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Shelterbelt Density Dynamics And Their Driving Forces In Grand Forks County, North Dakota, 1962 To 2014

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SHELTERBELT DENSITY DYNAMICS AND THEIR DRIVING FORCES
IN GRAND FORKS COUNTY, NORTH DAKOTA, 1962 TO 2014

by

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Morgen W. V. Burke
April 25, 2016

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To my wife Justine,

for all the love and support

these past two years.

ABSTRACT

Grand Forks County, ND, has one of the highest concentrations of shelterbelts in the World (Knutson 2011). As these trees aged and reached their expected lifespans, the quality of the shelterbelts has decreased and many have been removed. The rate of tree removal is thought to be increasing, with few shelterbelts being replanted. This raises concerns over possible increases in soil erosion caused by wind, such as was experienced in the 1930s. Using remotely sensed imagery and GIS, historic and recent shelterbelt densities can be measured and changes over time can be recorded. Geographic object-based image analysis (GEOBIA) can be used to automate shelterbelt density measurements on modern 4-band imagery, while older panchromatic imagery requires manual digitization. The wind erodibility index, soil pH, and surface geology were examined as possible agricultural driving factors.

Shelterbelt density was found to increase between the historic 1962 imagery and the modern 2014 imagery. A third image taken in 1995-1997 was used to confirm the finding. Shelterbelts in the county appear to have a spatial arrangement that stays fairly consistent between 1962 and 2014, with soil pH and surface geology helping to explain the observed spatial pattern.

CHAPTER I

INTRODUCTION

Shelterbelts, also known as tree-belts, windbreaks, hedgerows, and fencerows, are linear arrays of trees and shrubs planted to provide a variety of benefits for agricultural practices (Mize *et al.* 2008). Shelterbelts benefit agriculture by reducing wind erosion, reducing evapotranspiration from crops, increasing crop production, and improving crop economic returns (Kort 1988). Pressure to increase crop productivity while decreasing economic expenses requires using as much agricultural land as possible (Mize *et al.* 2008). Public interest in conservation has created the demand to increase the amount of protected land. The planting of shelterbelts is recognized as a conservation method to increase carbon sequestering (Czerepowicz, Case and Doscher 2012, Bahh-Acheamfour *et al.* 2014), reduce soil erosion (Mize *et al.* 2008), increase habitat for some wildlife (Sullivan, Sullivan and Thistlewood 2012), and to serve as visual and odor barriers (Mize *et al.* 2008).

Grand Forks County is situated within the Red River of the North Basin (Stoner *et al.* 1993), and within the state of North Dakota (Figure 1). Historically, Grand Forks County has had high wind events that can lead to increased soil erosion such as during the Dust Bowl of the 1930s (Todhunter and Cihacek 1999). A recent movement toward agricultural practices such as conservation tillage is reducing the amount of disturbance to the top organic layer of the soil, which may reduce the need for shelterbelts (Todhunter and Cihacek 1999, Bahh-Acheamfour *et al.* 2014).

The most recent large-scale planting of shelterbelts in Grand Forks County was in the 1950s and 1960s. During this time an estimated 120,000 to 230,000 trees were planted each year (Knutson 2011). From 1999 to 2006 approximately 24,000 trees were planted annually (Knutson 2011). Many of the trees planted during the 1950s and 1960s are now reaching the end of their lifespan and are being removed (Knutson 2011).

Measurements of shelterbelt densities in North Dakota have never been recorded, and data on the linear distance covered by shelterbelts is limited (Todhunter and Cihacek 1999). Knowing these densities, we can quantify the area of land removed from agricultural production for shelterbelts. Measurements across multiple years would establish how shelterbelt densities have changed over time. Grand Forks County contains 330,417 ha (816,478 ac) of farmland that consists of a variety of livestock, poultry, and cropland agricultural operations (USDA 2012). Establishing a protocol to measure shelterbelt density change over time for this county could serve as a model for mapping other parts of the state.

This study will answer two research questions: 1) has the density of shelterbelts in Grand Forks County changed between 1962 and 2014, and, if so, 2) what factors are driving the change? I use high spatial resolution aerial imagery to quantify shelterbelt density in Grand Forks County. Secondly, I use agricultural and soil survey data from the U.S. Department of Agriculture (USDA) and the Conservation Technology Information Center (CTIC) to examine trends in agricultural practices.

Policymakers can better understand how agricultural practices are changing and how this may affect the economy and the environment by understanding the factors that are driving changes in shelterbelt usage. Conversion in tillage practices may reduce the need for shelterbelts, but implementing this change would require an economic investment from the agricultural producer to purchase the needed equipment. Todhunter and Cihacek (1999) note that converting to a no-till operation requires buying seeding equipment that is compatible with one-pass field operations.

Soils characteristics in Grand Forks County may be a driving factor in the spatial distribution of shelterbelts in the county. The soil pH, wind erodibility index, and surface geology characteristics can be used to help better understand the placement of shelterbelts in the county. Using spatial statistics such as the Getis-Ord Gi* hotspot analysis, and the Bivariate Local Moran's I, relationships between these soil characteristics and shelterbelt densities in the county can be better understood.

Gerald, Tuskan, and Laughlin (1991) conducted a vegetation survey on shelterbelts in both North Dakota and Montana, and they found that a variety of tree species were used. Their survey disclosed eight species of coniferous trees with Colorado blue spruce (*Picea pungens*) and ponderosa pine (*Pinus ponderosa*) as the two most reported; 17 species of deciduous trees with green ash (*Fraxinus pennsylvanica*) and Russian-olive (*Elaeagnus angustifolia*) as the two most reported; and 13 species of shrubs with caragana (*Caragan arborescens*) and common lilac (*Syringa vulgaris*) as the two most reported. The survey shows the variety of tree species that historically have been used for shelterbelts in this region. This variety is attributed in part to the need for various species within different types of environments across North Dakota and Montana (Gerald, Tuskan and Laughlin 1991).

CHAPTER II

STUDY AREA

Grand Forks County (Figure 1) is located within the state of North Dakota in the Red River of the North Basin. In 2014 the county was estimated to have a population of 70,138 (U.S. Census Bureau 2014).

The county comprises fertile, fine, and loamy soils that make it well-suited to agriculture (Stoner *et al.* 1993). These soils were left after the retreat of Glacial Lake Agassiz (Stoner *et al.* 1993). Geological and climatic characteristics of Grand Forks County make soil vulnerable to wind erosion (Todhunter and Cihacek 1999). Glaciation resulted in a landscape with very little topographic relief (Stoner *et al.* 1993).

Todhunter and Cihacek (1999) note that wind speeds have been recorded in excess of 6.2 m/s (20.3 ft/s) on average over a period of 65 hours in North Dakota. These high wind speeds can result in a great amount of soil erosion by displacing the fine and loamy soils found in the Red River of the North Basin. In total Grand Forks County consists of 372,021 ha (919,283 ac) of land (U.S. Census Bureau 2014), with 970 farms occupying 330,417 ha (816,478 ac) (USDA 2012).

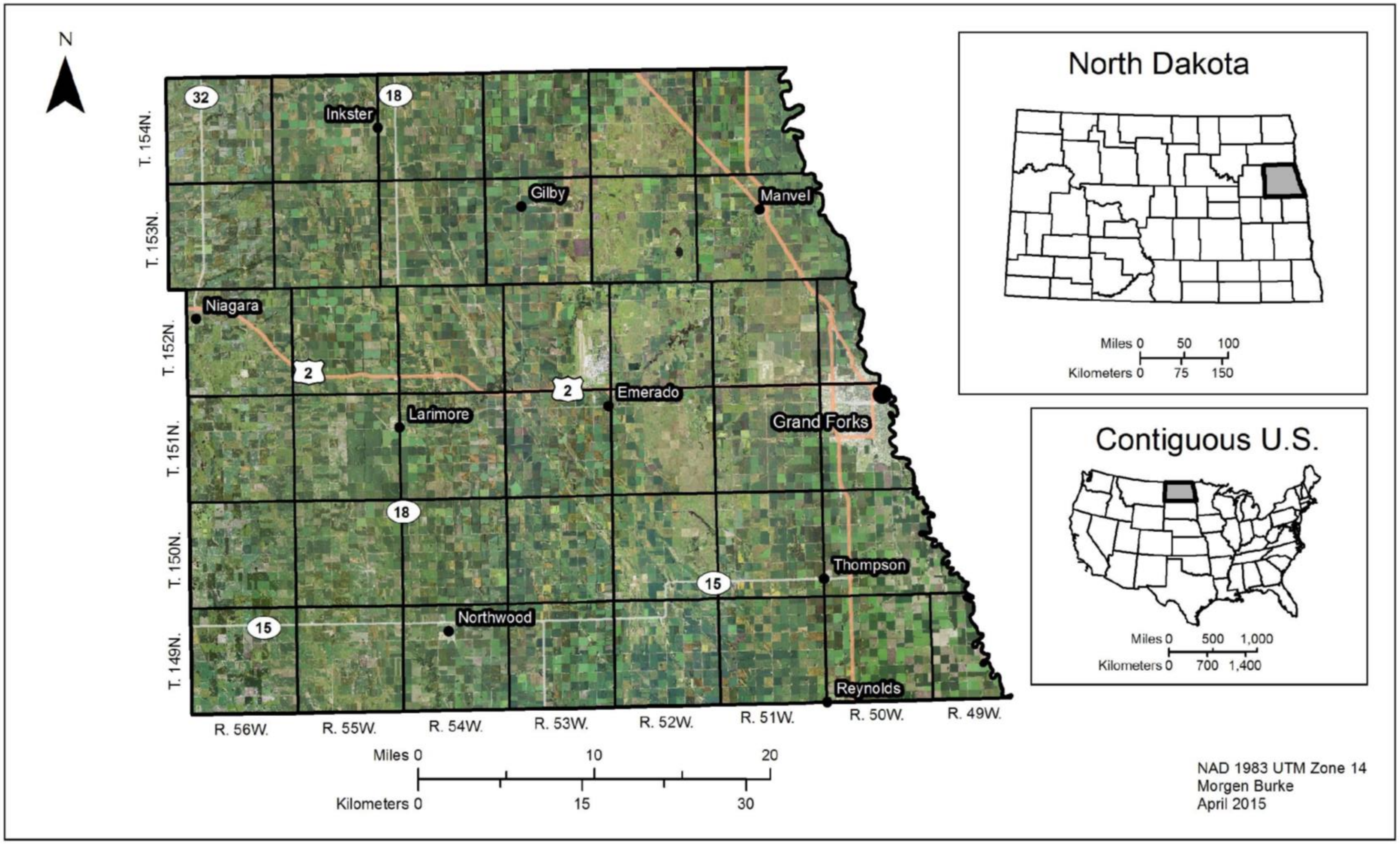

Figure 1: Grand Forks County, with an inset map showing its location within North Dakota (top), and an inset map showing the location of North Dakota within the Contiguous U.S. (bottom).

CHAPTER III

LITERATURE REVIEW

3.1 Shelterbelts

Shelterbelts were first used in the 1450s by the Scottish government to aid in the protection of agricultural production (Brandle, Hodges, and Zhou 2004). In the 1800s, U.S. settlers planted small-scale shelterbelts as a means to modify the environment around farms and homes. During the Dust Bowl of the 1930s, U.S. President Franklin Roosevelt established the Prairie States Forestry Project to plant shelterbelts stretching from North Dakota to Texas to combat increasing soil erosion and decreasing agricultural production caused by the drought (Brandle, Hodges, and Zhou 2004, Gardner 2009).

Since the early use of shelterbelts, several studies have identified other benefits of shelterbelts in the Great Plains. Kort (1988) found shelterbelts to have a strong positive impact on crop productivity. Even though shelterbelts occupy agricultural land, the increases in crop productivity outweigh the loss of land required for the shelterbelt. This increase in crop productivity was optimized when approximately 5 percent of the land was used for shelterbelts. Shelterbelts planted to protect cropland are often referred to as field shelterbelts or field windbreaks. Excessive planting of field shelterbelts can exist when more rows are planted than are needed to provide shelter for a given area (Kort 1988). Other benefits include: improving water usage in periods of drought by reducing rates of evaporation, reducing wind-chill impacts on livestock during the winter which improves livestock health, and reducing stress while working outdoors by providing protection from high winds (Mize *et al.* 2008). In urban environments, shelterbelts can act as visual and odor barriers between industrial and residential areas, and are often considered more aesthetically pleasing than a view of industrial or transportation infrastructure (Mize *et al.* 2008).

