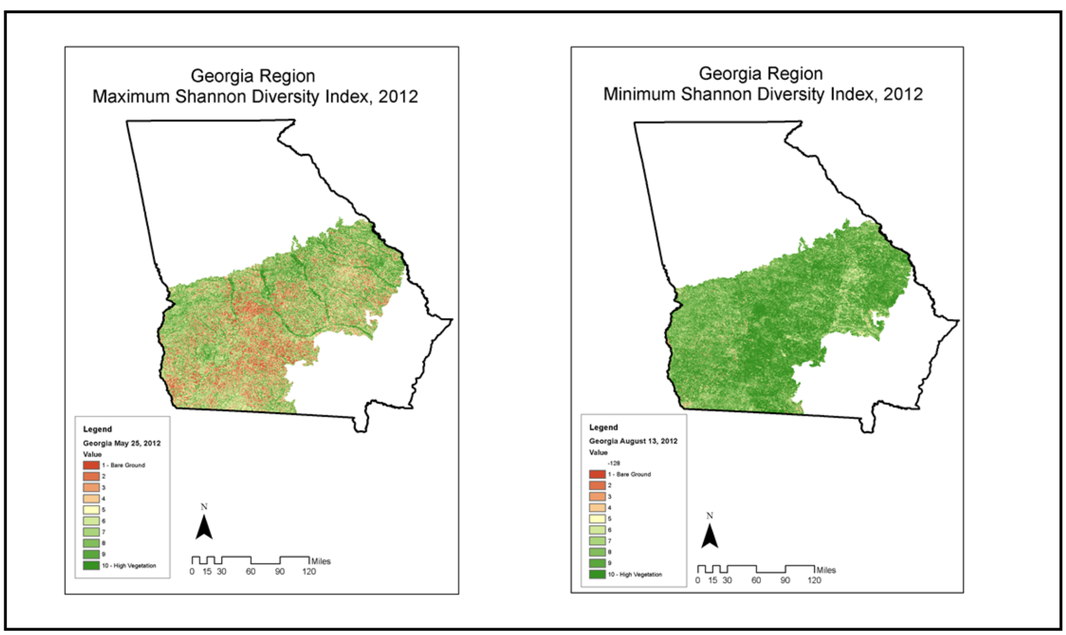

Figure 6: Shannon’s Diversity Index Minimum and Maximum in Georgia, 2012

APPENDIX B

DESCRIPTIVE STATISTICS

The following tables contain descriptive statistics for the dependent variable and all covariates included in the regressions reported in Chapter 3 (Results). Descriptive statistics are reported for the full dataset including all 22 state-regions, as well as separately for the Midwestern region (Table 23) and the Southeastern region (Table 24).

Table 22: Descriptive Statistics for Full Dataset

	Median	Mean	Variance	Std. Deviation
KG per HECTARE	0.02	40.17	164418.18	405.49
INCOMEPERCULTIVATEDHECTARE	0.34	-65.89	257117.50	507.07
PDSI	0.68	-0.09	4.61	2.15
ECOREGION	835.00	860.41	1864.92	43.18
PROPORTION_NONCROP	1.00	1.00	0.00	0.00
PROPORTION_CORN	0.39	0.37	0.04	0.19
PROPORTION_FRUITVEG	0.00	0.01	0.00	0.01
PROPORTION_COTTON	0.12	0.14	0.01	0.12
PROPORTION_SOYSMALLGRAIN	0.41	0.38	0.02	0.16
PRICE_CORN	4.78	5.01	1.37	1.17
PRICE_COTTON	0.71	0.70	0.02	0.14
PRICE_SOYBEANS	11.30	11.57	2.33	1.53
TE_81	83764.00	122219.93	14333045493.85	119720.70
TE_113	129956.00	147543.49	18829087553.28	137219.12
TE_145	130788.50	149035.11	18941474019.94	137628.03
TE_177	123145.13	139653.02	17063701956.43	130628.11
TE_209	76501.25	104848.74	11449547799.10	107002.56
TE_241	110922.88	129183.10	14773767664.21	121547.39
TE_273	123483.50	143315.96	17397457165.13	131899.42
AREA_AM_81	41471.42	273065.46	457679326707.00	676520.01
AREA_AM_113	1836.67	30747.65	13493442232.60	116161.28
AREA_AM_145	2286.44	31428.95	26537821503.96	162904.33
AREA_AM_177	16943.91	128923.10	163134402983.56	403899.00
AREA_AM_209	97676.74	906612.89	3297467898497.15	1815893.14
AREA_AM_241	45947.65	278152.79	421021139204.90	648861.42

AREA_AM_273	3348.79	16180.76	1722912577.35	41507.98
CONTAG_81	40.31	38.08	276.38	16.62
CONTAG_113	25.21	26.18	111.31	10.55
CONTAG_145	25.79	24.49	70.28	8.38
CONTAG_177	36.46	35.90	205.48	14.33
CONTAG_209	53.30	50.77	372.59	19.30
CONTAG_241	38.56	41.84	166.84	12.92
CONTAG_273	30.37	30.52	59.16	7.69
GYRATE_AM_81	6.33	12.77	280.94	16.76
GYRATE_AM_113	1.54	3.50	37.89	6.16
GYRATE_AM_145	1.51	3.21	37.28	6.11
GYRATE_AM_177	4.18	8.77	164.99	12.84
GYRATE_AM_209	12.85	27.17	916.27	30.27
GYRATE_AM_241	8.44	14.82	337.68	18.38
GYRATE_AM_273	2.04	3.11	12.15	3.49
CONNECT_81	0.01	0.03	0.00	0.04
CONNECT_113	0.01	0.02	0.00	0.03
CONNECT_145	0.01	0.02	0.00	0.03
CONNECT_177	0.01	0.03	0.00	0.04
CONNECT_209	0.01	0.02	0.00	0.03
CONNECT_241	0.01	0.03	0.00	0.04
CONNECT_273	0.01	0.02	0.00	0.04
CONTIG_AM_81	0.49	0.49	0.02	0.16
CONTIG_AM_113	0.39	0.39	0.01	0.10
CONTIG_AM_145	0.40	0.39	0.01	0.08
CONTIG_AM_177	0.46	0.44	0.01	0.10
CONTIG_AM_209	0.55	0.56	0.02	0.16
CONTIG_AM_241	0.45	0.48	0.01	0.10
CONTIG_AM_273	0.42	0.42	0.01	0.08
PLADJ_81	51.53	51.38	252.72	15.90
PLADJ_113	41.97	41.81	109.72	10.47
PLADJ_145	42.52	41.37	68.15	8.26
PLADJ_177	47.93	45.83	104.06	10.20
PLADJ_209	57.01	58.02	232.06	15.23
PLADJ_241	47.53	49.53	106.26	10.31
PLADJ_273	44.73	44.00	79.04	8.89
CORE_AM_81	13545.46	159737.88	200802902453.23	448110.37
CORE_AM_113	406.02	9787.58	1378944983.52	37134.15
CORE_AM_145	519.15	12824.85	5698513701.36	75488.50
CORE_AM_177	3295.31	41979.75	28582821580.46	169064.55
CORE_AM_209	41041.54	579706.12	1663481495998.84	1289760.25
CORE_AM_241	9307.15	88035.29	51254929936.37	226395.52
CORE_AM_273	583.81	4940.85	201819591.75	14206.32

AI_81	51.71	51.63	254.26	15.95
AI_113	42.41	42.06	110.58	10.52
AI_145	42.88	41.61	68.78	8.29
AI_177	48.19	46.06	104.83	10.24
AI_209	57.35	58.25	232.40	15.24
AI_241	47.78	49.76	107.00	10.34
AI_273	44.87	44.25	80.14	8.95
GYRATE_CV_81	0.15	0.16	0.00	0.07
GYRATE_CV_113	0.11	0.11	0.00	0.03
GYRATE_CV_145	0.10	0.11	0.00	0.02
GYRATE_CV_177	0.14	0.14	0.00	0.05
GYRATE_CV_209	0.20	0.19	0.00	0.07
GYRATE_CV_241	0.15	0.17	0.00	0.06
GYRATE_CV_273	0.12	0.12	0.00	0.03
ENN_MN_81	709.05	739.85	10383.34	101.90
ENN_MN_113	662.45	676.38	2136.30	46.22
ENN_MN_145	659.87	663.34	792.13	28.14
ENN_MN_177	692.28	691.25	1668.34	40.85
ENN_MN_209	754.60	757.91	5811.43	76.23
ENN_MN_241	708.24	719.09	2974.79	54.54
ENN_MN_273	682.45	693.31	1758.84	41.94
CORE_MN_81	6.85	21.08	908.68	30.14
CORE_MN_113	2.19	3.94	23.83	4.88
CORE_MN_145	2.21	2.95	6.80	2.61
CORE_MN_177	5.14	6.57	41.92	6.47
CORE_MN_209	13.34	27.42	861.17	29.35
CORE_MN_241	4.69	10.10	109.94	10.49
CORE_MN_273	3.04	4.45	22.38	4.73
ENN_CV_81	97.47	111.83	3261.27	57.11
ENN_CV_113	71.75	77.20	858.69	29.30
ENN_CV_145	67.31	69.72	478.63	21.88
ENN_CV_177	90.26	102.60	2602.81	51.02
ENN_CV_209	125.93	125.50	3019.28	54.95
ENN_CV_241	93.64	108.09	1746.51	41.79
ENN_CV_273	81.18	87.75	810.41	28.47
COHESION_81	96.33	90.11	150.65	12.27
COHESION_113	86.64	82.62	167.31	12.93
COHESION_145	85.87	83.53	130.60	11.43
COHESION_177	94.96	89.51	125.97	11.22
COHESION_209	98.43	95.76	34.69	5.89
COHESION_241	97.22	94.01	56.55	7.52
COHESION_273	89.83	87.69	66.80	8.17
CONTIG_MN_81	0.17	0.16	0.00	0.04

