Determining the Suitability of Yak-Based Agriculture in Illinois:
A Site Suitability Analysis Using Fuzzy Overlay

by

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For Gordon, Josephine, Rita, Kevin, and Marion: so that what is dead may never die

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List of Abbreviations

AOI	Area of Interest
ASC	Armored ASCII
ASCII	American Standard Code for Information Interchange
BIL	Band Interleaved by Line
CIAT	International Centre for Tropical Agriculture
DEM	Digital Elevation Model
GIB	Geospatial Information Branch
GIS	Geographic information system
IDOT	Illinois Department of Transportation
IPA	Illinois Precipitation Anomaly
KML	Keyhole Markup Language
MMU	Minimum Mapping Unit
NASS	National Agricultural Statistics Service
NOAA	National Oceanic and Atmospheric Administration
NRCS	National Resources Conservation Services
PRISM	Parameter-elevation Regressions on Independent Slopes Model
RDD	Research and Development Division
SARS	Spatial Analysis Research Section
SRTM	Shuttle Radar Topography Mission
SSA	Site Suitability Analysis
TIFF	Tagged Image File Format
TIGER	Topologically Integrated Geographic Encoding and Referencing

USDA	United States Department of Agriculture
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
VPD	Vapor Pressure Deficit
WGS	World Geodetic Survey
WSS	Web Soil Survey

Abstract

Yak are a high yielding but underutilized commodity in American agriculture; a sector that could benefit both economically and ecologically from diversification. Diversification in agriculture is important to help alleviate stress on the environment and provide economic security. This analysis used fuzzy overlay to conduct a statewide site suitability analysis in Illinois to locate the most favorable counties and subcounty divisions to begin yak-based agriculture. Yak-based agriculture refers to a farming or ranching operation where yak are raised as a commodity. Based on a review of literature regarding the conditions for successful yak-based agriculture, the fuzzy overlay analysis undertaken here incorporated both continuous data forms, particularly the climate criteria of temperature, precipitation, and vapor pressure deficit, and the categorical data of cropland use and soil associations. While initially considered to be key criteria for successful yak-based agriculture, the factors of slope and market proximity were removed from this analysis. Slope was not included because nowhere in the study area was the slope a limiting factor. Market proximity was not included due to the dense road network and easy road accessibility throughout the state. However, it is noted that these factors should be incorporated in any future studies that replicate this approach. In the final results, Will, Kankakee, and Iroquois counties were found to be suitable locations for potential yak-based agriculture but not highly suitable as Illinois' climate is not similar to the yak's native range of Tibet. Conclusions from this analysis and similar ones undertaken in the future have potential to assist county farm bureaus in better understanding how to diversify farming to protect the farmer from potential economic disasters and the soil from the harmful effects of monocropping.

Chapter 1 Introduction

Yak, a herd animal common in the Tibetan steppe, is an undiscovered opportunity for American agriculture. While growing in popularity within some Western states, such as Colorado and Montana, they are slowing expanding to other areas of the United States. Adopting yak as a standard breed can assist with both the biological and economic diversification of small farms. Seeking to identify locations with suitable geographic conditions, this project aims to encourage the introduction of yak-based agriculture into the Illinois agricultural sector. Illinois is a particularly strong target for considering the adoption of this breed because of its current monocropping economy and resulting lack of agricultural diversity.

Bos gurnniens (Figure 1), known as the domesticated yak or more commonly just yak, is a domesticated species in the Bovine family and is related to aurochs, gayal, zebu, and domesticated cattle. Yak are domesticated from *Bos mutus,* or wild yak, which still inhabit their native range in the Tibetan Plateau. Yak are a versatile agricultural commodity. Byproducts of the yak are used to make a range of products including dairy products, fibers, and meat (Cincotta et al. 1991).

Figure 1: Two yak cows. Photo courtesy of Goat Trax Farm.

Raising yak with the intention of creating byproducts is considered here to be encompassed by the general term yak-based agriculture. Yak-based agriculture can vary in form from maintaining large herds primarily for meat, often referred to as ranching, to non-meat oriented operations with animals for fiber or milk, frequently distinguished as farming. Yak-based agriculture does not differentiate between the production type, facility type or size, the size of the herd, or the manner in which the animals are confined (free-range, pastured, or feedlot).

1.1. Motivation

Monocropping is the monoculture, or singular curation, of a species. This agricultural practice raises a single species, or even breed, of animal or plant (Jacques and Jacques 2012). Due to a variety of historical economic factors, monocropping has become the standard farming technique in Illinois and a proven detriment to the native ecosystems and soil. Large feedlot operations limit biological diversity and place a strain on the environment (Ilbery et al. 1996; Katchova 2005; Sumner 2014).

To encourage farmers to move beyond monocropping, they should be encouraged to increase the biological diversity of their farms in an ecologically and economically beneficial manner. Farmers can expand their operations to include rare and historic breeds of livestock. Yak are efficient for a large breed as they require less acreage and less feed than conventional cattle (Clark and Inwood 2015; Leslie and Schaller 2009). This biological diversification, which potentially includes yak-based agriculture, benefits farms economically as well by being a secondary option for profit in case another source of income fails (Sumner 2014).

This site suitability analysis (SSA) is distinctive as it ascertains measurable potential for the expansion of animal husbandry, the breeding and care of animals, in Illinois. The analysis developed a set of criteria for application to this particular problem with the intention of it being appropriate for replication and modification for other regions or domesticated species. The fuzzy overlay method ranks and combines hard to quantify data using mathematical or logical functions to produce a scale of suitability (Mitchell 2012). This scale illustrates the potential for yak-based agriculture as it is distributed across the state.

Illinois was selected as the area of interest (AOI) for two particular reasons: the state has a large monocropping industry that can benefit from diversity and open source geospatial data is available. As discussed in more detail in Chapter 2, an agricultural sector dominated by monocropping has room to diversify. If there were little to no monocropping present, the location would be diverse, regardless of the species or methods used to accomplish the diversification. Yak are already present in the Western United States and are starting to expand east. As an option for diversification, Illinois has the potential to benefit from the introduction of this species. Additionally, using an AOI with open source geographic data will help ensure that the study can be replicated in a variety of other locations. Illinois was a good option for ensuring the analysis' purposes of diversification and repetition were fulfilled.

A set of criteria was created to establish the likelihood of particular areas being more suitable than others (Mitchell 2012). The criteria selected for suitable areas, which will be discussed in Chapter 3, is based on background research into yak foraging, production, and farming techniques. This analysis is one of the few SSAs applied to the American agricultural sector to assist with the diversification of farms. The agricultural economy of the United States is experiencing a boom in the farm-to-table sector that encourages farm-direct purchasing, organic produce, and rare meats (Clark 2003; Family Farmed 2016; Freehill-Maye 2014; Sumner 2014). Yak is poised to join bison as a recognizable beef-like exotic meat. However, as both Clark and Freehill-Maye observe, yak help the local environment by eating less and are easier for the farmer to maintain than bison.

Given the goal of encouraging the expansion of yak-based agriculture and encouraging the use of fuzzy overlay techniques, this analysis developed two specific research questions:

- Which counties in Illinois are most suitable for yak-based agriculture?
- What subcounty divisions within these counties are the most suitable for yak-based agriculture?

Answering these questions will provide information of value to agriculture agencies seeking to expand local opportunities.

1.2. Study Outline

This research includes a literature review in Chapter 2, about yak habitats and preferences, Illinois ecosystems, and farming techniques to develop the criteria for a site suitability analysis, described in Chapter 3. These criteria became the factors of the fuzzy overlay after appropriate preparation of the data. Each of the factors was placed on a relative scale, and these values were used to generate membership layers that were overlaid to generate a final favorability map of Illinois. Moreover, vector overlays were added to assist in analyzing the results, seen in Chapter 4, by agricultural region, county, and subcounty divisions within Illinois. The final results of this analysis, discussed in Chapter 5, identify suitable county and subcounty divisions in Illinois for yak-based agriculture. This research will facilitate the discussion of agriculture diversification.

Chapter 2 Background Information

While literature regarding yak-based agriculture in the United States is limited, previous research help in identifying the conditions about how yak-based agriculture may be successful. Importantly, the rich prairie soils of Illinois provide an advantageous ecology for yak-based agriculture (Johnson 2016). The following review of literature discussing suitable yak habitat and the ecology and economy of Illinois helped to identify the factors used in the analysis. This chapter concludes with a brief overview of fuzzy overlay analysis.

2.1. *Bos grunniens*: The Domestic Yak

An SSA depends on an appropriate understanding of the subject matter: in this case, yak. There are many sources that collectively provide a baseline understanding of a yak's preferred environment and the facts needed to define the criteria for a suitability analysis. Leslie and Schaller (2009) provide a basis for understanding the species and its environmental needs and preferences. The authors note the species' adaptation to high elevation and low temperatures and their diverse grazing habits. The authors mention the animal's predisposition to heat exhaustion at temperatures above 13°C: an important concern for building criteria in a suitability analysis.

Cincotta et al. (1991) provide a similar number as the animal's upper limits, 15°C, but, unlike Leslie and Schaller, focus less on the yak itself and instead put the animal's capabilities into an environmental context. Because of this, Cincotta et al. is the cornerstone source for this analysis' ecological criteria. The article offers a comparison of suitable grazing lands and provides key environmental details regarding elevation, precipitation, and grass height. The authors note the versatility of yak with regards to elevation change as some pastures in their native habitat are as high as 5500 meters down to a few hundred meters above sea level. The plateau experiences a monsoonal precipitation pattern, meaning most of the average annual of

250 millimeters of precipitation occurs primarily in the summer months. According to Cincotta et al. (1991) yak consume mostly species in the genus *Stipa* but also forage from the genera of *Poa, Calamagrostis,* and *Koeleria.* Some species in *Stipa* and *Koeleria* grow upwards of 2 to 3 feet, whereas others do not even grow to 1 foot. These height differences demonstrate the foraging diversity of yak. All the other sources discussed here that were used to develop environmental criteria provided enhancements to the in-depth analysis and explanations of Cincotta et al.

Wu (2016) provides more specifics regarding yak breeds than is necessary for the general understanding needed to develop a suitability analysis. However, Wu is a supporter of selecting breeds and actively breeding yaks to adapt to a local environment and notes the historical precedent for this process. The ability to adapt yak locally is an idea that lends support to raising yak outside the Tibetan Plateau as a viable possibility. Wu looks at the climate shift of the Tibetan Plateau from 1960 to 2010, and tracks the changes of grass and yak ranges in decade increments. The distribution of the yak shifted in response to the shifts in grass distribution. The potential for adaptability brings a better understanding of forage types to support the finds of Cincotta et al. (1991) as some yak breeds are more suited for certain forage types than other breeds.

The possible adaptability of yak is evident when the animal's native range is viewed on a Köppen-Geiger climate classification map (see Figure 2). Köppen-Geiger climate classification is an international standard for defining climate zones. The classification system uses a three part schema to define the main climate group, the precipitation type, and heat. Most of Illinois is defined as a fully humid climate with hot to warm summers with snowy winters. Tibet is defined as a polar tundra, but other areas of the yak's range are various incarnations of cold and arid climates. While Illinois has the potential to be too warm for yak-based agriculture, the humidity may be advantageous in generating grass as a food source.

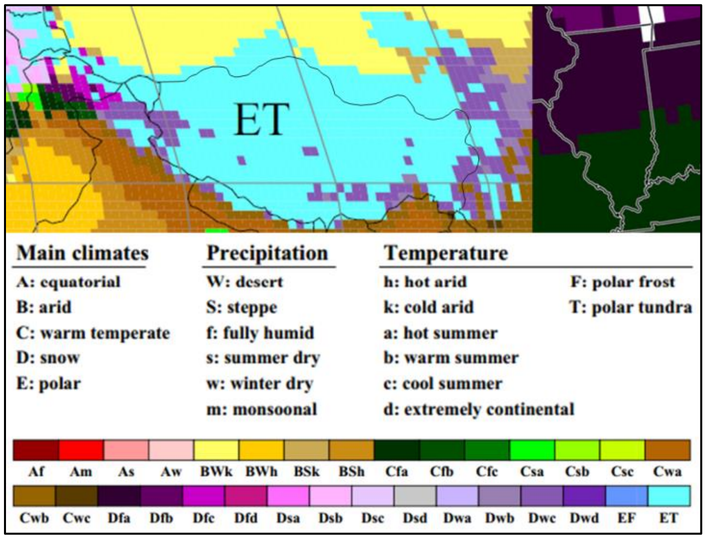


Figure 2: The Köppen-Geiger climate classification maps of Tibet and Illinois (Source: Kottek et al. 2006)

Miao et al. (2015) is the complimentary cornerstone to Cincotta et al. (1991) in clarifying the ecological needs of yaks. Miao et al.'s focus is the yak's food source and the environmental factors, particularly precipitation, that encourage large amounts of biomass. Large amounts of biomass are important for producing enough grass for the yak to comfortably graze without risk of starvation or over-grazing (Cincotta et al. 1991; Miao et al. 2015). In the Tibetan Plateau this biomass is accumulated through a 150 day warm season with an annual average precipitation of 416 millimeters. Miao et al. (2015) indicate the best soils for growing grasses are nitrogen rich as well as the plants known to be toxic to yak: *Stellera chamaejasme*, *Oetropis coeruelea*, and *Gentinana farreri*. The pairing of Miao et al. (2015) with Cinotta et al. (1991) allows the use of more recent data to influence the inclusion of criteria for locating the most likely areas to find yak's food source, grass, in conjunction with the animal's physiological capabilities.

Haynes (1996) focuses on the changing climate of the Tibetan Plateau and its impact on yak grazing areas. Haynes, much like Miao et al. (2015), elevates the importance of the quality of feed over the specific elevation ranges or physical geography conditions. Haynes' point is that the location of the yak is less important than the location of their food source. Tibetan Plateau locals described to Haynes the necessity of prescribed burns to keep shrubs off the monsoonal grasslands. A similar situation occurs on the prairies of Illinois. Both of the ecosystems, the Tibetan steppe and Illinois prairie, benefit from human interference in the management of shrub and wooded plants.

Table 1 summarizes the specific criteria mentioned in the previously discussed literature. Some of these, to be discussed later in Chapter 3, were used to create the factors for this analysis. Others were noted as important but not necessarily pertinent to the SSA. For example, the plants toxic to yak are important, but none are native to Illinois and are therefore not included in the analysis.

Table 1: Summary of observations from yak literature

Source	Observations
Leslie and Schaller (2009)	Increased risk of heat exhaustion above 13° Celsius Ingest short and long grasses Adapted to high elevations
Cincotta et al. (1991)	Increased risk of heat exhaustion above 15° Celsius Grazing elevations up to 5500 meters above sea level Average annual precipitation of 250 millimeters Ingest grasses and sedges varying in height up to 3 feet
Wu (2016)	Ingest grasses and sedges Herds follow the shifts in grassland distribution
Kottek et al. (2006)	Tibet is mostly polar tundra Illinois is split between warm temperate winters with fully humid hot summers and snowy winters with fully humid hot summers Yak native range includes variance between warm summers, dry and arid to fully humid continental
Maio et al. (2015)	150 day growing season Average annual precipitation of 416 millimeters Nitrogen rich soils Toxic species list
Haynes (1996)	Prescribed burns to eliminate woody plants Grazing quality is more important than elevation or other geographic factors

2.2. Ecology: Illinois Prairies

Copeland et al. (2002) build an environmental understanding specific to the Illinois prairie ecosystem. The authors highlight the historical impacts of prescribed burns and their potential use for current restoration efforts. Also, their discussion about the seasonality of the prairie provided essential insight when developing criteria for this analysis. Specifically, the increased moisture acquired earlier in the spring is held on to by soils with poor drainage until the hot, dry season in the summer when all the moisture is expended. While not as drastic as Tibet's monsoon is still a seasonal dichotomy important to grass development. The timing of burns is significant to ensure species can recover before the later summer droughts. A deeper understanding of the grasses' growing season was developed from Copeland et al.'s explanation.

A unique contribution to this background review was provided by a course offered through a local farm museum by Jerome Johnson M.A., the director, attended by this author in February 2016. Johnson hosts an annual seminar in conjunction with other professionals from the region regarding the restoration and care of natural areas with a focus on prairies. This course offered supplementary materials for planning burns, finding invasive species, and use of livestock to maintain the prairie. Usually, the livestock used to maintain prairies is cattle, but it was noted that their grazing preference differs from the native bison (Johnson, seminar, February 20, 2016). Cattle only consume medium and short grasses, often resulting in the tall grass and invasive species overwhelming the area. This is contrasted with bison who eat the whole spectrum of heights. Yak prefer to consume a mixture of grasses and sedges of all lengths, similar to bison.

Given this insight into the role of grazing animals in maintaining the prairie, the establishment of ecological criteria to be used in this study through the lenses of Haynes (1996), Cincotta et al. (1991) and Miao et al. (2015)'s work was thus refined with an understanding of the Illinois prairie through the work of Copeland et al. (2002) and Johnson (February 20, 2016). Table 2 summarizes the relevant factors mentioned in this literature about Illinois' ecology.

Table 2: Summary of factors discussed in Illinois ecology literature

Source	Discussed Factors
Copeland et al. (2002)	Fire is used to removed woody plants Fire helps tall grass reproduction Avoid use of fire in the warm, dry season of late summer Prairie soils with poor drainage hold on to moisture Fire is used to help suppress dominant species
Johnson, seminar, February 20, 2016	Cattle graze a limited grass height Bison graze all grass heights Illinois mesic prairies have a wet and dry season Fire helps grass reproduction Fire is used to removed woody plants

2.3. Economy: Farming Communities and Urban Consumers

Economic factors are a significant influence on the purpose of this analysis. In order to positively impact a farm or region switching to yak-based agriculture, there must be economic benefits to sustain the change: most notably having to ability sell byproducts for a profit. To better predict the impacts of yak-based agriculture on the economic climate, the current economic climate must be understood. In 1996, Ilbery et al. observed movement of the agricultural sector towards overproduction for the sake of efficiency, often resulting in negative climate effects, an economy they named "post-productivism." While they focused on the United Kingdom, the general principals of how farms diversified in a post-productivism economy applied equally to Illinois because the United States experienced the same economic climate in the agricultural sector.

Nearly a decade later, Katchova (2005) observed an intentional adjustment by farmers in an attempt to exit the post-productivism phase. Recently, Sumner (2014) notes the agricultural sector is pulling in two directions. One part of the sector is remaining in the post-productivism economy with farm size dramatically increasing, while the other part is growing organically which appeals directly to consumers. Sumner shows that large farms, which produce the most yield and profit, diversify faster than small farms. This leaves smaller farms with less diversity in their product and risk management plan, and less profit.

Diversifying farming beyond monocropping adds economic benefits to environmental benefits (Barrows et al. 2014). Economically, diversifying farming strategies and income helps to minimize risk if a particular strategy fails (Ilbery et al. 1996; Katchova 2005; Sumner 2014). There are also ecological benefits to diversifying farming as stress is spread to multiple resources and not compounded on a single resource (Sumner 2014; Tomasek and Davis 2017). In Illinois, the stressed resource is soil (Tomasek and Davis 2017). The stress on this resource can be alleviated through diversity, which assists in maintaining the health of the soil.

Finally and importantly, in recent years, some authors have observed a new social movement among consumers that is showing a preference for local and sustainable foods (Clark 2003; Freehill-Maye 2014). This emerging social movement provides a new market opportunity for yak. Yak-based agriculture can take advantage of consumer's desires to have more locally available food that is more ecologically beneficial to the environment.

Given these various changes in the agricultural economy, the economic criteria of this analysis tried to bridge the gap between profitability and diversification. The main economic focus of this analysis comes from Ilbery et al. (1996), Katchova (2005), and Sumner (2014) with clarification through the interpretations of Clark (2003) and Freehill-Maye (2014).

2.4. Fuzzy Overlay as a Suitability Analysis

Fuzzy overlay was selected as the methodology for this analysis as it is particularly well suited for the continuous datasets used in the analysis while also accommodating discrete datasets. The methodology used in this analysis was adapted from Mitchell's 2012 *Esri Guide to GIS Analysis Volume 3*, with supplementation from other sources. The method is described in more detail in the following chapter. Here it is useful to briefly note why fuzzy overlay is the appropriate method for this analysis.

As a habitat site suitability analysis, fuzzy overlay is frequently used for the prediction of locations within a species' native range and can be validated through observations of the species' actual location. Breininger et al. (1998)'s study serves as an example of combining fuzzy overlay techniques with a site suitability analysis in this manner. The process of Breininger et al. (1998) applied the factors of a suitable habitat to determine suitable locations within the Florida scrub-jay's native range. The analysis described here applied a similar process to select a habitat range for yak within the AOI. There are two important distinctions between Breininger et al. (1998)'s use of fuzzy overlay and this analysis' use: Breininger et al. (1998) used the analysis within a species' native range and can be validated through observation. This analysis looks beyond a species' native range and cannot necessarily be validated through observations. The validation used for this analysis is discussed in the next chapter.

The first half of Qiu et al. (2014) highlights the three classic models used to screen land suitability: Boolean overlay, weighted overlay, and fuzzy overlay. The Boolean overlay, or what Qiu et al. describe as binary or pass/fail screening, is the best option when discrete limits can be set for land suitability. Due to this analysis' heavy use of continuous datasets, the Boolean overlay was not a useful option. However, a weighted overlay was a potential option for this analysis. It is similar to fuzzy overlay in that each factor is placed on a scale of favorability, but each factor is weighted against the others before being combined in the final overlay. Weighted overlay was not used for this analysis due to the lack of flexibility in deriving a final result. As Qiu et al. explain, weighted overlay combines all factors into the final product, and a low rating of one factor can be compensated for by a higher rating of another factor. This was not desired for this analysis because there are instances where a poor rating for one factor, such as an urban environment, should remove the area from suitability and not leave the potential for another factor to reenter the cell into the analysis. Qiu et al. explain fuzzy overlay or graduated overlay, is a preferred method for agricultural site suitability analysis due to the previously mentioned flexibility in deriving a final result and the ease of using continuous datasets. Fuzzy overlay, as it is explained, can use continuous datasets because they are placed within a ranking system similar to the weighted overlay without necessarily eliminating certain values like the Boolean overlay. The fuzzy overlay method was adapted for this agricultural analysis because it can handle, according to Qiu et al., the continuous datasets without having all layers contribute to the final result.

Reshmidevi et al. (2009) take advantage of fuzzy overlay's ability to handle uncertainty and vagueness within continuous datasets. Like this analysis, Reshmidevi et al. utilize fuzzy overlay for land suitability analysis that incorporates continuous datasets. A rule-based system is imployed by Reshmidevi et al. to create a ranking system within the analysis. This system stipulates what factors follow a combination sequence and is expressed as "if…then" statements. A similar process to Reshmidevi et al.'s rule-based system was almost employeed in this analysis and is discussed more in the fuzzy overlay procedures. Reshmidevi et al. used the rule-based system to establish an element of weighted analysis to the fuzzy overlay because a weighted overlay, like that described by Qiu et al., could not be employed due to the level of vagueness within the continuous datasets. Like this analysis, Reshmidevi et al. did not want to discount poential areas as unfavorable if there were no discrete limits that could be applied to the datasets. Instead, Reshmidevi et al. used logic operators to overlay the fuzzy membership layers in the most favorable manner for the analysis without creating arbitrary limits on the data.

Mitchell (2012) provides a step by step process for various types of suitability analysis with theoretical examples. The fuzzy overlay method was adopted for this analysis because of its flexibility in handling both discrete and continuous data. Many of the criteria chosen for the suitability analysis did not have discrete limits for acceptability, such as slope or temperature. However, placing the criteria on a scale made a continuum of favorability instead of discounting areas that might be partially suitable because there are no well-defined ranges for yak habitat.

Hyneman (2014)'s thesis also pulls from Mitchell (2012)'s methodology and provides a concrete example of how to implement fuzzy overlay, compared to Mitchell's theoretical applications. As with Mitchell's explanation, Hyneman notes the importance of using fuzzy overlay when the criteria do not have distinct thresholds of acceptability and allow for more leniencies in the analysis. Hyneman commends the process' flexibility in incorporating Boolean and discrete data.

The literature presented in this chapter provided the groundwork for the factors used in the following chapter. Specifically, the literature regarding yak physiology and Illinois ecology affected the decision of which factors were determined significant enough for predicting yak suitability and adaptation to the AOI's climate. Sources such as Cincotta et al. (1991), Miao et al. (2015), and Wu (2016) indicated factors should emphasize a balance between the yak's ability to survive a warmer, lower elevation climate and the production of grass as the primary food source. While understanding the economic climate of the agricultural economy is important, as further described in Chapter 3, the information was ultimately unused in the analysis. These sources were placed into a framework of fuzzy overlay, particularly Mitchell's procedures for use with ArcMap.

Chapter 3 Methodology

The focus of this research was to find suitable county and subcounty divisions for yak-based agriculture in Illinois. The fuzzy overlay technique was selected to complement a variety of data types to be used in the analysis. Fuzzy overlay techniques are advantageous here because the analysis makes use of continuous datasets that are difficult to divide into binary suitability classes. All datasets were prepared as fuzzy membership layers, discussed in the data preparation section, before undertaking the final fuzzy overlay. Finally, vector overlays were used in conjunction with the statewide fuzzy membership map to provide summaries specific to county and subcounty divisions.

3.1. Methods Overview

In addition to fuzzy overlay, which is the integral cornerstone of this analysis, the following section also introduces several additional concepts that are important in conjunction with fuzzy overlay. Specifically, it includes a discussion of the scale of analysis used in this procedure and the significance of using a snap raster to align the data properly. Because this study uses fuzzy overlay in a manner more difficult to validate, the process of how the results were validated is also outlined as part of the procedure for the analysis.

3.1.1. Methodology of Fuzzy Overlay

Fuzzy overlay methodology is integral to this analysis because it is particularly well suited for data that is continuous, difficult to define, or derived from expert opinion. Most of the data in this analysis, especially the ecological factors, are continuous datasets without mutually exclusive groupings. Fuzzy overlay provides flexibility to the determination of favorability in the analysis for handling continuous datasets (Mitchell 2012). The implementation of fuzzy overlay described throughout the rest of this chapter follows the guidelines described by Mitchell (2012) and uses a process specific to the ArcMap software produced by Esri.

Fuzzy overlay analysis requires two stages. First, each criterion to be used in the analysis must be converted to fuzzy membership values using the fuzzy membership functions. Then the fuzzified data is overlaid using fuzzy overlay functions.