Shelterbelts have both positive and negative effects on local biodiversity. In some cases shelterbelts provide habitat and increase biodiversity in an agricultural setting consisting of homogenous crops, but at the same time provide habitat for species of animals that damage the crops (Baltensperger 1987, Mize *et al.* 2008, Sullivan, Sullivan and Thistlewood 2012). Quamen (2008) showed that shelterbelts reduce the biodiversity of native grassland bird populations by suppressing species associated with native grasslands with those that prefer habitat comprised of sparse tree and shrub species. Finally, in recent years, shelterbelts have been recognized as a strategy for carbon sequestration because of increased concerns about global climate change (Czerepowicz, Case and Doscher 2012). This has brought about an interest in methods that can be used to measure carbon reserves in shelterbelts and to determine if they can be used to mitigate global warming (Mize *et al.* 2008, Czerepowicz, Case and Doscher 2012, Bahh-Acheamfour *et al.* 2014).

Studies conducted throughout the Great Plains show decreased maintenance of planted shelterbelts, and well as their gradual removal. Schaefer, Dronen and Erickson (1987) examined the health of 2,875 shelterbelts in South Dakota. Their survey assessed the age, maintenance, spacing, and number of rows of trees as well as the grazing practices of livestock. While they hypothesized that the age of a shelterbelt would have the biggest impact on its health, they concluded this was inaccurate. Instead, they found that the maintenance conducted in the first five-to-ten years had the biggest impact on shelterbelt health. Trees that had adequate time to establish and had weeds and grasses removed were much healthier and survived longer than younger shelterbelts that had poor maintenance. Of the 2,875 shelterbelts surveyed, about 1,150 were in a healthy condition with no renovation needed.

A similar study conducted on field shelterbelts by Baltensperger (1987) who used historic aerial imagery in Iowa and Kansas to measure linear distances covered by the shelterbelts. The study area in Iowa found field shelterbelts had decreased from 1,600 km (994 mi) in 1885 to 72 km (45 mi) in 1979. The researchers found a similar trend in Kansas with 3,200 km (1988 mi) in 1882 decreasing to 1,100 km (684 mi) in 1978. Both of these studies suggest a decreased use of shelterbelts as a management strategy for wind erosion through both a decrease in maintenance of shelterbelts and the complete removal of shelterbelts from the field. Both studies focus on the need for shelterbelts on the prairie landscape to help prevent soil erosion during periods of drought during which the soil is most susceptible to erosion (Baltensperger 1987, Schaefer, Dronen and Erickson 1987).

One issue addressed by neither Baltensperger (1987) nor Schaefer, Dronen and Erickson (1987) is the reason for the decrease in maintenance and the increase in removal of shelterbelts. Wachenheim (2013) addressed these issues and found that economic factors drive agricultural producers to remove shelterbelts. Agricultural producers recognized the need to stop machinery operation in order to remove fallen branches and trees from the edges of fields, in turn reducing the efficiency of their field operations. Increases in farm machinery size mean that shelterbelts need to be spaced further apart to provide a large enough turning radius. Aerial spraying can be difficult and not as effective along shelterbelts. Shelterbelts require increased cost and time for maintenance and renovation, and may trap snow on the edge of fields longer into the spring possibly delaying the planting of crops. Finally, shelterbelts compete with the adjacent crops for water and nutrient resources.

While economics may provide a motivation for reducing shelterbelts within agricultural production, some agricultural producers, soil scientists, and government policy makers suggest the need for shelterbelts to reduce soil erosion (Knutson 2011, Franzen 2013). Even temporary periods of drought may result in topsoil loss if high wind conditions occur. Methods such as conservation tillage may reduce the effect of wind erosion. However, not all shelterbelts that are being removed are next to fields on which farmers use conservation tillage practices (Franzen 2013).

Government subsidies for planting shelterbelts in Grand Forks County reduce the economic burden on agricultural producers to replace existing shelterbelts. Organizations such as the Grand Forks County Soil Conservation District (SCD), and the U.S. Department of Agriculture's Natural Resources Conservation Service (NRCS) offer programs such as the Continuous Conservation Reserve Program (CCRP) that helps to fund a large amount of the shelterbelt planting costs (Knutson 2011). Programs such as these help to ensure that shelterbelts remain an economically sustainable agricultural operation.

3.2 Conservation tillage

Conservation tillage is an agricultural practice that may reduce the need for shelterbelts by decreasing soil erosion through reduced tillage practices (Bahh-Acheamfour *et al.* 2014). The term conservation tillage is often used interchangeably with different forms of tillage practice that reduce the disturbance to the top layer of the soil and increase the crop residue left on the field each year. Mannering and Fenester (1983) recognize conservation tillage as a tillage system that helps to reduce soil erosion from wind and water. With this definition conservation tillage is not a single method or practice, but describes a variety of practices used to reduce soil erosion. Gould, Saupe, and Klemme (1989) describe conservation tillage as any form of tillage that does not use a moldboard plow. The moldboard plow completely turns over the top layer of the soil, removing all crop residue, and is typically referred to as conventional tillage. Conventional tillage is used to decrease weeds and insects, incorporate fertilizer, and improve the seedbed. With conservation tillage increased use of herbicides and pesticides may be needed (Mannering and Fenester 1983).

An increase in crop residue left on the field leaves the soil rough, porous, cloddy, or ridged, which helps to reduce soil erosion. By leaving residue, surface soil particles become harder to detach, while rough surfaces reduce runoff velocity and slow wind velocity. Porous soils help increase infiltration rates and reduce total runoff. Having soils with a variety of these characteristics, as well as crop residue, will greatly decrease soil erosion (Mannering and Fenester 1983).

The Conservation Technology Information Center (CTIC) conducted a county-level tillage survey called the National Crop Residue Management (CRM) Survey to identify the type of tillage used by each crop variety. CTIC conducted the CRM survey yearly from 1989 to 2004 (excluding 1999, 2001, and 2003). Beginning in 2005, the CRM survey became voluntary and only a small fraction of the 3,092 counties now submit the survey annually. The CRM survey grouped together three tillage practices (no-till, ridge-till and mulch-till) as conservation tillage (greater than 30 percent residue left on the field), recognized a single reduced tillage practice (15 percent to 30 percent residue left on the field), and recognized a single conventional tillage practice (0 percent to 15 percent residue left on the field). In 1989 the mean usage of conservation tillage for the U.S. was 25.6 percent, while reduced tillage made up 25.3 percent, and convention tillage made up 49.1 percent. In 2004 these values had changed to 40.7 percent, 21.5 percent, and 37.8 percent, respectively. This accounts for a greater than 10 percent decrease in conventional tillage while conservation tillage increased more than 15 percent.

Adoption of conservation tillage practices has been slow, in part because of the financial investment that is required by the agricultural producer to purchase the new equipment required to operate a conservation tillage practice (Todhunter and Cihacek 1999). Secondly, Gould, Saupe, and Klemme (1989) found that younger farmers are more likely to change their tillage practices, but are less likely to recognize soil erosion as a problem. Because of this, more education for young agricultural producers is needed to encourage and show the benefits of using conservation tillage practices. The Food Security Act of 1995 helped to increase the shift to reduced tillage by mandating its use and was later extended by the 1990 Farm Act (Todhunter and Cihacek 1999).

Further understanding of how conservation tillage practices have changed in Grand Forks County over time and how this compares to the rest of the U.S. may help in understanding changes in shelterbelt densities at the county level. This can be determined by examining data from the CTIC gathered in the CRM survey specifically for Grand Forks County. Unfortunately, the CRM survey does not date back to the 1960s and Grand

Forks County did not submit the survey after 2004. Examining the data available may still provide some insight into how agricultural practices have changed within the county.

3.3 Aerial photography classification

Aerial photography and satellite image classification are used to automatically classify or group pixels within an image into categories or classes. Automatic classification typically requires multispectral data in which differing radiance measurements are exploited to classify each individual pixel. An example of this is land-cover classification, which often uses spectral patterns on a pixel-by-pixel basis (Lillesand, Kiefer, and Chipman 2008). The recent increase in availability of high-resolution aerial and satellite imagery has made it easier to extract landscape features at a smaller spatial resolution and with greater accuracy. Traditional classification methods, however, do not capture as much information from high spatial resolution imagery as does human interpretation. This information includes relationships in texture and shape between groups of pixels within the image (Wiseman, Kort and Walker 2009).

Geographic-object-based image analysis (GEOBIA) is a more recent image classification method that uses the information typically ignored in pixel-based classification (Hay and Castilla 2008). GEOBIA can be used to segment imagery into homogeneous segments called objects. These objects are then classified rather than the individual pixels (Hay and Castilla 2008, Czerepowicz, Case, and Doscher 2012, Meneguzzo, Liknes, and Nelson 2013). Users define settings based on mean spectral brightness, tone, and color; object size, shape, texture, and pattern; as well as relationships to adjacent objects (Wiseman, Kort, and Walker 2009). GEOBIA can be used at various scales, does not contain the salt-and-pepper appearance of pixel-based classification, and can be used to obtain information on an object's mean and standard deviation values (Meneguzzo, Liknes, and Nelson 2013). GEOBIA can also use elevation data such as digital elevation models (DEM) that can greatly improve classification accuracy (Tansey *et al.* 2009).

Using GEOBIA, shelterbelts can be extracted from high resolution imagery with high accuracy. Shelterbelts appear as linear shapes along the edge of fields and this length-to-width ratio can be used as part of the object classification method (Wiseman, Kort and Walker 2009, Ghimire *et al.* 2014). Because of the clear advantage in GEOBIA for the extraction of shelterbelts, it has been identified as the most commonly reported method used for this purpose (Czerepowicz, Case and Doscher 2012). Accuracies for the classification of shelterbelts using GEOBIA have varied with an overall accuracy ranging from 92 percent to 96 percent. Variations in accuracy can be attributed to variation in the imagery data available for each study, the software used, and user settings of the GEOBIA (Wiseman, Kort and Walker 2009, Czerepowicz, Case and Doscher 2012, Meneguzzo, Liknes, and Nelson 2013, Ghimire *et al.* 2014).

A variety of software is available for conducting a GEOBIA, with most of the software offering similar features and methods to conduct an analysis. The software eCognition Developer (Trimble Geospatial, Sunnyvale, CA) has been used in several studies for the extraction of shelterbelts (Tansey *et al.* 2009, Wiseman, Kort, and Walker 2009, Meneguzzo, Liknes, and Nelson 2013). Meneguzzo, Liknes, and Nelson (2013) use imagery available from the USDA's Farm Service Agency National Agriculture Imagery Program (NAIP), most of which has a 1 × 1 m (3.28 × 3.28 ft) spatial resolution and contains a near-infrared band as well as the standard color bands (red, green, and blue).

Using eCognition Developer 8.0, Meneguzzo, Liknes, and Nelson (2013) were able to segment the image into multiple objects. Then, using image object information such as the normalized difference vegetation index (NDVI) and object texture they separated the objects into two classes: tree and no tree. The overall accuracy of the resulting classification was 95 percent. Their study provides a good framework for repeating this GEOBIA using the NAIP data available for other parts of the U.S. This framework could be easily applied to the 4-band NAIP data available for Grand Forks County.

Image classification requires an image accuracy assessment. Image classification error matrices are often calculated to determine errors of omission and commission. This is typically done by sampling areas of the classified image and manually identifying if pixels were assigned to the correct class (Lillesand, Kiefer, and Chipman 2008). Errors of omission are pixels that should have been, but were not, included as part of a class. Errors of commission are pixels that were included in a class that should not have been. Both errors of omission and commission are used in the error matrix to determine the accuracy of the classification (Meneguzzo, Liknes, and Nelson 2013). Wiseman, Kort and Walker (2009) use a similar method of accuracy assessment for their study. Instead of visually analyzing the classified imagery, they randomly selected sample areas and, through field inspection, identified the shelterbelts. The main reason for using a manual field inspection for their sample site was to identify the tree species within the sample shelterbelts. Using these techniques, a similar accuracy assessment can be conducted on Grand Forks County. Visual inspection of the classified image will likely provide the most efficient method of accuracy assessment because shelterbelt species identification is not a concern in this study.

CHAPTER IV

METHODOLOGY

4.1 Defining a shelterbelt

In this study, I measured the change in shelterbelt density in Grand Forks County between 1962 and 2014, and then I examined how changes in agricultural technology and practices have affected the use of shelterbelts as a method for controlling wind erosion. With this specific goal in mind, the term shelterbelt was defined to ensure imagery classification is consistent throughout the study area and will meet the needs of the study. For the purposes of this study, a shelterbelt is defined as a linear array of trees and shrubs that exist adjacent to an agricultural field. Shelterbelts consist of a single or multiple rows of both trees and shrubs and all of these features will be included within the study classification.