CONTIG_MN_113	0.16	0.16	0.00	0.03
CONTIG_MN_145	0.16	0.15	0.00	0.03
CONTIG_MN_177	0.15	0.15	0.00	0.03
CONTIG_MN_209	0.13	0.13	0.00	0.01
CONTIG_MN_241	0.14	0.14	0.00	0.02
CONTIG_MN_273	0.17	0.16	0.00	0.04
ENN_AM_81	558.86	559.59	255.56	15.99
ENN_AM_113	568.78	567.96	77.43	8.80
ENN_AM_145	569.48	570.15	68.12	8.25
ENN_AM_177	555.05	555.89	223.79	14.96
ENN_AM_209	544.90	547.36	279.09	16.71
ENN_AM_241	552.32	550.29	177.86	13.34
ENN_AM_273	563.05	563.06	64.12	8.01
FRAC_CV_81	4.09	4.09	0.05	0.22
FRAC_CV_113	4.04	4.02	0.06	0.24
FRAC_CV_145	3.96	3.94	0.05	0.21
FRAC_CV_177	4.19	4.14	0.06	0.24
FRAC_CV_209	4.00	3.99	0.06	0.24
FRAC_CV_241	4.12	4.12	0.02	0.15
FRAC_CV_273	4.22	4.24	0.04	0.19
FRAC_MN_81	1.03	1.03	0.00	0.00
FRAC_MN_113	1.03	1.03	0.00	0.00
FRAC_MN_145	1.03	1.03	0.00	0.00
FRAC_MN_177	1.03	1.03	0.00	0.00
FRAC_MN_209	1.03	1.03	0.00	0.00
FRAC_MN_241	1.03	1.03	0.00	0.00
FRAC_MN_273	1.03	1.03	0.00	0.00
NP_81	41930.00	77070.45	8934578912.58	94522.90
NP_113	74341.50	101439.38	10176014103.03	100876.23
NP_145	87913.00	105221.27	10128654499.65	100641.22
NP_177	54583.00	85343.43	8358354883.86	91424.04
NP_209	34441.00	61568.06	5311618454.65	72880.85
NP_241	40781.00	70211.81	5659927199.09	75232.49
NP_273	53762.50	85473.95	6958046183.27	83414.90
DIVISION_81	0.97	0.93	0.01	0.10
DIVISION_113	1.00	0.99	0.00	0.03
DIVISION_145	1.00	0.99	0.00	0.03
DIVISION_177	0.99	0.96	0.01	0.07
DIVISION_209	0.87	0.76	0.06	0.25
DIVISION_241	0.96	0.91	0.01	0.11
DIVISION_273	1.00	0.99	0.00	0.03
CWED_81	6.09	6.48	11.18	3.34
CWED_113	7.68	8.30	8.57	2.93

CWED_145	7.75	8.67	7.11	2.67
CWED_177	6.44	7.34	8.23	2.87
CWED_209	4.69	5.48	8.78	2.96
CWED_241	6.33	6.36	5.70	2.39
CWED_273	6.76	7.28	4.89	2.21
SHDI_81	1.58	1.58	0.15	0.39
SHDI_113	1.89	1.88	0.05	0.23
SHDI_145	1.91	1.91	0.04	0.20
SHDI_177	1.60	1.58	0.13	0.36
SHDI_209	1.15	1.22	0.23	0.48
SHDI_241	1.53	1.43	0.10	0.32
SHDI_273	1.78	1.77	0.03	0.18

Table 23: Descriptive Statistics for Midwestern United States

	Median	Mean	Variance	Std. Deviation
KG per HECTARE	0.01	0.02	0.00	0.02
INCOMEPERCULTIVATEDHECTARE	0.48	0.49	0.07	0.27
PDSI	1.57	1.43	0.67	0.82
ECOREGION	923.00	881.58	2442.28	49.42
PROPORTION_NONCROP	1.00	1.00	0.00	0.00
PROPORTION_CORN	0.52	0.51	0.01	0.08
PROPORTION_FRUITVEG	0.00	0.00	0.00	0.01
PROPORTION_COTTON	0.00	0.00	0.00	0.00
PROPORTION_SOYSMALLGRAIN	0.43	0.44	0.01	0.09
PRICE_CORN	4.78	5.01	1.38	1.18
PRICE_COTTON	0.71	0.70	0.02	0.14
PRICE_SOYBEANS	11.30	11.57	2.35	1.53
TE_81	64837.88	88334.54	7067034701.46	84065.66
TE_113	89375.13	124096.44	15195282268.83	123269.15
TE_145	105583.63	133769.18	17828675078.82	133524.06
TE_177	82431.00	119073.31	14331629363.91	119714.78
TE_209	46059.63	69948.64	4774373746.33	69096.84
TE_241	82746.13	108766.19	11891041448.79	109046.05
TE_273	89081.13	123998.64	14596944308.55	120817.81
AREA_AM_81	82996.24	434480.64	742104370772.99	861454.80
AREA_AM_113	3705.52	54509.22	23647895584.01	153778.72
AREA_AM_145	3211.36	14734.65	1014343133.66	31848.75
AREA_AM_177	37090.19	222266.98	280303638301.74	529437.10
AREA_AM_209	625825.94	1614148.54	4965898272806.44	2228429.55
AREA_AM_241	145297.34	491174.86	675449750300.98	821857.50
AREA_AM_273	4815.01	25444.13	2914670047.26	53987.68

CONTAG_81	50.30	48.49	171.50	13.10
CONTAG_113	30.81	31.99	70.63	8.40
CONTAG_145	26.90	27.42	21.79	4.67
CONTAG_177	47.59	46.02	70.65	8.41
CONTAG_209	68.13	65.56	122.88	11.09
CONTAG_241	51.89	50.78	93.65	9.68
CONTAG_273	33.52	34.23	42.82	6.54
GYRATE_AM_81	12.52	18.76	356.52	18.88
GYRATE_AM_113	1.95	5.44	60.40	7.77
GYRATE_AM_145	1.76	2.79	6.59	2.57
GYRATE_AM_177	8.23	13.84	237.24	15.40
GYRATE_AM_209	42.47	44.18	1015.84	31.87
GYRATE_AM_241	15.76	23.82	434.87	20.85
GYRATE_AM_273	2.45	4.10	17.29	4.16
CONNECT_81	0.01	0.04	0.00	0.05
CONNECT_113	0.01	0.03	0.00	0.04
CONNECT_145	0.01	0.02	0.00	0.03
CONNECT_177	0.01	0.03	0.00	0.05
CONNECT_209	0.01	0.03	0.00	0.03
CONNECT_241	0.01	0.03	0.00	0.04
CONNECT_273	0.01	0.03	0.00	0.04
CONTIG_AM_81	0.61	0.60	0.01	0.11
CONTIG_AM_113	0.46	0.46	0.00	0.07
CONTIG_AM_145	0.43	0.43	0.00	0.05
CONTIG_AM_177	0.51	0.51	0.00	0.06
CONTIG_AM_209	0.70	0.68	0.01	0.10
CONTIG_AM_241	0.56	0.55	0.01	0.07
CONTIG_AM_273	0.47	0.48	0.00	0.05
PLADJ_81	64.19	62.69	118.23	10.87
PLADJ_113	49.40	49.29	44.08	6.64
PLADJ_145	45.62	46.43	21.65	4.65
PLADJ_177	53.69	53.16	29.62	5.44
PLADJ_209	71.16	69.43	98.83	9.94
PLADJ_241	57.84	56.89	49.93	7.07
PLADJ_273	50.12	50.36	30.73	5.54
CORE_AM_81	33599.35	265309.59	337088860003.59	580593.54
CORE_AM_113	1117.31	17567.37	2411261921.12	49104.60
CORE_AM_145	756.68	5058.12	146786395.88	12115.54
CORE_AM_177	10438.18	71107.41	50508771332.45	224741.57
CORE_AM_209	405379.40	1045311.22	2586911817361.47	1608387.96
CORE_AM_241	33927.04	155885.38	84280684874.19	290311.36
CORE_AM_273	1016.12	8128.01	341074920.56	18468.21
AI_81	64.63	62.98	118.06	10.87