Fuzzy membership operates by favoring criteria in a dataset along a continuous scale instead of creating discrete binary categories of suitability (Mitchell 2012). This flexibility prevents the creation of unnecessary or inaccurate binary relationships in the analyzed data. The creation of a fuzzy membership layer assigns a membership value to the observed values of the dataset. Favored values within the dataset are given a status referred to as membership and values beyond acceptable limits have the status of non-membership. All values in-between are ranked on the likelihood of membership to the set. The membership value scale is from zero to one with zero being non-membership, one is full membership and the infinite values in-between are likely or partial members. Most data points fall in between zero and one.

A function, either mathematical or logical, determines the relationship between the observed values and the membership values created, controlling the dataset distribution between membership and non-membership. Assigning a fuzzy membership value to the observed data can manifest through a variety of relationships. Linear relationships occur when full membership is assigned to large or small observed values, and the rate of change to non-membership is consistent. The smallest or largest observed values in the linear function can be altered to create thresholds called minimums and maximums. These thresholds are useful for complete exclusion of large or small observed values. Figure 3 demonstrates what a positive linear relationship between membership and observed values would look like with a minimum placed on the lower observed values to exclude low values and include values above the minimum.

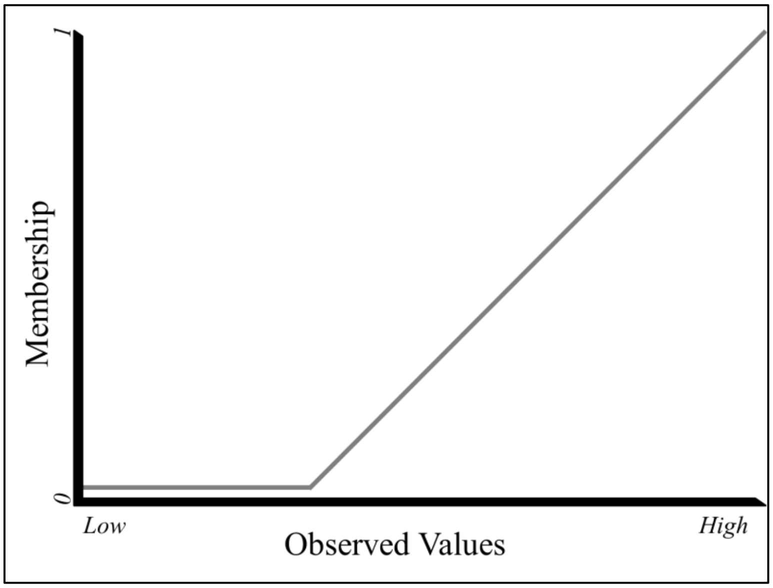


Figure 3: Example graph of a fuzzy membership linear relationship with a minimum threshold

Non-linear relationships can be created between the datasets using the Small or Large functions. The Small function gives membership preference to small observed values, and the Large function does the opposite. A rate of change can be manipulated to alter the nature of the function's spread. Additionally, a midpoint can be stipulated in the observed data where the fuzzy membership value will equal 0.5 (the midpoint between membership and non-membership). Figure 4 demonstrates a graph for a Small relationship between observed and membership values with a midpoint. There are other relationships possible with fuzzy membership functions, but they are not particularly relevant to this analysis as they require less emphasis on expert opinions and more on mathematical relationships.

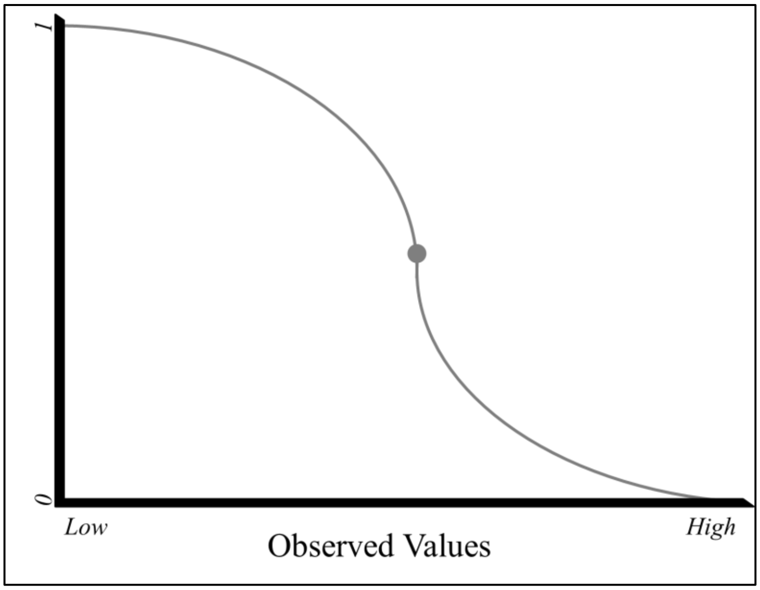


Figure 4: Example graph of a fuzzy membership non-linear “Small” relationship with a midpoint

Once all datasets have been fuzzified, then they are overlaid using a fuzzy overlay function. The method and order of fuzzy overlay operations used is one of the most influential components of the analysis, as it drastically affects the outcome. The method of operations determines the degree to which each membership layer contributes to the result, often referred to as the weight of its contribution (Mitchell 2012). The two key logical functions available in ArcMap to control the fuzzy overlay are AND and OR. The use of the AND operator returns the minimum value of the factors at the cell’s location. The OR operator does the opposite and returns the maximum value of the factors at the cell’s location. Mathematical operations, including product and sum, are available but are not particularly relevant to this analysis. The product operator multiplies the values of each factor at the cell’s location and was not used here because the resulting fuzzy overlay would have contained extremely small values overall. The sum operator adds the values of each factor at the cell’s location and was not used because it would have unnecessarily over-emphasized the high value range of the fuzzy membership inputs.

3.1.2. Scale of Analysis

The scale of analysis is the baseline scale to which all datasets are converted, ensuring that all layers can be integrated. Thus, the cell sizes for each dataset were noted. The digital elevation model (DEM) rasters acquired were 90 by 90 meters, the Cropland Use raster was 30 by 30 meters, and the climate rasters were 4 by 4 kilometer cells. Ultimately, a 1 kilometer spatial resolution was selected as a compromise between the 4 kilometer and 30 meter scales used by the datasets. A 1 kilometer scale allows for a detailed depiction of the data at the subcounty division level, as the divisions are about 6 miles (approximately 10 kilometers) across, without severely compromising the information from the large-scale data while keeping the small-scale data relevant. One concern about the scale was the size of river valleys, particularly around the Illinois River, which present a very different suitability. After multiple measurements of several river valleys, the 1 kilometer scale was confirmed to be acceptable because even at their widest, none of the river valleys exceed a subcounty division's typical width. Therefore, generalizing these river valley regions using the 1 kilometer scale will not affect an area greater in size than the smallest region used to summarize the analysis.

3.1.3. Projection

WGS 1984 Universal Transverse Mercator (UTM) Zone 16N was the projection chosen for use in this analysis. It is one of the preferred projections for viewing Illinois. Each of the following data sources was projected to this during the data preparation process. The UTM is a projection system that uses a Cartesian (2 dimensional) coordinate model. This system divides the planet into 60 vertically oriented zones that allows for the mapping of an area with a large north-south extent, like Illinois, with minimal distortion. Zone 16N is the 16^{th} zone of the UTM in the northern hemisphere and encompasses most of Illinois (Wilson and Fotheringham 2008).

In summary, this projection is a particular zone of a Cartesian system based on the WGS 1984 datum. All data sources were projected to this during the data preparation.

3.1.4. Snap Raster

A snap raster is the key to successfully align data in each step of the model; it is the foundation for all raster creation within the model. Each time a raster was created, or altered in some way, it was aligned to the pre-determined snap raster to ensure all cells in overlaid rasters were properly aligned. Only when this alignment is correct, then the final fuzzy overlay membership values can be correct. If the alignment is done poorly, or not at all, cell values cannot be overlaid. For this particular analysis, the slope raster was the snap raster.

To create the snap raster, the slope raster was resampled and then aggregated to the 1 kilometer analysis scale. The raster had a cell size of 90 meters but required geoprocessing to create the 1 kilometer grid. First, the raster was resampled to 10 meter cells, dividing each original cell into 81 equal value cells, and then aggregating 100 cells to become the final 1 kilometer cells. This aggregated raster, as seen in Figure 13, was used as the snap raster. Further details of how the slope raster was created for use as the snap raster is in the data preparation section below.

3.1.5. Validating Results

Many validation options were not available for this analysis as there is virtually no precedence of yak-based agriculture in Illinois against which to confirm results. There are numerous studies where fuzzy overlay is used to determine potential locations for species. Other studies try to predict where the species can be found but this analysis looks to place the species in the favorable locations. One option was to compare the final overlay raster to locations of existing yak farms in Illinois. However, there is currently only one farm, as discussed in the results section, which further indicates the need for dissemination of information about raising yak (Hall and Sarver 2016). Various statistical reviews of the final numbers in the fuzzy overlay raster are possible for evaluating the normal curve and other indicators of statistical soundness. However, results of statistical tests cannot provide value to this study nor validate the results.

As a result, the validation in this study process began with intentionally selected points as well as generating twelve random points. The intentionally selected points were chosen as their location should tell the story behind the data and have a predictable result. For example, points located in an urban center should have a membership value of zero because they are not a favorable location for livestock. A table was created to compare the fuzzy membership values to the fuzzy overlay favorability value. This table allows the visualization of how the factors influenced the final result and was used to verify if the factor behaved as anticipated.

3.2. Source Data

Each dataset was carefully examined. A close look at all the data helped better understand the datasets, know what sort of preparation was necessary before the creation of the fuzzy membership layers, and what outcomes were expected from the data preparation and fuzzy membership creation. This analysis used 128 different datasets collapsed into 7 factors.
Table 3 shows a brief summary of the datasets collected for the analysis and their association with the analysis' criteria.

Table 3: Summary of Factor Data Sources

Factor	Data	Criteria
Slope	Slope	Favor gentle grade
Soil association	Soil type and soil association	Favor grass areas
Cropland Use	Cropland Use	Favor grass areas and disallow urban areas
Temperature	Temperature	Favor low values
Humidity	Vapor pressure deficit	Favor low values
Precipitation	Precipitation	Favor high values
Economy	Roads and farmer's markets	Favor proximity

3.2.1. Boundaries

A 2016 shapefile of Illinois county lines acquired from the United States Census Bureau served as an overlay for the analysis. The data was in the geographic coordinate system (GCS) with the North American Datum of 1983. A state boundary to define the AOI was created by using the Merge tool on the counties; it was used for clipping rasters. Additionally, a shapefile similar to the county line layer for subcounty divisions was acquired from the United States Census Bureau. Subcounty divisions are a type of census county division for use in presenting statistical data. Before it was overlaid, the subcounty divisions dataset was also projected. Figure 5 shows the state boundaries as a bold black line, counties as bold blue lines, and the subcounty divisions as thin red lines.

Figure 5: State, county, and subcounty divisions boundaries of Illinois

An additional set of boundaries was acquired for use in the analysis. The Illinois Department of Agriculture's Bureau of Meat and Poultry has six regions, displayed in Figure 6. These are the administrative districts of Illinois' livestock industry. This dataset is a polygon shapefile created by the researcher using the map image available on the Illinois Department of Agriculture's website.

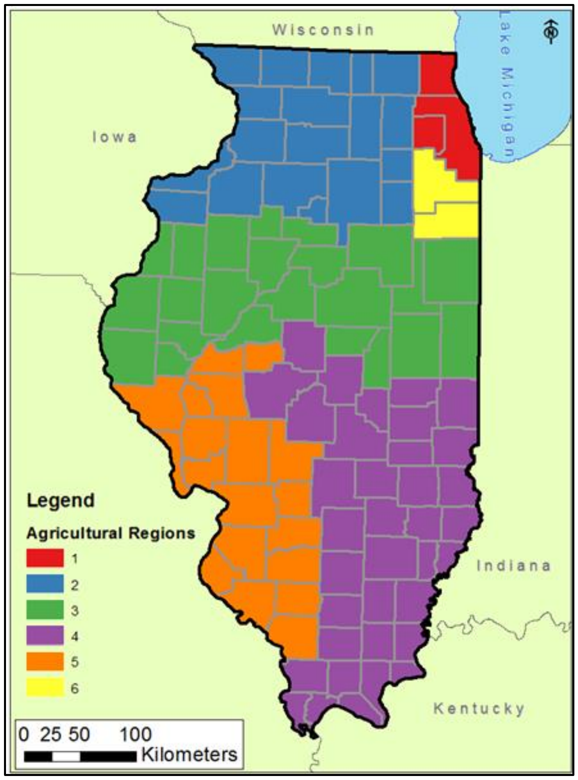


Figure 6: The 6 agricultural regions of Illinois

3.2.2. Elevation

To depict the topography of the state, digital elevation models (DEMs) created by the International Centre for Tropical Agriculture (CIAT) from the Shuttle Radar Topography Mission (SRTM) data (Jarvis et al. 2007) were acquired from the United States Geological Survey (USGS). While this shuttle mission's primary concern was the collection of elevation data outside the United States, it is an easily accessible source with global availability, supporting this study's intention to be suitable in other study areas. Information collected from the mission were also used to fill in voids of previous NASA datasets. The mission's datasets are available in the tile size of one degree latitude by one degree longitude. Issues with the data collected on the mission arise in high relief areas where limited visibility resulted in not data being returned. These areas are small and not within the AOI, which is characterized by very even topography. Four DEMs were required to cover the entirety of Illinois because the AOI resides within more than one degree of latitude and longitude. These rasters were unprojected geoTIFFs with 90 meter cells using the WGS 1984 datum. The distribution of elevation across the AOI is characterized by low elevation numbers and slight changes in elevation around river valleys. Other USGS datasets were not used for this analysis because the scales, at 30 meter cells and smaller, were unnecessarily accurate for a dataset that was to be aggregated to a 1 kilometer analysis scale.

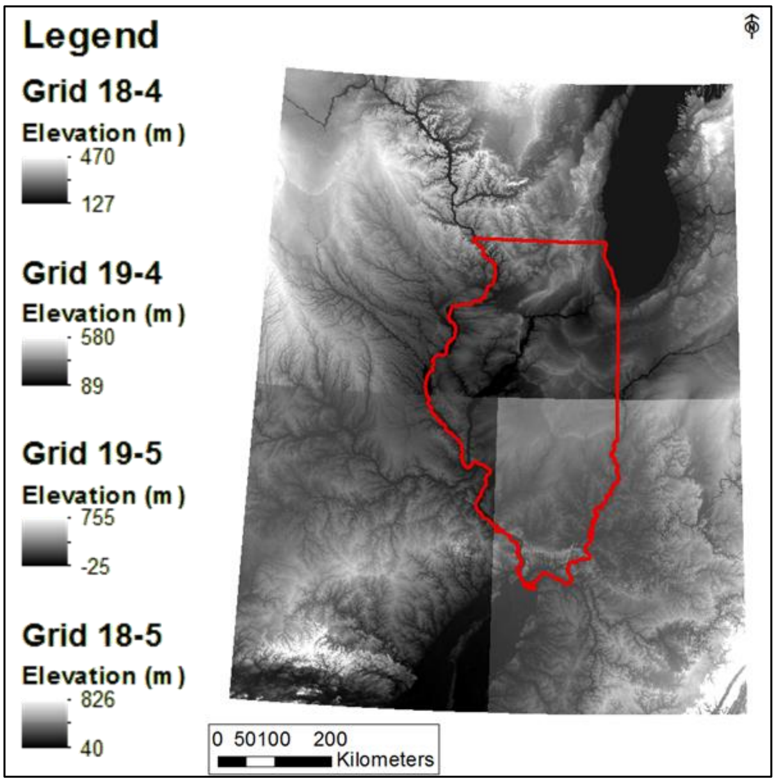


Figure 7: Source elevation rasters, before becoming a mosaic, with Illinois outlined in red.

3.2.3. Soil

Two datasets were attained for use in preparing a soil association fuzzy membership raster. The first dataset, a raster soil association map, contained the necessary information for creating a fuzzy membership layer but was not as spatially detailed or up-to-date as the soil type vector map available. These two datasets were joined so that the required information from the association map could be used with the detailed soil polygons. More details on the joining process are discussed in the data preparation section below, but it is necessary to understand the classification for the soil fuzzy membership layer derives from the soil association data and the geometry derives from the soil types data.

The first dataset was a soil map created by the Illinois State Geological Survey in 1983 with 500 meter cells. This raster contained two sets of information: the soil's parent material and the soil association. It is with the associations that this analysis is concerned. Soil associations are categorizations of soil types according to the plant types it grows (Cincotta et al. 1991). This dataset had three categories of soil association: prairie-type, forest-type, and water-type soils. The prairie-type had 25 subcategories and the forest-type had 26 subcategories. The dataset was unprojected in GCS North American Datum of 1983.

The second dataset was obtained through the national Natural Resources Conservation Service (NRCS) Web Soil Survey (WSS) website. It was a polygon shapefile of the official NRCS soil classifications, distributed unprojected in WGS 1984 datum with a map scale of 1:1,000,000. This dataset's attribute information contains alphanumeric keys that are associated with specific soil types according to the NRCS' database. There are 98 unique soil types in Illinois according to the dataset. While the soil maps in Figure 8 are displayed without legends due to the large number of categories both contain, they are used here to illustrate the amount of spatial detail included in each.

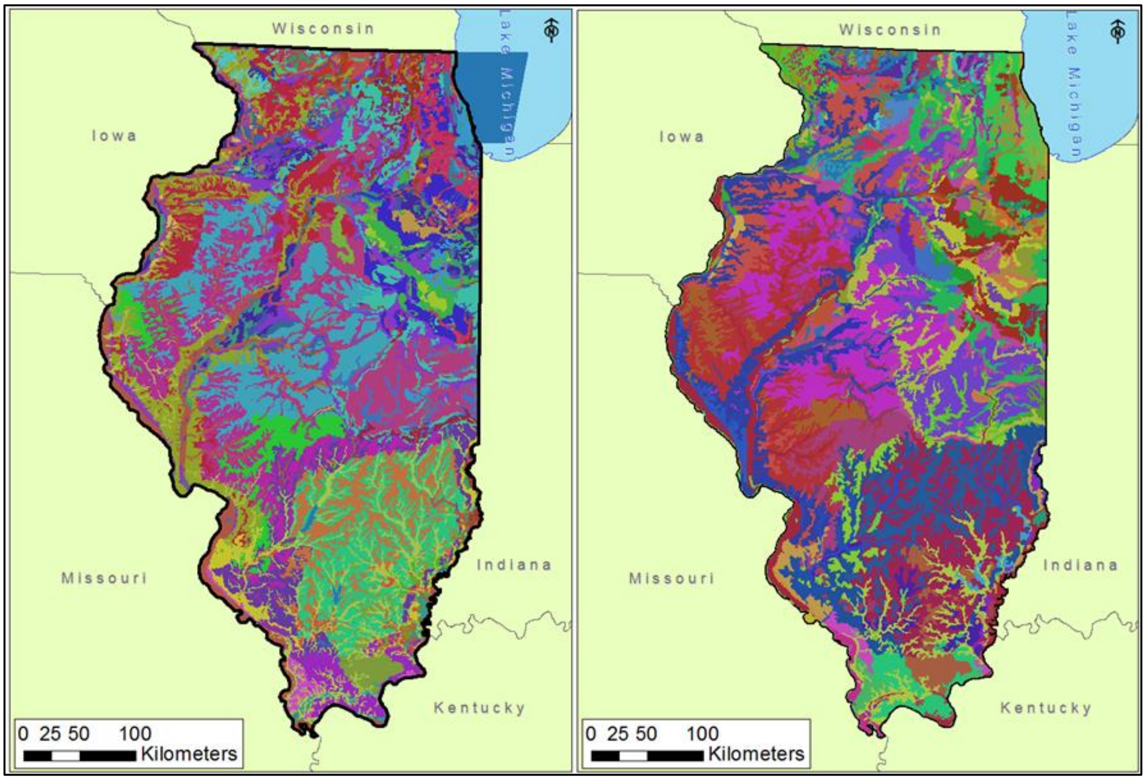


Figure 8: The soil association raster map (left) and soil type vector map (right).

3.2.4. Cropland Use

A 2007 Cropland Use raster dataset with 30 meter cells was obtained from the United States Department of Agriculture (USDA). This raster was acquired in IMAGINE image format in WGS 1984 UTM Zone 16N projection. “Cropland Use” is a term coined by the USDA to succinctly describe a land plot’s specific use at the time of data collection. The raster contains 255 unique values for various use types, including soybean fields, developed land, peach orchards, and mixed forest. However, it was manually reclassified, as discussed in the data preparation section, because the layer is contains many functionally similar categories. This dataset plays an important role in the analysis by distinguishing between plant types as well as the urbanized areas, areas under cultivation, and natural areas. Figure 9 shows the spatial detail of the Cropland Use raster but has no legend because 255 values are too many to display.

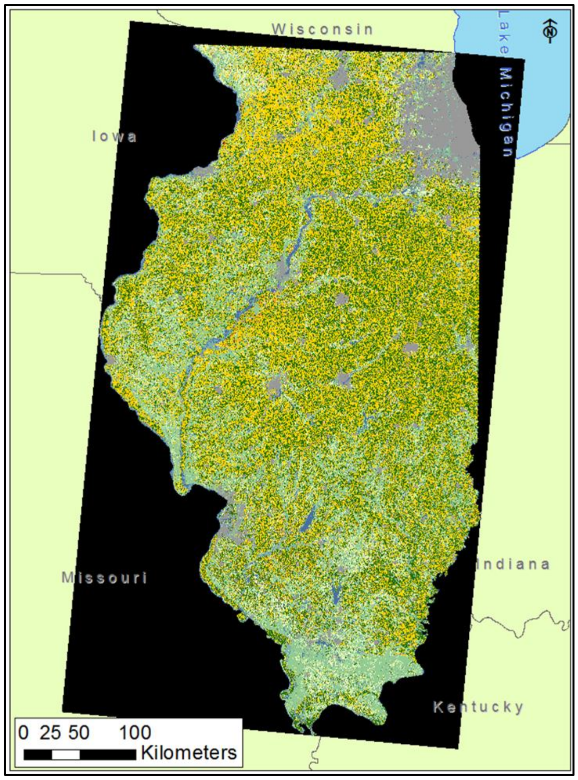


Figure 9: Cropland Use raster

3.2.5. Climate

All climate datasets were acquired from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) Climate Group at Oregon State University through a direct link on the National Oceanic and Atmospheric Administration (NOAA)'s website. PRISM ingests climate information from a number of sources, including NOAA, and models them using interpolation to produce a wide variety of datasets.

The data used for this analysis comes from PRISM's "Recent Years" collection, which contains data from 1981 onward. This information can be downloaded for daily, monthly, or yearly summaries for the following climate variables: total precipitation, mean temperature, minimum temperature, maximum temperature, mean dewpoint temperature, minimum vapor pressure deficit, and maximum vapor pressure deficit. Data was not available at the state level and was attained for the contiguous United States with a cell size of 4 kilometers. Each raster was in the GCS North American Datum of 1983. Figure 10 is an example of how the downloaded rasters looked before data preparation.

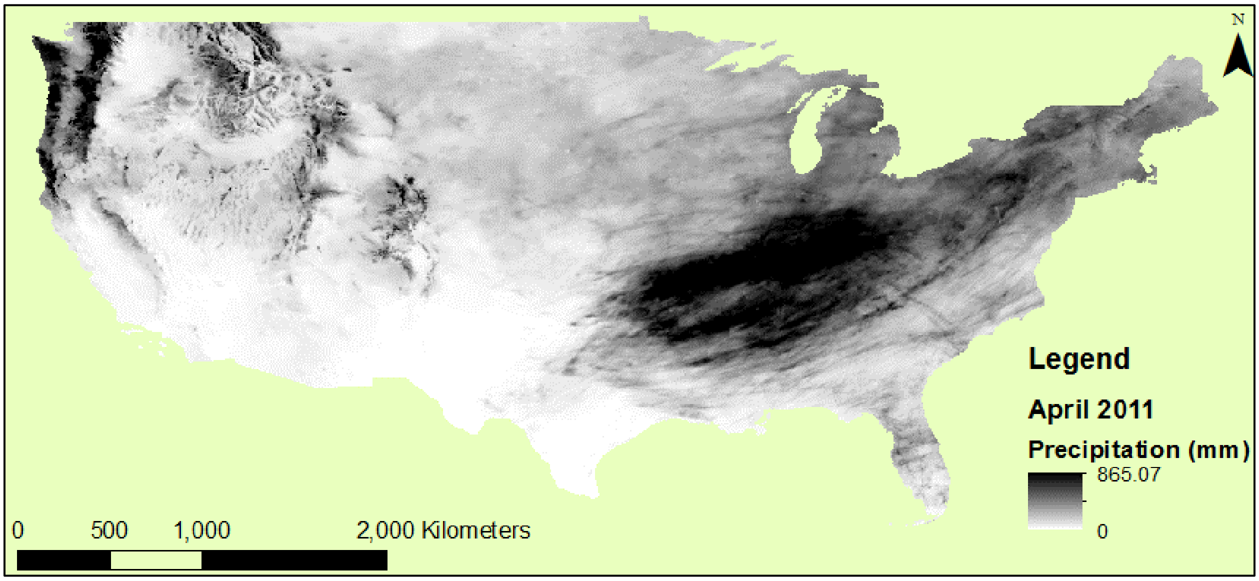


Figure 10: A map of unprepared total precipitation data from April 2011

The climate factors acquired for this analysis were total precipitation, mean temperature, and maximum vapor pressure deficit (VPD). The initial intention was to use humidity as a climatic measure because of its importance in the literature; however, the closest data type available in the PRISM data was maximum vapor pressure deficit (VPD). VPD is the difference between how much moisture is in the atmosphere and how much moisture the atmosphere can hold. This measurement is similar to humidity, which is the total measure of moisture in the atmosphere.

An entire years' worth of data was not desired because winter does not have a significant impact on the yak's food source (Cai et al. 2009; Song et al. 2014). Instead, the growing season was defined as March through October (Dai et al. 2015; Tomasek and Davis 2017). Limiting the temperature data to the growing season places the focus on yak having a tolerance threshold in the summer heat, not the winter cold. Also, using data from the growing season ensures the temperatures are the warmest of the year. Because of this, the monthly averages were used for each of the climate factors instead of the available daily or yearly averages.