A few studies have justified classifying only shelterbelts adjacent to fields based on an interest in how they affect soil erosion within a cropped landscape (Tansey *et al.* 2009, Wiseman, Kort and Walker 2009). Studies examining a broader range of shelterbelts, such as those around farm yards and homesteads, are often interested in other benefits such as carbon sequestering and wildlife habitats (Czerepowicz, Case and Doscher 2012, Meneguzzo, Liknes, and Nelson 2013). However, it should be noted that shelterbelts around farm yard and homesteads may also reduce wind erosion in adjacent cropland. Identifying only shelterbelts adjacent to fields for the aspect of this study helps to decrease possible variation in data. For example, an increase in farm yards and homesteads over time could cause an increase in the shelterbelts typically surrounding these features and could greatly affect density measurements. To avoid these possible effects, I will only examine shelterbelts adjacent to agricultural fields.

4.2 Georeferencing and digitizing of 1962 aerial imagery

I obtained historical aerial photography of Grand Forks County from the USDA's Farm Service Agency Aerial Photography Field Office (APFO). I purchased 832 images that were taken in 1962 and provide complete county coverage. This imagery is panchromatic (e.g., it includes reflectance in red, green, and blue wavelengths in a single grey-scale band) and was scanned with a spatial resolution of 25 × 25 cm (9.84 × 9.84 in) by the USDA APFO. Before the imagery could be georeferenced it was modified to remove all fiducial marks, borders, scanning errors, and index numbers. I cropped the images to remove the borders and markings around their edges using the open source software called GNU Image Manipulation Program 2.8.14 (http://www.gimp.org). Next, I filtered the images to remove scanning errors or stripping. I used ERDAS Imagine 2015 (Hexagon Geospatial, Norcross, GA) to run a focal analysis filter that targets no data value cells in the imagery and uses a 5-by-5 roving window to give a mean value to each cell with no data. After this, the images were ready for georeferencing.

I used ArcGIS Desktop 10.3 (Environmental Systems Research Institute, Redlands, CA) to manually georeference the 832 images. I used 2014 NAIP imagery for Grand Forks County to establish tie points for the georeferencing process. I aligned the panchromatic images with the 2014 NAIP imagery using the best tie locations that could be determined for each individual image. From here, I mosaicked the images into a single image, and then clipped the image to properly fit the boundary of the county and to remove the footprints of cities and towns.

The last step in the process was to manually digitize every shelterbelt within the imagery. I visually interpreted shelterbelts from the image, as single band panchromatic imagery cannot be accurately classified with GEOBIA. To digitize shelterbelts, I used a fixed scale of 1:3000, and all shelterbelts were digitized one section at a time. With the shelterbelts digitized as polygon features their total area could be calculated and used to find the density in the county, by section.

4.3 Geographic-object-based image analysis of 2014 aerial imagery

I conducted a GEOBIA using 4-band NAIP aerial imagery taken in 2014. To run the analysis, I clipped the imagery to the boundary of Grand Forks County and the footprints of cities and towns were removed. Using the framework established by Meneguzzo, Liknes and Nelson (2013), I ran the GEOBIA on the county. Some of the processes within their framework were altered because they included shelterbelts that I excluded from this study, such as those around homesteads. This includes aspects such as object size and shape in which case the framework established by Wiseman, Kort and Walker (2009) was used instead. By adding object shape, size, compactness, and length-width parameters, trees could be separated into shelterbelt and non-shelterbelt classes.

I produced two indices in ERDAS Imagine 2015 using the indices tool. The two indices I produced were NDVI and the green normalized difference vegetation index (GNDVI). These two indices were then used in combination with the NAIP 2014 imagery to carry out the GEOBIA. Using these indices, objects that are vegetation were classified using the mean values.

The NAIP Imagery and the NDVI and GNDVI bands were divided into 20 equal sized areas to help reduce the computational hardware requirements after finding that I could not run the GEOBIA in one process on the entire county with available hardware. These areas contained a 1.61 km (1 mi) overlap on all sides to reduce the possibility of an edge effect occurring during the GEOBIA. This process was done using the software ArcGIS Desktop 10.3. First the county was divided into 20 equal sized parts. Then a buffer of 1.61 km was applied to each part. Finally, the imagery and two indices were clipped using each of the buffered areas.

I used eCognition Developer 9.1.2 (Timble Geospatial, Sunnyvale, CA) to carry out the GEOBIA. The 20 sets of imagery and indices were each loaded into the eCognition workspace as a separate project, and then each area was processed one at a time. I ran a multiresolution segmentation algorithm to segment the images into homogenous objects. I ran this algorithm with a scale of 10, a shape of 0.2, and a compactness of 0.7. I set these values based on Meneguzzo, Liknes and Nelson (2013) except for the scale parameter which was changed from 15 after I used trial-and-error and found a scale of 10 produced more desirable object sizes. From this point, I then merged the image objects using the spectral difference segmentation algorithm with a maximum spectral difference of 2. For both of the segmentation algorithms a weight of 0 was given to the two indices while Red, Green, and Blue received a weighting of 1, and NIR received a weighting of 3 (Appendix A, Section 1). I carried out further manipulation of image objects using features such as NDVI and GNDVI mean values, object texture, length-to-width ratio, object asymmetry, object standard deviation value, mean object value, and mean difference between adjacent objects (Appendix A, Section 2). Once optimal settings for these values had been refined, I classified the objects into either shelterbelt or non-shelterbelt classes (Appendix A, Section 2.3). I then exported the resulting shelterbelt classes as a vector polygon data layer (Appendix A, Section 3).

I used ArcGIS Desktop 10.3 to manually clean up classification errors from the GEOBIA. This included splitting polygons to remove homestead shelterbelts that had been merged with field shelterbelts. Manual cleanup was done a section at a time, with a maximum scale of 1:5000. The 20 shelterbelt layers were merged together, and areas of overlap between the layers were examined and modified as necessary. This produced a single geospatial data layer containing all the digitized shelterbelts from the GEOBIA.

4.4 Change detection accuracy assessment

I carried out an accuracy assessment using a change error matrix (Congalton and Green 2009). I used ArcGIS Desktop 10.3 to carry out the accuracy assessment. I first extracted areas of change in which either a shelterbelt was digitized in 1962 and not in 2014, or a shelterbelt was digitized in 2014 and not in 1962. Next, I created a random sample of 500 locations, at least 1 m apart, and placed them throughout the areas of detected change. I visually interpreted each of the 500 points for both the 1962 imagery and the 2014 imagery and identified each point as either being a shelterbelt or not for the two years, producing a binary matrix. The matrix produced four possible combinations, with a yes (Y) being an area in which a shelterbelts existed when visually interpreted, and a no (N) being an area in which a shelterbelt did not exist when visually interpreted. Both a Y or a N could be assigned to the 1962 imagery, and then to the 2014 imagery. Using this binary matrix, three outcomes were found: areas in which a change was accurately detected (Y, N or N, Y), areas in which shelterbelt polygons were misaligned (Y, Y), and areas in which there was an error identifying a shelterbelt (N, N). This error matrix was then used to assess the overall accuracy of the change detected using the shelterbelt polygons. From the change error matrix, the percentage of error because of a misalignment in polygons (Y, Y) was removed from the total change detected, as this error represents change detected because of misalignment in the digitized polygon and not real change.

4.5 Temporal accuracy assessment of shelterbelt densities

I assessed the lack of temporal resolution between the shelterbelt density data measurements, with only one measurement in 1962 and one in 2014 by finding the density measurement for a third point in time. To reduce the time commitment to produce this third data point, a subset of Grand Forks County sections was used. I acquired aerial imagery taken between 1995 to 1997 from a joint program between the U.S. Geological Survey (USGS) and the USDA, and projected and mosaicked by the North Dakota State Water Commission. The imagery has a spatial resolution of 1 m, with a panchromatic band.

Using the shelterbelts drawn for 1962 and 2014 I identified all sections that contained a shelterbelt in at least one of the two years. Next, 150 of these sections were randomly chosen, representing 10.2 percent of the sections in the county. I then digitized all 150 sections using the same methods as the 1962 imagery. I calculated total density for the 150 sections using the digitized shelterbelts for all three points in time.

4.6 Identifying driving factors in agricultural technology and practice

Once shelterbelt densities were calculated for Grand Fork County in 1962 and in 2014, I examined the driving factors behind this change. I acquired soil tillage data from the CTIC for Grand Forks County from 1989 to 2004. I graphed the tillage data to identify trends in both conservation tillage and conventional tillage over time. Using this information, I made comparisons between shelterbelt densities and soil tillage practices over time.

Using both the 1962 and 2014 digitized shelterbelts, I used a hotspot analysis on the county to identify how evenly shelterbelts are dispersed throughout the county. To do this I used ArcGIS Desktop 10.3 to perform a spatial join to sum the total area of shelterbelts in each section of land in the county. From here the sum of shelterbelts in each section was divided by the total area of the section of land. This produced a shelterbelt density value in each section in m^2/km^2. Next, I used a hot spot analysis (Getis-Ord Gi*) to identify areas with significantly higher or lower shelterbelt densities using 90 percent, 95 percent, and 99 percent confidence intervals. The Getis-Ord Gi* statistic identifies areas in which are significantly higher than what would be expected from a random distribution (Mitchell 2009). A single section of land with a high shelterbelt density would not necessarily be a hotspot, but a section of land with a high shelterbelt density surrounded by other sections with high densities would be. The analysis was run using inverse distance weighting in which each polygon was given a centroid and the distance weighting threshold was automatically calculated so that each centroid would have at least one neighbor using a Euclidean distance. The assumptions of the Getis-Ord Gi* hot spot analysis were met with more than 30 features being used in the analysis, all features had at least one neighbor, and no one feature had all other features as a neighbor (Mitchell 2009). With locations of high or low shelterbelt densities identified, further analysis can be done to recognize why these areas had significantly different densities than the rest of the county.

I acquired soils data for Grand Forks County from the USDA's Soil Survey Geographic Database (SSURGO). This database contains various information about soils across the U.S. collected over the past century. These data were used to determine if areas with high shelterbelt densities tend to exist in areas with highly erodible soil from wind erosion. I used the wind erodibility index which represents the potential loss of soil by wind in tons/acre/year and is available in the SSURGO data for Grand Forks County. Using the shelterbelt densities calculated by section (~259 ha) for the hotspot analysis, I added the SSURGO wind erodibility index data in a spatial join done in ArcGIS Desktop 10.3, and the average wind erodibility index per section was calculated. The same SSURGO data were added to both the 1962 and the 2014 shelterbelt densities, and I assumed that the wind erodibility index did not change between the two years.

To determine if a relationship exists between shelterbelt densities and the wind erodibility index I conducted a Bivariate Local Moran's I as a local indicator of spatial association (LISA) (Anselin 1995). The analysis was done using the software GeoDa 1.6.7 (GeoDa Center for Geospatial Analysis and Computation, Arizona State University, Tempe, AZ). The Moran's I is a test of spatial autocorrelation, with the bivariate being used to test correlation between a variable at a given location to a different variable at the neighboring location (Anselin, Syabri, and Kho 2006). The assumptions for the Moran's I statistic were met, and are the same as the Getis-Ord Gi*, with more than 30 features being used in the analysis, all features had at least one neighbor, and no one feature had all other features as a neighbor (Mitchell 2009). Using this analysis, I identified overlaps in sections of land that have high or low wind erodibility index values and sections of land that have high or low shelterbelt densities and made a comparison between 1962 and 2014. I mapped the results for both 1962 and 2014 to help examine if shelterbelts tend to exist in areas with high wind erodibility index values, and if there are areas of land with high wind erodibility index values that have low shelterbelt densities.

I also extracted soil pH from the SSURGO dataset to test for a relationship with shelterbelt density. The soil pH data contains a negative logarithm to the base 10, of the hydrogen ion activity in the soil using a 1:1 soil-water ratio method. The dataset contains the relative acidity or alkalinity of the soil across the county. Gerald, Tuskan, and Laughlin (1991) found in their survey of agricultural producers in Montana and North Dakota that only 106 of the 856 producers, who returned a survey, had planted shelterbelts in alkaline soils. Hussain *et al.* (1994) found that trees grown in soil with increased pH had significantly lower survival rates. This suggests that shelterbelts in Grand Forks County may have lower densities in sections of land with high pH. I used the same process to test the wind erodibility index variable to test the soil pH data. I aggregated the data by section with each section containing the shelterbelt density for both 1962 and 2014 and the average soil pH using ArcGIS Desktop 10.3.