AI_113	49.82	49.58	43.46	6.59
AI_145	46.21	46.71	21.30	4.62
AI_177	53.90	53.41	29.65	5.45
AI_209	71.43	69.68	98.19	9.91
AI_241	58.13	57.14	50.15	7.08
AI_273	50.32	50.65	30.73	5.54
GYRATE_CV_81	0.20	0.20	0.00	0.06
GYRATE_CV_113	0.12	0.13	0.00	0.03
GYRATE_CV_145	0.11	0.11	0.00	0.02
GYRATE_CV_177	0.17	0.17	0.00	0.04
GYRATE_CV_209	0.24	0.24	0.00	0.05
GYRATE_CV_241	0.20	0.21	0.00	0.05
GYRATE_CV_273	0.13	0.13	0.00	0.02
ENN_MN_81	810.91	807.68	7772.62	88.16
ENN_MN_113	691.81	698.86	1938.55	44.03
ENN_MN_145	664.01	666.11	351.17	18.74
ENN_MN_177	710.33	710.71	902.41	30.04
ENN_MN_209	802.36	803.81	4589.32	67.74
ENN_MN_241	741.12	744.90	3131.92	55.96
ENN_MN_273	697.48	710.59	1653.54	40.66
CORE_MN_81	27.16	36.49	1140.53	33.77
CORE_MN_113	4.91	6.35	29.87	5.47
CORE_MN_145	3.01	3.89	6.33	2.52
CORE_MN_177	8.96	10.21	42.74	6.54
CORE_MN_209	44.58	46.25	776.61	27.87
CORE_MN_241	14.17	16.24	116.47	10.79
CORE_MN_273	5.38	6.82	25.42	5.04
ENN_CV_81	138.97	146.00	3031.37	55.06
ENN_CV_113	89.13	93.28	692.47	26.31
ENN_CV_145	77.71	80.23	418.77	20.46
ENN_CV_177	124.14	133.67	2079.99	45.61
ENN_CV_209	154.04	161.44	2031.68	45.07
ENN_CV_241	128.42	134.46	1431.53	37.84
ENN_CV_273	99.54	105.02	710.75	26.66
COHESION_81	98.51	96.24	35.39	5.95
COHESION_113	89.35	90.46	36.04	6.00
COHESION_145	87.39	87.95	36.47	6.04
COHESION_177	98.25	96.54	12.31	3.51
COHESION_209	99.56	98.87	5.68	2.38
COHESION_241	98.95	97.95	8.65	2.94
COHESION_273	91.50	91.72	18.89	4.35
CONTIG_MN_81	0.20	0.19	0.00	0.02
CONTIG_MN_113	0.18	0.18	0.00	0.02

CONTIG_MN_145	0.18	0.18	0.00	0.02
CONTIG_MN_177	0.17	0.17	0.00	0.01
CONTIG_MN_209	0.14	0.14	0.00	0.01
CONTIG_MN_241	0.15	0.16	0.00	0.02
CONTIG_MN_273	0.19	0.19	0.00	0.02
ENN_AM_81	553.24	556.05	400.60	20.02
ENN_AM_113	568.18	566.90	68.24	8.26
ENN_AM_145	568.68	569.18	60.98	7.81
ENN_AM_177	544.40	546.15	132.73	11.52
ENN_AM_209	534.87	535.36	71.17	8.44
ENN_AM_241	541.03	541.89	129.46	11.38
ENN_AM_273	561.40	561.84	79.29	8.90
FRAC_CV_81	4.15	4.16	0.03	0.17
FRAC_CV_113	4.07	4.09	0.04	0.20
FRAC_CV_145	4.04	4.04	0.03	0.17
FRAC_CV_177	4.29	4.31	0.02	0.13
FRAC_CV_209	3.97	3.97	0.08	0.29
FRAC_CV_241	4.15	4.16	0.02	0.15
FRAC_CV_273	4.37	4.36	0.02	0.13
FRAC_MN_81	1.03	1.03	0.00	0.00
FRAC_MN_113	1.03	1.03	0.00	0.00
FRAC_MN_145	1.03	1.03	0.00	0.00
FRAC_MN_177	1.03	1.03	0.00	0.00
FRAC_MN_209	1.03	1.03	0.00	0.00
FRAC_MN_241	1.03	1.03	0.00	0.00
FRAC_MN_273	1.04	1.04	0.00	0.00
NP_81	20671.00	34907.37	1508636371.80	38841.17
NP_113	39197.00	65273.10	3971492115.21	63019.78
NP_145	64669.50	76461.57	5225057706.66	72284.56
NP_177	33325.50	48469.43	2292720063.98	47882.36
NP_209	26039.00	29370.78	741789371.70	27235.81
NP_241	32361.00	42134.48	1974424915.58	44434.50
NP_273	34803.00	56701.57	2789424525.16	52815.00
DIVISION_81	0.91	0.89	0.01	0.11
DIVISION_113	0.99	0.99	0.00	0.04
DIVISION_145	1.00	0.99	0.00	0.01
DIVISION_177	0.95	0.93	0.01	0.08
DIVISION_209	0.56	0.58	0.05	0.22
DIVISION_241	0.85	0.85	0.01	0.11
DIVISION_273	1.00	0.99	0.00	0.02
CWED_81	3.56	3.98	2.70	1.64
CWED_113	6.09	6.23	1.68	1.30
CWED_145	6.88	6.88	0.98	0.99

CWED_177	5.06	5.13	0.92	0.96
CWED_209	2.91	3.20	1.49	1.22
CWED_241	4.20	4.54	1.27	1.13
CWED_273	5.70	5.61	0.92	0.96
SHDI_81	1.27	1.36	0.12	0.35
SHDI_113	1.80	1.79	0.05	0.23
SHDI_145	1.90	1.88	0.02	0.14
SHDI_177	1.30	1.34	0.06	0.24
SHDI_209	0.79	0.85	0.08	0.28
SHDI_241	1.21	1.22	0.07	0.26
SHDI_273	1.73	1.74	0.04	0.19

Table 24: Descriptive Statistics for Southeastern United States

	Median	Mean	Variance	Std. Deviation
KG per HECTARE	0.05	84.33	345169.77	587.51
INCOMEPERCULTIVATEDHECTARE	0.27	-138.90	535332.97	731.66
PDSI	-1.35	-1.90	3.27	1.81
ECOREGION	835.00	835.00	0.00	0.00
PROPORTION_NONCROP	1.00	1.00	0.00	0.00
PROPORTION_CORN	0.20	0.21	0.03	0.16
PROPORTION_FRUITVEG	0.01	0.01	0.00	0.02
PROPORTION_COTTON	0.13	0.15	0.01	0.11
PROPORTION_SOYSMALLGRAIN	0.30	0.31	0.03	0.18
PRICE_CORN	4.78	5.01	1.39	1.18
PRICE_COTTON	0.71	0.70	0.02	0.14
PRICE_SOYBEANS	11.30	11.57	2.36	1.54
TE_81	116954.13	162882.41	20281262407.41	142412.30
TE_113	133672.38	175679.95	22107755629.54	148686.77
TE_145	130788.50	167354.23	20040130856.97	141563.17
TE_177	126612.75	164348.68	19560656129.37	139859.42
TE_209	110944.50	146728.87	16439477271.37	128216.52
TE_241	116727.13	153683.39	17423367356.22	131997.60
TE_273	126046.75	166496.75	20119308944.66	141842.55
AREA_AM_81	3071.62	79367.24	54360144600.92	233152.62
AREA_AM_113	382.88	2233.77	21032053.40	4586.07
AREA_AM_145	1530.00	51462.11	57060978522.10	238874.40
AREA_AM_177	1967.70	16910.46	1910385209.83	43707.95
AREA_AM_209	23209.98	57570.10	7263620632.00	85226.88
AREA_AM_241	10410.27	22526.31	1016734803.33	31886.28
AREA_AM_273	1932.51	5064.73	91939349.40	9588.50
CONTAG_81	24.61	25.57	115.84	10.76