Additionally, due to the impacts of climate change, only the past five years' data was used (Cai et al. 2009; Robeson 2002; Tomasek and Davis 2017). Going farther back would place the data in a different climate cycle. And because complete 2016 data is not yet available, only information for March through October of 2011 through 2015 was collected for this analysis. To encompass the entire time range desired, 40 rasters for each climate factor, 120 rasters total, were downloaded for use in the analysis.

3.2.6. Market Proximity

This dataset is a point shapefile created by the researcher using a list of farmer's markets registered to the Illinois Department of Agriculture (AgriHappenings n.d.; Bamberger 2017). Each market's address was plotted on Google Earth and saved as a Keyhole Markup Language (KML) file. This KML file was converted to a point shapefile, displayed in Figure 11. The KML file has since been made available for public use using Google's My Maps website with attributes for the market's name, street address, and the web page when available (Bamberger 2017).

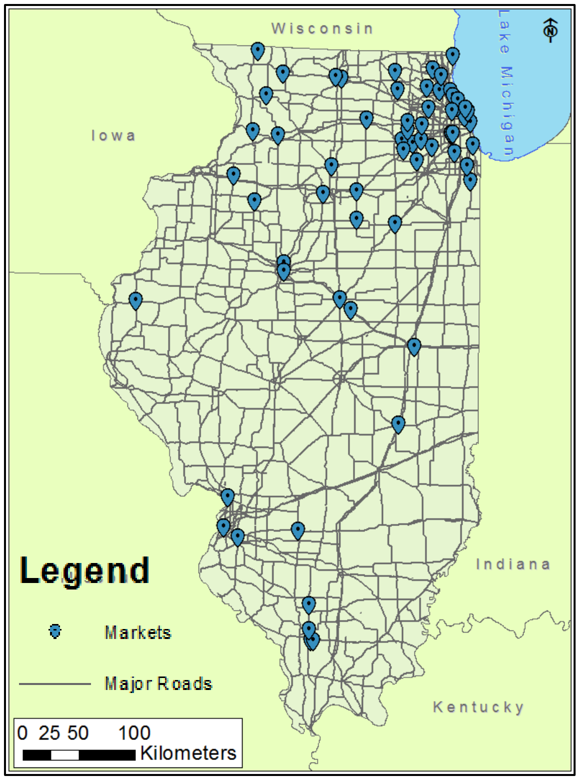


Figure 11: Location of registered farmer's markets in Illinois

Additionally, a dataset of Illinois' road network was acquired to complete a network analysis to incorporate into the market proximity layer (United States Census Bureau 2013). This line shapefile shows all roads in Illinois and demonstrates the dense road network in Illinois and is seen in Figure 12. The network is so dense that when all roads are symbolized with 0.25 point lines it still difficult to find an area of the state not covered in roads.

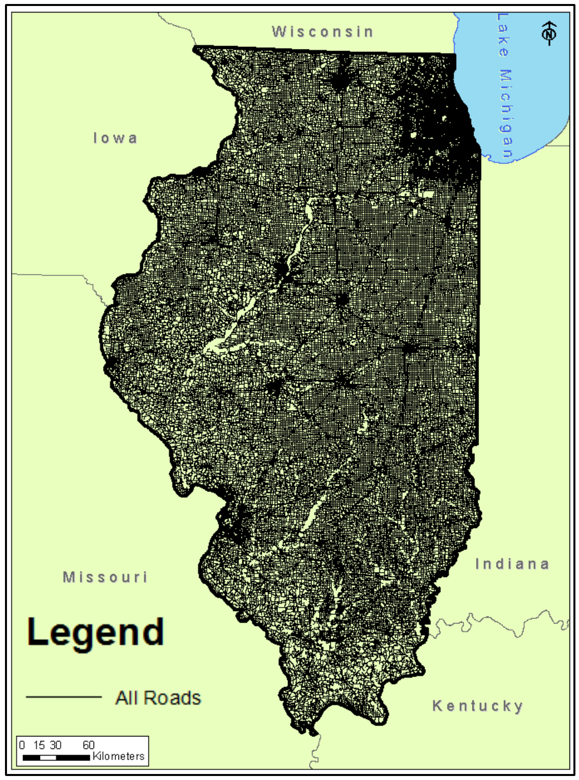


Figure 12: Road network of Illinois

3.3. Data Preparation

Once all of the datasets were collected, described, and recorded, the work of preparing the data for use in the fuzzy overlay began. Each of the datasets had a unique combination of preparation steps before creating the fuzzy membership layers. Some data simply need projection while others need categorization, mosaic creation, or other processes.

3.3.1. Boundaries

The county and subcounty division layers only required projection to WGS 1984 UTM Zone 16N to prepare for use in the analysis. However, a state boundary file to match this set was only available with a national download. Instead, a state boundary was created by using the Merge tool on the projected county shapefile. This layer became the AOI extent, as seen in Figure 5. The dataset for the agricultural regions (as seen in Figure 6 above) was not available as a dataset but as a static map. The dataset was created by adding an attribute field to the projected county layer and manually entering the region observed on Department of Agriculture's map and published to Google's My Maps for public reference (Bamberger 2017; Illinois Department of Agriculture 2014).

3.3.2. Slope

The four DEMs were combined into a raster mosaic and projected to WGS 1984 UTM Zone 16N. The raster mosaic was run through the Slope tool before clipping to the AOI extent to prevent any edge bias in the analysis. Next, the raster was resampled and aggregated as described in the previously mentioned snap raster description. When the raster was aggregated to the 1 kilometer scale of analysis, the mean technique that averages the inputted cells of the neighborhood was selected (Esri 2016). The resulting raster can be seen in Figure 13.

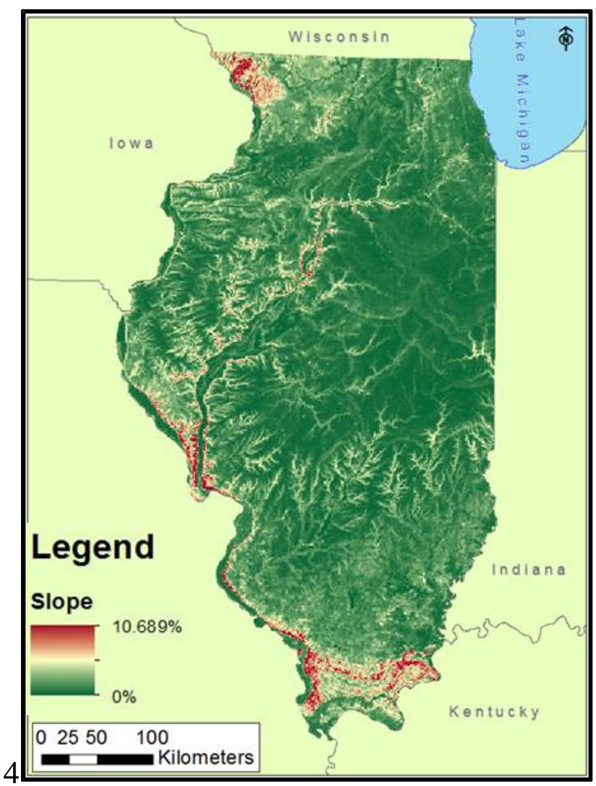
4


Figure 13: Map of the prepared slope raster

There are various options available for the aggregation tool, and any repetition of this analysis should use the appropriate method used for the selected AOI. A brief slope study was conducted to demonstrate the mean aggregation technique was the best option for Illinois. Each raster was clipped to the AOI's boundaries before aggregation to prevent the higher elevations outside of Illinois present in the raster mosaic from influencing the analysis.

Aggregations were run using five variations: mean, maximum, median, maximum minus mean (largeness), and median minus mean (skewness). The maximum minus mean technique preserves the larger value in the raster's data. AOIs with great amounts of topographic variation can use this method to be very selective in what is considered a feasible area before running the fuzzy membership. Median minus mean depicts the skewness of the data and visually represents the distribution of the data and acts like a spatial histogram. This measurement can show if the data is close to a normal distribution or if the data is skewed negative or positive.

Basic statistics and histograms were collected for each variation of aggregation (see Figure 14). Larger versions of these histograms and maps of the slope study are included for closer examination in Appendices A and B. It is important to note that the five maps in Figure 14 are displayed using the same symbology range for consistency when visually comparing, but only one map actually has a negative slope. The map on the far right, derived from the median minus mean (skewness) aggregation technique, has a negative slope due to the subtraction calculation performed on the raster.

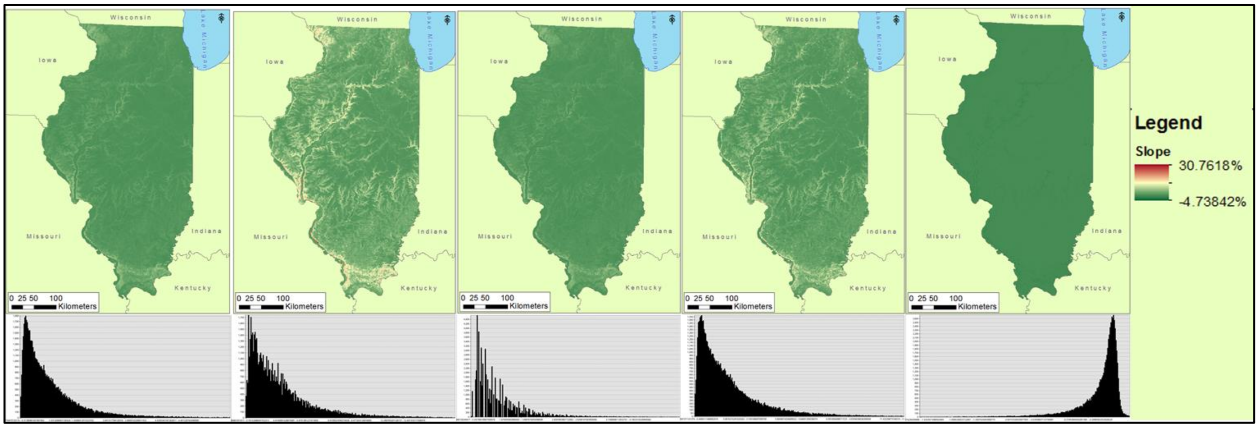


Figure 14: Collection of maps and histograms from the slope study. From left to right: aggregation with mean technique, aggregation with maximum technique, aggregation with median technique, aggregation with maximum minus mean (largeness) technique, aggregation with median minus mean (skewness) technique.

The statistics summary of Table 4 strongly indicates mean aggregation as the best selection for representing Illinois. Mean technique's standard deviation is closest to one and has a small difference between the mean and standard deviation: statistical indicators of reliability.

Table 4: Summary of slope study statistics

Aggregation method	Mean	Maximum	Median	Maximum minus mean (largeness)	Median minus mean (skewness)
Minimum	0	0	0	0	-4.738
Maximum	10.69	30.76	9.86	25.94	1.062
Mean	1.14	3.42	0.999	2.279	-0.14
Standard Deviation	0.93	2.78	0.84	1.97	0.219

A close runner up is the median technique, which has a smaller difference between the mean and standard deviation, but the standard deviation is farther way from one, meaning the distribution of the data is less normal. However, it is important to notice the results of the skewness method (median minus mean). Each of the numbers collected, particularly the negative value for the mean, strongly indicates the distribution of the slope is heavily skewed towards lower values. This skew is one of the pieces of evidence used to support the removal of slope as an analysis component from this particular model.

Once the slope raster was aggregated, the use of a fuzzy membership function favoring gentle slopes and excluding slopes too steep for farming equipment was intended. Slopes with a grade of 11% or more are often too difficult for standard farming equipment, such as tractors and trailers. However, since no cell in the aggregated raster has a value over the threshold of 11%, slope was omitted as a factor in this analysis.

3.3.3. Soil

The soil association raster had 500 x 500 meter cells and was aggregated in alignment to the snap raster so that 4 cells became the final 1 kilometer cells. The values in the original soil association dataset were 1 to 98. Prairie-type soils were coded with values 1 to 15, forest-type soils were valued 31 to 57, nothing was valued from 58 to 97, and water-type soils were valued at 98. For use in this analysis, the soil association raster was reclassified to a ordinal favorability scale after it was projected. The favorability scale places prairie-type soils at 1, forest-type soils at 2, and water-type soils at 3 (as seen in Figure 15).

As mentioned in the data description, the soil type map had more accurate and current geometry than the soil association raster. It was decided the two soil maps would be spatially joined to place the soil association information into the geometry of the soil type map. The reclassified soil association raster was converted to a polygon shapefile and spatially joined with the soil type dataset set as the target features. A few polygons had null values after the spatial join because of the difference in scales. These values were set manually by referencing the soil type of the polygon and manually finding the matching association. The resulting shapefile was rasterized to the appropriate 1 kilometer grid with the snap raster, seen in Figure 15.

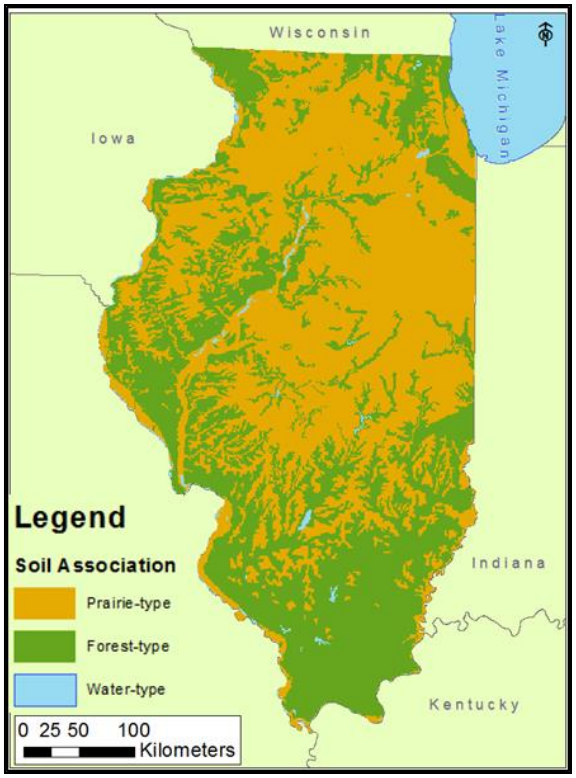


Figure 15: The prepared soil association raster

3.3.4. Cropland Use

The Cropland Use raster was categorical in nature and reclassified on an ordinal favorability scale. The scale used was 0 to 4, which is shown in Table 5. Areas in which agriculture are not possible, such as surface water and urban environments, were classified as 0 to ensure the cells were non-members in the fuzzy membership layer. This minimum in the data creates noticeable areas of urbanization on any maps that use this raster, visible in brown on Figure 16. Areas with low favorability, specifically naturally woody areas, such as forests, orchards (tree crops), and shrublands were classified as 1. It is possible to raise yak in these areas, but a significant amount of preparation to the land would be required. The medium favorability category, value of 2, contains non-tree crops, such as corn and soybean fields. Some preparation would be required to raise yak in these areas, but not as much as clearing trees. A high favorability value of 3 was given to pastures, flower crops, hay, and fallow fields because little preparation is needed. The highest favorability of 4 was given to the class of land which could graze yak immediately; grass and prairie. Cultivated lands were valued lower on the nominal favorability scale than uncultivated grasslands because it is more difficult to raise yak in a place where infrastructure intended for other purposes already exists.

Table 5: Cropland Use favorability categories

Scale	Favorability	Cropland Use
0	None	Urban Areas, Water, Wetlands, Background/Null
1	Low	Forest, Tree Crops, Shrubs
2	Medium	Non-Tree Crops
3	High	Pasture, Flowers, Hay, Fallow
4	Very High	Grass, Prairie

Adjustments were still necessary once the favorability scale was complete because the raster had a 30 meter cell size. Using the slope raster as precedent, the Cropland Use raster was first resampled to 10 meters and then aggregated with the median to the desired 1 kilometer the result to the snap raster. The final raster is seen in Figure 16.

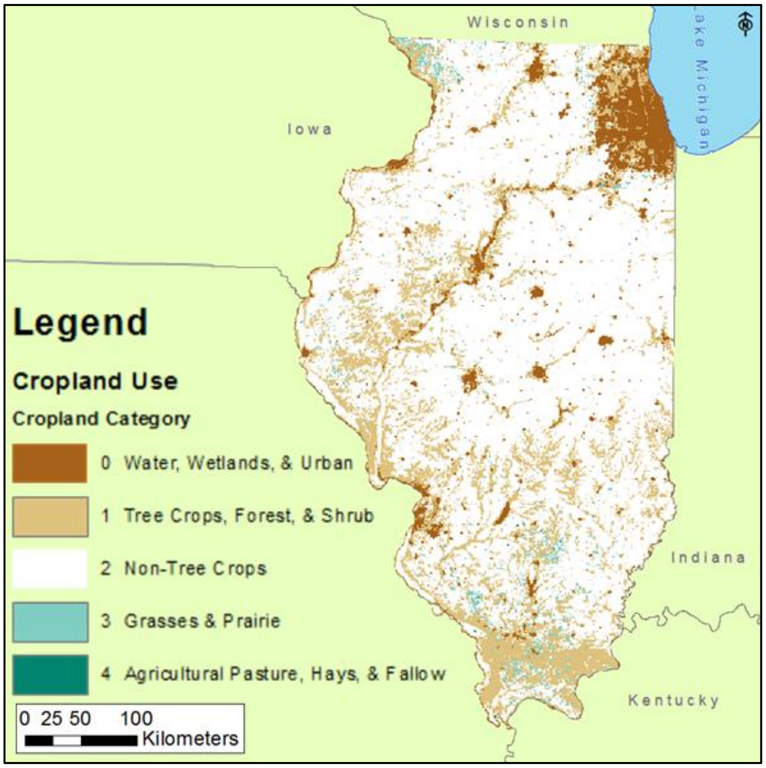


Figure 16: The prepared Cropland Use raster

3.3.5. Climate

Climate data preparation required processing 120 nationwide rasters into three statewide rasters, one for each climate factor: precipitation, temperature, and VPD. A rough clip was performed on each of the rasters, beyond the boundaries of the AOI to prevent edge bias, to save processing time for the rest of the preparation steps. The values of each cell across the set of 40 rasters for each of the three climate factors were averaged using the raster calculator to produce one overall average raster for each climate factor. Each of the rasters was then appropriately projected and clipped to the AOI. Resampling each raster from 4 kilometers to 1 kilometer was accomplished with the snap raster. Then, the Focal statistics tool was used to smooth the resampled rasters using a rectangular neighborhood of 3 by 3 with a mean statistic. The resulting rasters (shown in Figure 17) represent the average climate of the growing seasons from 2011 to 2015.

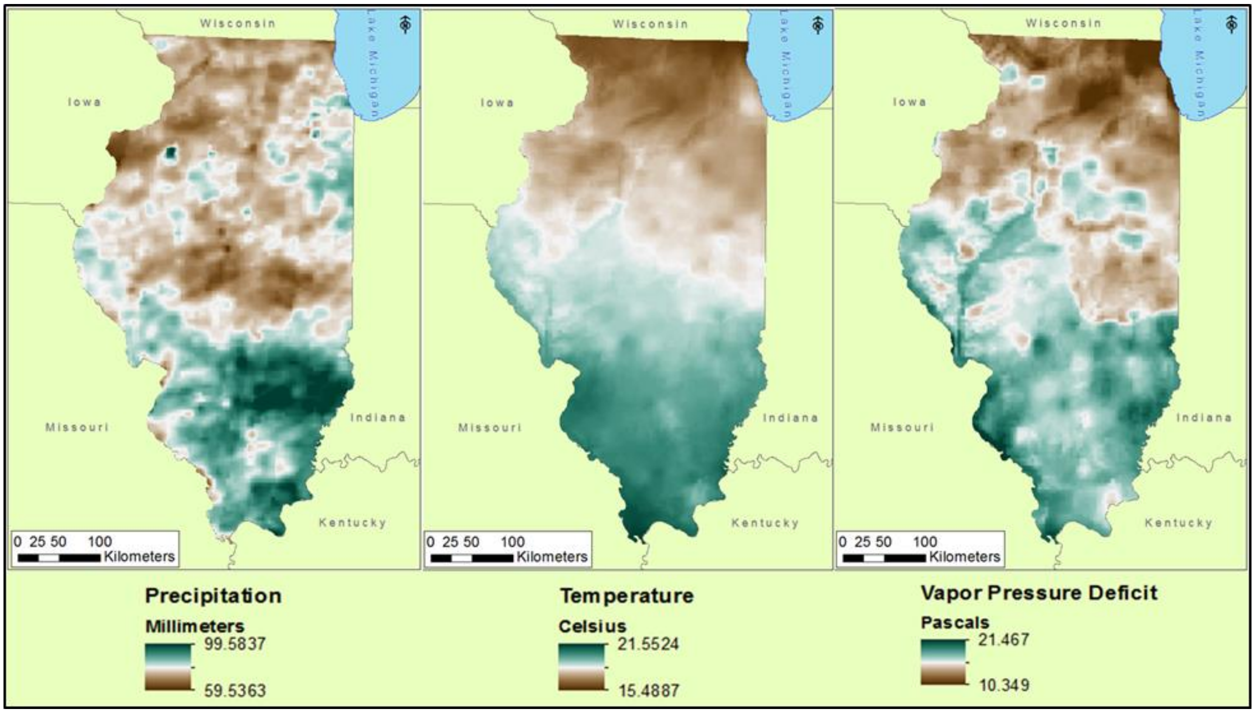


Figure 17: Illinois' average climate for the 2011-2015 growing seasons

A strange phenomenon the researcher named the Illinois Precipitation Anomaly (IPA) was noted in the northwestern area of Central Illinois (centered in Figure 18). This same pattern carried forward into the precipitation fuzzy membership raster. The IPA is an area of about 225 square kilometers where the average daily total precipitation is significantly greater than the immediate surrounding region. There is no significant change in topography or hydrology in the region to explain the phenomenon. Some individuals were contacted to assist in providing potential reasoning with no response. It is quite possible this results from an outlier in the original weather data, but it was not possible to correct this anomaly.

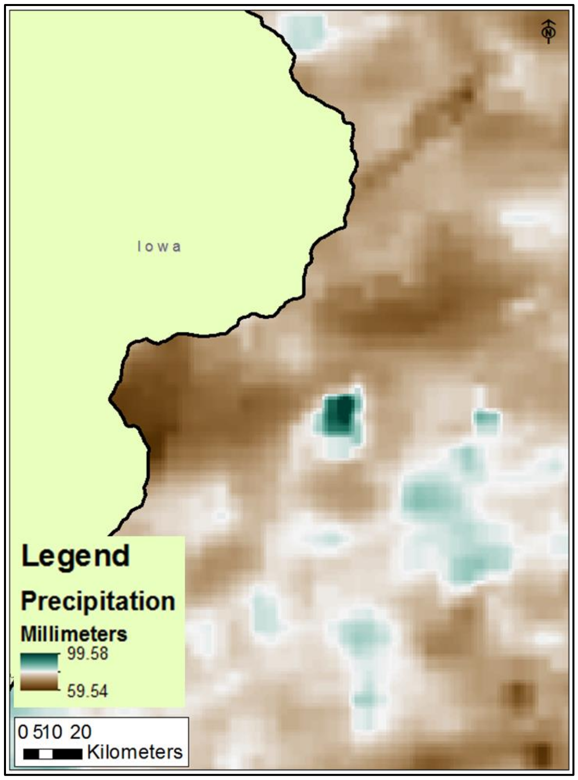


Figure 18: A map centered on the Illinois precipitation anomaly, which is symbolized as a teal spot.

3.3.6. Market Proximity

Numerous procedures were considered for determining a feasible analysis for market proximity, which included preparing a simple Euclidean distance surface from markets or, more appropriately, calculating distance along the road network from farms to markets. However, since network analysis can only calculate distances along the network, anything off the network, such as farmlands with potential for yak-based agriculture, cannot be easily accounted for. Even if the network is rasterized, it is not possible to perform this sort of analysis, and there is no precedence for combining fuzzy membership overlays and network analysis.

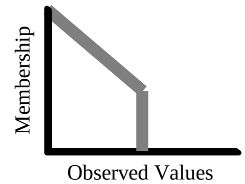
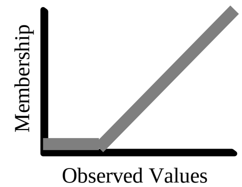
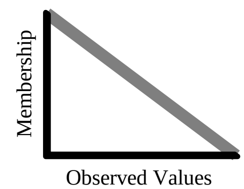
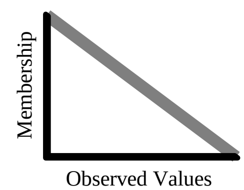
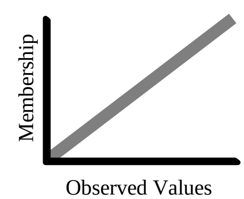
As Illinois has a dense road network, a large metropolis, and a lack of unnavigable topography, the idea of a network analysis was abandoned. The next option was to use Euclidean distance across the landscape from the farmer's markets. However, due to the density of the road network, any farmer's market is within hours. Additionally, such markets are not the only option for selling byproducts. Large-scale distributors can transport products across great distances on a reliable basis, regardless of a farm's isolation (Armendariz et al. 2016; Clark and Inwood 2015). Market access was a non-issue due to Illinois' uniform topography and dense road network, making the use of market proximity layers unnecessary. Even when roads are symbolized to display only major highways, as seen in Figure 11, market access correlates to road access. How to model this factor remains unresolved for any repetition of this analysis in other regions with unreliable and sparse road networks.

3.4. Fuzzy Membership Procedures

Each of the criteria has a particular relationship with the observed values that must be appropriately represented with the creation of their respective fuzzy membership layers (Esri 2016). Fuzzy overlay was chosen as the method of analysis because it allows consideration of each criterion without arbitrarily limiting values. Appropriate assignment of functions for each criterion is necessary to create reliable fuzzy membership layers. The functions applied to the input data are summarized in

Table 6 and described in the following subsections.

Table 6: Membership functions of study factors

Criterion	Membership	Function	Graph
Soil Association	Favor prairie-type and exclude water-type	Linear with maximum	
Cropland Use	Favor grass and exclude developed areas	Linear	
Temperature	Favor low values	Linear	
Humidity	Favor low values	Linear	
Precipitation	Favor high values	Linear	

After the appropriate background research and data preparation were completed, five criteria remained for inclusion in the study: soil association, Cropland Use, temperature, vapor pressure deficit, and precipitation. Importantly, when displaying the fuzzy membership rasters the symbology must be kept uniform from 0 to 1 in order to visually compare fuzzified layers with one another and the fuzzy overlay.