I then analyzed soil pH and shelterbelt density by section using GeoDa 1.6.7 to run a Bivariate Local Moran's I. This method was used to identify locations in which soil pH and shelterbelt density produced a significant correlation with a significance value of $p = 0.05$. I then mapped the results for both 1962 and 2014 showing the sections in which a significant value was found.

Surface geology for Grand Forks County was the final driving factor examined to explain the spatial pattern of shelterbelts in the county. I acquired surface geology data from the North Dakota State Government that was produced by the North Dakota Geological Survey (NDGS). This digital map contains information of the various surface sedimentary types found across the state. I spatially joined the 1962 and 2014 shelterbelt densities by section to the surface geology layer to find the sediment type with the highest average density. I then used a spatial join to connect the 1962 and 2014 shelterbelt polygons to the surface geology data to find the sediment type with the highest total area of shelterbelts.

CHAPTER V

RESULTS

5.1 Change detection accuracy assessment

The overall accuracy of the GEOBIA was 95.6 percent, this high accuracy was obtained after the shelterbelt polygons were manually cleaned to remove tree polygons that were not shelterbelt polygons. This overall accuracy is similar to the 92 to 96 percent overall accuracy seen in other studies (Wiseman, Kort and Walker 2009, Czerepowicz, Case and Doscher 2012, Meneguzzo, Liknes, and Nelson 2013, Ghimire *et al.* 2014). However, this accuracy does not evaluate the ability to detect density change between the 1962 and 2014 shelterbelt polygons. To do this I conducted the change detection accuracy assessment (Table 1) and found an overall accuracy of 59.8 percent with a total of 299 out of 500 points being randomly placed in areas in which an accurately detected change occurred. Of the 500 points, I visually interpreted 179 as a shelterbelt in both 1962 and 2014 resulting in an error of 35.8 percent. This error appeared to be largely caused by shelterbelts polygons between the two years not having an identical overlap, and therefore producing areas around the edges of the digitized polygons that were identified as areas of change (Figure 3). Finally, I interpreted 22 of the 500 points as not being a shelterbelt in either 1962 or 2014. This error of 4.4 percent was most likely caused by misclassification from the GEOBIA creating a shelterbelt polygon in an area in which a shelterbelt did not exist.

Table 1. Change detection accuracy assessment. This error matrix was used to assess the overall quality of detected change between the 1962 and the 2014 digitized shelterbelt polygons. The assessment used 500 points placed randomly in areas of detected change to test if change actually occurred or not. Points that were found to have a shelterbelt in 2014 and not in 1962 or points that had a shelterbelt in 1962 and not in 2014 resulted in an accurately detected change (Y,N or N,Y). An inaccurately detected change resulted from points which either had a shelterbelt in both 1962 and 2014 or both did not (Y,Y or N,N).

		Was a shelterbelt in 2014: Yes	Was a shelterbelt in 2014: No
Was a shelterbelt in 1962	Yes	179/500	27/500
	No	272/500	22/500

Overall Accuracy (Y,N or N,Y)	59.8%
Error in Shelterbelt Overlap/Misaligned (Y,Y)	35.8%
Error in identifying a Shelterbelt (N,N)	4.4%

5.2 Grand Forks County shelterbelt density

Based on information reported in the news (Knutson 2011, Knutson 2014, Wachenheim 2013), I expected that shelterbelt densities would decrease over time, as shelterbelt planting in Grand Forks County is reported to have decreased. Using the digitized shelterbelts (Figure 2), I determined the change between 1962 and 2014 was positive, and the opposite of what I expected. The 1962 shelterbelt density was calculated at 6,765 m^2/km^2 (188,586 ft^2/mi^2), while the 2014 shelterbelt density was calculated at 12,821 m^2/km^2 (357,427 ft^2/mi^2). I calculated the 2014 density using a 35.8 percent decrease (Table 1) from the originally calculated density (19,970 m^2/km^2) because of the error found in change detection for misaligned shelterbelt polygons (Figure 3). I found the change in density between 1962 and 2014 to increase by 89.5 percent. These calculations were done using total farmland in Grand Forks County, as calculated by the USDA (2012), which has a total area of 3,304 km^2 (1,276 mi^2). In 1964 Grand Forks County had 3,471 km^2 (1,340 mi^2) in farmland (USDA 1964). If I use this value instead, shelterbelt density in 1962 is 6,440 m^2/km^2 (179,537 ft^2/mi^2), resulting in a 99.1 percent increase between 1962 and 2014. I calculated shelterbelt densities by section of land for the county to be used in spatial analysis (Figures 4 and 5). I also calculated change in density between 1962 and 2014 by section to visually interpret where the majority of shelterbelt density change has occurred (Figure 6). Overall, 11 percent of sections decreased, 16 percent of sections had no change, and 73 percent of section increased in shelterbelt density.

To help improve the overall temporal resolution of the study, I used a subset of data to measure shelterbelt density at three different points in time (Figure 7). I calculated shelterbelt density using 150 selected sections that represented 10.2 percent of Grand Forks County. I found that density increased over time with 13,453 m^2/km^2 (375,048 ft^2/mi^2) in 1962, 19,767 m^2/km^2 (551,053 ft^2/mi^2) in 1995-1997, and 28,754 m^2/km^2 (801,627 ft^2/mi^2) in 2014. Because the 150 selected sections had to contain a shelterbelt in either 1962 or 2014 the densities calculated were greater than those for the entire county.

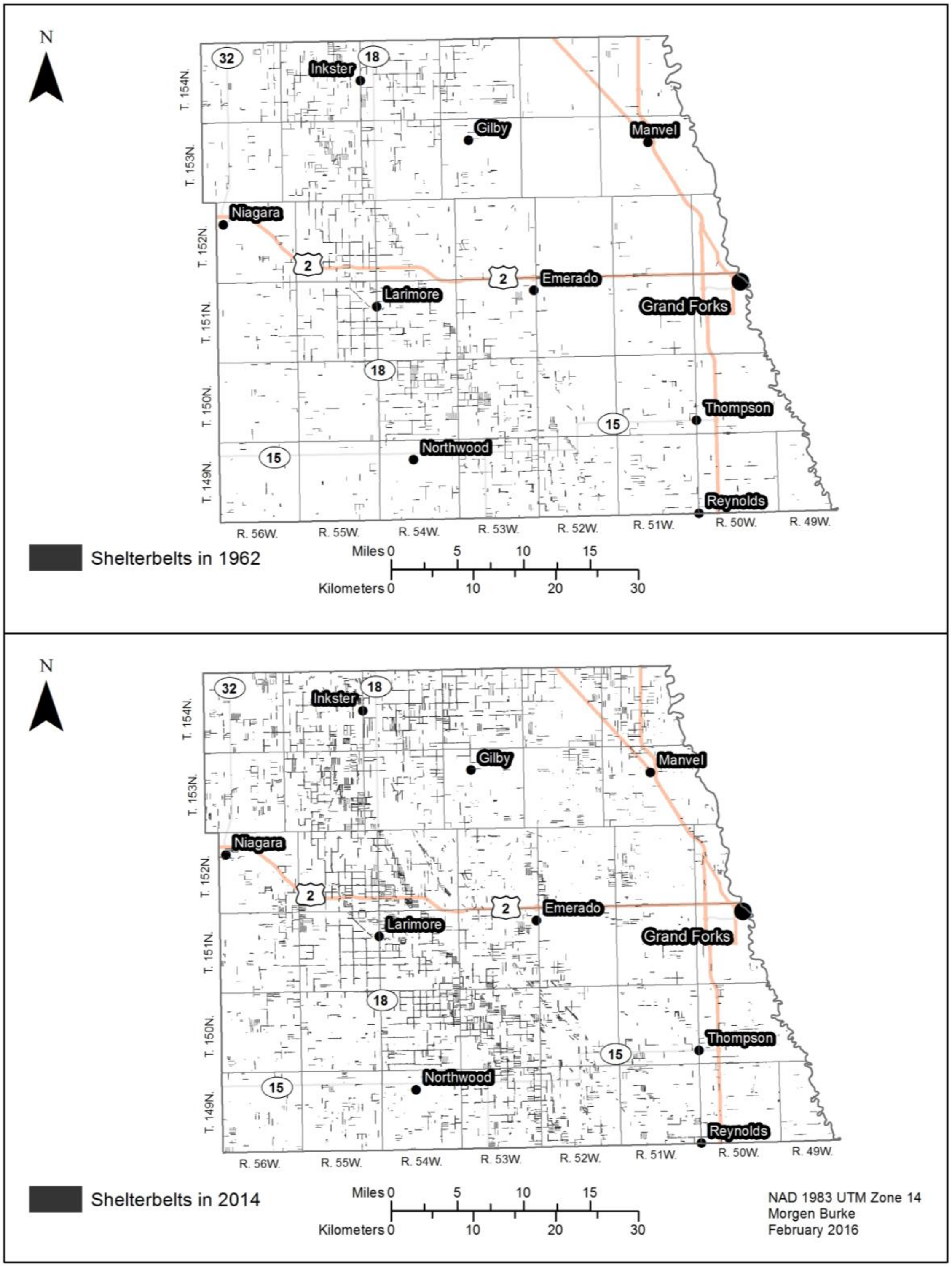

Figure 2: Grand Forks County; comparing the digitized shelterbelts in 1962 (top), with the digitized shelterbelts in 2014 (bottom).

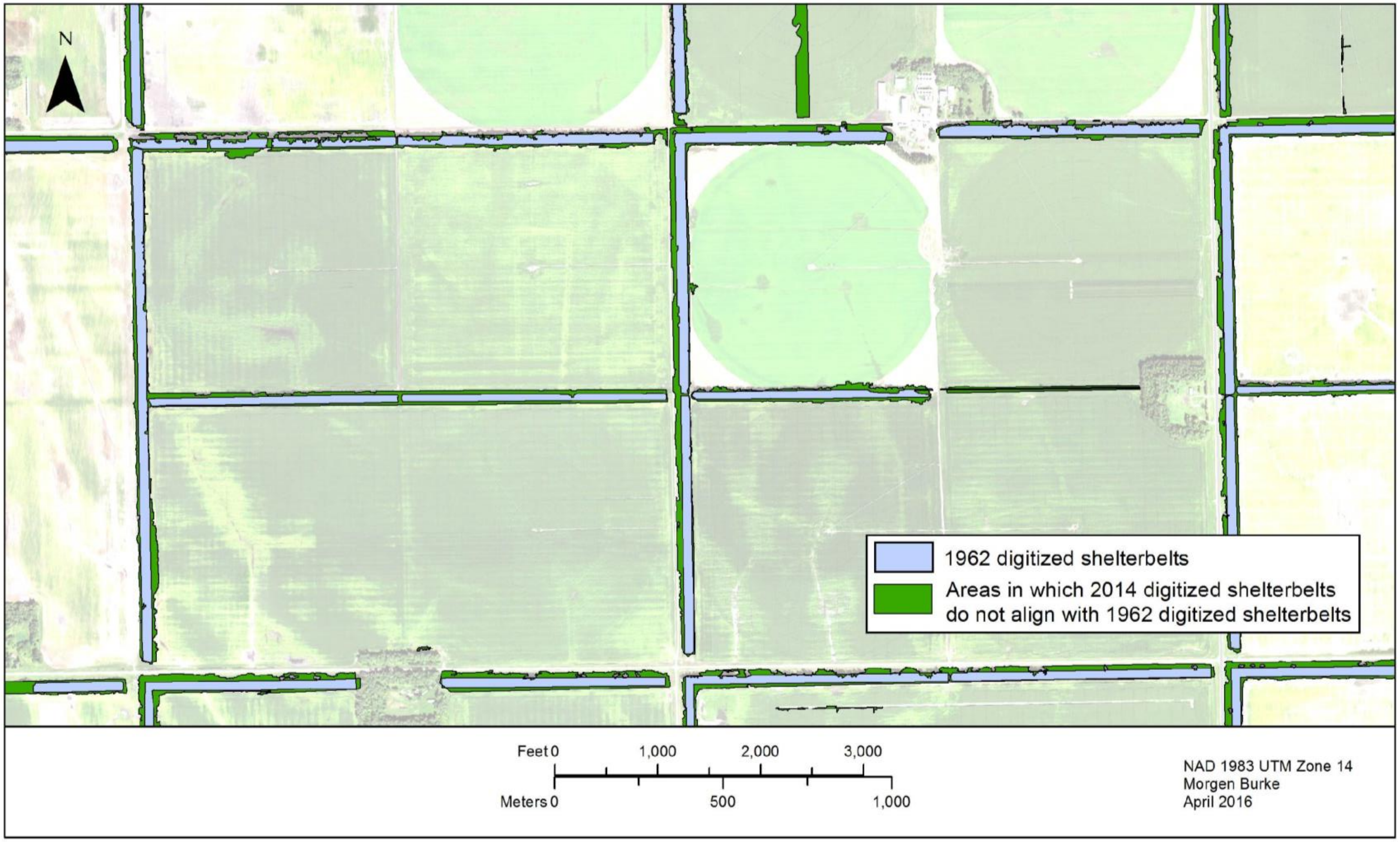

Figure 3: Comparing the 1962 digitized shelterbelt polygons with the 2014 shelterbelt polygons. The 1962 shelterbelts are surrounded by the 2014 shelterbelts in areas in which the GEOBIA overestimated the width of the shelterbelts because of increased foliage. This was recognized as an inaccurate detection in shelterbelt density increase and was removed from 2014 density calculations by decreasing the 2014 shelterbelt polygon areas by 35.8%.