CONTAG_113	19.43	19.22	71.76	8.47
CONTAG_145	21.14	20.98	106.98	10.34
CONTAG_177	20.84	23.77	96.44	9.82
CONTAG_209	31.37	33.02	91.53	9.57
CONTAG_241	32.08	31.13	43.48	6.59
CONTAG_273	25.17	26.07	42.95	6.55
GYRATE_AM_81	1.69	5.59	99.21	9.96
GYRATE_AM_113	0.69	1.16	1.35	1.16
GYRATE_AM_145	1.27	3.71	74.53	8.63
GYRATE_AM_177	1.31	2.69	12.24	3.50
GYRATE_AM_209	4.64	6.75	35.03	5.92
GYRATE_AM_241	3.18	4.03	9.64	3.10
GYRATE_AM_273	1.28	1.91	3.54	1.88
CONNECT_81	0.00	0.02	0.00	0.03
CONNECT_113	0.00	0.02	0.00	0.02
CONNECT_145	0.00	0.01	0.00	0.02
CONNECT_177	0.01	0.02	0.00	0.02
CONNECT_209	0.01	0.02	0.00	0.03
CONNECT_241	0.01	0.02	0.00	0.02
CONNECT_273	0.01	0.02	0.00	0.02
CONTIG_AM_81	0.36	0.36	0.01	0.09
CONTIG_AM_113	0.31	0.31	0.00	0.06
CONTIG_AM_145	0.33	0.33	0.01	0.07
CONTIG_AM_177	0.33	0.35	0.01	0.07
CONTIG_AM_209	0.42	0.42	0.00	0.07
CONTIG_AM_241	0.38	0.39	0.00	0.05
CONTIG_AM_273	0.35	0.35	0.00	0.05
PLADJ_81	37.73	37.80	75.18	8.67
PLADJ_113	32.57	32.84	40.43	6.36
PLADJ_145	34.74	35.29	56.55	7.52
PLADJ_177	35.24	37.04	51.10	7.15
PLADJ_209	44.03	44.32	46.32	6.81
PLADJ_241	40.15	40.70	30.34	5.51
PLADJ_273	36.45	36.37	29.88	5.47
CORE_AM_81	697.33	33051.83	10777196964.75	103813.28
CORE_AM_113	59.88	451.83	1045489.89	1022.49
CORE_AM_145	293.98	22144.93	12337042312.13	111072.24
CORE_AM_177	386.26	7026.57	479971243.73	21908.25
CORE_AM_209	7951.31	20980.01	1543999969.87	39293.77
CORE_AM_241	2143.84	6615.19	133617415.23	11559.30
CORE_AM_273	315.18	1116.27	10899296.62	3301.41
AI_81	37.94	38.00	76.11	8.72
AI_113	32.79	33.04	41.41	6.44

AI_145	34.95	35.49	57.28	7.57
AI_177	35.33	37.24	51.88	7.20
AI_209	44.13	44.54	46.85	6.84
AI_241	40.26	40.90	30.78	5.55
AI_273	36.52	36.56	30.76	5.55
GYRATE_CV_81	0.10	0.11	0.00	0.03
GYRATE_CV_113	0.09	0.09	0.00	0.02
GYRATE_CV_145	0.10	0.10	0.00	0.03
GYRATE_CV_177	0.10	0.11	0.00	0.03
GYRATE_CV_209	0.13	0.14	0.00	0.04
GYRATE_CV_241	0.12	0.13	0.00	0.02
GYRATE_CV_273	0.10	0.11	0.00	0.02
ENN_MN_81	647.46	658.45	1343.56	36.65
ENN_MN_113	643.47	649.41	1056.53	32.50
ENN_MN_145	652.97	660.02	1318.58	36.31
ENN_MN_177	651.66	667.90	1604.61	40.06
ENN_MN_209	693.16	702.84	1727.37	41.56
ENN_MN_241	683.99	688.11	1051.17	32.42
ENN_MN_273	664.87	672.58	1117.33	33.43
CORE_MN_81	1.57	2.60	8.82	2.97
CORE_MN_113	0.68	1.06	1.48	1.22
CORE_MN_145	1.12	1.83	5.14	2.27
CORE_MN_177	1.44	2.21	6.12	2.47
CORE_MN_209	3.40	4.82	25.36	5.04
CORE_MN_241	2.28	2.73	2.74	1.66
CORE_MN_273	1.21	1.60	4.03	2.01
ENN_CV_81	66.57	70.83	459.23	21.43
ENN_CV_113	57.27	57.92	380.67	19.51
ENN_CV_145	56.30	57.11	262.78	16.21
ENN_CV_177	57.99	65.32	685.65	26.18
ENN_CV_209	77.12	82.38	790.90	28.12
ENN_CV_241	74.04	76.45	288.47	16.98
ENN_CV_273	64.62	67.02	143.23	11.97
COHESION_81	87.29	82.77	191.57	13.84
COHESION_113	72.13	73.21	163.21	12.78
COHESION_145	81.52	78.21	193.81	13.92
COHESION_177	82.72	81.07	132.13	11.49
COHESION_209	94.20	92.03	44.30	6.66
COHESION_241	92.87	89.28	73.48	8.57
COHESION_273	83.19	82.86	82.10	9.06
CONTIG_MN_81	0.12	0.12	0.00	0.01
CONTIG_MN_113	0.12	0.12	0.00	0.01
CONTIG_MN_145	0.12	0.12	0.00	0.01

CONTIG_MN_177	0.12	0.12	0.00	0.01
CONTIG_MN_209	0.12	0.12	0.00	0.01
CONTIG_MN_241	0.12	0.12	0.00	0.01
CONTIG_MN_273	0.12	0.12	0.00	0.01
ENN_AM_81	563.20	563.83	52.48	7.24
ENN_AM_113	571.98	569.24	87.03	9.33
ENN_AM_145	571.73	571.31	75.61	8.70
ENN_AM_177	569.31	567.58	82.45	9.08
ENN_AM_209	560.17	561.75	147.67	12.15
ENN_AM_241	560.00	560.39	49.27	7.02
ENN_AM_273	563.92	564.52	43.19	6.57
FRAC_CV_81	4.01	4.00	0.05	0.23
FRAC_CV_113	3.93	3.92	0.06	0.24
FRAC_CV_145	3.84	3.83	0.04	0.20
FRAC_CV_177	3.92	3.93	0.03	0.17
FRAC_CV_209	4.02	4.01	0.03	0.17
FRAC_CV_241	4.07	4.07	0.02	0.13
FRAC_CV_273	4.09	4.09	0.02	0.14
FRAC_MN_81	1.03	1.03	0.00	0.00
FRAC_MN_113	1.03	1.03	0.00	0.00
FRAC_MN_145	1.03	1.03	0.00	0.00
FRAC_MN_177	1.03	1.03	0.00	0.00
FRAC_MN_209	1.03	1.03	0.00	0.00
FRAC_MN_241	1.03	1.03	0.00	0.00
FRAC_MN_273	1.03	1.03	0.00	0.00
NP_81	92463.50	127666.16	13269382168.26	115192.80
NP_113	127819.00	144838.92	14330847148.56	119711.52
NP_145	118338.00	139732.92	14011530700.69	118370.31
NP_177	108837.50	129592.22	12169610814.95	110315.96
NP_209	76394.50	100204.80	8129817903.06	90165.50
NP_241	81357.50	103904.60	8089400273.84	89941.09
NP_273	99639.00	120000.82	9889280547.58	99444.86
DIVISION_81	1.00	0.97	0.00	0.06
DIVISION_113	1.00	1.00	0.00	0.01
DIVISION_145	1.00	0.98	0.00	0.05
DIVISION_177	1.00	0.99	0.00	0.04
DIVISION_209	0.99	0.97	0.00	0.05
DIVISION_241	1.00	0.98	0.00	0.04
DIVISION_273	1.00	0.99	0.00	0.04
CWED_81	9.48	9.48	4.80	2.19
CWED_113	10.52	10.79	5.46	2.34
CWED_145	10.27	10.83	5.96	2.44
CWED_177	10.43	9.98	4.12	2.03

CWED_209	8.16	8.22	3.72	1.93
CWED_241	8.43	8.56	2.16	1.47
CWED_273	9.38	9.28	2.28	1.51
SHDI_81	1.89	1.84	0.07	0.26
SHDI_113	1.96	1.98	0.04	0.19
SHDI_145	1.98	1.94	0.06	0.24
SHDI_177	1.93	1.87	0.06	0.23
SHDI_209	1.68	1.66	0.06	0.24
SHDI_241	1.64	1.68	0.02	0.15
SHDI_273	1.80	1.80	0.02	0.16

APPENDIX C

FULL MODEL RESULTS

Tables 25 and 26 contain the full model results of the most extensive model described in Chapter 3 (Results), which contains observations of each of the eight important metrics at each of seven monthly dates throughout the growing season. Table 25 displays the results of the iteration in which net farm income per harvested hectare is not included, while Table 6 displays results of the regression with the farm income covariate included.