3.4.1. Soil Association

The three category favorability scale for soil associations created in data preparation made the fuzzy membership tool simple to run to favor prairie-type soils (fuzzy value = 1), disfavor forest-type soils (fuzzy value = 0.5), and ensure non-membership of water-type soils (fuzzy value = 0) with a maximum (Mitchell 2012), as shown in Figure 19. These preferences are due to the foraging habits of yak for varying lengths of grass and ineptitude at foraging shrubs (Cincotta et al. 1991; Haynes 2011; Leslie and Schaller 2009; Loeser 1968; Miao et al. 2015). Forest-type soils were included as partial members because it is possible to prepare the area and raise yak. However, it is significantly more difficult to prepare and maintain areas as grazing lands that are predisposed to growing trees. Trees would need to be felled, nutrients injected into the soil, grasses planted, and then maintained because the soil lacks the inherent properties desired for cultivating grasses. The exclusion of water-type soils ensures the model does not accept lakes, rivers, swamps, and wetlands as acceptable areas to raise yak.

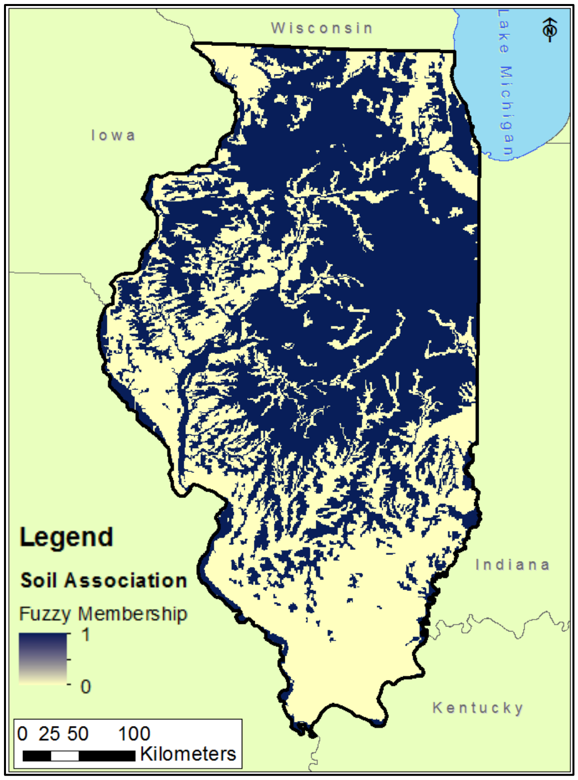


Figure 19: Fuzzy membership raster of soil association

3.4.2. Cropland Use

The fuzzy membership tool was run on the prepared Cropland Use raster with a minimum to give non-membership to areas with a 0 on the nominal favorability scale (e.g. urban and water) and a linear relationship with membership increasing towards locations with a scale ranking of 4 (grass and prairie). Table 7 shows the membership values of Cropland Use raster as they relate to the actual use of the land. Cultivated lands were valued lower on the nominal favorability scale than uncultivated grasslands since it is more difficult for a farmer to prepare cultivated land for use in raising yak than an unused grassy area. Cultivated locations, both tree crops and non-tree crops, require plants to be cleared, nutrients injected into the soil, and appropriate grazing plants sowed. These preparations cost time and money and led to the ranking seen in Table 7.

Table 7: Summary of Cropland Use membership values

Cropland Use	Favorability	Membership Value
Urban Areas, Water, Wetlands, Background/Null	0	0
Forest, Tree Crops, Shrubs	1	0.25
Non-Tree Crops	2	0.5
Pasture, Flowers, Hay, Fallow	3	0.75
Grass, Prairie	4	1

The result is shown in Figure 20. The majority of the region is not at the highest membership level because most of the landscape is under cultivation (categories 2 and 3).

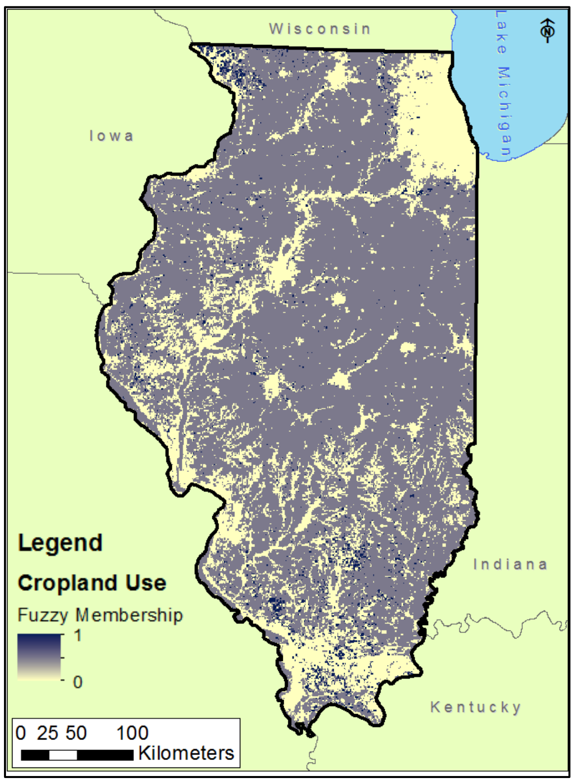


Figure 20: Fuzzy membership raster of cropland use

3.4.3. Climate

Yak prefer cold climates with a feasible amount of humidity ensuring the large amount of precipitation necessary for grasses to produce a beneficial amount of nutrition (Cincotta et al.

1991; Haynes 2011; Leslie and Schaller 2009; Loeser 1968; Miao et al. 2015; Wu 2016). To reflect a preference for cold temperatures, the use of a fuzzy membership spread function with a midpoint at 15° Celsius was initially planned. This midpoint placement was intended to strongly discourage membership of temperatures above this threshold because yak are susceptible to heat exhaustion (Cincotta et al. 1991; Leslie and Schaller 2009; Mitchell 2012). However, there are no cells with a value below 15° Celsius in the prepared temperature raster of the study area. Therefore, the fuzzy membership raster for temperature was created using a linear relationship to favor the lower values that represent the colder temperatures, across the available range of the dataset (see Figure 21). Thus, the maximum membership of 1 was set at the lowest value, 15.48°C, and the minimum membership of zero was set just beyond the highest value, 21.56°C, to ensure all values from the prepared raster had some degree of membership. For repetition of this analysis in other AOIs, the 15°C midpoint with a spread function should be used.

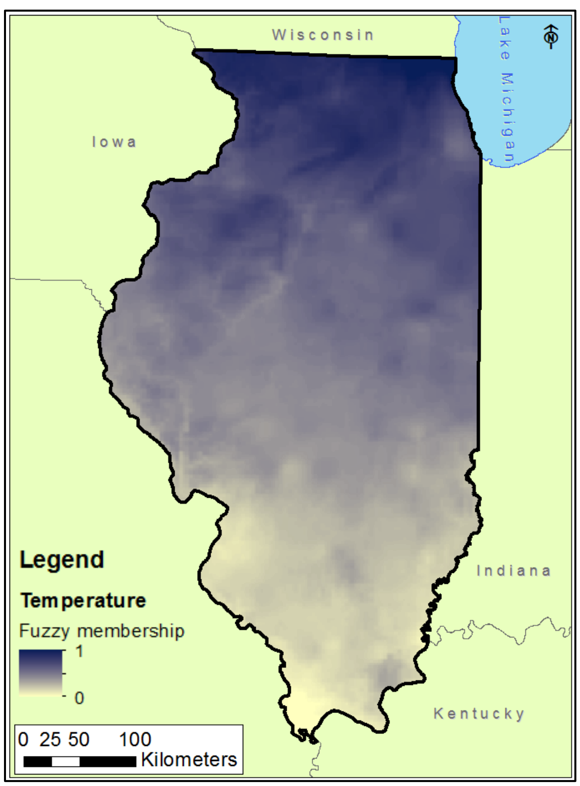


Figure 21: Temperature fuzzy membership raster

Precipitation was the next climatic factor to be fuzzified. The Tibetan Plateau is dry for most of the year but the region experiences torrential amounts of monsoonal rains for a few months a year. Illinois is in a fully humid continental climate zone, which reduces the likelihood of areas as dry as the Tibetan Plateau and can grow the necessary amount of biomass to raise yak (Kottek et al. 2006). A linear function was selected to represent the correlation between precipitation and plant growth. Illinois precipitation patterns, as mentioned above, cannot mimic the Tibetan Plateau, however, for this analysis, a linear function that is acceptable for this analysis focuses on finding the most suitable locations in Illinois to raise yak. To ensure fuzzy membership favored large amounts of precipitation, which correlates to high amounts of biomass yields in pastures, full membership was set to the highest available value of 99.59 millimeters and the membership value of 0 was assigned just beyond the lowest precipitation value of 59.54 millimeters to ensure all precipitation values fell within the range of membership. The resulting raster is shown in Figure 22.

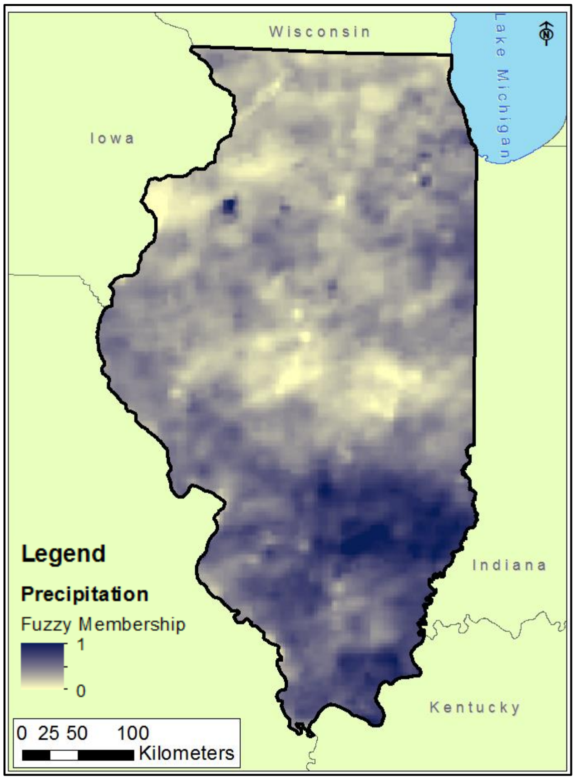


Figure 22: Precipitation fuzzy membership raster

Vapor pressure deficit was the final climatic factor to be fuzzified. During research, no concrete numbers were found for humidity preferences by yak, only expert opinions focused on the combination of heat and humidity. Generic descriptions note favorability towards less humidity due to a correlation with heat exhaustion when in warmer locations (Cincotta et al. 1991; Leslie and Schaller 2009). Fuzzy overlay was selected for this analysis due to similar situations where uncertainty is present. The entire range of VPD within the prepared raster was used when calculating membership due to a lack of detailed expert opinions beyond lower is favored (Cincotta et al. 1991; Leslie and Schaller 2009). Limiting the membership values to the range of the AOI is also acceptable as the analysis seeks the most favorable Illinois locations for raising yak. The linear function was used to create a relationship favoring smaller values of vapor pressure. The membership value of 1 was set to the lowest VPD value of 10.35 hPa and the membership value of 0 was set just beyond the highest VPD value of 21.47 hPa to ensure all values from the prepared raster had a membership value (see Figure 23).

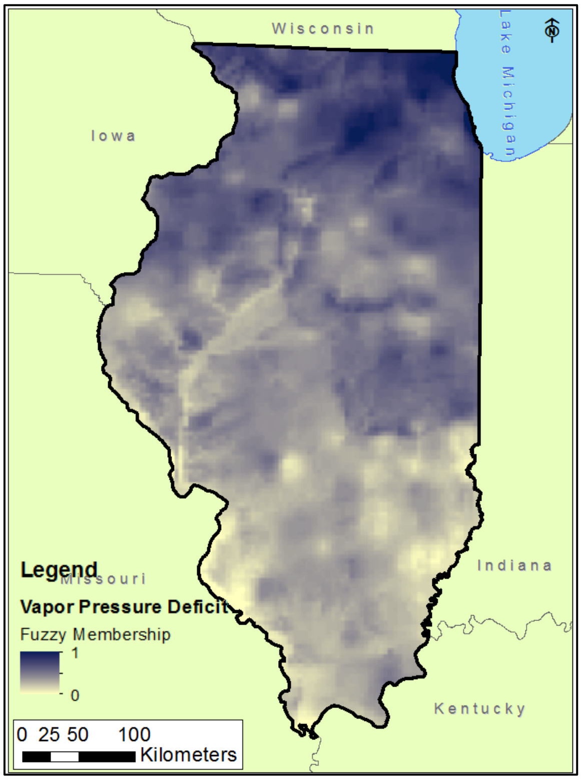


Figure 23: Vapor pressure deficit fuzzy membership raster

3.5. Fuzzy Overlay Procedures

When put into an overlay, the fuzzy membership rasters can be weighted to have varying prominence in comparison to other layers. The weight of the rasters is dependent on how the operations are ordered and combined. Each variation has the potential to affect the analysis drastically (Mitchell 2012). For this particular study, an initial sequence was created but ultimately abandoned for another. Any replicated study must determine the appropriate operations for the AOI.

3.5.1. Initial Logic Sequence

A logic sequence was conceptualized for the final overlay before the data preparation was complete. The sequence looked at the process as a tiered system; combining the fuzzy membership rasters with the ultimate goal of a fuzzy overlay result that favored all grasses, kept all available options for temperature and slope, but narrowed favorable areas with VPD and precipitation amounts (see Figure 24). The first combination of soil types and Cropland Use would have produced a fuzzy membership raster for grasses. Combining temperature and slope would have generated a fuzzy membership raster for steppe-like conditions. Overlaying precipitation and VPD would have created a fuzzy membership raster for moisture conditions. Another fuzzy overlay would have combined the steppe-like conditions with moisture conditions for a fuzzy membership raster reflecting climate. This climate layer would be combined with the grasses fuzzy membership raster for a fuzzy membership raster reflecting ecological conditions. A final overlay using the fuzzy membership raster representing the economic conditions produced by the market proximity analysis would have been combined with the ecological conditions to provide a final fuzzy overlay raster representing favorability for yak-based agriculture in Illinois.

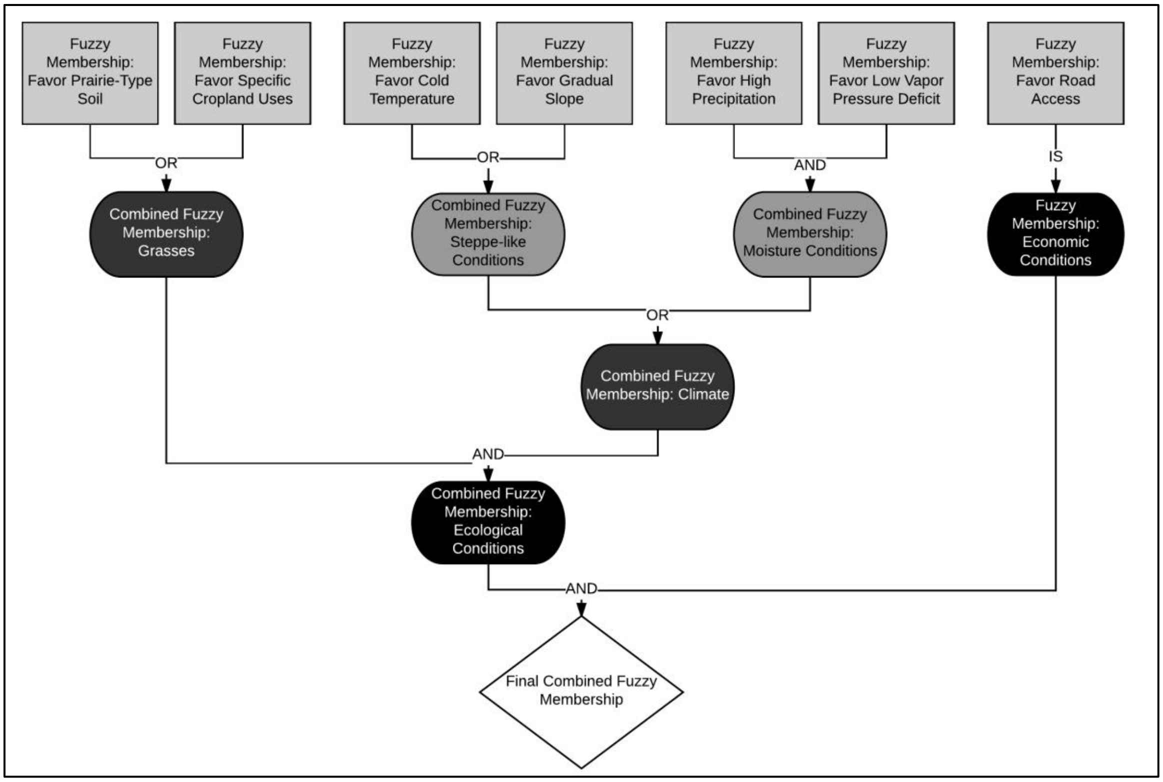


Figure 24: The initial logic sequence

3.5.2. Choosing the Fuzzy Operators

Choosing the operators to use to combine the fuzzy layers is critical. Table 8 was created to explore options in changing the fuzzy operators to assess their impact on the desired outcome. This table was created before any of the factors were eliminated and with the intention of providing weight to the analysis using a combination of logic operator like in Qiu et al. (2014) or Reshmidevi et al. (2009). The removal of economic factors and slope spurred the need to reevaluate the analysis' logic. Table 8 was created by referencing Figure 24 to begin looking at which logic operators should be changed. Recall that AND is a logic operator that returns the minimum value of factors at the cell's location and OR is a logic operator that returns the maximum value of factors at the cell's location.

Table 8: Potential changes in logic flow

Factors	Potential Change	Effects of Change	Notes
Prairie-type Soil and Cropland Use	OR to AND	Limits the type of grass areas	Limiting
Temperature and Slope	OR to AND	Would more accurately reflect a steppe environment while restricting potential	Possibly the better option, but slope was eliminated from the study
Precipitation and Vapor Pressure Deficit	AND to OR	Would allow more extreme combinations by removing some variability	Not an acceptable option
Climatic Variables	OR to AND	Severely limit acceptable areas	Limiting and needs to be reevaluated as slope was eliminated from the study
Ecological Variables	AND to OR	Would place the actual presence of grass as more or less important than other ecological factors	Not an acceptable option and needs to be reevaluated as slope was eliminated from the study
Ecological and Economic Variables	AND to OR	Would make markets equal to all other factors	Cannot be done as this would make markets option or ecological factors option but needs to be reevaluated as market proximity was eliminated from the study

3.5.3. Final Logic Sequence

An important observation from an examination of Table 6 is the disinclination with replacing certain AND functions. The initial logic sequence just described did not take into account the removal of the slope and economic criteria from the study. It was particularly important to have the economic factors have the greatest weight in the initial logic sequence. Once the most important criterion was removed, the weight of the remaining rasters became less important.

As a result of this analysis, it was determined to overlay all fuzzy membership layers with a single logical operation AND (see Figure 25). Combining all the fuzzy membership rasters with an AND operator in a single step gives all criteria equal weight in the analysis. An area is just as likely to be marked as unfavorable due to urbanization as for warm annual average daily temperatures.

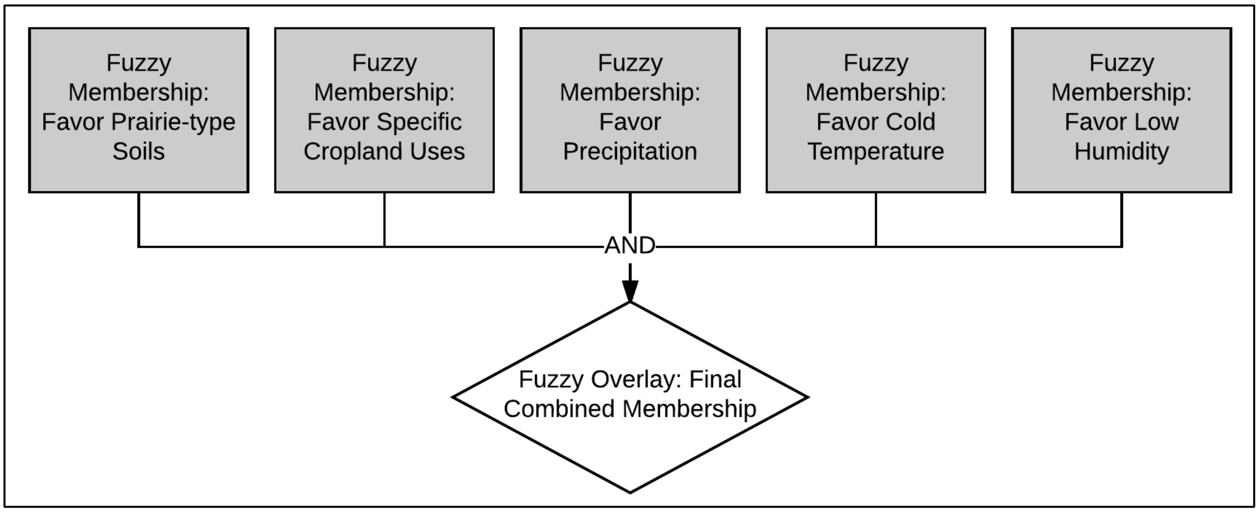


Figure 25: Final logic sequence

3.6 Vector Overlay

The final piece of the procedure involved a series of vector overlays. The results for the regions, counties, and subcounty divisions were summarized by the range, total area, total area above a suitability threshold of 0.4, and total area above a suitability threshold of 0.35. Those suitability thresholds are further discussed in the next chapter. First, to provide a statewide overview, a summary of results by Illinois' agricultural regions was performed. Next, a summary by Illinois counties shows which specific counties have significant suitability for yak-based agriculture. Finally, to surmise which subcounty divisions can be suggests to the county farm bureaus of the most suitable counties, a summary by subcounty divisions was performed. A table was exported containing the results for each cell and the information of which region, county, and subcounty division the cell belongs to from the vector overlay and arranged in the aforementioned summary format.

Chapter 4 Results

Due to the large region under consideration, the results were summarized in stages. First, all statewide information was collected. Then, data relating to each agricultural region and county was collected. These data were summarized and used to determine the most suitable counties. Finally, to properly articulate the results to these county farm bureaus, information was collected from the top counties at the subcounty division level. Arbitrary limits, referred to as favorability thresholds, were selected to provide a measure of preferred suitability. As the maximum cell value was 0.491967767 (rounded to 0.49), the suitability thresholds were selected to represent the top 70% (suitability over 0.35) and 80% (suitability over 0.40) of the raster. The top 90%, above a suitability value of 0.44, was too restrictive and would have left only 840 cells statewide.

4.1. Statewide & County-level Summary

The fuzzy overlay, seen in Figure 26 with a larger version in Appendix C, resulted in favorability values that varied across that state. While it is possible to achieve a favorability value of 1 from a fuzzy overlay, the highest favorability value resulting from this analysis was 0.491967767 (rounded to 0.49). For this reason, the suitability thresholds used to summarize the results represent the top 70% and 80% of the favorability values. The top 90% would have been too restrictive and represents 840 cells in the raster out of approximately 150,000.

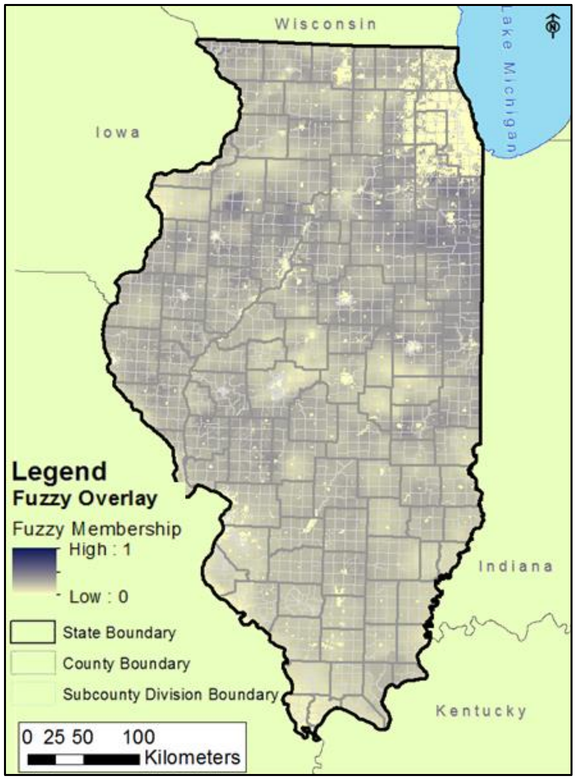


Figure 26: Fuzzy overlay results with state, county, and subcounty division vector overlays

The full table of summarized information from the fuzzy overlay can be seen in Appendix D. The table was checked to ensure the total area of the counties were greater than 0. A column was created containing a simple conditional formatting to ensure the total area of the county greater than a favorability value of 0.4 was not more than the total area of the county with a favorability value over 3.5. This relationship is expected because the values are on a scale and therefore no county will have more area with a favorability value above 0.4 than 0.35. Once these numbers were validated, Excel was used to calculate the percentages necessary for summarizing the data.

4.2. County and Subcounty Summary

The counties that emerged with the highest percentage of area above the favorability threshold of 0.4 were Will, Kankakee, and Iroquois counties. The data for these three counties is summarized in Table 9. Figure 27 shows a map of the fuzzy overlay results of these suitable counties. A natural break of nearly 10% occurred between Will County and the next most suitable area, Henry County, which has only 10.68% of its land above the favorability threshold. No other county comes near 10%.