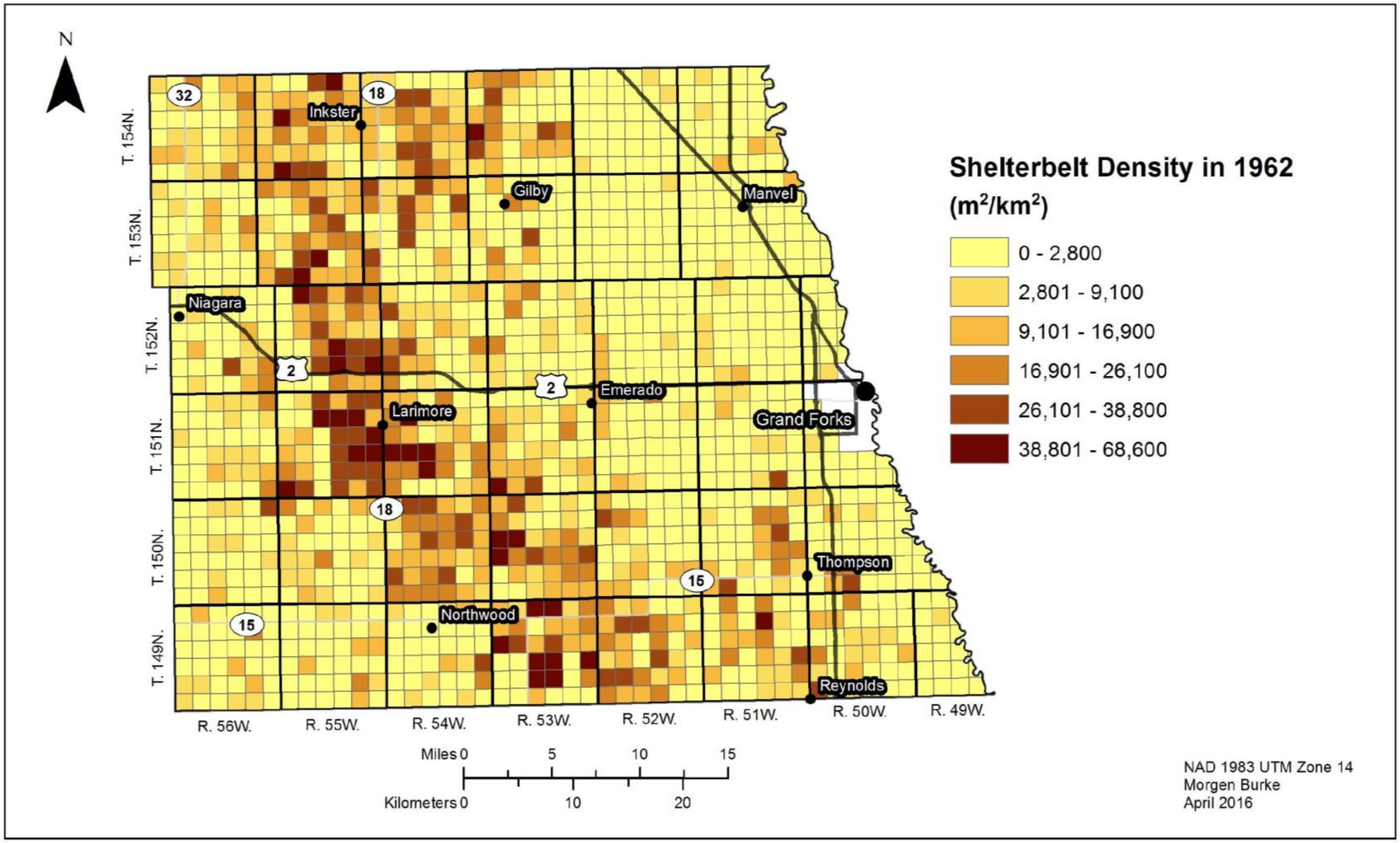

Figure 4: Shelterbelt density by section for Grand Forks County in 1962.

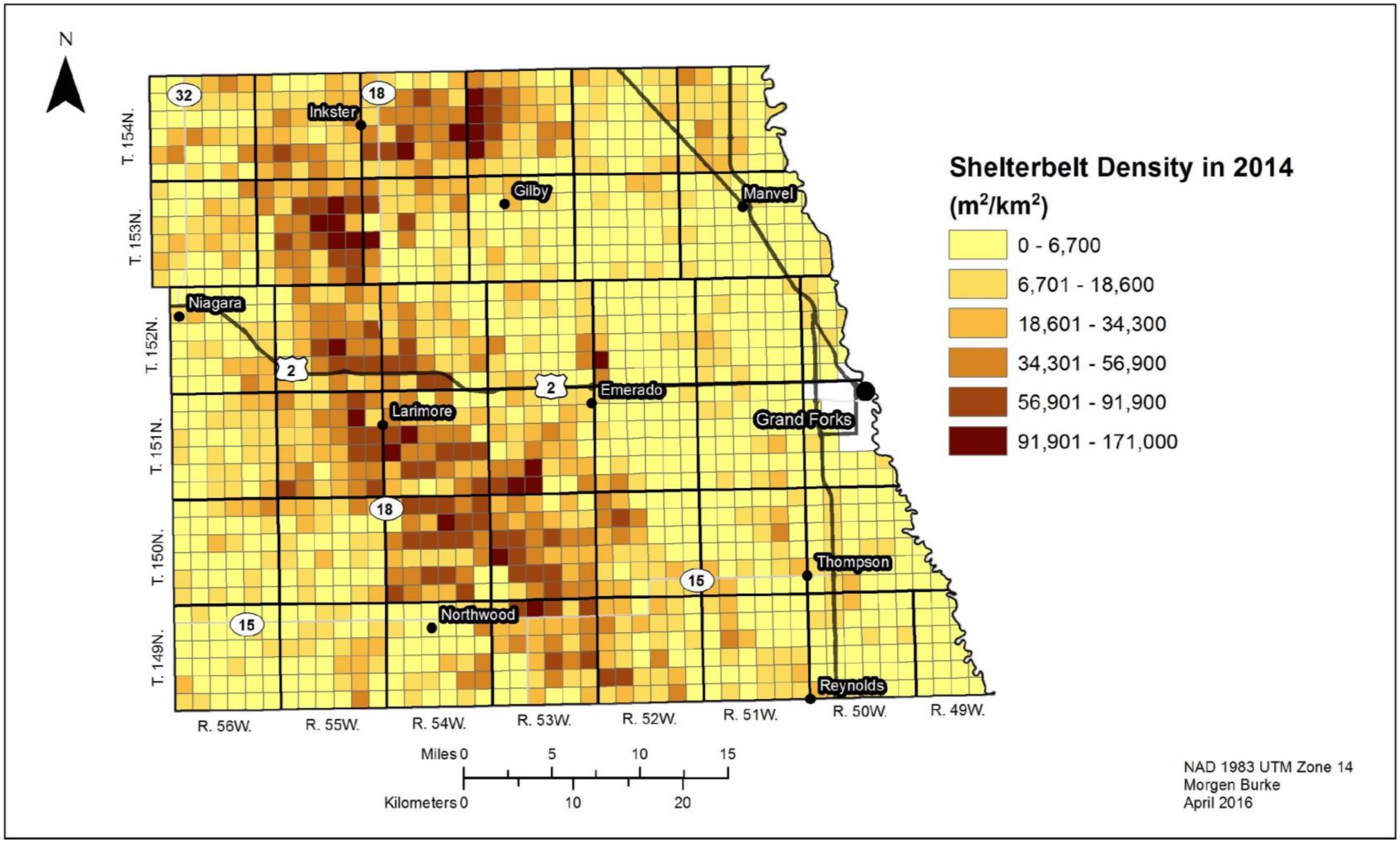

Figure 5: Shelterbelt density by section for Grand Forks County in 2014.

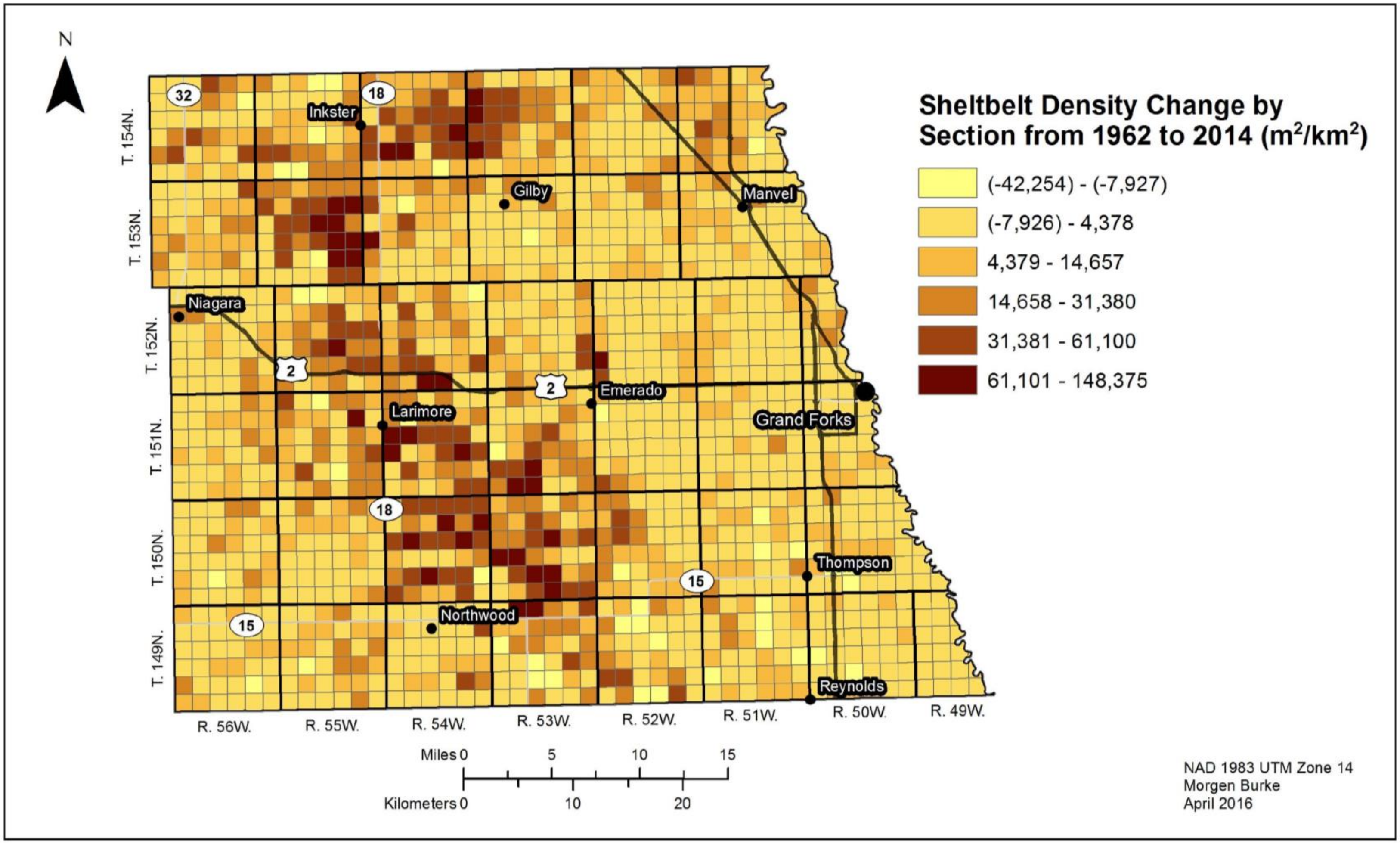

Figure 6: Shelterbelt density change by section from 1962 to 2014 for Grand Forks County.