Table 25: Model Results, all Important Metrics, Income not Included

	F(86,23)	Prob > P	R-Squared	Adj-R2
	8.30414595	2.30E-07	0.96879903	0.85213453
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-1.75E+06	4.90E+05	-3.58E+00	1.58E-03
YEAR	2.21E+02	9.05E+01	2.44E+00	2.28E-02
STATE Florida	2.97E+02	9.65E+02	3.08E-01	7.61E-01
STATE Georgia	1.17E+02	3.98E+02	2.94E-01	7.71E-01
STATE Illinois	-1.47E+03	8.12E+02	-1.81E+00	8.34E-02
STATE Indiana	-1.33E+03	9.61E+02	-1.39E+00	1.79E-01
STATE Iowa	-6.32E+01	1.38E+03	-4.59E-02	9.64E-01
STATE Kansas	-1.78E+03	1.14E+03	-1.57E+00	1.31E-01
STATE Louisiana	9.64E+02	1.09E+03	8.81E-01	3.88E-01
STATE Maryland	2.62E+03	1.20E+03	2.18E+00	3.98E-02
STATE Michigan	1.20E+03	1.18E+03	1.02E+00	3.21E-01
STATE Minnesota	-1.07E+03	8.24E+02	-1.30E+00	2.07E-01
STATE Mississippi	-4.67E+01	3.26E+02	-1.43E-01	8.87E-01
STATE Missouri	-1.41E+03	1.21E+03	-1.17E+00	2.56E-01
STATE Nebraska	-1.46E+03	9.43E+02	-1.55E+00	1.34E-01
STATE North Carolina	-2.30E+02	1.00E+03	-2.30E-01	8.20E-01
STATE Ohio	-8.77E+02	9.41E+02	-9.33E-01	3.61E-01
STATE South Carolina	-2.78E+02	9.56E+02	-2.91E-01	7.74E-01
STATE South Dakota	-1.06E+02	1.05E+03	-1.01E-01	9.21E-01
STATE Tennessee	-2.22E+02	1.09E+03	-2.03E-01	8.41E-01

STATE Virginia	-2.56E+02	1.11E+03	-2.30E-01	8.20E-01
STATE Wisconsin	1.27E+03	1.40E+03	9.09E-01	3.73E-01
TE_81	8.18E-03	4.13E-03	1.98E+00	5.96E-02
TE_113	3.82E-03	6.62E-03	5.77E-01	5.69E-01
TE_145	-4.12E-03	6.16E-03	-6.69E-01	5.10E-01
TE_177	-1.31E-02	4.77E-03	-2.74E+00	1.17E-02
TE_209	-5.10E-03	4.36E-03	-1.17E+00	2.54E-01
TE_241	-3.25E-04	4.54E-03	-7.15E-02	9.44E-01
TE_273	9.12E-03	6.55E-03	1.39E+00	1.77E-01
CONTAG_81	1.53E+02	4.86E+01	3.14E+00	4.61E-03
CONTAG_113	-5.78E+01	7.06E+01	-8.19E-01	4.21E-01
CONTAG_145	-1.21E+02	5.50E+01	-2.21E+00	3.77E-02
CONTAG_177	-3.10E+01	3.78E+01	-8.21E-01	4.20E-01
CONTAG_209	-1.09E+02	4.76E+01	-2.29E+00	3.13E-02
CONTAG_241	-1.11E+02	4.12E+01	-2.69E+00	1.32E-02
CONTAG_273	8.18E+01	5.50E+01	1.49E+00	1.50E-01
SHDI_81	4.95E+03	1.42E+03	3.48E+00	2.03E-03
SHDI_113	-2.56E+03	2.21E+03	-1.15E+00	2.60E-01
SHDI_145	-3.59E+03	1.74E+03	-2.06E+00	5.12E-02
SHDI_177	-6.33E+01	1.21E+03	-5.23E-02	9.59E-01
SHDI_209	-3.70E+03	1.62E+03	-2.29E+00	3.17E-02
SHDI_241	-2.90E+03	1.33E+03	-2.18E+00	3.98E-02
SHDI_273	2.94E+03	1.66E+03	1.77E+00	8.99E-02
CWED_81	-1.01E+02	1.08E+02	-9.39E-01	3.58E-01
CWED_113	-9.65E+01	1.15E+02	-8.39E-01	4.10E-01
CWED_145	-9.13E+01	9.07E+01	-1.01E+00	3.24E-01
CWED_177	5.88E+01	8.86E+01	6.64E-01	5.13E-01
CWED_209	-9.74E+01	1.05E+02	-9.24E-01	3.65E-01
CWED_241	-3.03E+02	8.61E+01	-3.52E+00	1.83E-03
CWED_273	4.69E+01	1.09E+02	4.29E-01	6.72E-01
AREA_AM_81	4.38E-04	3.77E-04	1.16E+00	2.56E-01
AREA_AM_113	3.82E-03	2.18E-03	1.76E+00	9.25E-02
AREA_AM_145	6.34E-05	5.84E-04	1.09E-01	9.14E-01
AREA_AM_177	-6.85E-04	4.36E-04	-1.57E+00	1.30E-01
AREA_AM_209	-2.30E-05	1.93E-04	-1.19E-01	9.06E-01
AREA_AM_241	-9.55E-05	2.81E-04	-3.40E-01	7.37E-01
AREA_AM_273	2.17E-03	4.52E-03	4.81E-01	6.35E-01
DIVISION_81	-8.87E+02	1.16E+03	-7.64E-01	4.53E-01
DIVISION_113	2.71E+03	8.11E+03	3.34E-01	7.41E-01
DIVISION_145	-5.18E+03	5.25E+03	-9.86E-01	3.34E-01
DIVISION_177	-4.76E+03	1.69E+03	-2.81E+00	9.84E-03
DIVISION_209	-8.70E+00	9.08E+02	-9.58E-03	9.92E-01
DIVISION_241	-4.96E+02	1.65E+03	-3.02E-01	7.66E-01

DIVISION_273	3.63E+01	3.04E+03	1.20E-02	9.91E-01
GYRATE_AM_81	-1.37E+01	1.46E+01	-9.40E-01	3.57E-01
GYRATE_AM_113	-7.19E+01	4.69E+01	-1.53E+00	1.39E-01
GYRATE_AM_145	-3.05E+01	2.39E+01	-1.28E+00	2.15E-01
GYRATE_AM_177	-8.96E+00	1.16E+01	-7.74E-01	4.47E-01
GYRATE_AM_209	-5.24E+00	6.82E+00	-7.68E-01	4.50E-01
GYRATE_AM_241	-1.09E+01	1.05E+01	-1.03E+00	3.13E-01
GYRATE_AM_273	-8.39E+01	5.34E+01	-1.57E+00	1.30E-01
CONNECT_81	-1.65E+04	5.94E+03	-2.77E+00	1.09E-02
CONNECT_113	-1.98E+04	1.47E+04	-1.35E+00	1.90E-01
CONNECT_145	-3.16E+03	1.23E+04	-2.57E-01	7.99E-01
CONNECT_177	2.53E+03	5.83E+03	4.34E-01	6.68E-01
CONNECT_209	-3.51E+03	4.85E+03	-7.23E-01	4.77E-01
CONNECT_241	-7.05E+03	9.55E+03	-7.38E-01	4.68E-01
CONNECT_273	-3.02E+03	1.16E+04	-2.60E-01	7.97E-01
PROPORTION_CORN	4.00E+03	4.11E+02	9.75E+00	0.00E+00
PROPORTION_SOYSMALLGRAIN	-1.60E+03	4.85E+02	-3.30E+00	3.13E-03
PROPORTION_FRUITVEG	-2.49E+02	5.25E+03	-4.74E-02	9.63E-01
PROPORTION_COTTON	8.81E+02	8.46E+02	1.04E+00	3.09E-01
PROPORTION_NONCROP	1.34E+06	4.22E+05	3.18E+00	4.14E-03
PRICE_CORN	8.86E+02	6.30E+02	1.41E+00	1.73E-01
PRICE_SOYBEANS	-6.95E+02	4.33E+02	-1.60E+00	1.22E-01
PRICE_COTTON	-4.66E+02	1.36E+03	-3.43E-01	7.35E-01
PDSI	1.11E+02	4.09E+01	2.72E+00	1.22E-02

Table 26: Model Results, all Important Metrics, Income Included

	F(87,22)	Prob > P	R-Squared	Adj-R2
	32.651855	0	0.99231498	0.961924
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-8.66E+05	2.71E+05	-3.20E+00	4.17E-03
YEAR	7.75E+01	4.91E+01	1.58E+00	1.29E-01
STATE Florida	-4.71E+02	4.99E+02	-9.44E-01	3.55E-01
STATE Georgia	-3.40E+01	2.03E+02	-1.67E-01	8.69E-01
STATE Illinois	-1.54E+03	4.12E+02	-3.74E+00	1.12E-03
STATE Indiana	-1.55E+03	4.88E+02	-3.18E+00	4.30E-03
STATE Iowa	-4.66E+02	7.02E+02	-6.64E-01	5.13E-01
STATE Kansas	-1.73E+03	5.78E+02	-2.99E+00	6.70E-03
STATE Louisiana	-8.08E+02	5.96E+02	-1.36E+00	1.89E-01
STATE Maryland	5.14E+02	6.62E+02	7.76E-01	4.46E-01