Table 9: Results summary of Illinois's top 3 counties

Results	Kankakee	Iroquois	Will
Region	6	3	6
Total Area (km^2)	1,770	2,925	2,181
Total Area (km^2) > 0 Favorability Value	1,692	2,902	1,549
Area > 0 Favorability Value	95.59%	99.21%	71.02%
Total Area (km^2) > 0.35 Favorability Value	1,265	1732	780
Area > 0.35 Favorability Value	71.47%	59.21%	35.76%
Total Area (km^2) > 0.4 Favorability Value	909	898	434
Area > 0.4 Favorability Value	51.36%	30.7%	19.9%
Minimum Favorability Value	0	0	0
Minimum Favorability Value > 0	0.25	0.23	0.18
Maximum Favorability Value	0.47	0.47	0.49

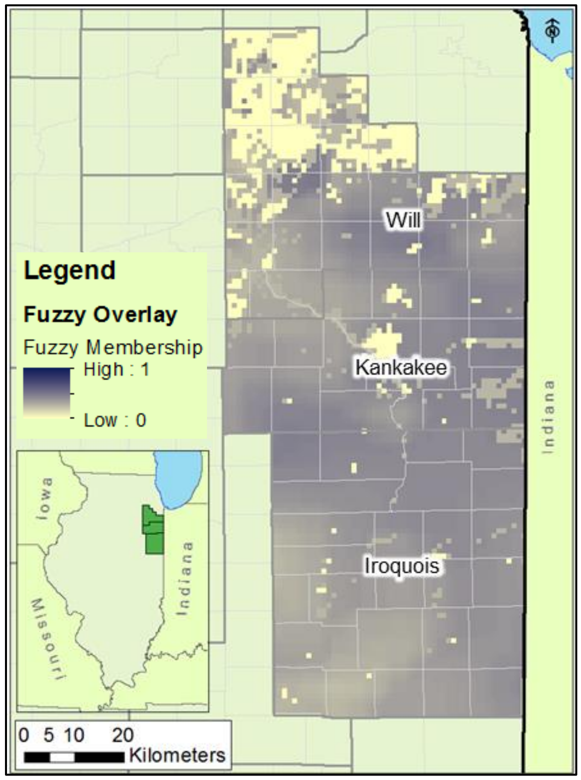


Figure 27: Fuzzy overlay results of Will, Kankakee, and Iroquois counties with state, county, and subcounty vector overlays

A table, seen in Appendix E, was created to highlight the data of these three counties in order to articulate to the county farm bureaus the favorability of their county for yak-based agriculture at the subcounty division level. The most suitable subcounty divisions in these counties are Milks Grove, Beaver, Stockton, Martinton, Sheldon, Chebanse, Papineau, Prairie Green, Concord, Middle Port, Beaverville, Yellowhead, Gancer, Saint Anne, Sumner, Momence, Peotone, Will, and Wilton. Figure 28 shows the spatial distribution of these highly favorable subcounty divisions, outlined in red, based on the percentage of area with a favorability value over the threshold of 0.4.

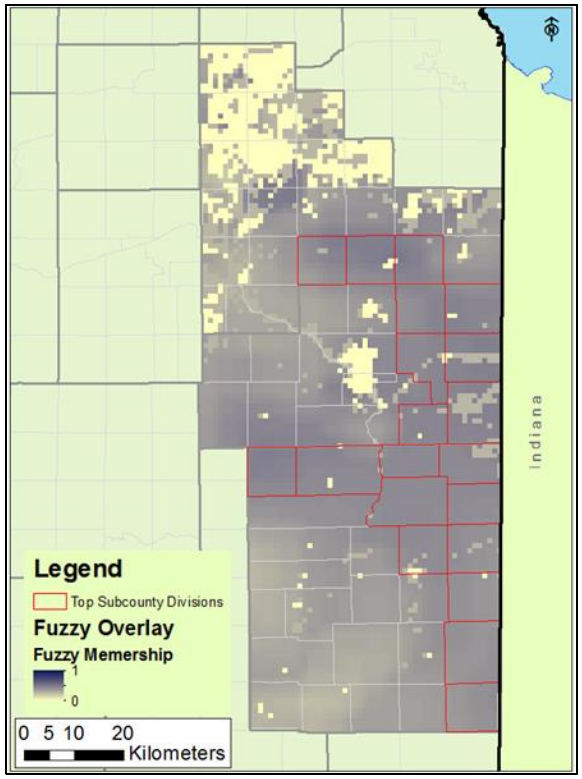


Figure 28: Fuzzy overlay results of the most favorable subcounty divisions

4.3. Validating Results

Before these summaries are analyzed and conclusions drawn, it is important to ensure the results are not only correct but useful. One form of validation was the location of Illinois' first, and only, yak farm. Goat Trax Farm is successfully raising yak in Kankakee County. Additionally, a directed point sample was collected to verify the favorability values from the fuzzy overlay were influenced by the factors as expected. Finally, a review of the fuzzy overlay's histogram was conducted to assess the effects of an anomaly.

4.3.1. Goat Trax Farm

Jim and Barb Miedema own and run Goat Trax Farm in Momence, Illinois. Goat Trax Farm is currently the only yak farm in Illinois. The location of this farm is an important validation of this analysis as it is located in one of the three most suitable counties for yak-based agriculture in Illinois. Momence is located in eastern Kankakee County, just a few miles from the Illinois-Indiana border. Goat Trax Farm is located within a cell with a favorability value of 0.46, one of the highest values resulting from the fuzzy overlay. The success of the farm and its location within a highly favorable area, according to this analysis, help lend validity to the results.

4.3.2. Directed Point Sample

A directed point sample was collected to examine the values of the fuzzy overlay at particular locations in order to verify the factors influenced the results as anticipated. The location of each point selected is displayed on the map in Figure 29. A point within the city limits of Chicago was selected as the anticipated fuzzy value would be 0, due to the lack of available cropland. The cell with the highest fuzzy value was selected because all factors were anticipated to contribute to the cell's high value. The cell where Goat Trax Farm is located was selected as it was anticipated to have a high fuzzy value. Additionally, twelve random points were selected in order to compare the fuzzy membership values from each factor to the fuzzy overlay favorability value, as seen in Table 10. In the next chapter this table is analyzed to see how the factors influenced the final result of the overlay and if the factor's influence behaved as anticipated.

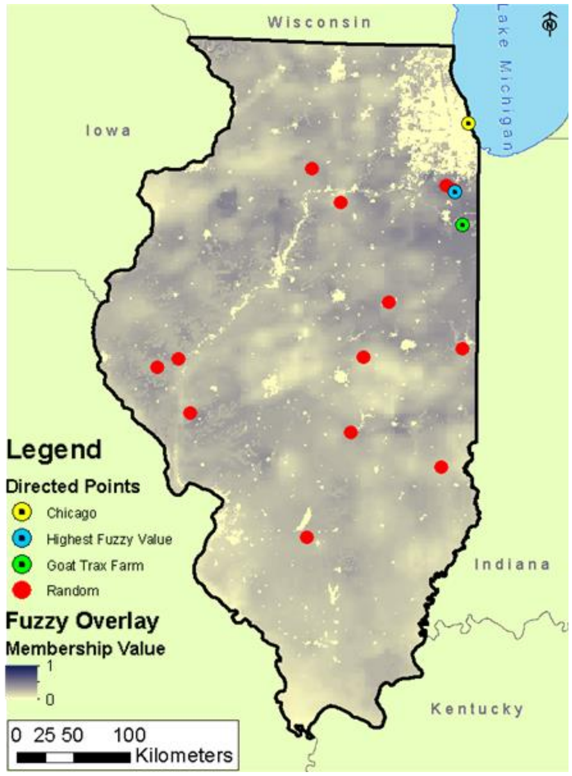


Figure 29: Point locations used in the directed point sample used for validation

Table 10: Directed point results

Selected Cell Location	Fuzzy Overlay Value	Vapor Pressure Deficit Fuzzy Membership Value	Temperature Fuzzy Membership Value	Precipitation Fuzzy Membership Value	Cropland Use Fuzzy Membership Value	Soil Association Fuzzy Membership Value
Chicago	0	0.70	0.61	0.47	0	1
Goat Trax Farm	0.45	0.45	0.65	0.52	0.50	1
Highest Favorability	0.49	0.50	0.66	0.49	0.50	1
Random	0	0.30	0.39	0.32	0	1
Random	0.17	0.38	0.47	0.17	0.50	1
Random	0.18	0.35	0.57	0.18	0.25	0.50
Random	0.19	0.19	0.30	0.45	0.50	1
Random	0.22	0.42	0.56	0.28	0.50	1
Random	0.25	0.30	0.43	0.38	0.25	0.50
Random	0.25	0.27	0.25	0.52	0.50	1
Random	0.25	0.31	0.45	0.32	0.25	0.50
Random	0.25	0.28	0.43	0.46	0.25	0.50
Random	0.29	0.45	0.68	0.29	0.50	1
Random	0.34	0.35	0.48	0.34	0.50	1
Random	0.46	0.51	0.65	0.46	0.50	1

4.3.3. Histogram Evaluation

An issue presented itself during the analysis of the overlay results. A histogram demonstrating the distribution of the 1 kilometer cell favorability values (see Figure 30) exhibits a spike in the middle, at the favorability value of 0.25. It was important to determine the cause of this as it could be an error in the data or procedure. To see the spatial distribution of these 0.25 values, a shapefile was produced (Figure 31). These values account for 8.75% of Illinois' total area.

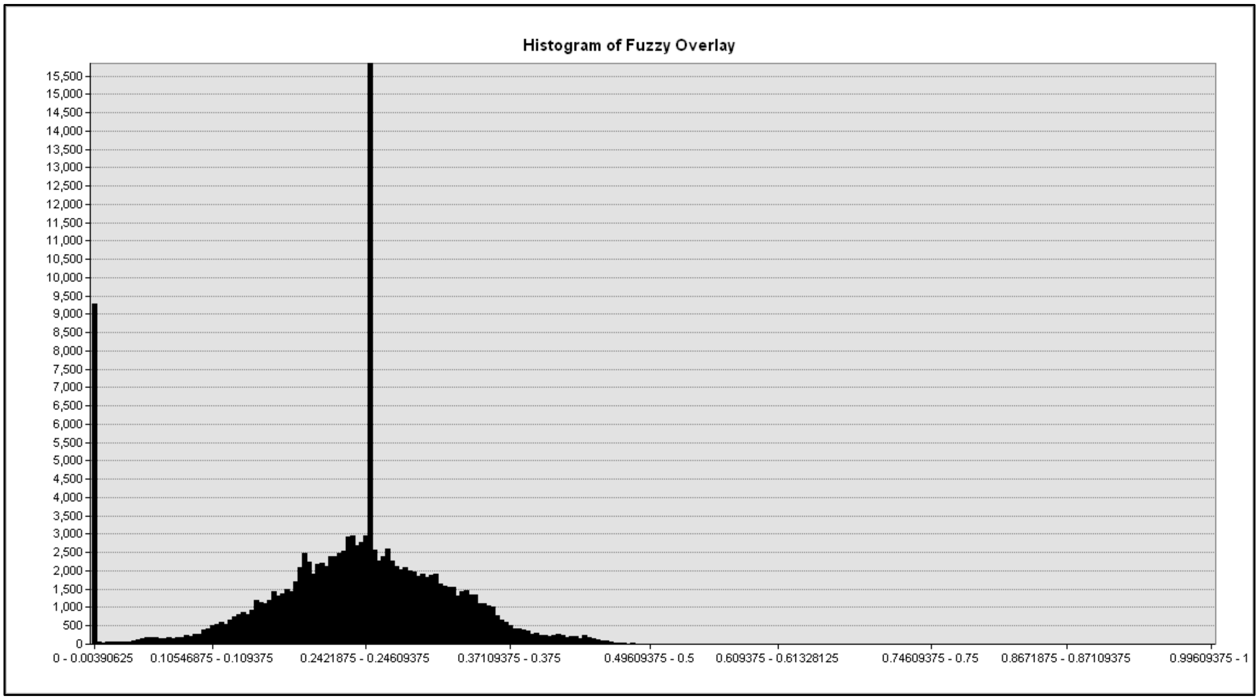


Figure 30: Histogram of fuzzy overlay

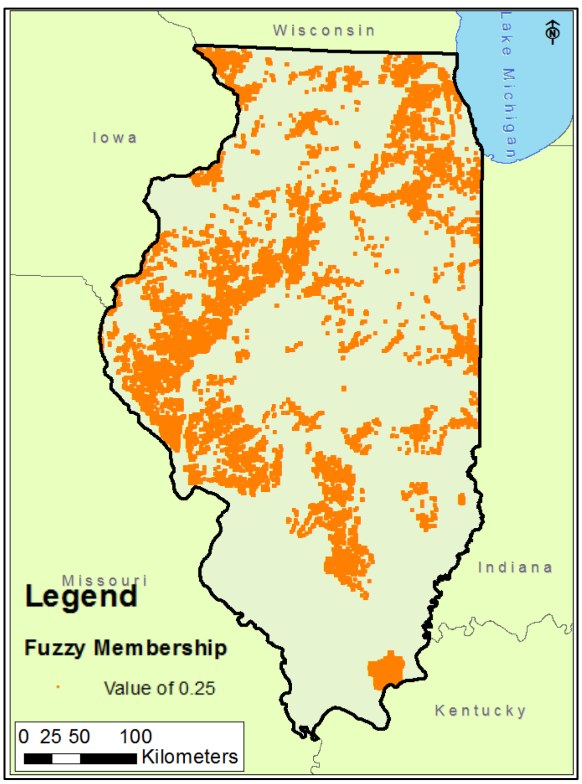


Figure 31: Fuzzy overlay cells with a value of 0.25

A process of deductive reasoning was used to determine the cause of so many 0.25 values. The fuzzy overlay analysis was repeated multiple times with a different membership layer missing each time. Maps of these overlay results with histograms for the associated distribution values are shown in Figure 32.

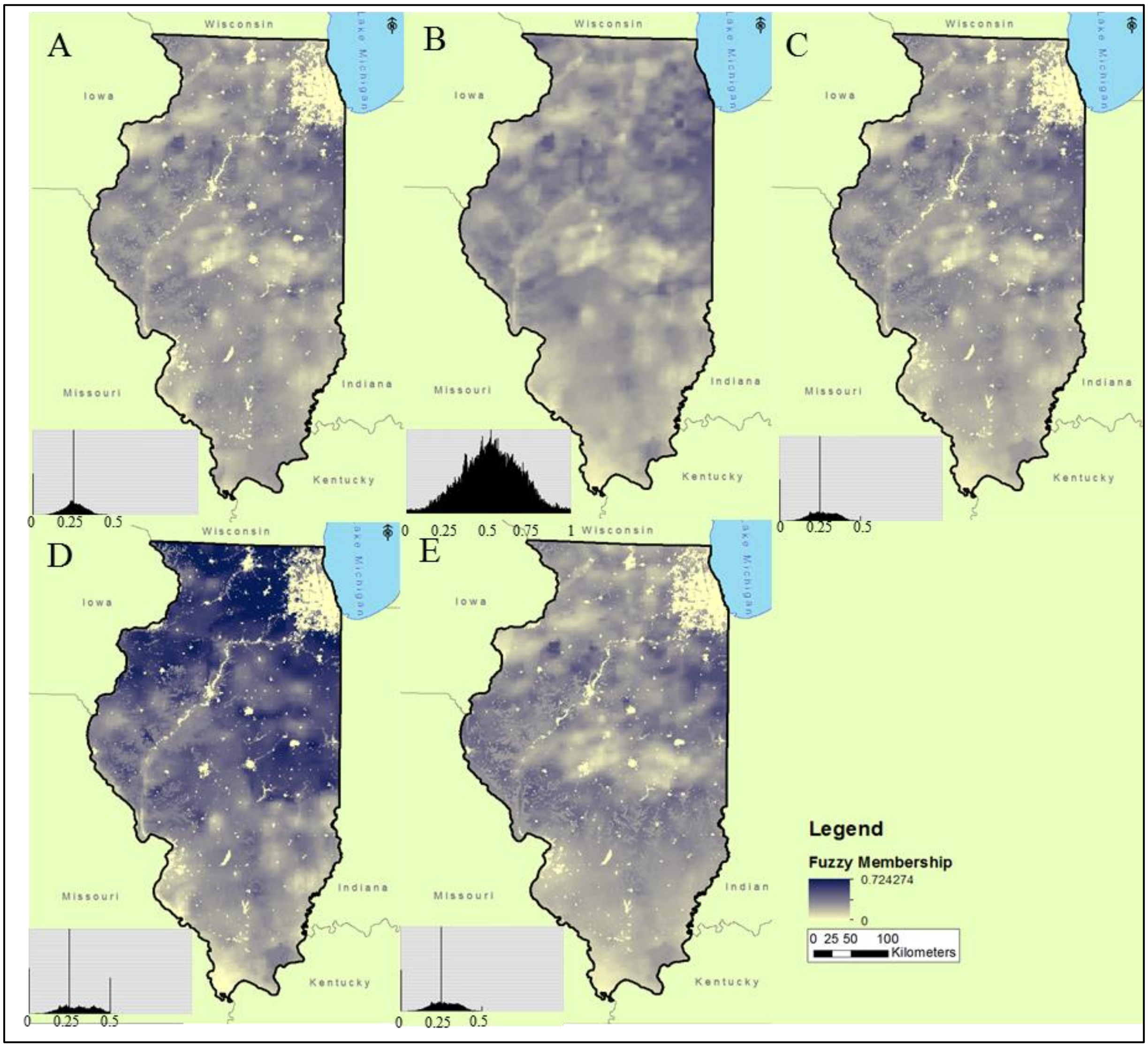


Figure 32: Comparison of fuzzy overlays and their respective histograms. Map A is the fuzzy overlay, Map B is the fuzzy overlay without the Cropland Use factor, Map C is the fuzzy overlay without the temperature factor, Map D is the fuzzy overlay without the precipitation factor, and Map E is the fuzzy overlay without the vapor pressure deficit factor.

The histogram of the fuzzy overlay without Cropland Use was the only graph without a central spike in the data distribution and was the closest to a normal distribution. This missing spike indicates the Cropland Use fuzzy membership layer was the cause. The Cropland Use fuzzy membership histogram demonstrates two spikes at the favorability values of 0.25 and 0.5. To verify the data spike was from the Cropland Use layer, the histogram from the fuzzy overlay without Cropland Use (Figure 33) was compared to the histograms when the Cropland Use layer was present in the fuzzy overlay (Figure 30). No spike in the data's distribution was present when the Cropland Use layer was omitted. As determined in the methods chapter, the favorability value of 0.25 means the cells represent uncultivated and cultivated land with trees and tree crops. The favorability value of 0.5 means the cells represent cultivated lands with non-tree crops. These cells account for 66.46% of the total area of Illinois. This large set of values in a single layer is a significant enough to weight the distribution.

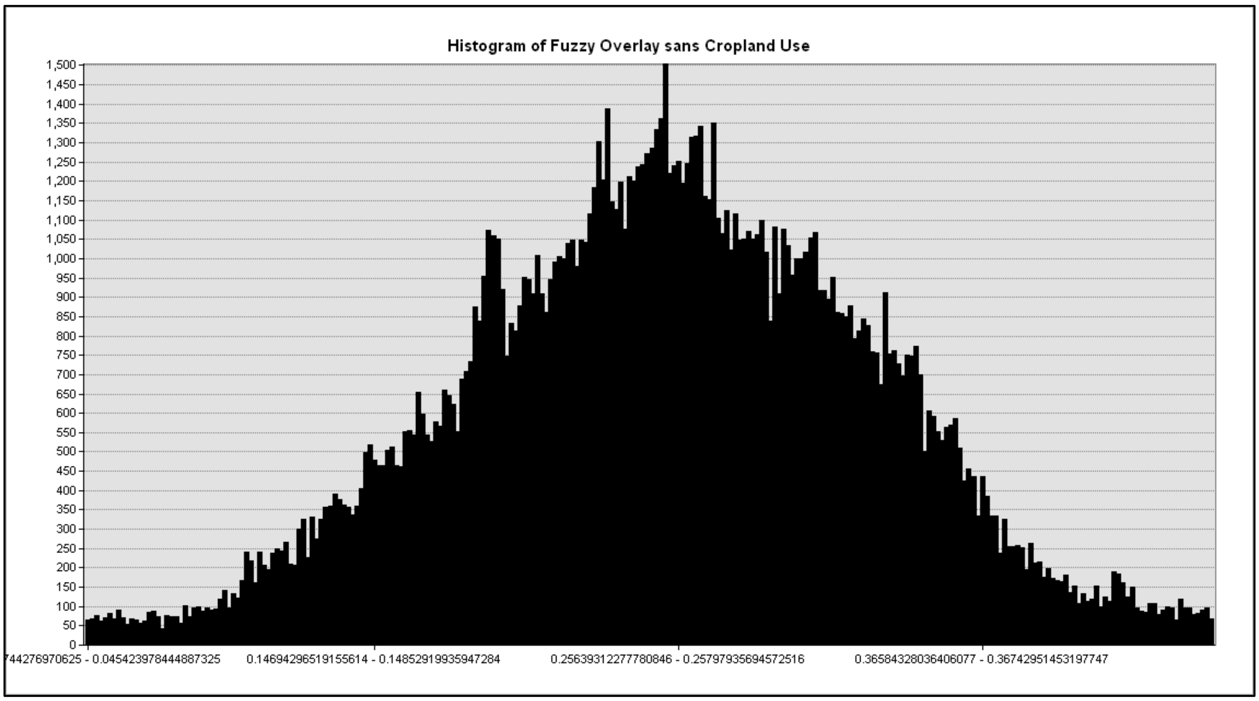


Figure 33: Histogram of the fuzzy overlay results without Cropland Use.

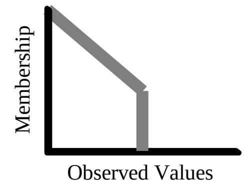
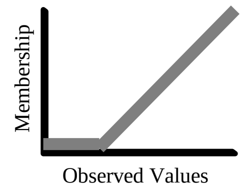
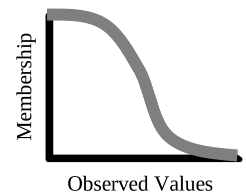
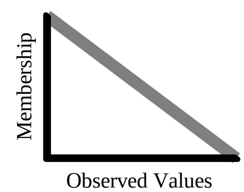
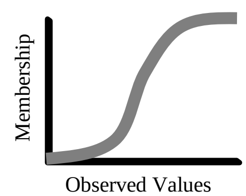
4.4. Sensitivity Analysis

The analysis described throughout this document is based on information available for Illinois. It is a land suitability analysis that was seeking the most suitable locations in the AOI for yak-based agriculture. It sought to find which locations and farmers were in the most suitable position for a transition to yak. However, how would the analysis differ if performed to see how sensitive the animals are to the AOI? The fuzzy membership functions were adjusted to favor conditions on behalf of the yak's preferred conditions instead of the best areas for yak farms in the AOI.

4.4.1. Fuzzy Membership Functions and Overlay

Not all fuzzy membership functions were redone for the sensitivity analysis. Table 11 is a summary of the membership functions used in this sensitivity analysis. The logic behind the soil association and Cropland Use functions remained consistent for this portion of the analysis. No adjustments were made to either membership function. The VPD membership function remained unchanged due to a lack of information. The desired number would be a definition or expert opinion on what is an "uncomfortable" about of humidity for yak. With this information lacking the membership function and settings remained unchanged. However, temperature and precipitation were adjusted to favor yak preferences over farmers.

Table 11: Membership functions of sensitivity study factors

Criterion	Membership	Function	Graph
Soil Association	Favor prairie-type and exclude water-type	Linear with maximum	
Cropland Use	Favor grass and exclude developed areas	Linear	
Temperature	Favor low values	Small	
Humidity	Favor low values	Linear	
Precipitation	Favor high values	Large	

Temperature membership was changed to the Small function in order to favor lower values. As previously explained in the fuzzy membership procedures, 15°C is when yak start to experience discomfort and risk of heat stroke. This value was set as the midpoint (fuzzy value = 0.5) of the spread when generating the fuzzy membership for the sensitivity analysis. The range of this new fuzzy membership layer was 0.14 to 0.46 because no values within the state reach the midpoint value (see Figure 34).

Figure 34: Sensitivity study's temperature fuzzy memership raster

Precipitation membership was changed to the Large function in order to favor higher values. As previously mentioned in the literature review, the annual precipitation for the Tibetan Plateau can range from 250 millimeters to 416 millimeters. Nearly all of this precipitation accumulates in a few months of the year during the monsoon season. Therefore, the maximum value of the function was set to 416 millimeters (fuzzy value = 1) with the midpoint at 250 millimeters (fuzzy value = 0.5) to encourage large amounts of precipitation. The range of this new fuzzy membership layer was 0.001 to 0.01 because no values within the state reach even half of the midpoint value (see Figure 35). While Illinois has more evenly distributed precipitation throughout the year, the Tibetan Plateau sees a higher amount of precipitation overall.

Figure 35: Sensitivity study's precipitation fuzzy membership raster

The fuzzy overlay was performed with these new membership layers using the AND operator, as described in Chapter 3, which returns the minimum value of factors at the cell's location. The range of this fuzzy overlay was 0 to 0.01. The resulting map can be seen in Figure 36. The map on the left side of the figure is symbolized as a percent clip to show the subtle variations present with in the overlay that cannot be seen in the map on the right side. This map is displayed properly with the full membership range of 0 to 1 and is the map to visually compare to any other membership or overlay map.

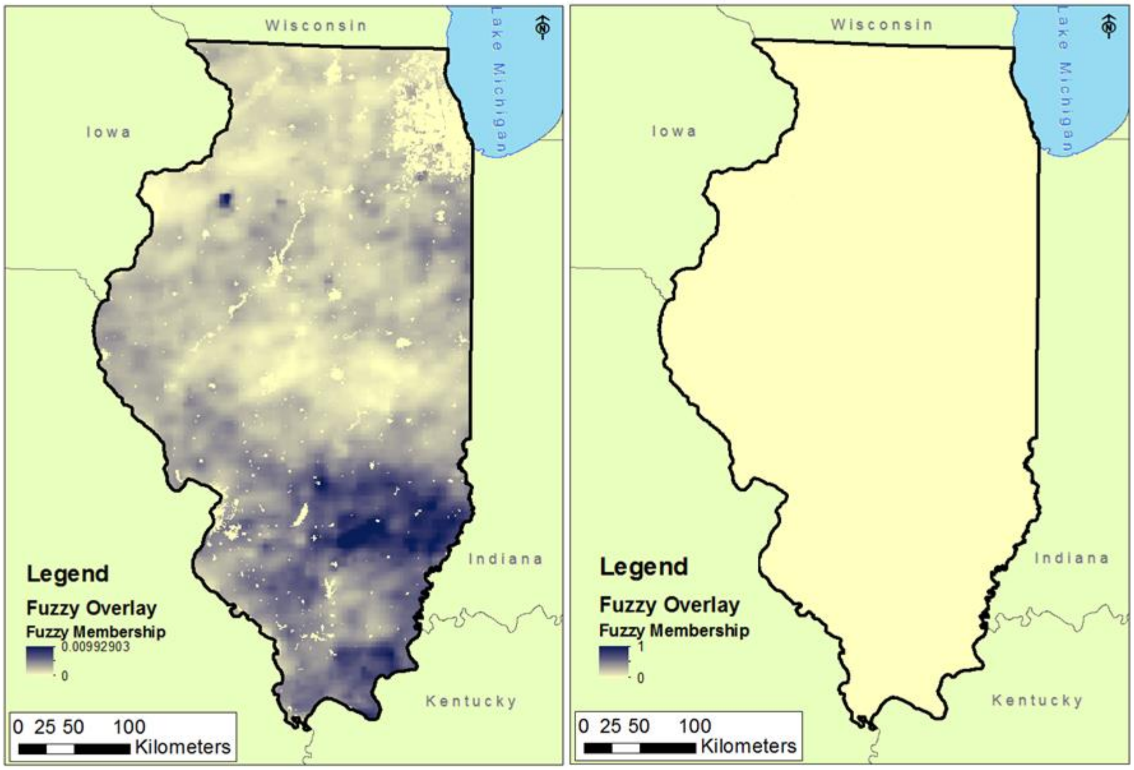


Figure 36: The fuzzy overlay of the sensitivity analysis. The map at left is displayed with values ranging only within the range of results and the one at right shows the colors ramp through the full membership range from 0 to 1.