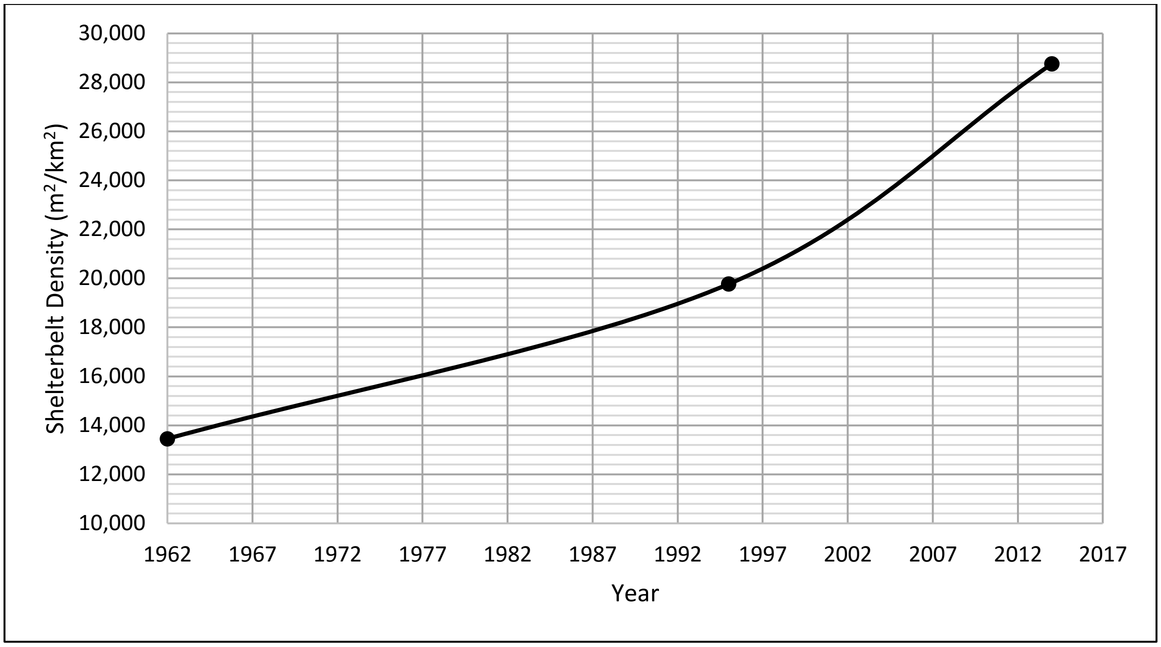

Figure 7: Shelterbelt density for Grand Forks County using a subset of 150 sections for all three data points. These density values represent 10.2 percent of sections in the county, and are expected to be higher than the density for the entire county because the sections selected contained a shelterbelt in either 1962 or 2014.

5.3 Tillage practices

The data provided by the CTIC on the adoption of conservation tillage only covered 15 of the 52-year study period (Figure 8). Unfortunately, this temporal resolution does not appear to provide much insight into changes in tillage methods used in the county. For the years 1989 to 2004 tillage practices appear to fluctuate over time with conservation tillage starting at 22 percent in 1989, increasing to 59 percent by 1997, but then dropping down to 14 percent by 2004.

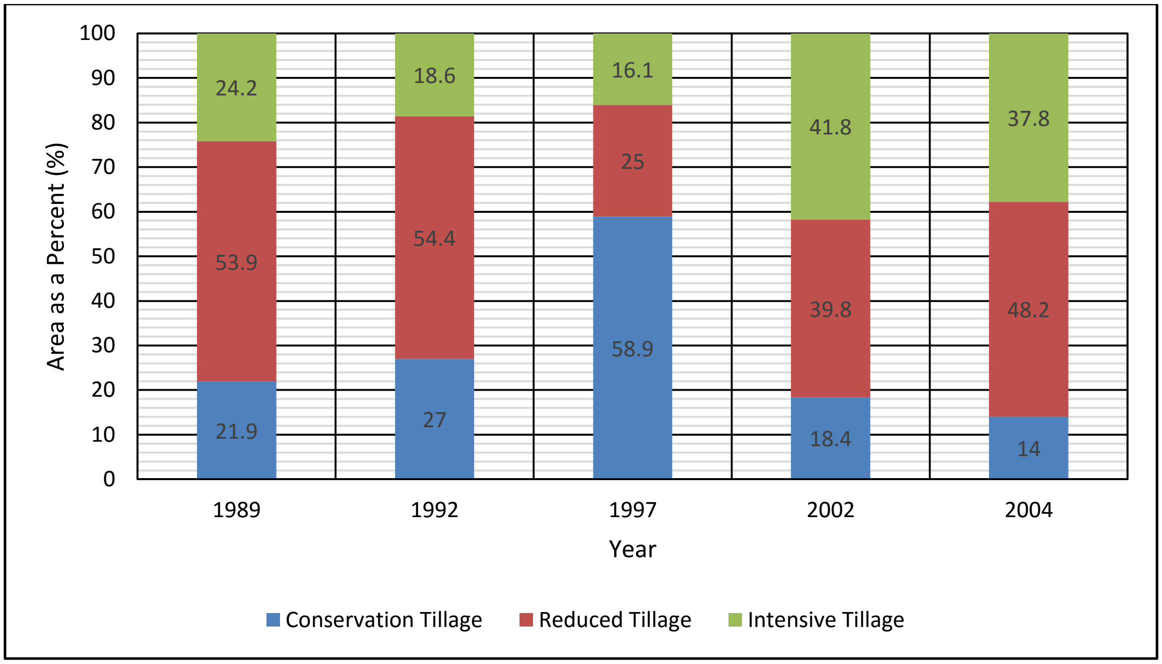

Figure 8: The change in tillage methods for Grand Forks County over time, using data acquired from the Conservation Technology Information Center (CTIC) from the National Crop Residue Management (CRM) Survey.

5.4 Hotspot analysis of shelterbelt density by section

I ran the hotspot analysis on both the digitized shelterbelts for 1962 (Figure 9) and the digitized shelterbelts for 2014 (Figure 10). Areas of significantly higher density were found for both years. In 1962 the hotspot analysis found 16.1 percent of sections had a significantly higher density of shelterbelts (Table 2). In 2014 15.8 percent of sections had a significantly higher density (Table 2). An examination of Figures 9 and 10 shows that shelterbelts appear to have a similar spatial pattern between 1962 and 2014.

Table 2: Results of shelterbelt density hotspot analysis. Percent of sections that were found to have either a significantly high or low density at three different confidence levels (99%, 95%, and 90%).

	Significantly high density (confidence level)			Significantly low density (confidence level)		
Year	99%	95%	90%	99%	95%	90%
1962	8.1%	5.6%	2.4%	0%	0%	0%
2014	9.7%	4.1%	1.9%	0%	0%	0.2%

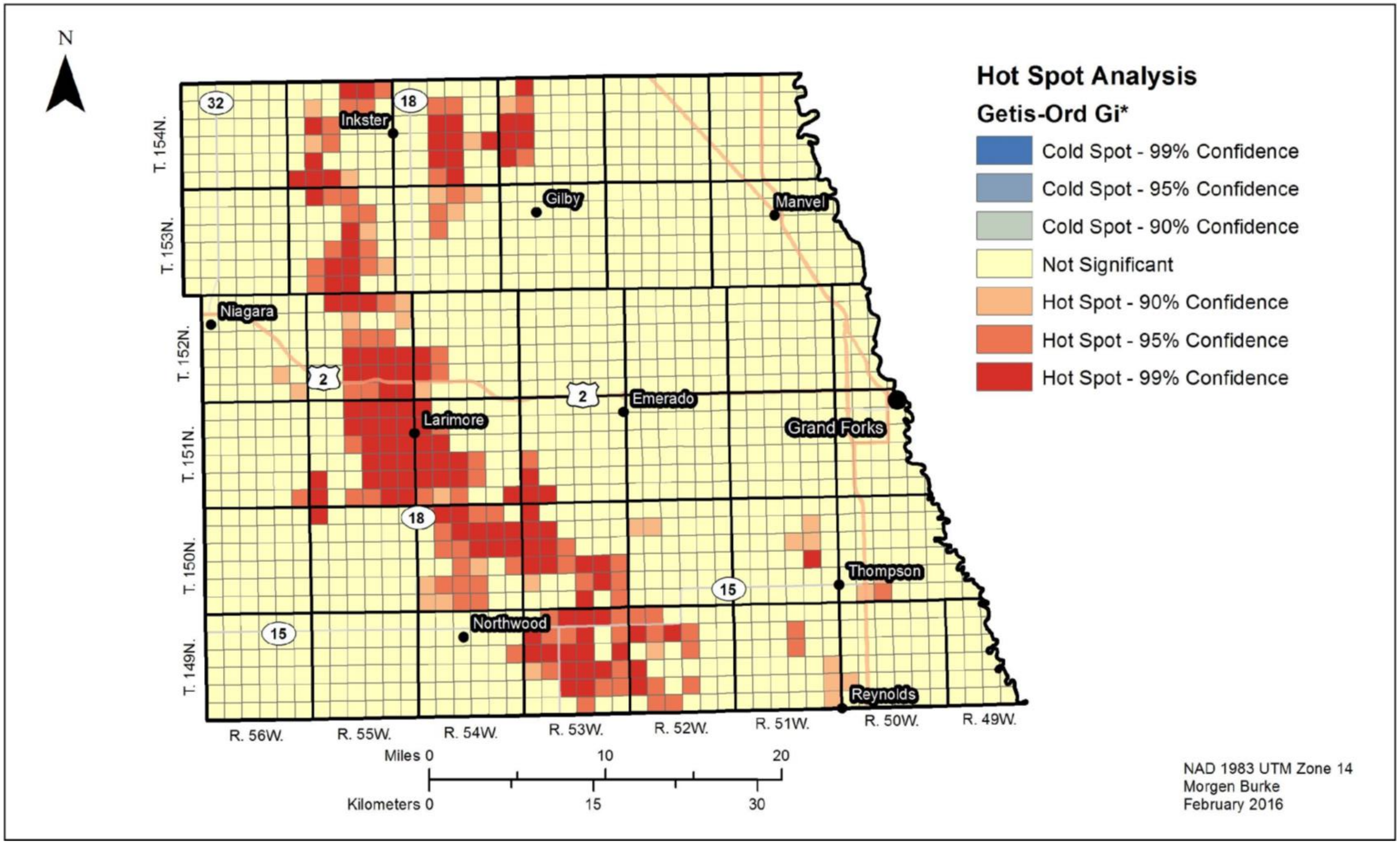

Figure 9: Hotspot analysis using Getis-Ord Gi* on shelterbelt density in 1962 by section in Grand Forks County. Getis-Ord Gi* was run using a fixed distance band that ensured that each feature would have at least one neighbor to calculate the Gi* Statistic.