STATE Michigan	-5.21E+02	6.36E+02	-8.20E-01	4.21E-01
STATE Minnesota	-1.34E+03	4.19E+02	-3.20E+00	4.11E-03
STATE Mississippi	-4.01E+02	1.71E+02	-2.34E+00	2.86E-02
STATE Missouri	-1.64E+03	6.14E+02	-2.67E+00	1.41E-02
STATE Nebraska	-1.49E+03	4.78E+02	-3.12E+00	4.99E-03
STATE North Carolina	-5.64E+02	5.09E+02	-1.11E+00	2.80E-01
STATE Ohio	-1.26E+03	4.80E+02	-2.64E+00	1.51E-02
STATE South Carolina	-7.76E+02	4.89E+02	-1.59E+00	1.27E-01
STATE South Dakota	-9.45E+02	5.43E+02	-1.74E+00	9.57E-02
STATE Tennessee	-1.02E+03	5.62E+02	-1.82E+00	8.20E-02
STATE Virginia	-9.12E+02	5.70E+02	-1.60E+00	1.24E-01
STATE Wisconsin	1.13E+02	7.26E+02	1.55E-01	8.78E-01
TE_81	2.38E-03	2.21E-03	1.08E+00	2.93E-01
TE_113	-4.48E-04	3.40E-03	-1.32E-01	8.96E-01
TE_145	-1.69E-03	3.14E-03	-5.38E-01	5.96E-01
TE_177	-8.06E-03	2.49E-03	-3.23E+00	3.83E-03
TE_209	-1.29E-03	2.26E-03	-5.71E-01	5.74E-01
TE_241	-4.06E-04	2.30E-03	-1.76E-01	8.62E-01
TE_273	6.85E-03	3.33E-03	2.05E+00	5.20E-02
CONTAG_81	3.66E+01	2.84E+01	1.29E+00	2.12E-01
CONTAG_113	-2.87E+01	3.60E+01	-7.98E-01	4.33E-01
CONTAG_145	-8.91E+01	2.82E+01	-3.16E+00	4.51E-03
CONTAG_177	-6.03E+01	1.95E+01	-3.09E+00	5.30E-03
CONTAG_209	-1.18E+01	2.69E+01	-4.38E-01	6.66E-01
CONTAG_241	-3.72E+01	2.27E+01	-1.64E+00	1.16E-01
CONTAG_273	8.38E+01	2.79E+01	3.00E+00	6.54E-03
SHDI_81	1.40E+03	8.42E+02	1.66E+00	1.11E-01
SHDI_113	-1.25E+03	1.13E+03	-1.10E+00	2.84E-01
SHDI_145	-2.65E+03	8.92E+02	-2.97E+00	7.13E-03
SHDI_177	-1.05E+03	6.26E+02	-1.68E+00	1.08E-01
SHDI_209	-4.53E+02	9.11E+02	-4.98E-01	6.24E-01
SHDI_241	-8.52E+02	7.19E+02	-1.19E+00	2.49E-01
SHDI_273	2.68E+03	8.45E+02	3.17E+00	4.40E-03
CWED_81	-8.58E+01	5.47E+01	-1.57E+00	1.31E-01
CWED_113	-9.23E+01	5.84E+01	-1.58E+00	1.28E-01
CWED_145	-9.00E+01	4.60E+01	-1.96E+00	6.33E-02
CWED_177	-8.20E+01	4.81E+01	-1.70E+00	1.03E-01
CWED_209	2.09E+01	5.54E+01	3.78E-01	7.09E-01
CWED_241	-8.56E+01	5.11E+01	-1.67E+00	1.08E-01
CWED_273	7.42E+01	5.56E+01	1.34E+00	1.95E-01
AREA_AM_81	8.72E-05	1.96E-04	4.45E-01	6.60E-01
AREA_AM_113	2.49E-03	1.12E-03	2.23E+00	3.60E-02
AREA_AM_145	-2.87E-04	2.99E-04	-9.58E-01	3.48E-01

AREA_AM_177	-2.97E-04	2.26E-04	-1.31E+00	2.04E-01
AREA_AM_209	6.71E-05	9.85E-05	6.82E-01	5.03E-01
AREA_AM_241	-9.61E-05	1.43E-04	-6.74E-01	5.07E-01
AREA_AM_273	3.04E-03	2.30E-03	1.32E+00	2.00E-01
DIVISION_81	-1.02E+03	5.90E+02	-1.73E+00	9.69E-02
DIVISION_113	2.19E+03	4.12E+03	5.33E-01	5.99E-01
DIVISION_145	-3.37E+03	2.67E+03	-1.26E+00	2.20E-01
DIVISION_177	-1.19E+03	9.63E+02	-1.23E+00	2.30E-01
DIVISION_209	4.80E+01	4.61E+02	1.04E-01	9.18E-01
DIVISION_241	-8.89E+02	8.36E+02	-1.06E+00	2.99E-01
DIVISION_273	-9.03E+01	1.54E+03	-5.86E-02	9.54E-01
GYRATE_AM_81	-7.32E+00	7.43E+00	-9.85E-01	3.35E-01
GYRATE_AM_113	-5.14E+01	2.40E+01	-2.14E+00	4.33E-02
GYRATE_AM_145	-8.13E+00	1.24E+01	-6.54E-01	5.20E-01
GYRATE_AM_177	-1.19E+00	5.95E+00	-2.00E-01	8.43E-01
GYRATE_AM_209	-4.65E-01	3.51E+00	-1.32E-01	8.96E-01
GYRATE_AM_241	-9.00E+00	5.34E+00	-1.69E+00	1.06E-01
GYRATE_AM_273	-6.44E+01	2.72E+01	-2.37E+00	2.71E-02
CONNECT_81	-9.95E+03	3.12E+03	-3.19E+00	4.22E-03
CONNECT_113	-1.48E+04	7.47E+03	-1.98E+00	6.09E-02
CONNECT_145	-4.05E+03	6.24E+03	-6.48E-01	5.24E-01
CONNECT_177	-6.77E+02	2.98E+03	-2.27E-01	8.23E-01
CONNECT_209	2.26E+03	2.56E+03	8.83E-01	3.87E-01
CONNECT_241	4.39E+03	5.04E+03	8.70E-01	3.94E-01
CONNECT_273	-6.36E+03	5.91E+03	-1.07E+00	2.94E-01
PROPORTION_CORN	2.52E+03	2.76E+02	9.13E+00	1.00E-08
PROPORTION_SOYSMALLGRAIN	-4.90E+02	2.81E+02	-1.74E+00	9.51E-02
PROPORTION_FRUITVEG	4.18E+03	2.72E+03	1.54E+00	1.39E-01
PROPORTION_COTTON	1.51E+02	4.39E+02	3.44E-01	7.34E-01
PROPORTION_NONCROP	7.28E+05	2.27E+05	3.21E+00	4.05E-03
INCOMEPERCULTIVATEDHECTARE	-4.15E-01	5.06E-02	-8.20E+00	4.00E-08
PRICE_CORN	3.89E+02	3.25E+02	1.20E+00	2.44E-01
PRICE_SOYBEANS	-3.08E+02	2.25E+02	-1.37E+00	1.84E-01
PRICE_COTTON	6.16E+01	6.94E+02	8.89E-02	9.30E-01
PDSI	4.51E+01	2.23E+01	2.02E+00	5.53E-02

APPENDIX D

MODEL RESULTS UTILIZING ALTERNATIVE DEPENDENT VARIABLE

For additional comparison with the studies conducted by Meehan et al (2011) and Larsen (2013), I tested my model against their dependent variable. In their analysis, the dependent variable was proportion of harvested area treated with insecticides. This is a highly aggregated measure which fails to capture the actual amount of pesticide being applied, and only provides a description of land area which received insecticide applications. For these reasons, I chose a different dependent variable which includes information on the amount of insecticide applied. I then calculated the rate of insecticide application per harvested hectare. Additionally, the dependent variable used by Meehan et al and Larsen is available through the Agricultural Census, and is thus available only for every fifth year. In order to conduct a study examining the temporal aspects of the landscape, I was forced to rely on a different data source which provided annual observations of pesticide use.

Table 27 displays the results from the model with my independent variables, in the same comparison format as described in Chapter 3 (Results). The analysis is limited, because the dependent variable of proportion of harvested area treated with insecticides is only available for the Ag Census years, and therefore only one year, 2012, overlaps with the time frame of my study. Table 28 contains results from the same year and independent variables, but using the dependent variable of insecticide application rates that I employed in my study, for comparison with the alternative dependent variable.