4.4.2. Directed Point Sample Comparison

To summarize how the sensitivity analysis set to favor yak preferences varies from the land suitability analysis values were collected to compare the previous directed point sample (Table 12). As expected after viewing the map, all fuzzy values were significantly lower than in the previous analysis. However, these values are not necessarily proportionally lower. For example, one location with a previous value of 0.19 has a new value of 0.003. Yet, a higher previous value of 0.25 has a lower new value of 0.002. Yet, a number of the directed points show new values that were expected. The urban area of Chicago still has a membership value of 0 and the high favorability areas like Goat Trax farm still have high values (relative to the overall values of the raster). Running the sensitivity analysis to favor yak preferences of site suitability instead of farming preferences of land suitability drastically change the outcome of the analysis.

Table 12: Sensitivity analysis directed point results

Selected Cell Location	Fuzzy Overlay Value	
	Original Analysis	Sensitivity Analysis
Chicago	0	0
Goat Trax Farm	0.45	0.003
Highest Favorability	0.49	0.003
Random	0	0
Random	0.17	0.001
Random	0.18	0.001
Random	0.19	0.003
Random	0.22	0.003
Random	0.25	0.002
Random	0.25	0.002
Random	0.25	0.002
Random	0.25	0.002
Random	0.29	0.002
Random	0.34	0.002
Random	0.46	0.003

To summarize, the results of the analysis were summarized on a state, county, and subcounty division level. The numbers used in these summaries provided a snapshot of each area’s suitability. The results were validated through a few methods, including the location of the current yak farm in Illinois, a directed point sample, and an evaluation of the results’ distribution. Finally, a sensitivity analysis was conducted to verify the volatility of the analysis when numbers and functions were adjusted to favor conditions similar to the native range of yak instead of looking for the most suitable areas in Illinois.

Chapter 5 Analysis

This analysis was designed to develop a method to investigate the potential for animal husbandry species expansion. When implemented to examine the potential for yak-based agriculture in Illinois, results indicate there are parts of the state with suitable conditions. While there is enough suitable area in each of the most favorable counties to potentially make it worthwhile to contact county farm bureaus with additional information about this analysis to encourage yak-based agriculture, the level of suitability is not particularly high. Even with severe alteration of the analysis by eliminating the economic factors and slope, the set of criteria compiled is still suitable for replication studies.

The results of the study have a few contexts by which they can be examined. Specifically, the quantifiable results allow the comparison of favorability values and an assessment of how different factors contributed to the final favorability values. Secondly, it is useful to examine how the input data contributes to the regional distribution of the fuzzy result. Finally, it is important to review how the results compare to the information garnered through the background research and the initial anticipated outcomes.

5.1. Quantifiable Results

Even with the relaxed assumptions in the model, such as eliminating economic factors and slope, and allowing temperatures over 15° Celsius, the highest suitability value in Illinois is only 0.49. It is disappointing but not unexpected that the maximum favorability value was lower than half the potential maximum possible. This analysis looks at bringing a steppe favoring animal to the Illinois prairies, finding full membership was not possible.

To better understand how the factors influence the final favorability values, the selected and random points and their associated fuzzy membership values were analyzed. For clarity, the contents of Table 10 are replicated below as Table 13 which shows the highest membership values of each category colored green, middle membership values as orange, and the lowest membership values are red. In this way, each row can be compared to see which datasets contributed the most to the final favorability value. The table is then ordered with the three intentionally selected points at the top and is followed by the twelve random points ordered from smallest to largest fuzzy overlay favorability value.

Table 13: Point validation analysis

Selected Cell Location	Fuzzy Overlay Value	Vapor Pressure Deficit Fuzzy Membership Value	Temperature Fuzzy Membership Value	Precipitation Fuzzy Membership Value	Cropland Use Fuzzy Membership Value	Soil Association Fuzzy Membership Value
Chicago	0	0.70	0.61	0.47	0	1
Goat Trax Farm	0.45	0.45	0.65	0.52	0.50	1
Highest Favorability	0.49	0.50	0.66	0.49	0.50	1
Random	0	0.30	0.39	0.32	0	1
Random	0.17	0.38	0.47	0.17	0.50	1
Random	0.18	0.35	0.57	0.18	0.25	0.50
Random	0.19	0.19	0.30	0.45	0.50	1
Random	0.25	0.30	0.43	0.38	0.25	0.50
Random	0.25	0.27	0.25	0.52	0.50	1
Random	0.25	0.31	0.45	0.32	0.25	0.50
Random	0.25	0.28	0.43	0.46	0.25	0.50
Random	0.28	0.42	0.56	0.28	0.50	1
Random	0.29	0.45	0.68	0.29	0.50	1
Random	0.34	0.35	0.48	0.34	0.50	1
Random	0.46	0.51	0.65	0.46	0.50	1

Unsurprisingly, due to the assigned minimum placed on the Cropland Use layer during the fuzzy membership raster creation and the use of the AND fuzzy operator, a zero in this category results in a zero favorability value. The higher favorability values of 0.46 and 0.34 have different contributing factors that result in their strong performance. The former has entirely beneficial values in each category which result in nearly achieving the highest possible value in the study. The latter achieved a relatively high value considering most of the contributing values are average, except for Cropland Use. All mediocre favorability values vary in how they achieve their value. Some were pulled low by a combination of bad climate values or climate and Cropland Use values. Other scores had entirely unexceptional values of contributing factors. This table indicates the factors behaved as expected in the final results.

5.2. Regional Context of Results

The most suitable counties are geographically clustered, represented with black outlines in Figure 37. There are other areas in the state, unsurprisingly along the same latitude, that appear as significantly favorable for yak. However, these other areas do not compare in size to the large swath in the northeast. The favorable subcounty divisions within these counties are also clustered together, represented with thin black outlines in Figure 37 or red outlines in the closer view of Figure 28.

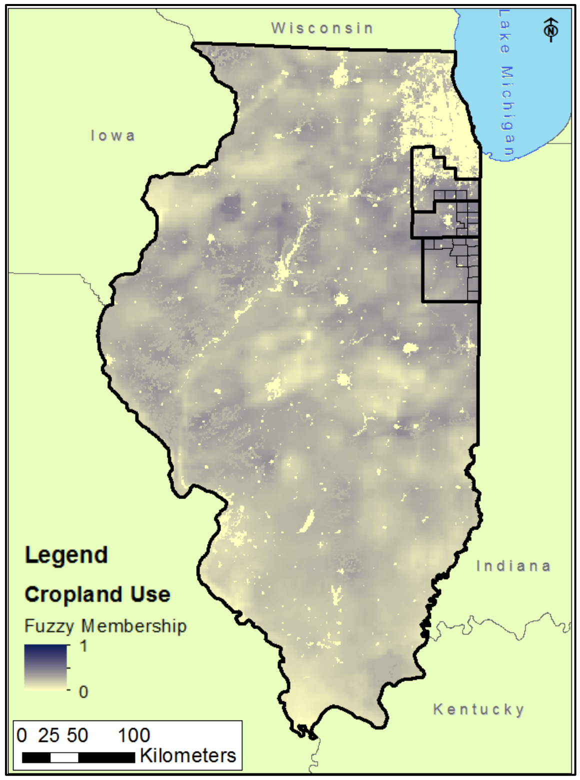


Figure 37: The top scoring counties and subcounty divisions outlined in black

This region of Illinois has a relatively high VPD, but that is expected as the region also has a high precipitation average. Most of Kankakee and Iroquois counties, plus the portions of Will County that are not already urbanized, are currently used for agriculture. While much of Illinois is prairie-type soil, including these three counties, the portions of Will County that are urbanized also have forest-type soil, which is an unexpected correlation.

While economic considerations were eliminated from the analysis, these counties possess some economic significance. Will County is a collar county with Chicagoland, making market and road network access easy. Additionally, Will and Kankakee counties are significant enough to the Illinois meat production sector to be their own agricultural region. This correlation between a beneficial climate for yak and already advantageous economic factors for farmers cannot be ignored.

Another significant geographic correlation is the location of Illinois' first operational yak farm in Kankakee County. The farm's location coincides with a favorable subcounty division within a favorable county. Goat Trax Farm in Momence, Illinois has been raising yak since 2014. Farm owner Barb Miedema read about the benefits of yak, including their high production yields and ecologically friendly grazing habits, and decided to give the animals a try (Hall and Sarver 2016; Miedema and Miedema n.d.).

5.3. Environmental Context of Results

Yak are domesticated and bred for a specific climate: steppe conditions. They thrive at high elevations and in the cold expanse of the Himalayas. However, this does not mean the species cannot succeed out of its homeland. With the correct combination of climatic factors, yak can survive with warmer and lower elevation conditions. Wu (2016) discusses the importance of breeding yak so that they can thrive under local climate and geographic conditions. For Will, Iroquois, and Kankakee counties this implies that breeding for heat tolerance--in addition to the usual high production goal--might be appropriate. Goat Trax Farm, according to the Miedemas, has already begun this process. Their yak are registered with the International Yak Registry so all individuals in the process can be appropriately tracked.

The literature discussed in the second chapter of this analysis repeatedly pointed at the significance of climate for yak, specifically, the cold steppe (Cincotta et al. 1991; Haynes 2011; Leslie and Schaller 2009; Miao et al. 2015; Miller 1986; Wu 2016). It should not be a surprise then, the most suitable counties for yak are located in the northern half of the AOI, where the average temperatures are colder and the soils are more suitable for grasses than trees (Dai et al. 2015; Kottek et al. 2006; Robeson 2002; Web Soil Survey 2006). The map in Figure 38 shows Illinois' soil types overlaid on average daily temperature for the 2011-2015 growing seasons.

The soils that would not promote grass growth, water- and forest-types, are shaded transparently to allow the temperature data that overlaps with prairie-type soils to be visible. Large swathes of northern Illinois have visible areas of brown which indicate large areas of prairie-type soils where the temperatures are typically cooler.

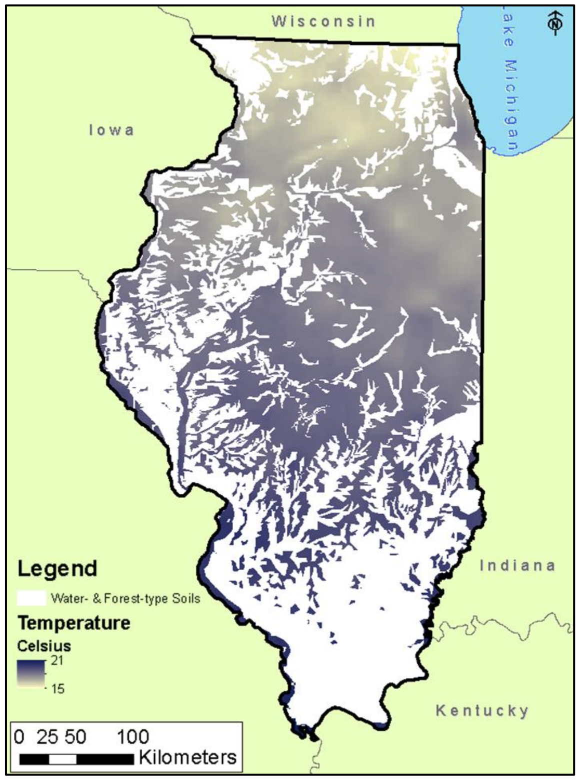


Figure 38: Map demonstrating the dichotomy between the northern and southern regions of Illinois in terms of temperature and soil type

5.4. Contributing Factors

Every factor that went into the fuzzy overlay assisted in making the best-suited counties stand out. They are located in an agrarian area with almost entirely prairie-type soils. The area is relatively humid for the high amount of precipitation, which also works in favor for the yak. While Iroquois County is getting into the central latitudes of Illinois, it is still relatively cold in these top performing counties compared to the southern counties. What worked in these counties' favor was the best combination of all the datasets. Figure 39 is a collection of maps created to illustrate the areas of higher favorability for each factor. White transparency masks the areas of Illinois with membership values below 0.5 for each factor and red outlines highlight the remaining portion of the state with higher membership values for those same factors. Higher resolution maps are available in Appendix F. Interestingly, the favorable areas are not consistent across the factors.

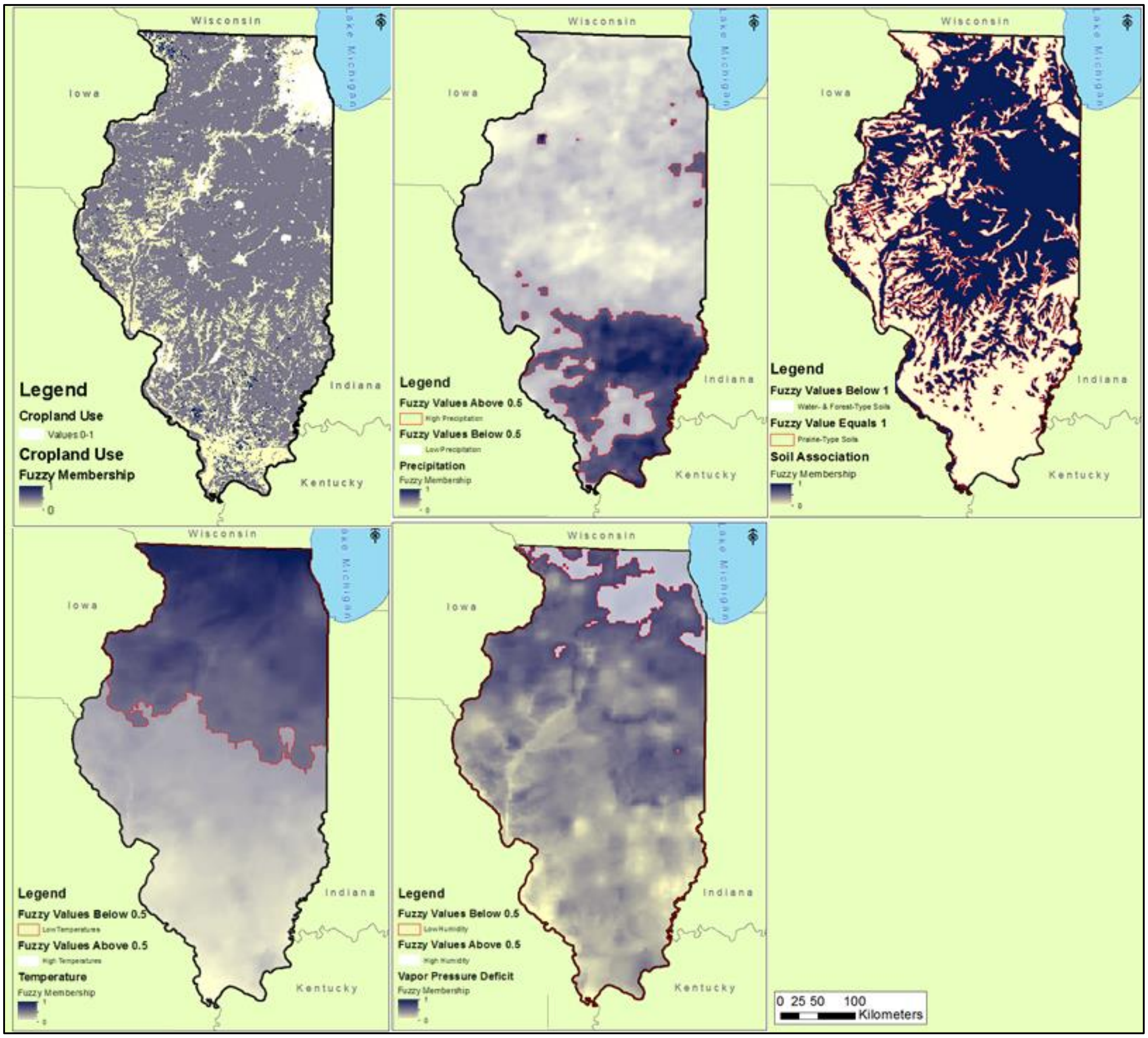


Figure 39: A collection of maps with transparency overlays to highlight the most favorable areas of each factor's membership raster

While a combination of agrarian areas and prairie-type soil is common throughout the northern regions of Illinois, this eastern area also had climatic factors that balanced the warm summer season with humidity and precipitation not seen elsewhere in the rest of northern Illinois. This combination of factors is best seen in the analysis of the points collected for validation. The highest scoring favorability value in Table 13 achieves a high value because all factors are contributing. Even the next highest score cannot be larger in value because there are two factors reducing the value.

While all factors are needed to attain a high favorability value, only one categorical factor is needed to achieve a mediocre favorability value. The two categorical datasets, Cropland Use and soil type, have discrete limits that carry over to the final favorability value. This distinction of categorical data is best seen in the validation study to solve which dataset was causing a spike in the data distribution. This is also a contributing factor to the limitations of this analysis.

Performing the fuzzy overlay multiple times, as done in the methodology, to reveal which dataset was contributing to the histogram spike was essential to understanding how individual factors contributed to the results. Because the only factor found to be contributing was the Cropland Use raster, it is simple to say that is the largest contributor. However, a closer look at the dataset types and the overlay being performed shows a different culprit: categorical data in general. The other categorical dataset used in this analysis, soil type, exhibited a similar data spike because it only contains 3 values. The resulting fuzzy values show a normal-like distribution while still having the possibility of eliminating the most amount of cells from the study than any other data source.

Chapter 6 Discussion and Conclusions

This analysis was developed to explore a methodology to expand the use of yak in American agriculture, specifically within the state of Illinois. The methods of this analysis were developed with the intention of repetition in later studies for other AOIs and species. The results indicated there are parts of Illinois with suitable conditions, but the level of suitability is not especially high. This discussion looks at the limitations of the analysis, revisions for replication, and potential future uses of the methodology.

6.1. Discussion

The incorporation of categorical data into a fuzzy overlay study appears to have a noticeable impact on the results of this analysis. While these discrete datasets were fuzzified, the categorical datasets outweighed the use of continuous datasets in the fuzzy overlay results. However, this situation is not always preventable, depending on the data available to the researcher and is a credit to the flexibility of the fuzzy overlay methodology, as mentioned in Chapter 2, to incorporate multiple types of data. These limitations are kept in mind when presenting the final conclusions of the analysis.

6.1.1. Overall Limitations of the Study

This analysis used fewer factors than intended, specifically eliminating economic factors and slope, due to the specific nature of the AOI's geography and the datasets available for use. These unforeseen exclusions skew the results towards categorical datasets which have discrete limits. Categorical datasets create discrete boundaries on the map and in the final results. Because of this skew, the study is only as strong at the categorical data used. Typically, the more categories present in the data, the closer to continuous it becomes. Fuzzy overlay thrives in an environment rich in continuous data. However, due to the limitations of available datasets the inclusion of categorical, or even Boolean, data may be unavoidable with certain AOIs. Categorical data inclusion does not need to be limited, as Hyneman (2014) indicates, fuzzy overlay can handle multiple data types. Future researchers should be aware that the distribution of values in discrete datasets may be strongly evident in the results.

While the researcher attempted to limit difficulties others may have in the replication process, it is reasonable to assume this research cannot be repeated everywhere. Difficulty in replication would most likely be due to lack of data but also due to this analysis's limited scope. No solution was found for incorporating economic factors into the fuzzy overlay and is left in the minds of future researchers to build on this analysis' foundations.

6.1.2. Revisions for Future Replication

Beyond typical clerical errors or any unintended misrepresentation, the researcher considered the lack of prescreening the Cropland Use raster to be a mistake. As earlier discussed in the validation of the data collection chapter there is a spike in the distribution of the raster's values around the center of the distribution. However, prescreening the data more thoroughly before the fuzzy overlay as was conducted would have potentially shown this spike was anticipated.

The original Cropland Use raster had significant cell count spikes at the values of 0, 1, 2, 141, and 176. These are the values for background, corn, soybean, deciduous forest, and grass/pasture respectively. The original rectangular raster dataset contains a large number of background cells surrounding the non-rectangular state boundary that are coded 0. Once the area of these cells is eliminated, corn represents 32.04% of the raster's cells, soybean 25.6%, deciduous forest 15.8%, and grass/pasture 8.9%. Assuming corn and soybean would be categorized together or in proximate categories, if the categories of the dataset had been redone in a replication study, they would highly influence the data distribution. Combined corn and soybean fields consist of 57.6% of the data's cells. Illinois has such an abundance of corn and soybean fields the data distribution would never be normal. While not relevant to the model, understanding the behavior of the datasets within the analysis is important.

6.1.3. Future Replication and Research

While the lenient prescreening of the Cropland Use data did not hinder the study, it is suggested for future replication that all datasets be scrutinized in advance of analysis. It is important to be aware of the potential behaviors, skews, and outliers when analyzing the results. Also, future replication studies should take care to use the appropriate aggregation technique for processing slope data for the AOI. Eliminating the road networks as an economic indicator also worked for the study's AOI but that may not be true for all future cases. A solution to incorporating economic criteria into the study must be found.

There are two other criteria that future replication studies may want to consider though they were deemed unnecessary for this study early in the process. First, there is the potential to add information about public lands. It can be as simple as a binary expression including private lands and excluding public lands. However, within the United States it is legal to raise livestock on public grazing lands (Bureau of Land Management n.d.). Therefore, it was not necessary to include in this analysis, but studies of other AOIs might find this additional criterion useful.

Access to clean water is becoming an issue around the world. Water access is not an issue in Illinois as it is geographically situated with large amounts of surface water, plentiful rainfall, and atop multiple aquifers (Illinois State Water Survey 2016). However, if this process were to be repeated for a different AOI, water access should be included. A fuzzy membership layer for aquifers is recommended, though each AOI will have a unique water situation to take into account. Be mindful that bovines require a large amount of water, both for ingestion and growing grass (Cincotta et al. 1991; Leslie and Schaller 2009; Loeser 1968). If water access is an issue, consider not raising bovines and seeking a different option.

6.2. Conclusions

The intention of this analysis was to find suitable areas in Illinois for yak-based agriculture based upon ecological and economic needs of the animal and farmer, and to outline a framework for future repetition of the analysis. Some data types were eliminated from the study, including economic factors and slope, but a viable answer still resulted. Three counties emerged with a high percentage of yak-suitable area with a favorability score above 0.4. These counties are Will, Kankakee, and Iroquois counties. Within these counties, a cluster of subcounty divisions emerged as the most suitable areas in which to contact the county farm bureaus with encouragement about exploring yak as a viable option to cattle.

During the process of finding these county and subcounty divisions, this analysis found new ways to look for geospatial solutions. The study encourages a greater use of fuzzy overlay as a viable and often overlooked, analysis type. Unlike other geospatial studies predicting wild animal habitats, this analysis looks to locate potential habitats for humans to raise animals. If more replication studies in this vein of thinking are conducted, American agriculture could become more diverse.