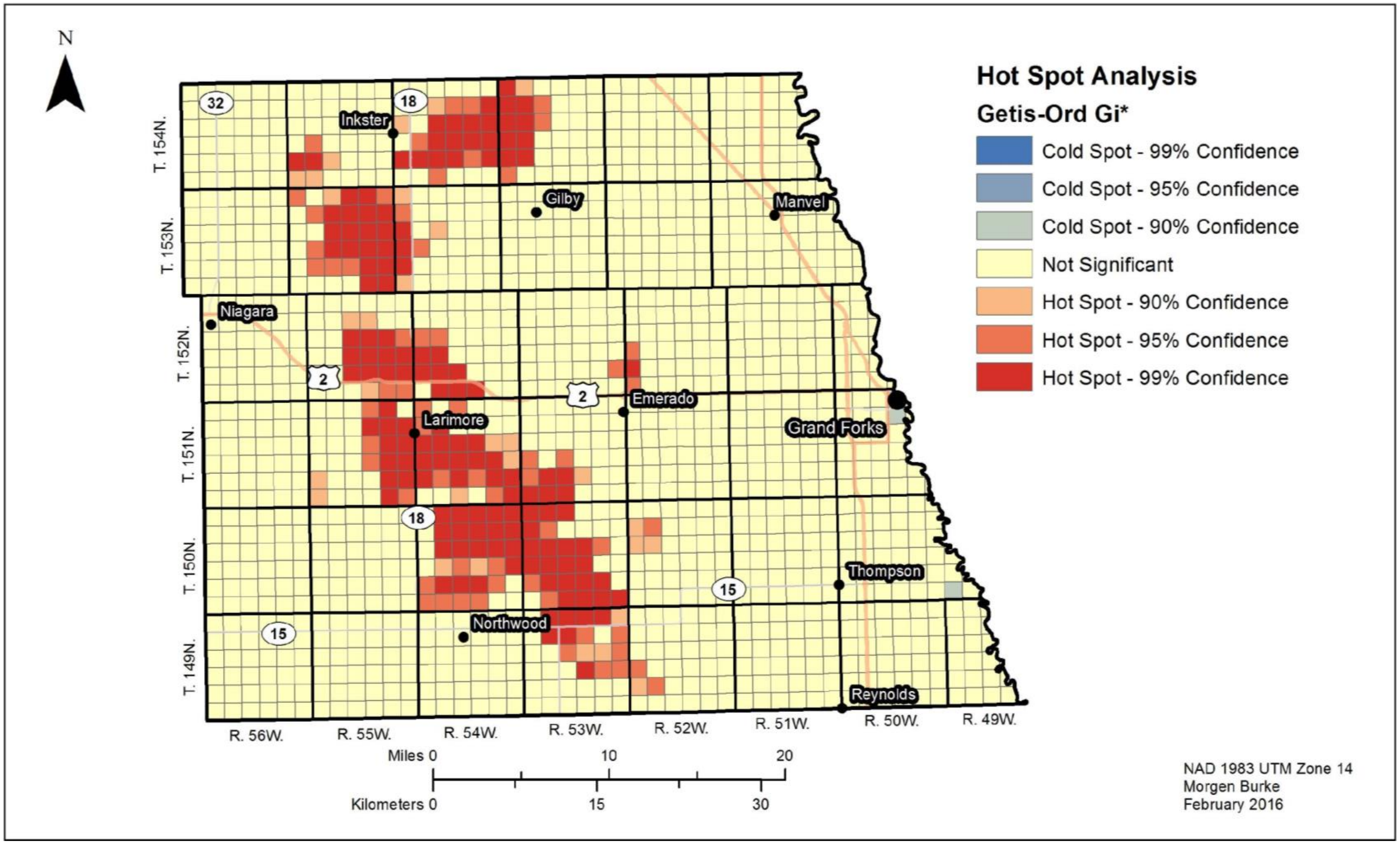

Figure 10: Hotspot analysis using Getis-Ord Gi* on shelterbelt density in 2014 by section in Grand Forks County. Getis-Ord Gi* was run using a fixed distance band that ensured each feature would have at least one neighbor to calculate the Gi* Statistic.

5.5 Bivariate Local Moran's I

I used a Bivariate Local Moran's I as a test for spatial autocorrelation to examine the relationship between the wind erodibility index (Figure 11) as the independent variable, and shelterbelt density as the dependent variable. I conducted the analysis for both 1962 (Figure 12) and 2014 (Figure 13). I ran the analysis using a confidence level of 95 percent.

In 1962, 37.3 percent of sections in the county produced a statistically significant result. Areas of high wind erodibility index values and high shelterbelt density made up 10.2 percent of sections; areas of low wind erodibility index values and low shelterbelt density made up 7.4 percent of sections; areas of low wind erodibility index values and high shelterbelt density made up 5.9 percent of sections; and areas of high wind erodibility index values and low shelterbelt density made up 13.3 percent of sections.

In 2014, 41.4 percent of sections in the county produced a significant result. Areas of high wind erodibility index values and high shelterbelt density made up 9.9 percent of sections; areas of low wind erodibility index values and low shelterbelt density made up 10.9 percent of sections; areas of low wind erodibility index values and high shelterbelt density made up 6.4 percent of sections; and areas of high wind erodibility index values and low shelterbelt density made up 14.2 percent of sections.

I used a second set of Bivariate Local Moran's I tests to examine the relationship between soil pH (Figure 14) and shelterbelt density. I conducted the analysis for both 1962 (Figure 15) and 2014 (Figure 16). I ran the analysis using a confidence level of 95 percent.

In 1962, 36.9 percent of sections produced a statistically significant result. Areas of high soil pH and high shelterbelt density made up 5.7 percent of sections; areas of low soil pH and low shelterbelt density made up 4.3 percent of sections; areas of low soil pH and high shelterbelt density made up 10.3 percent of sections; and areas of high soil pH and low shelterbelt density made up 16.6 percent of sections.

In 2014, 41.0 percent of sections in the county produced a statistically significant result. Areas of high soil pH and high shelterbelt density made up 4.6 percent of sections; areas of low soil pH and low shelterbelt density made up 8.1 percent of sections; areas of low soil pH and high shelterbelt density made up 11.7 percent of sections; and areas of high soil pH and low shelterbelt density made up 16.6 percent of sections.

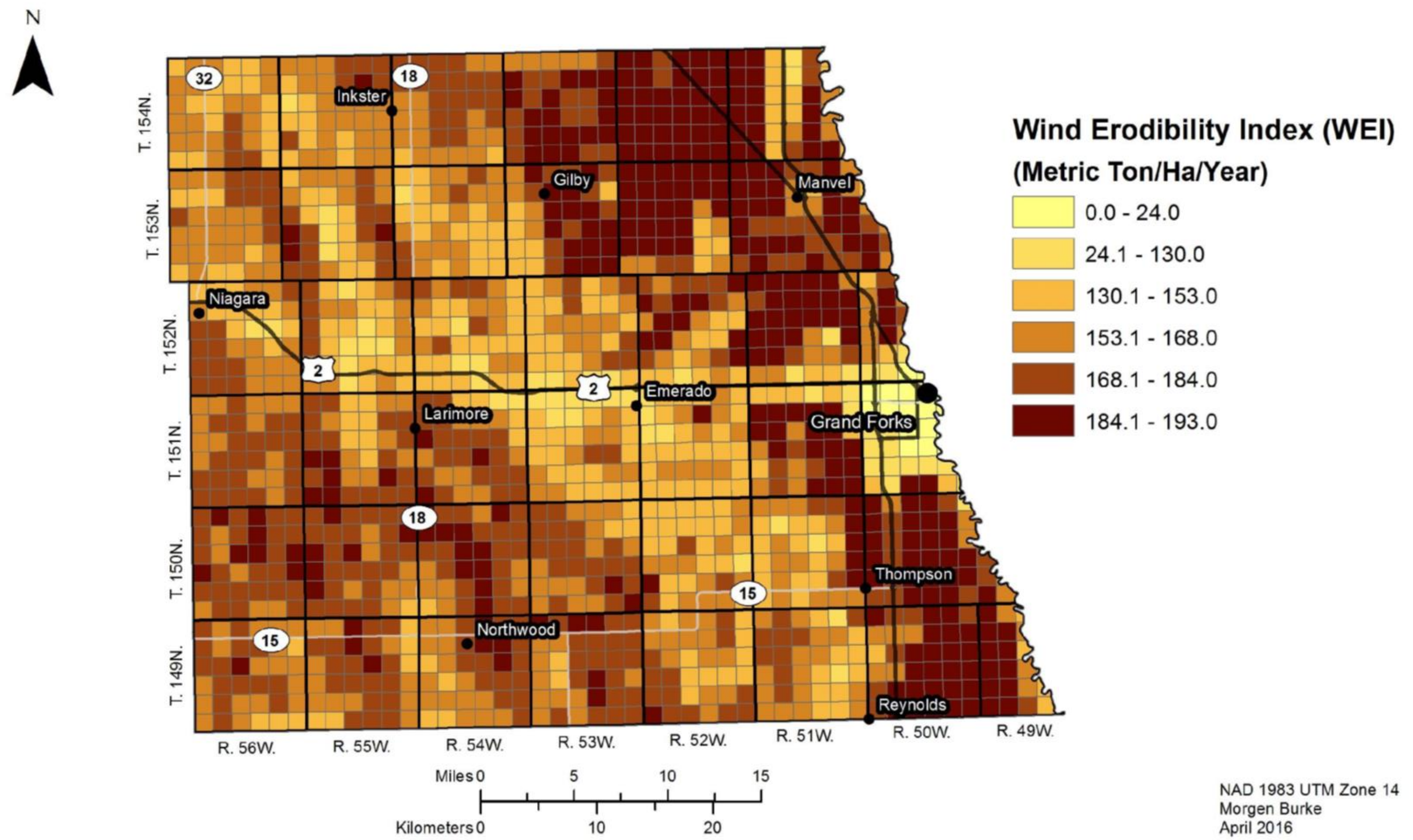

Figure 11: Wind erodibility index values in Grand Forks County. Wind erodibility index data acquired from USDA SSURGO dataset.

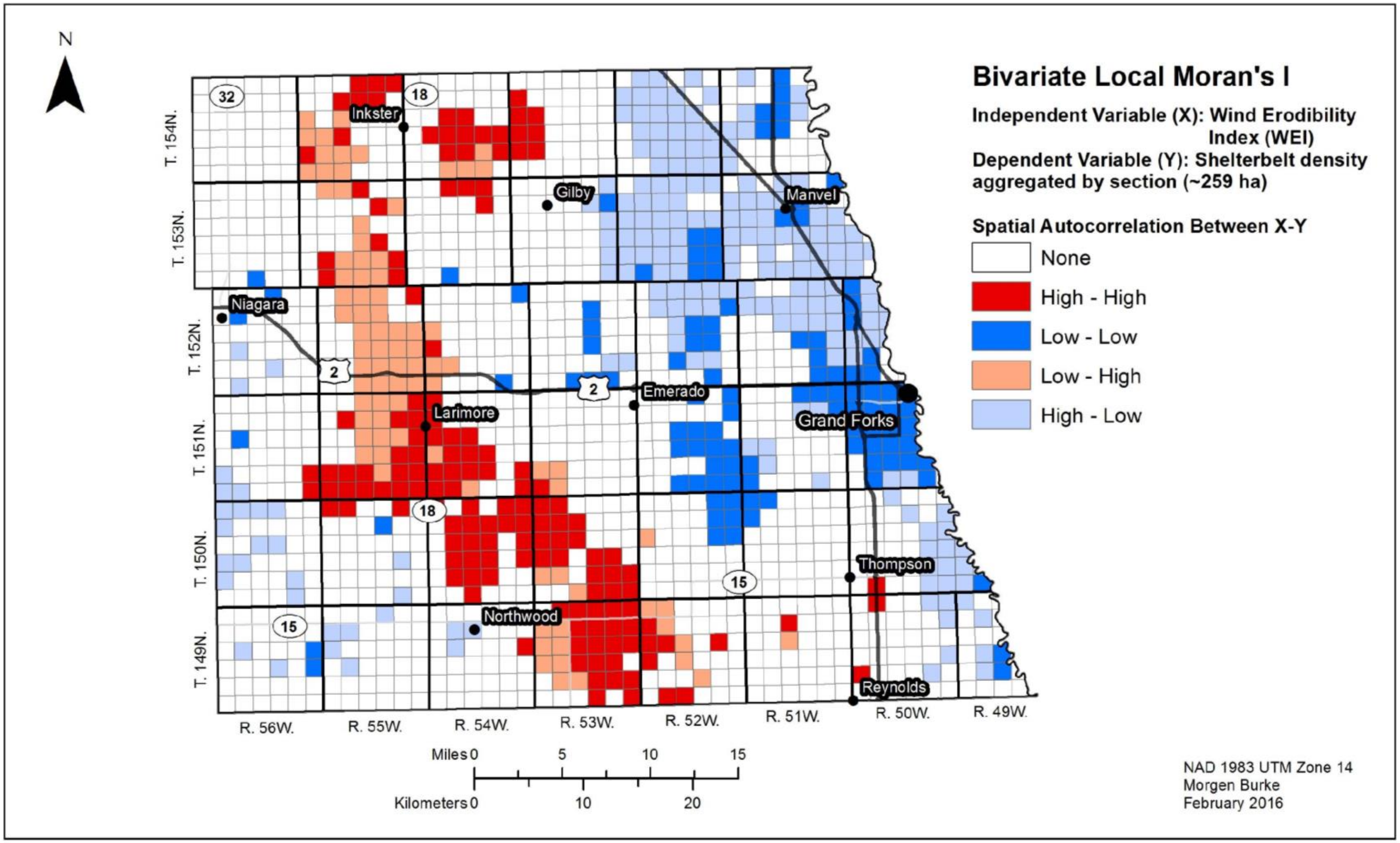

Figure 12: The Bivariate Local Moran's I for the 1962 shelterbelt polygons compared with the wind erodibility index. The analysis shows the spatial autocorrelation for areas of high or low wind erodibility values as the independent variable, and areas of high or low shelterbelt density as the dependent variable. Significance is set at 95 percent with p = 0.05, and randomization was set at 999 permutations. Moran's I = 0.0252.