Table 27: Total Area, Income Included, Proportion of Area Treated with Insecticides (Just 2012)

	Baseline Model All Regions	Baseline including Cotton	Baseline including PDSI and Cotton	Significant dates of chosen landscape metrics	Means of Metrics
Proportion Non-crop	0.264	0.434	0.367	1.622	-0.588
Proportion Soy and Small Grains	-0.326	-.417	-0.455	-1.42*	-1.920**
Proportion Corn	0.232	-0.018	0.118	-0.374	0.318
Proportion Fruit and Vegetable	2.344	4.908	5.76	10.58*	12.19**
Proportion Cotton	--	-1.19	-1.54	-1.647	-3.11**
Income per Harvested Hectare	-0.670***	-0.663***	-0.658***	-0.688***	-0.654***
Drought Severity	--	--	-0.098	0.142	--
TE (177)	--	--	--	-0.00001	--
TE (273)	--	--	--	0.00001	--
CONTAG (145)	--	--	--	0.012	--
CONTAG (177)	--	--	--	-0.001	--
CONTAG (273)	--	--	--	-4.29	--
SHDI (145)	--	--	--	-0.326	--
TE_MEAN	--	--	--	--	-2.1E-06
CONTAG_MEAN	--	--	--	--	-0.23825
SHDI_MEAN	--	--	--	--	-6.89529
CONNECT_MEAN	--	--	--	--	-9.24169**
CWED_MEAN	--	--	--	--	-0.43956
AREA_AM_MEAN	--	--	--	--	2.13E-06
DIVISION_MEAN	--	--	--	--	3.25797
GYRATE_AM_MEAN	--	--	--	--	-0.03796
R^2	0.986	0.987	0.987	0.996	0.999
Adjusted R^2	0.981	0.981	0.979	0.987	0.996
Number of observations	20	20	20	20	20

Table 28: Total Area, Income Included, Insecticide Application Rate (Just 2012)

	Baseline Model All Regions	Baseline including Cotton	Baseline including PDSI and Cotton	Significant dates of chosen landscape metrics	Means of Metrics
Proportion Non-crop	0.150**	0.165*	0.164	0.589	-0.129
Proportion Soy and Small Grains	-0.184*	-0.193*	-0.193	-0.495**	-0.583**
Proportion Corn	-0.044	-0.068	-0.065	-0.137	0.126
Proportion Fruit and Vegetable	0.953	1.189	1.205	3.25**	3.18**
Proportion Cotton	--	-0.109	-0.116	-0.323	-0.634*
Income per Harvested Hectare	-0.118***	-0.118***	-0.118***	-0.120***	-0.112***
Drought Severity	--	--	-0.002	0.041	--
TE (177)	--	--	--	-2.5E-06	--
TE (273)	--	--	--	1.99E-06	--
CONTAG (145)	--	--	--	-1.418*	--
CONTAG (177)	--	--	--	0.001376	--
CONTAG (273)	--	--	--	-0.00119	--
SHDI (145)	--	--	--	-0.08576	--
TE_MEAN	--	--	--	--	-5.8E-07*
CONTAG_MEAN	--	--	--	--	-0.06165
SHDI_MEAN	--	--	--	--	-1.75341
CONNECT_MEAN	--	--	--	--	-2.34131**
CWED_MEAN	--	--	--	--	-0.09111
AREA_AM_MEAN	--	--	--	--	4.9E-07
DIVISION_MEAN	--	--	--	--	0.798507
GYRATE_AM_MEAN	--	--	--	--	-0.00626
R^2	0.970	0.970	0.970	0.992	0.998
Adjusted R^2	0.959	0.956	0.952	0.976	0.991
Number of observations	20	20	20	20	20

In comparison, the results from the regressions on the different dependent variables are very similar, with similar R^2 values, similar significance of independent variables, and similar signs on coefficients. This indicates that the models I have specified with my chosen dependent variable are as representative of the data as those specified by Meehan and Larsen, and indicates comparability between my results and theirs.

APPENDIX E

INDIVIDUAL PESTICIDE MODELS

The pesticide application data in the EPest database is disaggregated to the application of specific active compounds. For my analysis described in the main body of this thesis, the dependent variable was an aggregated value of the various insecticides which were included in the EPest database. In the process of working with this data, however, I also ran several models using the rates of individual active ingredients for several compounds which are most frequently used in agricultural settings. These models seemed relatively inconsistent, however, as to model function and which variables were significant in the results. I decided to use the aggregated measure in the full analysis, since in many cases these compounds are substitutes for one another, and it would be very difficult to determine why a farmer chooses to use one particular compound over any other. This choice could be due to economic factors (compound price, for example, which I have included in the following regressions as a covariate), environmental factors, favoring a particular chemical, or the general availability of each compound. Based on this uncertainty in how a farmer would select any one compound, I decided that an aggregated measurement would best capture the actions of all farmers in general. Reported here are the results of the regressions estimated for each of four insecticides frequently used in agricultural production, Chlorpyrifos, Cyfluthrin, Carbofuran, and Carbaryl.

Table 29: Chlorpyrifos

Chlorpyrifos				
	F(36,71)	Prob > P	R-Squared	Adj-R2
	12.44480233	0	0.86320185	0.79383941
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-3.56E+06	1.37E+07	-2.60E-01	7.96E-01
YEAR	1.85E+03	6.87E+03	2.69E-01	7.88E-01
STATE Florida	-4.71E+04	1.58E+05	-2.97E-01	7.67E-01
STATE Georgia	1.45E+05	4.24E+04	3.41E+00	1.07E-03
STATE Illinois	-6.29E+04	1.12E+05	-5.61E-01	5.76E-01
STATE Indiana	-7.92E+04	1.93E+05	-4.12E-01	6.82E-01
STATE Iowa	1.73E+04	7.77E+04	2.23E-01	8.25E-01
STATE Kansas	-8.74E+04	1.90E+05	-4.60E-01	6.47E-01
STATE Louisiana	-6.95E+04	2.06E+05	-3.37E-01	7.37E-01
STATE Maryland	-8.73E+04	2.04E+05	-4.29E-01	6.69E-01
STATE Michigan	-1.02E+05	2.65E+05	-3.83E-01	7.03E-01
STATE Minnesota	1.47E+04	1.54E+05	9.59E-02	9.24E-01
STATE Mississippi	-4.56E+04	2.93E+04	-1.56E+00	1.24E-01
STATE Missouri	-7.44E+04	1.85E+05	-4.03E-01	6.88E-01
STATE Nebraska	-8.82E+03	1.49E+05	-5.91E-02	9.53E-01
STATE North Carolina	-1.39E+04	1.45E+05	-9.56E-02	9.24E-01
STATE Ohio	-9.04E+04	1.92E+05	-4.71E-01	6.39E-01
STATE South Carolina	-4.52E+04	1.52E+05	-2.96E-01	7.68E-01
STATE South Dakota	-9.72E+04	1.99E+05	-4.88E-01	6.27E-01
STATE Tennessee	-8.94E+04	1.81E+05	-4.95E-01	6.22E-01
STATE Virginia	-6.68E+04	1.78E+05	-3.76E-01	7.08E-01
STATE Wisconsin	-1.12E+05	2.04E+05	-5.48E-01	5.86E-01
ECOREGION824	2.62E+04	6.85E+04	3.83E-01	7.03E-01
TE Mean	-1.11E-04	5.44E-04	-2.04E-01	8.39E-01
TE Variance	0.00E+00	0.00E+00	2.41E+00	1.86E-02
CONTAG Mean	-3.39E+03	3.18E+03	-1.07E+00	2.89E-01
CONTAG Variance	1.05E+02	8.37E+01	1.26E+00	2.12E-01
GYRATE_CV Mean	1.32E+03	8.20E+02	1.61E+00	1.12E-01
GYRATE_CV Variance	-3.39E+00	8.76E-01	-3.87E+00	2.36E-04
COMPOUND_VALUE	-2.24E+03	2.85E+03	-7.87E-01	4.34E-01
ACRES_CORN	4.02E-03	4.85E-03	8.29E-01	4.10E-01
ACRES_SOYBEANS	-2.85E-03	6.81E-03	-4.18E-01	6.77E-01
ACRES_PEANUTS	9.78E-03	2.80E-02	3.49E-01	7.28E-01
ACRES_COTTON	-1.31E-02	1.32E-02	-9.94E-01	3.24E-01
PRICE_CORN	2.05E+03	7.38E+03	2.77E-01	7.82E-01
PRICE_COTTON	-1.04E+05	7.38E+04	-1.42E+00	1.61E-01
PDSI	-4.84E+03	3.96E+03	-1.22E+00	2.26E-01