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Appendix A: Slope Study Maps

Figure 40: Slope study using mean technique

Figure 41: Slope study using maximum

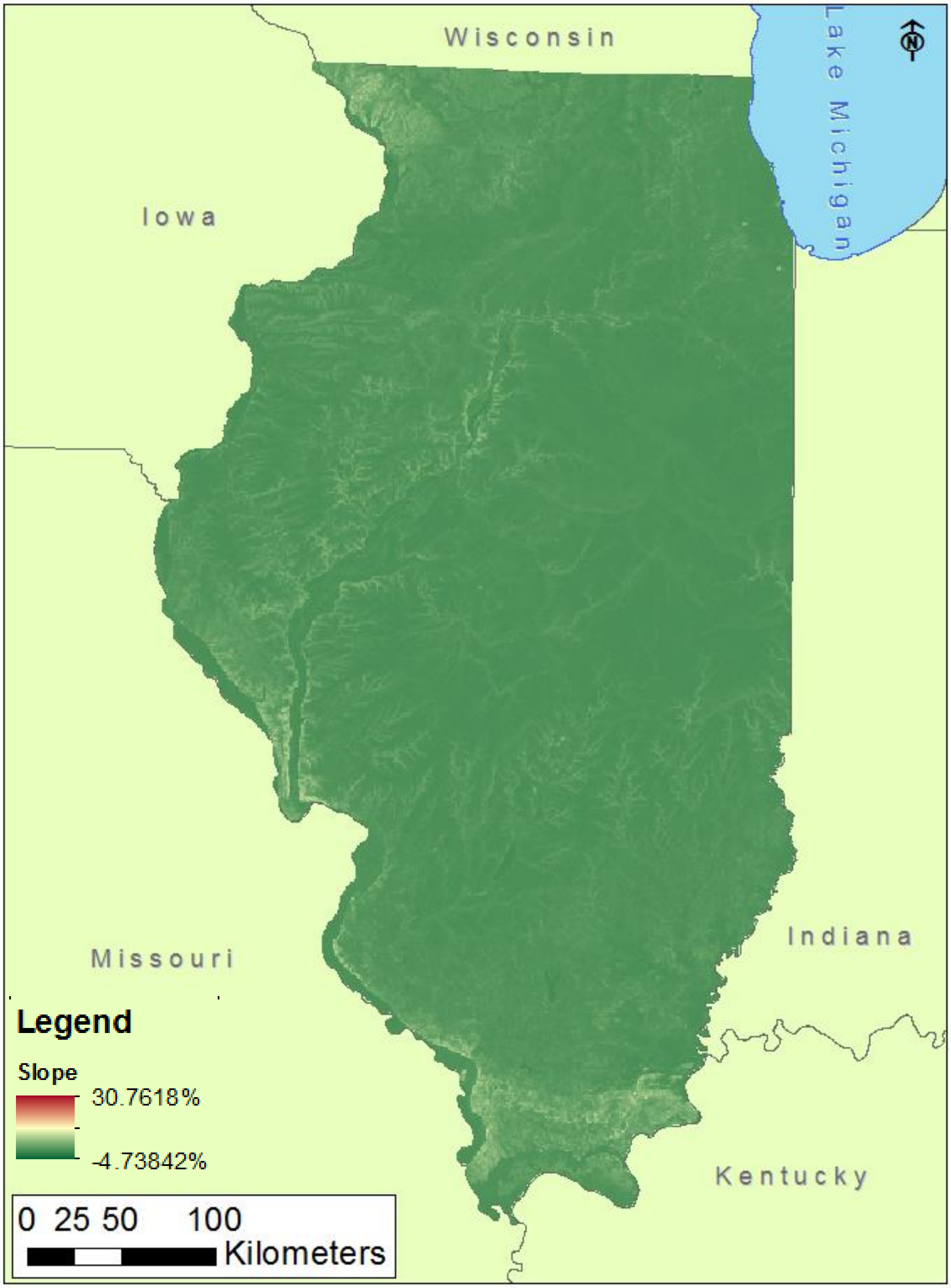

Figure 42: Slope study using median

Figure 43: Slope study using median minus mean

Figure 44: Slope study using maximum minus mean

Appendix B: Slope Study Histograms

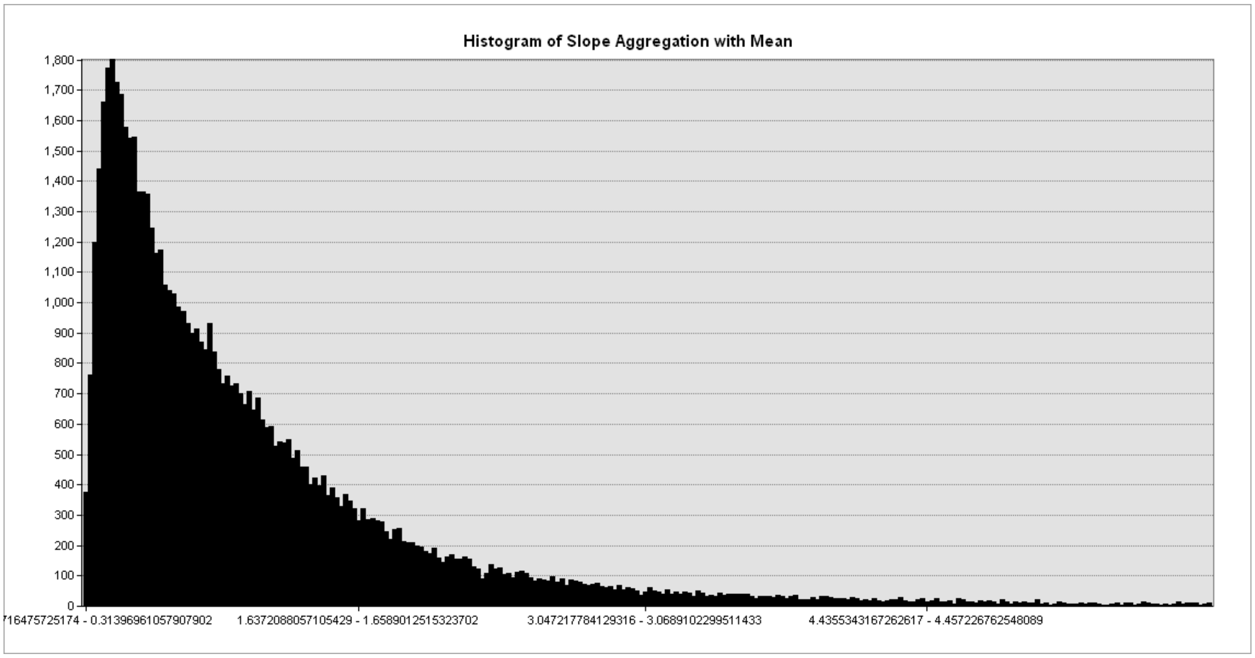

Figure 45: Histogram of the slope study raster aggregated with the mean technique

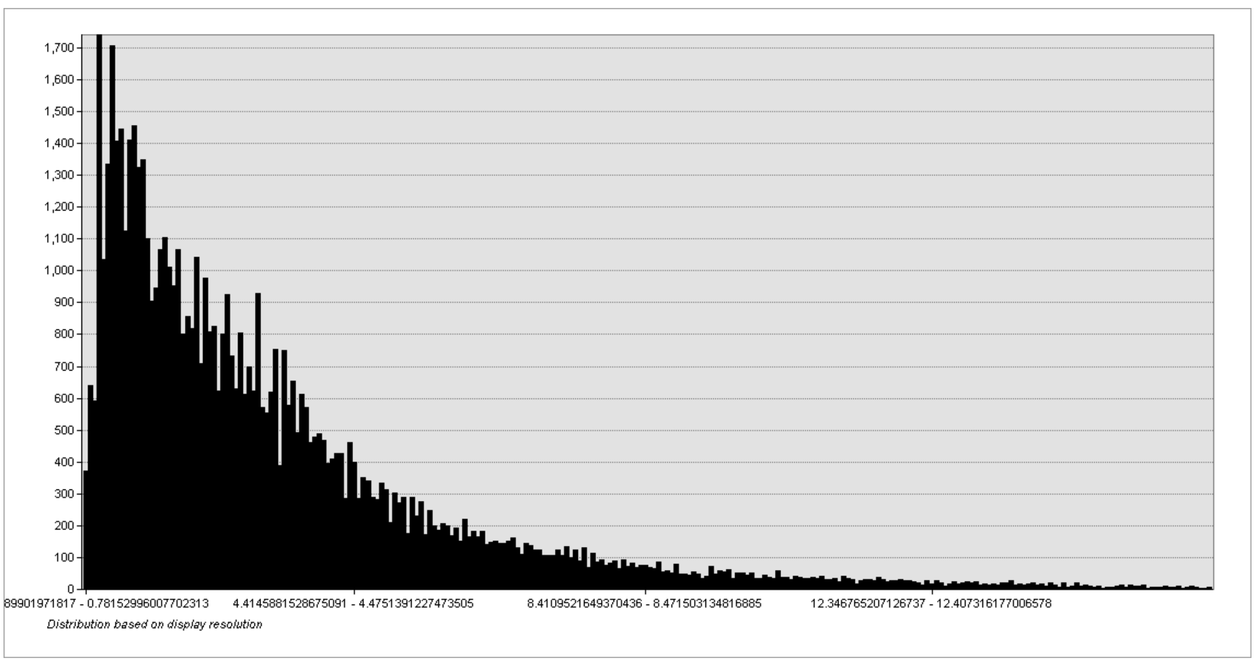

Figure 46: Histogram of the slope study raster aggregated with the maximum technique

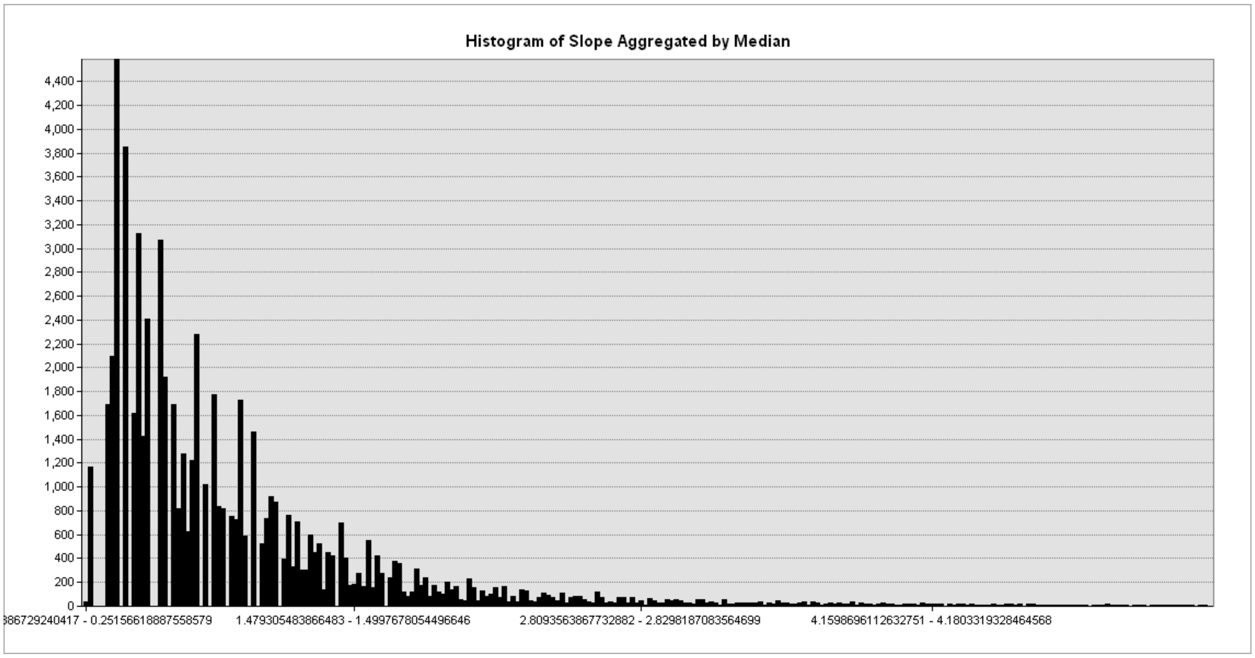

Figure 47: Histogram of the slope study raster aggregated with the median technique

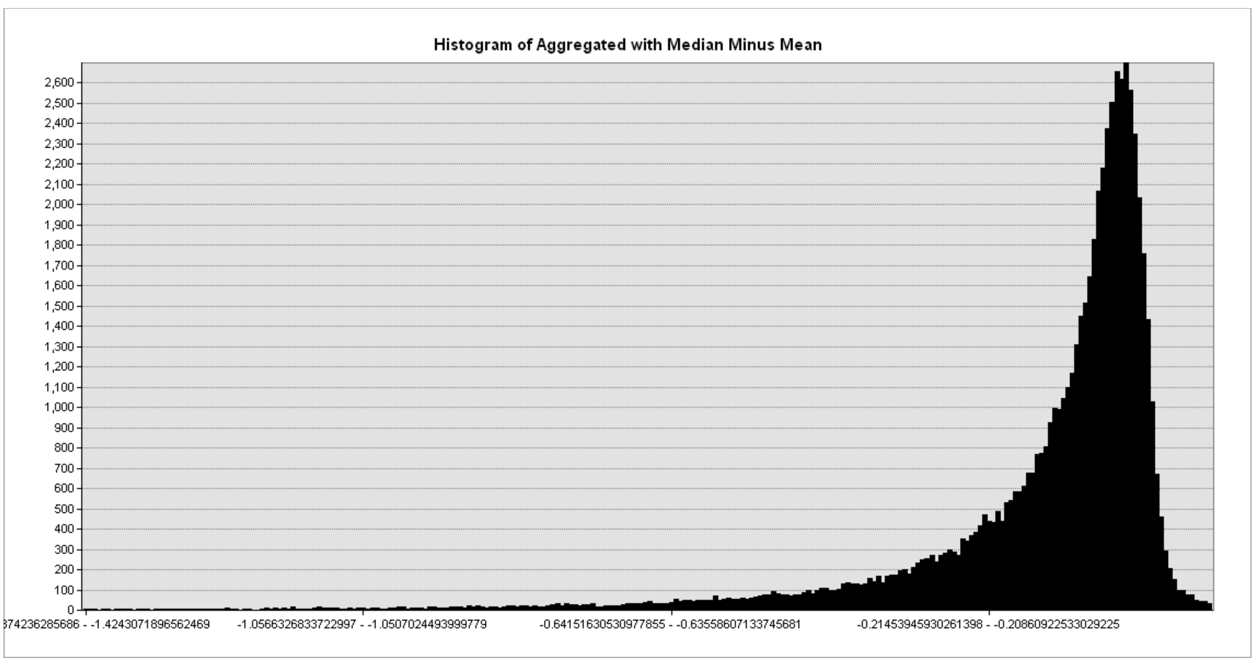

Figure 48: Histogram of the slope study raster aggregated with the median minus mean technique

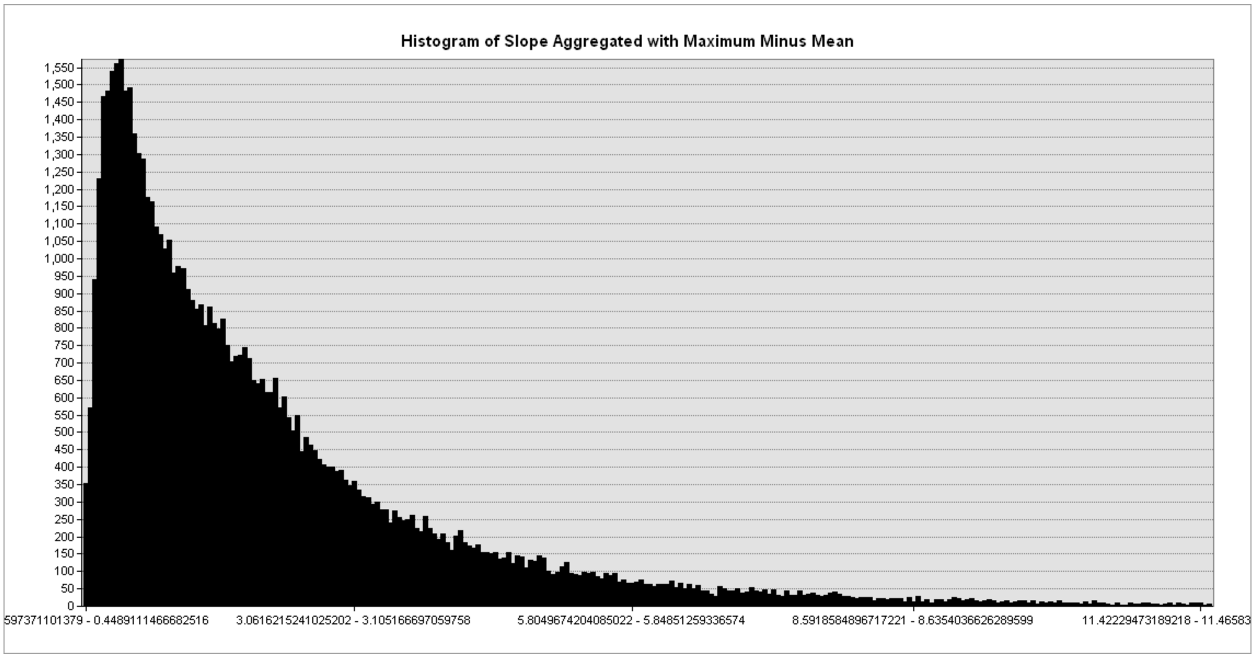

Figure 49: Histogram of the slope study raster aggregated with the maximum minus mean technique

Appendix C: Fuzzy Overlay

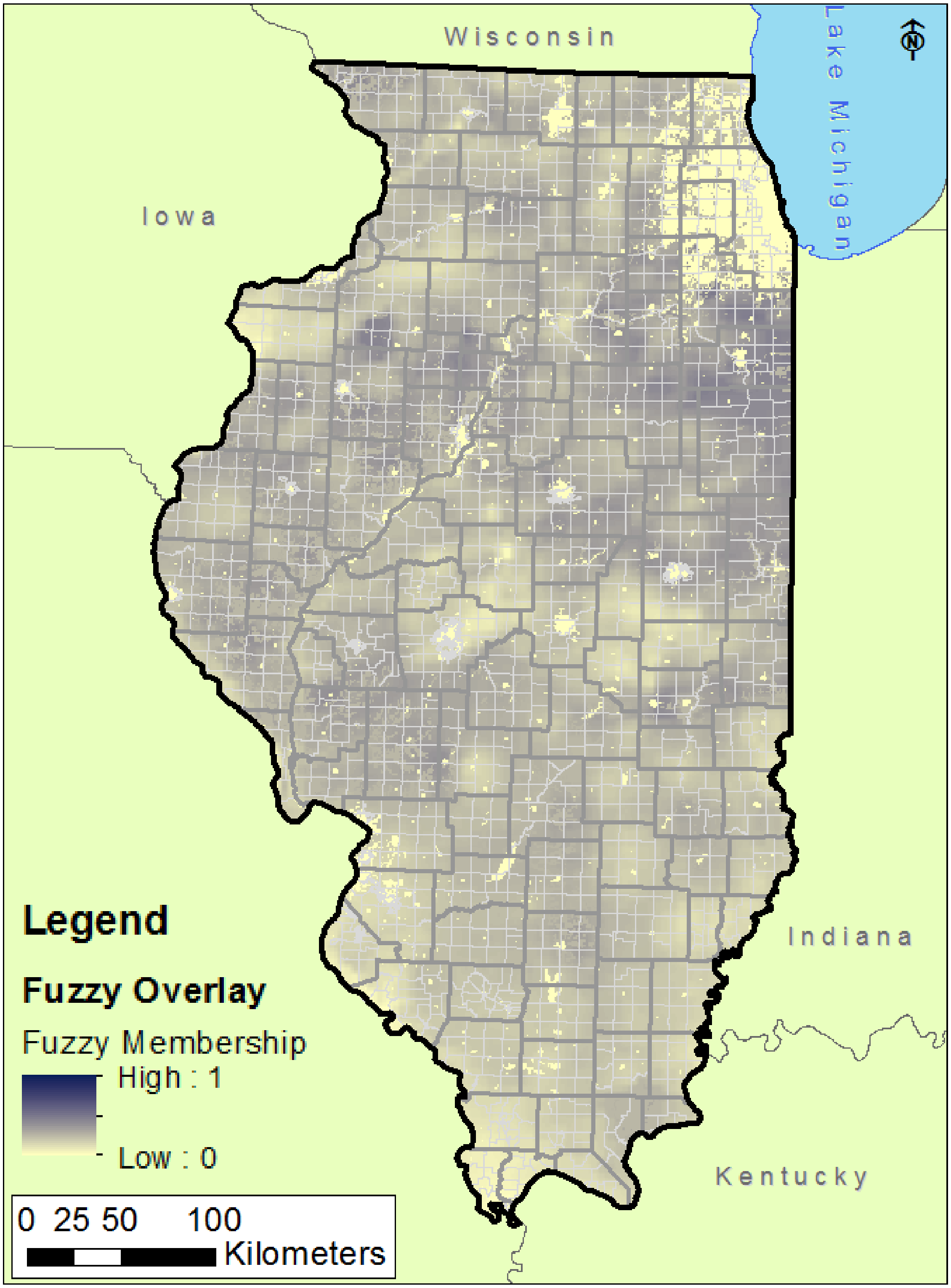

Figure 50: Fuzzy overlay results with state, county, and subcounty division boundaries overlaid

Appendix D: Membership Data of All Illinois Counties

County	Region	Total Area (km^2)	Total Area >0 (km^2)	% Area >0	Total Area >0.35 (km^2)	% Area >0.35	Total Area >0.4 (km^2)	% Area >0.4	Smallest Membership Value	Smallest Membership Value >0	Largest Membership Value
Adams	3	2266	2178	96.12%	39	1.72%	0	0.00%	0	0.161798328	0.3882882
Alexander	4	657	606	92.24%	0	0.00%	0	0.00%	0	0.000114669	0.091984339
Bond	5	994	987	99.30%	0	0.00%	0	0.00%	0	0.181980222	0.270650774
Boone	2	734	700	95.37%	0	0.00%	0	0.00%	0	0.143124357	0.326327354
Brown	3	799	794	99.37%	73	9.14%	0	0.00%	0	0.180211365	0.360611022
Bureau	2	2253	2227	98.85%	134	5.95%	44	1.95%	0	0.093132876	0.46522975
Calhoun	5	732	665	90.85%	0	0.00%	0	0.00%	0	0.02427659	0.326329231
Carroll	2	1212	1151	94.97%	0	0.00%	0	0.00%	0	0.142283559	0.295019209
Cass	5	995	975	97.99%	0	0.00%	0	0.00%	0	0.172831461	0.302223831
Champaign	3	2607	2482	95.21%	373	14.31%	0	0.00%	0	0.068277508	0.386211097
Christian	4	1875	1845	98.40%	0	0.00%	0	0.00%	0	0.176526576	0.31576699
Clark	4	1297	1282	98.84%	0	0.00%	0	0.00%	0	0.10041301	0.329070359
Clay	4	1226	1219	99.43%	0	0.00%	0	0.00%	0	0.145745441	0.256000668
Clinton	5	1314	1203	91.55%	0	0.00%	0	0.00%	0	0.181956187	0.265517116
Coles	4	1315	1283	97.57%	208	15.82%	55	4.18%	0	0.098820679	0.416159838
Cook	1	17284	1833	10.61%	214	1.24%	3	0.02%	0	0.25	0.434744745
Crawford	4	1159	1124	96.98%	0	0.00%	0	0.00%	0	0.10041301	0.265706122
Cumberland	4	880	875	99.43%	0	0.00%	0	0.00%	0	0.141008079	0.294180214
De Witt	3	1063	1036	97.46%	16	1.51%	0	0.00%	0	0.18110837	0.359964103
DeKalb	2	1644	1577	95.92%	2	0.12%	0	0.00%	0	0.133940592	0.354449689
Douglas	4	1072	1057	98.60%	0	0.00%	0	0.00%	0	0.075577356	0.279235989
DuPage	1	885	171	19.32%	1	0.11%	0	0.00%	0	0.237356469	0.354465127
Edgar	4	1602	1590	99.25%	119	7.43%	0	0.00%	0	0.161726445	0.383628875
Edwards	4	576	573	99.48%	0	0.00%	0	0.00%	0	0.093088925	0.191437274
Effingham	4	1230	1207	98.13%	0	0.00%	0	0.00%	0	0.168257251	0.300142139
Fayette	4	1891	1853	97.99%	0	0.00%	0	0.00%	0	0.212333024	0.321575046
Ford	3	1256	1246	99.20%	152	12.10%	69	5.49%	0	0.178009629	0.463739276

County	Region	Total Area (km^2)	Total Area >0 (km^2)	% Area >0	Total Area >0.35 (km^2)	% Area >0.35	Total Area >0.4 (km^2)	% Area >0.4	Smallest Membership Value	Smallest Membership Value >0	Largest Membership Value
Franklin	4	1123	1053	93.77%	0	0.00%	0	0.00%	0	0.172929645	0.256523281
Fulton	3	2290	2219	96.90%	192	8.38%	0	0.00%	0	0.179513246	0.396804959
Gallatin	4	853	839	98.36%	0	0.00%	0	0.00%	0	0.058059514	0.2578336
Greene	5	1422	1415	99.51%	156	10.97%	8	0.56%	0	0.112594038	0.405583501
Grundy	2	1131	1060	93.72%	342	30.24%	53	4.69%	0	0.228699118	0.414338201
Hamilton	4	1117	1114	99.73%	0	0.00%	0	0.00%	0	0.176832601	0.263416618
Hancock	3	2111	2034	96.35%	0	0.00%	0	0.00%	0	0.094819993	0.34105444
Hardin	4	467	458	98.07%	0	0.00%	0	0.00%	0	0.142035484	0.314993024
Henderson	3	1032	980	94.96%	0	0.00%	0	0.00%	0	0.044089079	0.343905181
Henry	2	2134	2103	98.55%	279	13.07%	228	10.68%	0	0.09645614	0.456580907
Iroquois	3	2925	2902	99.21%	1732	59.21%	898	30.70%	0	0.2290916	0.465563953
Jackson	5	905	898	99.23%	0	0.00%	0	0.00%	0	0.082227118	0.217271581
Jasper	4	1298	1284	98.92%	0	0.00%	0	0.00%	0	0.13582553	0.318413943
Jefferson	4	1505	1450	96.35%	0	0.00%	0	0.00%	0	0.194080114	0.34735325
Jersey	5	975	947	97.13%	0	0.00%	0	0.00%	0	0.118847273	0.307749152
Jo Daviess	2	1597	1539	96.37%	73	4.57%	35	2.19%	0	0.208089069	0.422762901
Johnson	4	1571	1510	96.12%	0	0.00%	0	0.00%	0	0.087919302	0.224771306
Kane	2	1355	979	72.25%	31	2.29%	0	0.00%	0	0.147984698	0.356824785
Kankakee	6	1770	1692	95.59%	1265	71.47%	909	51.36%	0	0.25	0.465563953
Kendall	2	812	736	90.64%	183	22.54%	0	0.00%	0	0.25	0.390451252
Knox	3	1867	1823	97.64%	339	18.16%	29	1.55%	0	0.210352138	0.432164311
Lake	1	1226	657	53.59%	0	0.00%	0	0.00%	0	0.090849794	0.260554045
LaSalle	2	2971	2849	95.89%	420	14.14%	44	1.48%	0	0.09438169	0.420389116
Lawrence	4	979	967	98.77%	0	0.00%	0	0.00%	0	0.121485807	0.242294684
Lee	2	1902	1881	98.90%	108	5.68%	0	0.00%	0	0.14529027	0.389901012
Livingston	3	2708	2685	99.15%	613	22.64%	121	4.47%	0	0.215927526	0.440362811
Logan	4	1607	1590	98.94%	0	0.00%	0	0.00%	0	0.01282267	0.284437746
Macon	4	1506	1388	92.16%	0	0.00%	0	0.00%	0	0.084433421	0.308749527
Macoupin	5	2256	2226	98.67%	117	5.19%	0	0.00%	0	0.25	0.386900663
Madison	5	1910	1647	86.23%	0	0.00%	0	0.00%	0	0.092261508	0.270023704

County	Region	Total Area (km^2)	Total Area >0 (km^2)	% Area >0	Total Area >0.35 (km^2)	% Area >0.35	Total Area >0.4 (km^2)	% Area >0.4	Smallest Membership Value	Smallest Membership Value >0	Largest Membership Value
Marion	4	1495	1466	98.06%	0	0.00%	0	0.00%	0	0.178768009	0.308185935
Marshall	3	1038	997	96.05%	364	35.07%	58	5.59%	0	0.234279841	0.448033035
Mason	3	1464	1400	95.63%	0	0.00%	0	0.00%	0	0.106098518	0.281930566
Massac	4	637	618	97.02%	0	0.00%	0	0.00%	0	0.095925689	0.217644155
McDonough	3	1529	1510	98.76%	41	2.68%	0	0.00%	0	0.189766824	0.363737613
McHenry	2	1581	1359	85.96%	4	0.25%	0	0.00%	0	0.14259927	0.398259044
McLean	3	3062	2934	95.82%	380	12.41%	0	0.00%	0.206295252	0.206295252	0.389778882
Menard	5	819	813	99.27%	0	0.00%	0	0.00%	0	0.106098518	0.280642062
Mercer	2	1473	1438	97.62%	0	0.00%	0	0.00%	0	0.003273655	0.257786453
Monroe	5	1021	973	95.30%	0	0.00%	0	0.00%	0	0.03526701	0.183676228
Montgomery	5	1822	1793	98.41%	60	3.29%	0	0.00%	0	0.128681406	0.38931635
Morgan	5	1484	1452	97.84%	11	0.74%	0	0.00%	0	0.172831461	0.37100184
Moultrie	4	892	863	96.75%	0	0.00%	0	0.00%	0	0.072864346	0.312214851
Ogle	2	1975	1943	98.38%	3	0.15%	0	0.00%	0	0.14970383	0.354198396
Peoria	3	1631	1469	90.07%	156	9.56%	6	0.37%	0	0.177474633	0.417250723
Perry	5	1141	1129	98.95%	0	0.00%	0	0.00%	0	0.178411335	0.237533078
Piatt	3	1128	1121	99.38%	60	5.32%	0	0.00%	0	0.072640285	0.368505985
Pike	5	2190	2149	98.13%	102	4.66%	0	0.00%	0	0.111052088	0.399635047
Pope	4	967	955	98.76%	0	0.00%	0	0.00%	0	0.106927782	0.311968625
Pulaski	4	524	518	98.85%	0	0.00%	0	0.00%	0	0.000620357	0.11729265
Putnam	2	454	410	90.31%	24	5.29%	0	0.00%	0	0.206342623	0.374920845
Randolph	5	1548	1486	95.99%	0	0.00%	0	0.00%	0	0.001316328	0.233275488
Richland	4	935	925	98.93%	0	0.00%	0	0.00%	0	0.164493814	0.288500845
Rock Island	2	1168	997	85.36%	0	0.00%	0	0.00%	0	0.096136533	0.285936058
Saline	4	1002	987	98.50%	0	0.00%	0	0.00%	0	0.155413091	0.272121578
Sangamon	4	2255	2072	91.88%	0	0.00%	0	0.00%	0	0.055735126	0.348198563
Schuyler	3	1140	1129	99.04%	63	5.53%	0	0.00%	0	0.219500139	0.374958009
Scott	5	658	655	99.54%	26	3.95%	0	0.00%	0	0.159673765	0.380518943
Shelby	4	1987	1956	98.44%	0	0.00%	0	0.00%	0	0.175349906	0.335047007

County	Region	Total Area (km²)	Total Area >0 (km²)	% Area >0	Total Area >0.35 (km²)	% Area >0.35	Total Area >0.4 (km²)	% Area >0.4	Smallest Membership Value	Smallest Membership Value >0	Largest Membership Value
St. Clair	5	1749	1492	85.31%	0	0.00%	0	0.00%	0	0.086381406	0.22403276
Stark	3	749	747	99.73%	262	34.98%	47	6.28%	0	0.25	0.448033035
Stephenson	2	1472	1449	98.44%	0	0.00%	0	0.00%	0	0.065484479	0.344654322
Tazewell	3	1701	1574	92.53%	0	0.00%	0	0.00%	0	0.078251302	0.348301321
Union	4	1090	1069	98.07%	0	0.00%	0	0.00%	0	0.049437959	0.158901289
Vermilion	3	578	573	99.13%	348	60.21%	0	0.00%	0	0.25	0.398833275
Wabash	4	585	567	96.92%	0	0.00%	0	0.00%	0	0.093371473	0.16906254
Warren	3	1412	1402	99.29%	119	8.43%	0	0.00%	0	0.1841425	0.389875293
Washington	5	1461	1454	99.52%	0	0.00%	0	0.00%	0	0.187145442	0.252309442
Wayne	4	1852	1844	99.57%	0	0.00%	0	0.00%	0	0.103008486	0.294319898
White	4	1303	1280	98.23%	0	0.00%	0	0.00%	0	0.104743287	0.213306949
Whiteside	2	1809	1758	97.18%	0	0.00%	0	0.00%	0	0.104046255	0.290463537
Will	6	2181	1549	71.02%	780	35.76%	434	19.90%	0	0.180333689	0.491967767
Williamson	4	1147	1066	92.94%	0	0.00%	0	0.00%	0	0.136576757	0.223776609
Winnebago	2	1332	1081	81.16%	0	0.00%	0	0.00%	0	0.125133857	0.329028457
Woodford	3	1406	1342	95.45%	108	7.68%	0	0.00%	0	0.248407394	0.393119574

Appendix E: Membership Data of the Top Subcounty Divisions in the Top Counties

Subcounty Division	County	Total Area (km^2)	Total Area >0 (km^2)	% Area >0	Total Area >0.35 (km^2)	% Area >0.35	Total Area >0.4 (km^2)	% Area >0.4	Smallest Membership Value	Smallest Membership Value >0	Largest Membership Value
Milks Grove	Iroquois	96	96	100%	96	100%	96	100%	0.416171	0.416171	0.465564
Beaver	Iroquois	88	88	100%	88	100%	88	100%	0.396837	0.396837	0.420283
Stockton	Iroquois	145	145	100%	145	100%	145	100%	0.36536	0.36536	0.418767
Martinton	Iroquois	133	133	100%	132	99.25%	132	92.25%	0.25	0.25	0.425534
Sheldon	Iroquois	108	107	99.07%	107	99.07%	106	98.15%	0	0.25	0.403768
Chebanse	Iroquois	158	155	98.1%	155	98.1%	155	98.1%	0.386089	0.386089	0.452689
Papineau	Iroquois	81	81	100%	79	97.53%	79	97.53%	0.25	0.25	0.433878
Prairie Green	Iroquois	105	102	97.14%	102	97.14%	102	97.14%	0	0.357287	0.421816
Concord	Iroquois	110	110	100%	104	94.55%	104	94.55%	0.25	0.25	0.411568
Middleport	Iroquois	100	97	97%	92	92%	89	89%	0	0.25	0.421568
Beaverville	Iroquois	102	102	100%	84	82.35%	84	82.35%	0.25	0.25	0.444311
Yellowhead	Kankakee	120	118	98.33%	117	97.5%	117	97.5%	0	0.25	0.45643
Gancer	Kankakee	98	98	100%	93	94.9%	93	94.9%	0.25	0.25	0.447224
St. Anne	Kankakee	80	79	98.75%	75	93.75%	73	91.25%	0	0.25	0.447832
Sumner	Kankakee	90	90	100%	90	100%	78	86.67%	0.38591	0.38591	0.456369
Momence	Kankakee	118	115	97.46%	98	83.05%	98	83.05%	0	0.25	0.462069
Peotone	Will	90	87	96.67%	87	96.67%	87	96.67%	0	0.405068	0.486876
Will	Will	100	99	99%	98	98%	88	88%	0	0.25	0.491968
Wilton	Will	100	100	100%	94	94%	68	68%	0.25	0.25	0.475904

Appendix F: Fuzzy Membership Maps

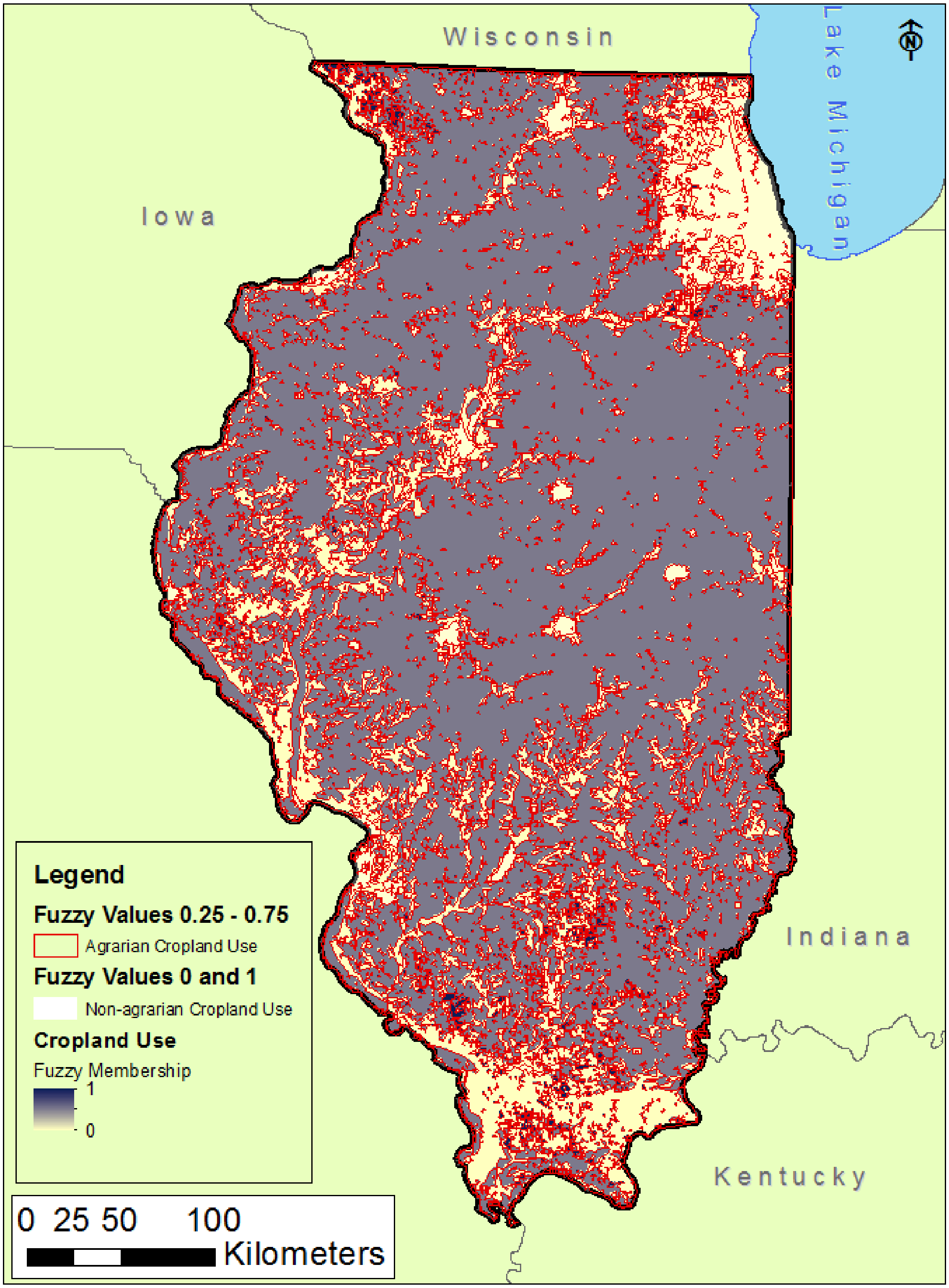

Figure 51: Fuzzy membership of Cropland Use with transparency overlay to accentuate high membership values

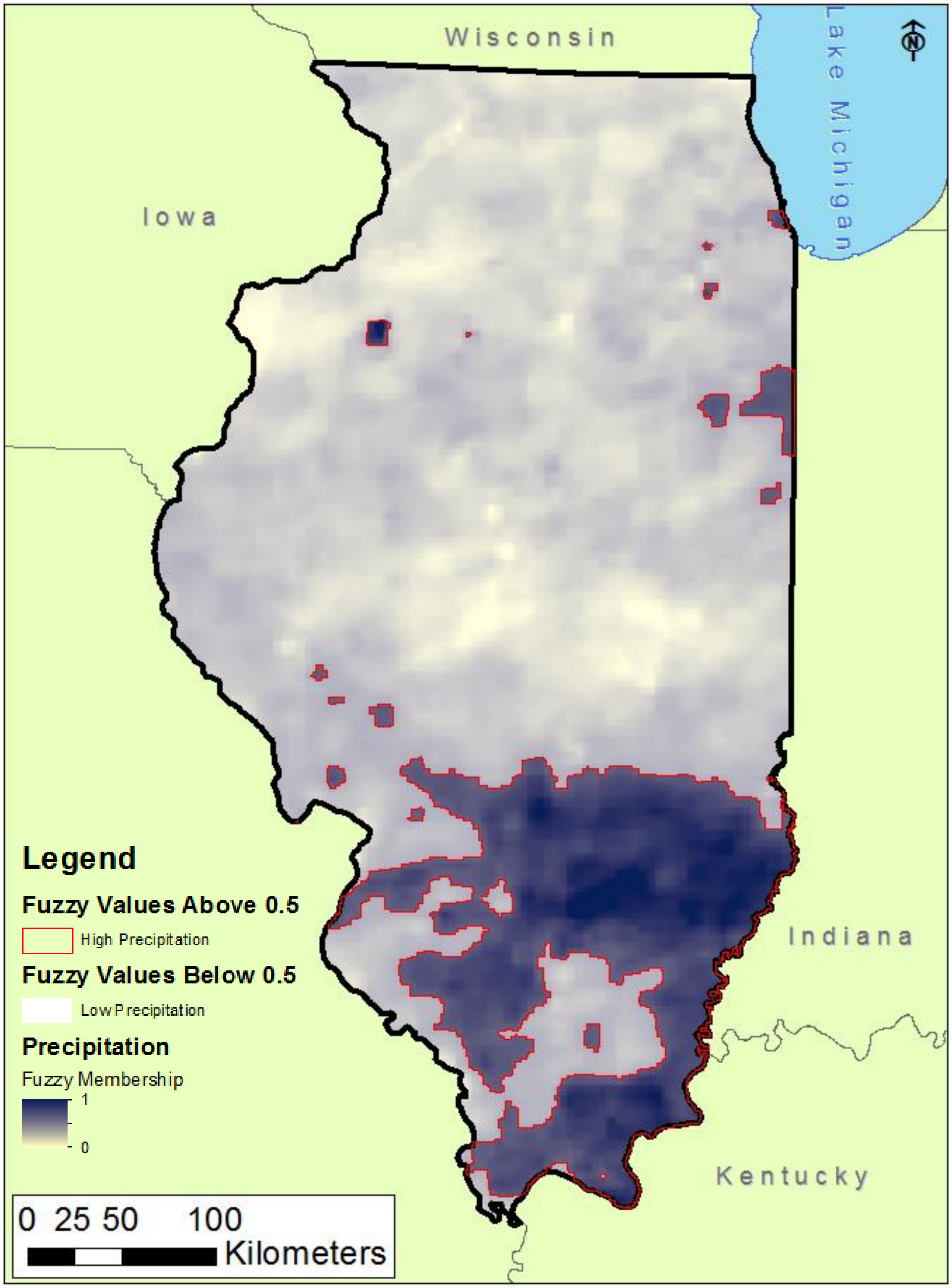

Figure 52: Fuzzy membership of precipitation with transparency overlay to accentuate high membership values

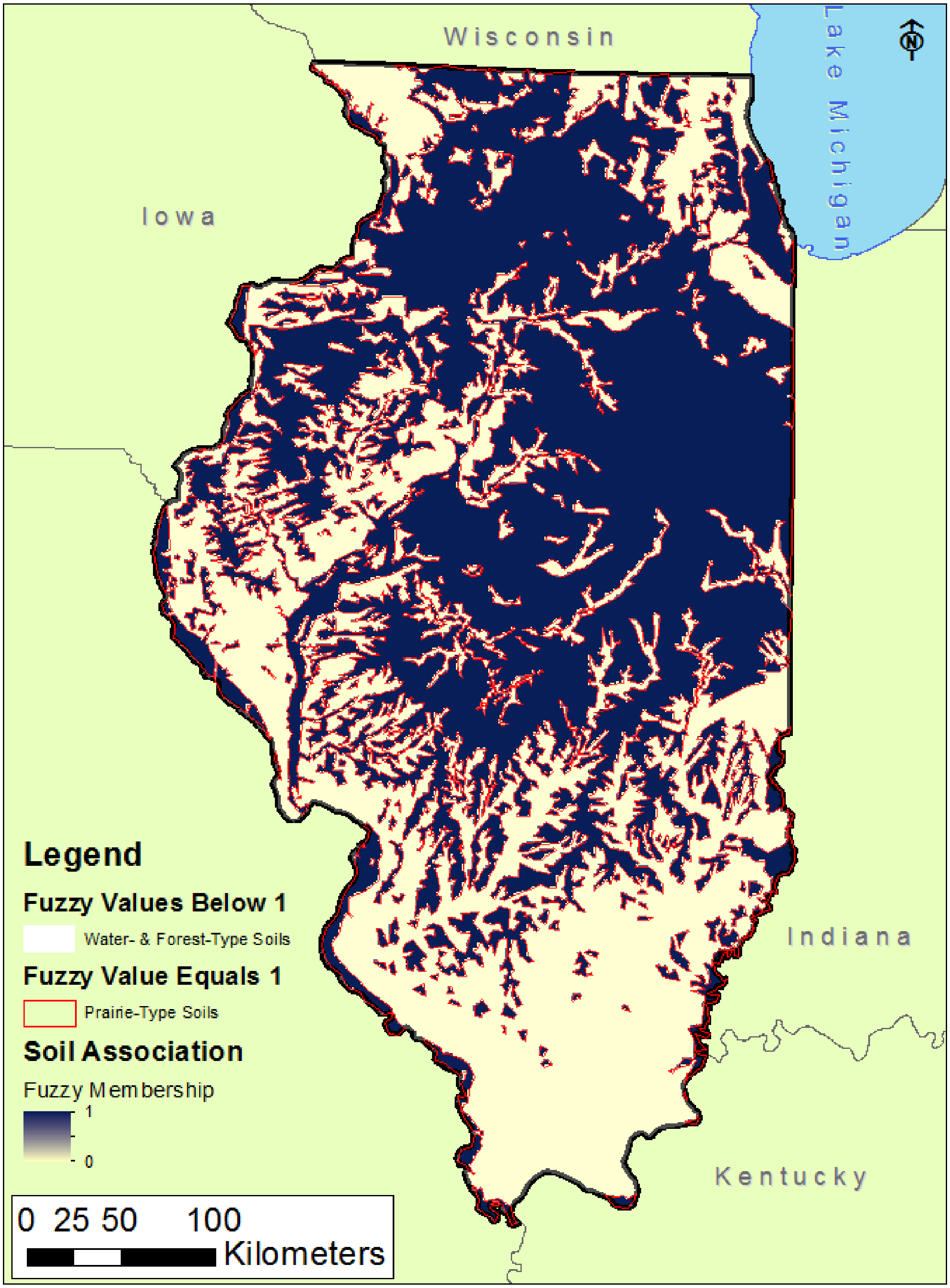

Figure 53: Fuzzy membership of soil types with transparency overlay to accentuate high membership values

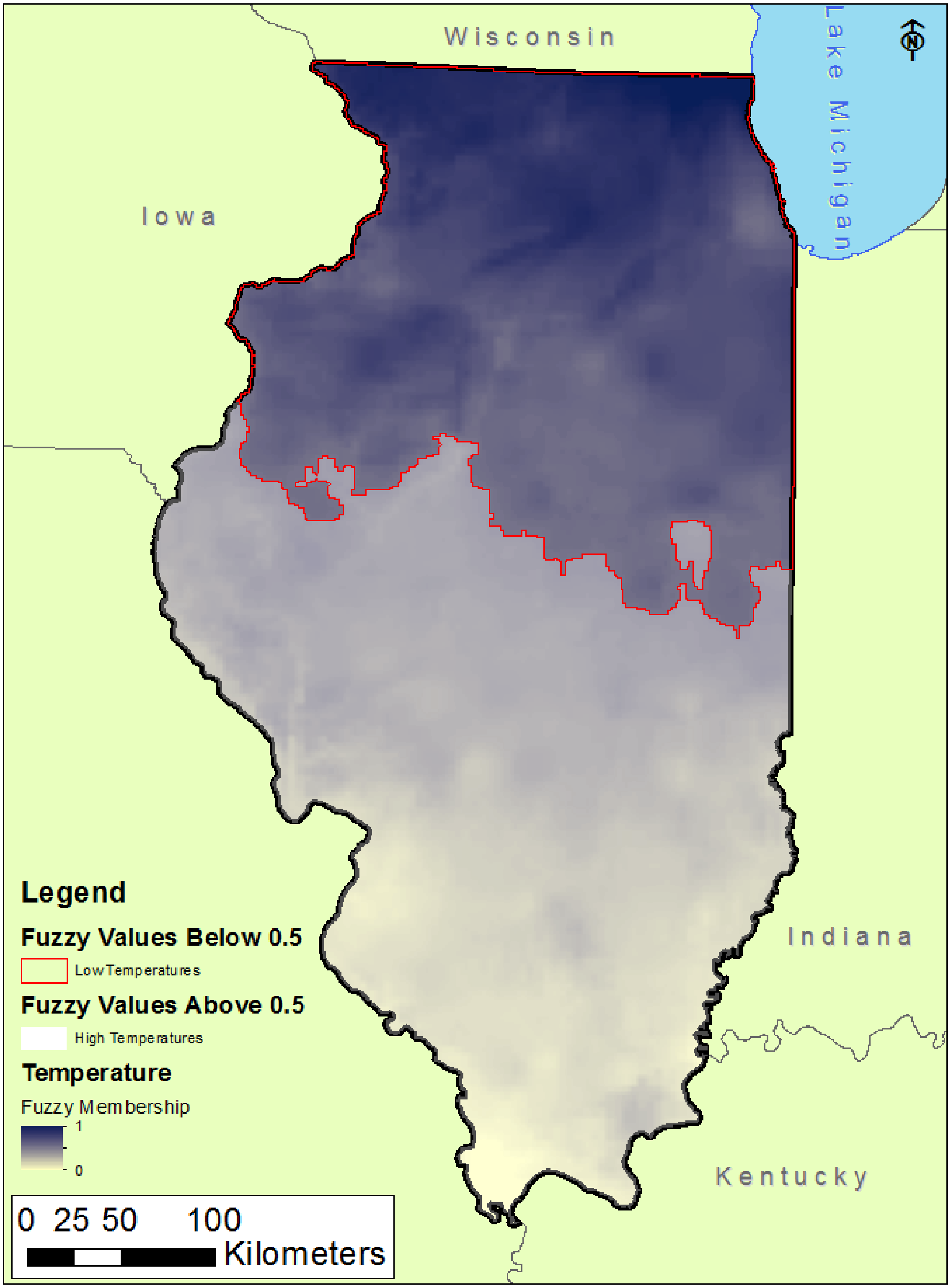

Figure 54: Fuzzy membership of temperature with transparency overlay to accentuate high membership values

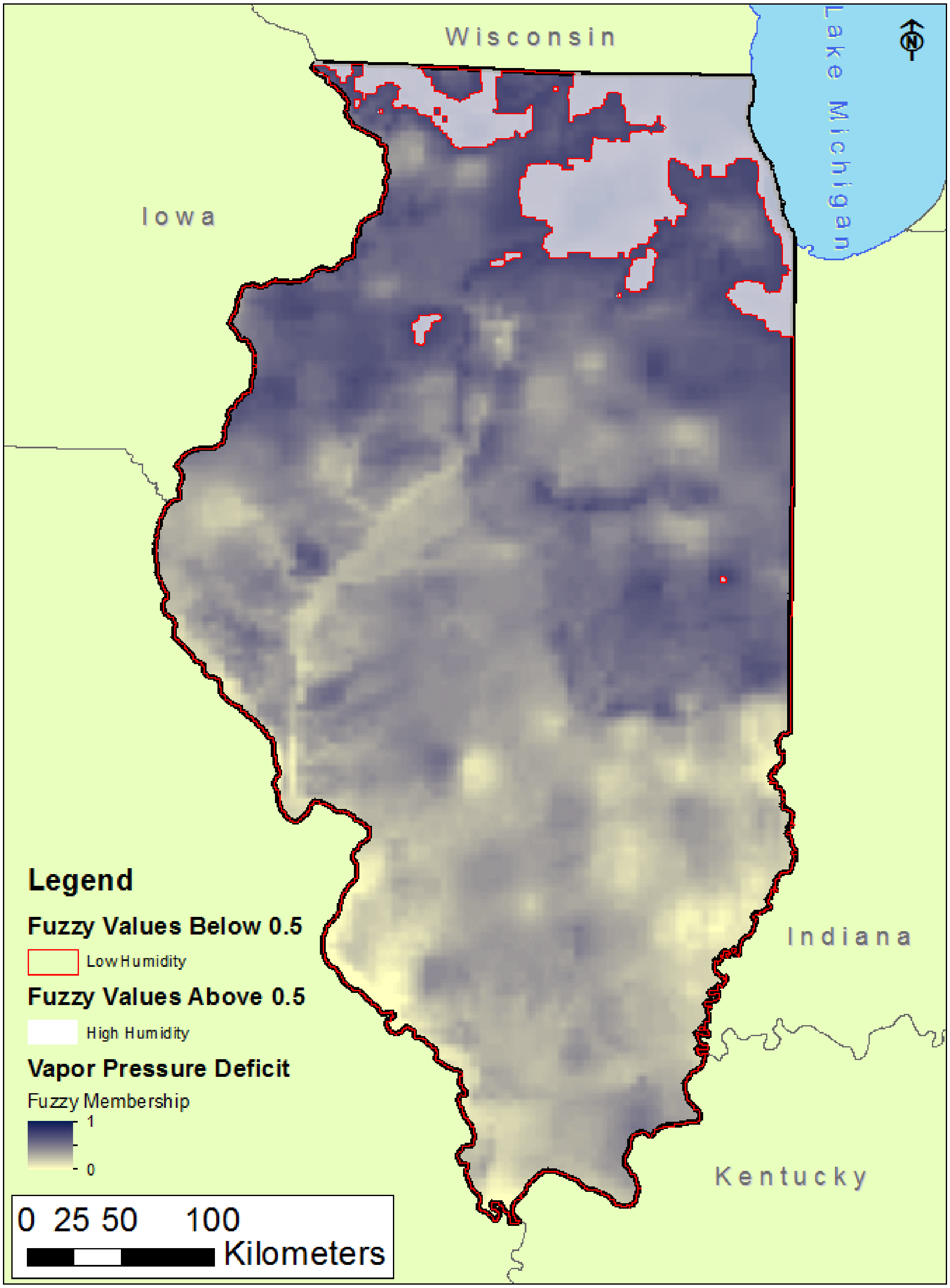

Figure 55: Fuzzy membership of vapor pressure deficit with transparency overlay to accentuate high membership values