Table 30: Cyfluthrin

Cyfluthrin				
	F(36,73)	Prob > P	R-Squared	Adj-R2
	11.33819589	0	0.84828806	0.77347121
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-5.32E+05	3.49E+05	-1.52E+00	1.32E-01
YEAR	2.64E+02	1.65E+02	1.60E+00	1.13E-01
STATE Florida	-1.09E+04	3.83E+03	-2.84E+00	5.92E-03
STATE Georgia	-5.85E+02	1.03E+03	-5.68E-01	5.72E-01
STATE Illinois	-6.25E+03	2.72E+03	-2.30E+00	2.43E-02
STATE Indiana	-1.40E+04	4.66E+03	-3.01E+00	3.59E-03
STATE Iowa	-1.88E+03	1.89E+03	-9.92E-01	3.24E-01
STATE Kansas	-1.37E+04	4.60E+03	-2.99E+00	3.85E-03
STATE Louisiana	-1.48E+04	4.99E+03	-2.97E+00	4.00E-03
STATE Maryland	-1.52E+04	4.94E+03	-3.09E+00	2.84E-03
STATE Michigan	-2.11E+04	6.42E+03	-3.28E+00	1.59E-03
STATE Minnesota	-1.07E+04	3.71E+03	-2.87E+00	5.31E-03
STATE Mississippi	-3.07E+02	7.12E+02	-4.31E-01	6.68E-01
STATE Missouri	-1.28E+04	4.46E+03	-2.88E+00	5.20E-03
STATE Nebraska	-9.55E+03	3.60E+03	-2.65E+00	9.82E-03
STATE North Carolina	-7.50E+03	3.51E+03	-2.13E+00	3.62E-02
STATE Ohio	-1.44E+04	4.65E+03	-3.09E+00	2.85E-03
STATE South Carolina	-8.94E+03	3.69E+03	-2.42E+00	1.80E-02
STATE South Dakota	-1.46E+04	4.82E+03	-3.03E+00	3.41E-03
STATE Tennessee	-1.31E+04	4.38E+03	-3.00E+00	3.67E-03
STATE Virginia	-1.21E+04	4.30E+03	-2.80E+00	6.48E-03
STATE Wisconsin	-1.49E+04	4.93E+03	-3.03E+00	3.42E-03
ECOREGION824	6.43E+03	1.66E+03	3.87E+00	2.36E-04
TE Mean	-4.08E-05	1.32E-05	-3.09E+00	2.79E-03
TE Variance	0.00E+00	0.00E+00	1.60E+00	1.15E-01
CONTAG Mean	-2.47E+01	7.66E+01	-3.22E-01	7.48E-01
CONTAG Variance	-5.89E-02	2.03E+00	-2.91E-02	9.77E-01
GYRATE_CV Mean	6.16E+00	1.99E+01	3.10E-01	7.57E-01
GYRATE_CV Variance	-1.65E-02	2.13E-02	-7.75E-01	4.41E-01
COMPOUND_VALUE	4.93E+01	8.38E+01	5.88E-01	5.59E-01
ACRES_CORN	3.46E-04	1.18E-04	2.93E+00	4.58E-03
ACRES_SOYBEANS	-3.57E-04	1.66E-04	-2.15E+00	3.48E-02
ACRES_PEANUTS	8.80E-04	6.80E-04	1.29E+00	2.00E-01
ACRES_COTTON	2.68E-04	3.22E-04	8.32E-01	4.08E-01
PRICE_CORN	-2.30E+02	1.54E+02	-1.49E+00	1.40E-01
PRICE_COTTON	3.64E+03	6.55E+03	5.55E-01	5.80E-01
PDSI	-1.02E+02	9.61E+01	-1.06E+00	2.91E-01

Table 31: Carbofuran

Carbofuran				
	F(29,10)	Prob > P	R-Squared	Adj-R2
	15.91158336	3.38E-05	0.97878821	0.91727402
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-2.02E+10	2.02E+10	-9.98E-01	3.42E-01
YEAR	1.03E+07	1.03E+07	9.98E-01	3.42E-01
STATE Georgia	7.33E+08	7.33E+08	9.99E-01	3.41E-01
STATE Illinois	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
STATE Indiana	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
STATE Iowa	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
STATE Kansas	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
STATE Louisiana	-2.50E+08	2.50E+08	-9.99E-01	3.41E-01
STATE Maryland	-2.66E+08	2.66E+08	-9.99E-01	3.41E-01
STATE Michigan	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
STATE Minnesota	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
STATE Missouri	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
STATE Nebraska	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
STATE Ohio	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
STATE South Dakota	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
STATE Virginia	-2.49E+08	2.50E+08	-9.99E-01	3.41E-01
STATE Wisconsin	-2.73E+08	2.73E+08	-9.99E-01	3.41E-01
ECOREGION824	6.90E+03	4.00E+04	1.73E-01	8.66E-01
TE Mean	9.95E-05	3.86E-04	2.58E-01	8.02E-01
TE Variance	0.00E+00	0.00E+00	-4.94E+00	5.86E-04
CONTAG Mean	-2.77E+03	1.69E+03	-1.64E+00	1.32E-01
CONTAG Variance	-1.33E+01	2.36E+01	-5.64E-01	5.85E-01
GYRATE_CV Mean	8.76E+02	3.57E+02	2.45E+00	3.40E-02
GYRATE_CV Variance	-1.02E+00	3.40E-01	-3.02E+00	1.30E-02
COMPOUND_VALUE	-2.34E+06	2.34E+06	-9.99E-01	3.42E-01
ACRES_CORN	-6.46E-04	1.01E-03	-6.39E-01	5.37E-01
ACRES_SOYBEANS	9.62E-04	1.58E-03	6.10E-01	5.55E-01
ACRES_PEANUTS	-5.71E+02	5.71E+02	-9.99E-01	3.41E-01
ACRES_COTTON	-8.34E+02	8.34E+02	-9.99E-01	3.41E-01
PDSI	4.68E+06	4.68E+06	9.99E-01	3.41E-01

Table 32: Carbaryl

Carbaryl				
	F(36,73)	Prob > P	R-Squared	Adj-R2
	10.29454111	0	0.83543862	0.75428507
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-7.54E+06	3.61E+06	-2.09E+00	4.03E-02
YEAR	3.61E+03	1.82E+03	1.98E+00	5.14E-02
STATE Florida	2.43E+05	3.13E+04	7.77E+00	0.00E+00
STATE Georgia	6.27E+04	8.40E+03	7.47E+00	0.00E+00
STATE Illinois	1.95E+05	2.22E+04	8.80E+00	0.00E+00
STATE Indiana	3.13E+05	3.80E+04	8.23E+00	0.00E+00
STATE Iowa	1.05E+05	1.54E+04	6.83E+00	0.00E+00
STATE Kansas	3.09E+05	3.75E+04	8.22E+00	0.00E+00
STATE Louisiana	3.21E+05	4.07E+04	7.88E+00	0.00E+00
STATE Maryland	3.26E+05	4.03E+04	8.09E+00	0.00E+00
STATE Michigan	4.18E+05	5.24E+04	7.99E+00	0.00E+00
STATE Minnesota	2.65E+05	3.03E+04	8.77E+00	0.00E+00
STATE Mississippi	2.70E+04	5.81E+03	4.65E+00	1.43E-05
STATE Missouri	3.00E+05	3.64E+04	8.25E+00	0.00E+00
STATE Nebraska	2.53E+05	2.94E+04	8.61E+00	0.00E+00
STATE North Carolina	2.29E+05	2.87E+04	7.99E+00	0.00E+00
STATE Ohio	3.09E+05	3.79E+04	8.15E+00	0.00E+00
STATE South Carolina	2.36E+05	3.01E+04	7.84E+00	0.00E+00
STATE South Dakota	3.24E+05	3.93E+04	8.24E+00	0.00E+00
STATE Tennessee	2.86E+05	3.57E+04	8.01E+00	0.00E+00
STATE Virginia	2.80E+05	3.51E+04	7.98E+00	0.00E+00
STATE Wisconsin	3.27E+05	4.02E+04	8.13E+00	0.00E+00
ECOREGION824	-9.22E+04	1.36E+04	-6.80E+00	0.00E+00
TE Mean	8.79E-04	1.07E-04	8.17E+00	0.00E+00
TE Variance	0.00E+00	0.00E+00	1.42E-03	9.99E-01
CONTAG Mean	7.72E+02	6.25E+02	1.23E+00	2.21E-01
CONTAG Variance	-1.97E+00	1.65E+01	-1.19E-01	9.06E-01
GYRATE_CV Mean	-9.62E+01	1.62E+02	-5.94E-01	5.55E-01
GYRATE_CV Variance	1.27E-01	1.74E-01	7.34E-01	4.65E-01
COMPOUND_VALUE	-5.68E+03	6.90E+03	-8.22E-01	4.14E-01
ACRES_CORN	-6.61E-04	9.65E-04	-6.84E-01	4.96E-01
ACRES_SOYBEANS	7.11E-04	1.36E-03	5.24E-01	6.02E-01
ACRES_PEANUTS	-4.37E-04	5.54E-03	-7.89E-02	9.37E-01
ACRES_COTTON	-2.32E-03	2.63E-03	-8.85E-01	3.79E-01
PRICE_CORN	-4.29E+03	3.42E+03	-1.25E+00	2.14E-01
PRICE_COTTON	-1.26E+04	1.68E+04	-7.51E-01	4.55E-01
PDSI	-1.11E+03	7.84E+02	-1.41E+00	1.63E-01