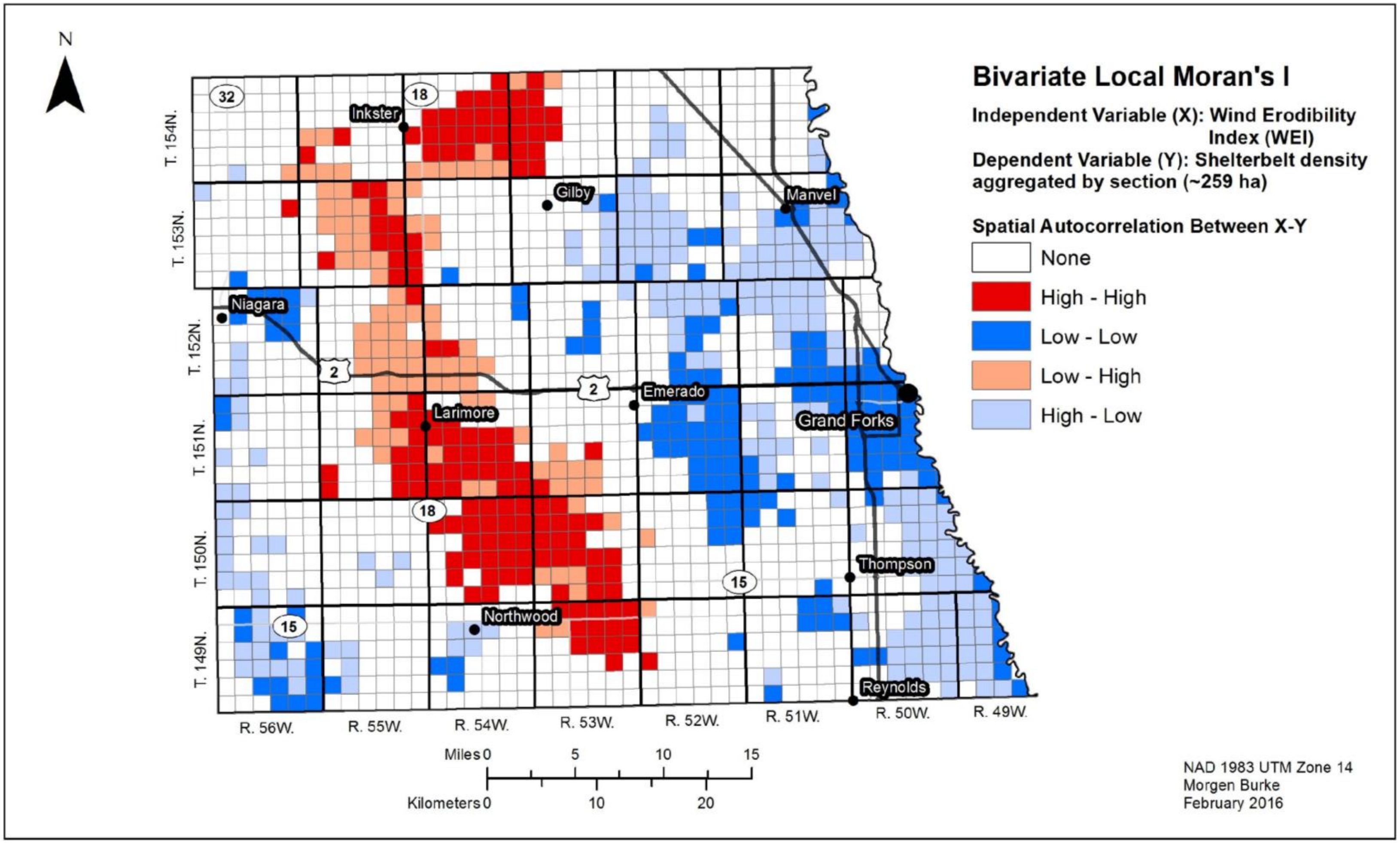

Figure 13: The Bivariate Local Moran's I for the 2014 shelterbelt polygons compared with the wind erodibility index. The analysis shows the spatial autocorrelation for areas of high or low wind erodibility index values as the independent variable, and areas of high or low shelterbelt density as the dependent variable. Significance is set at 95 percent with p = 0.05 and randomization was set at 999 permutations. Moran's I = 0.0331.

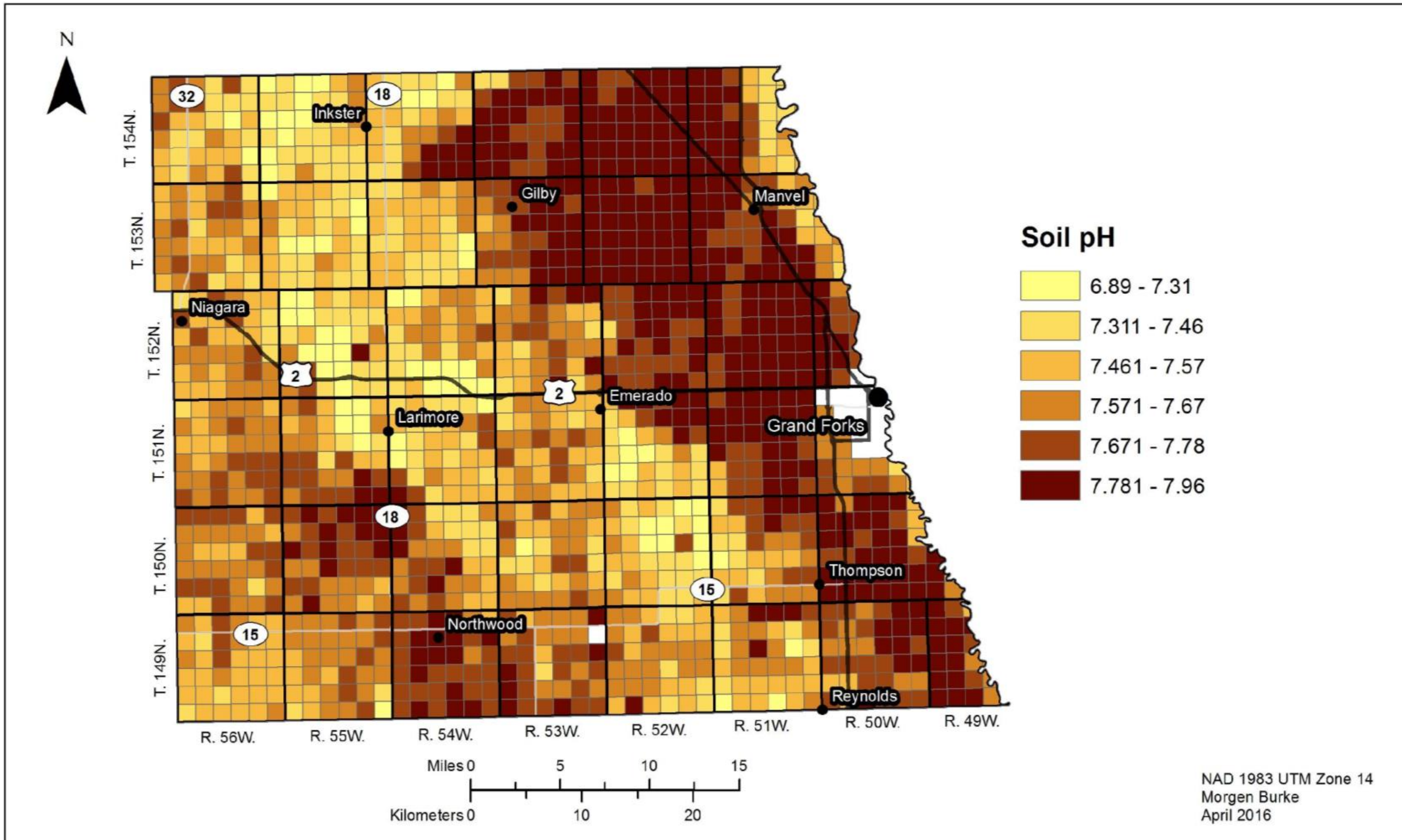

Figure 14: Soil pH in Grand Forks County. Soil pH data acquired from USDA SSURGO dataset. Values represent the negative logarithm to the base 10, of the hydrogen ion activity in the soil using a 1:1 soil-water ratio, and represent the relative acidity or alkalinity of a soil sample.

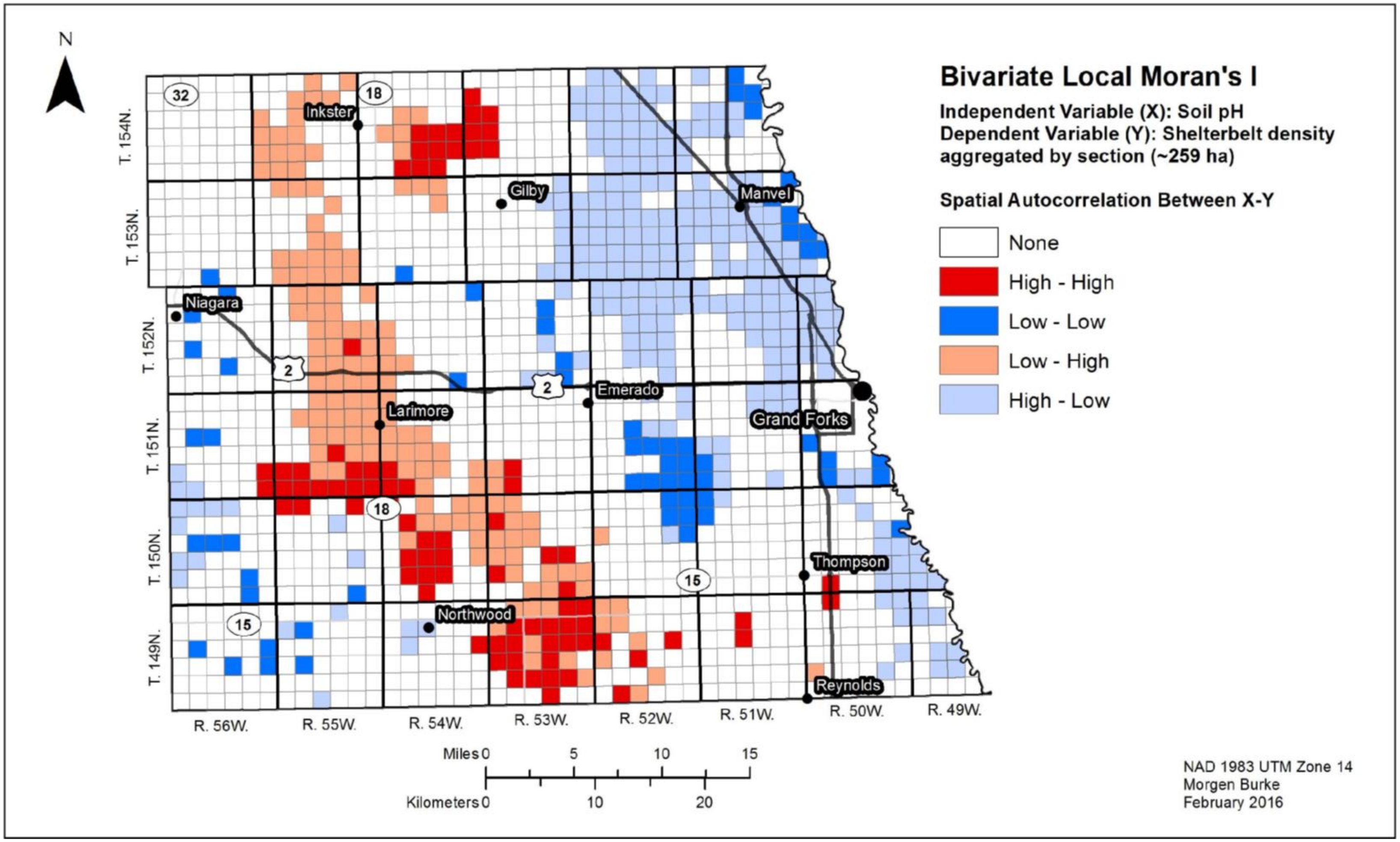

Figure 15: The Bivariate Local Moran's I for the 1962 shelterbelt polygons compared with soil pH. The analysis shows the spatial autocorrelation for areas of high or low soil pH as the independent variable, and areas of high or low shelterbelt density as the dependent variable. Significance is set at 95 percent with p = 0.05 and randomization was set at 999 permutations. Moran's I = -0.2145.

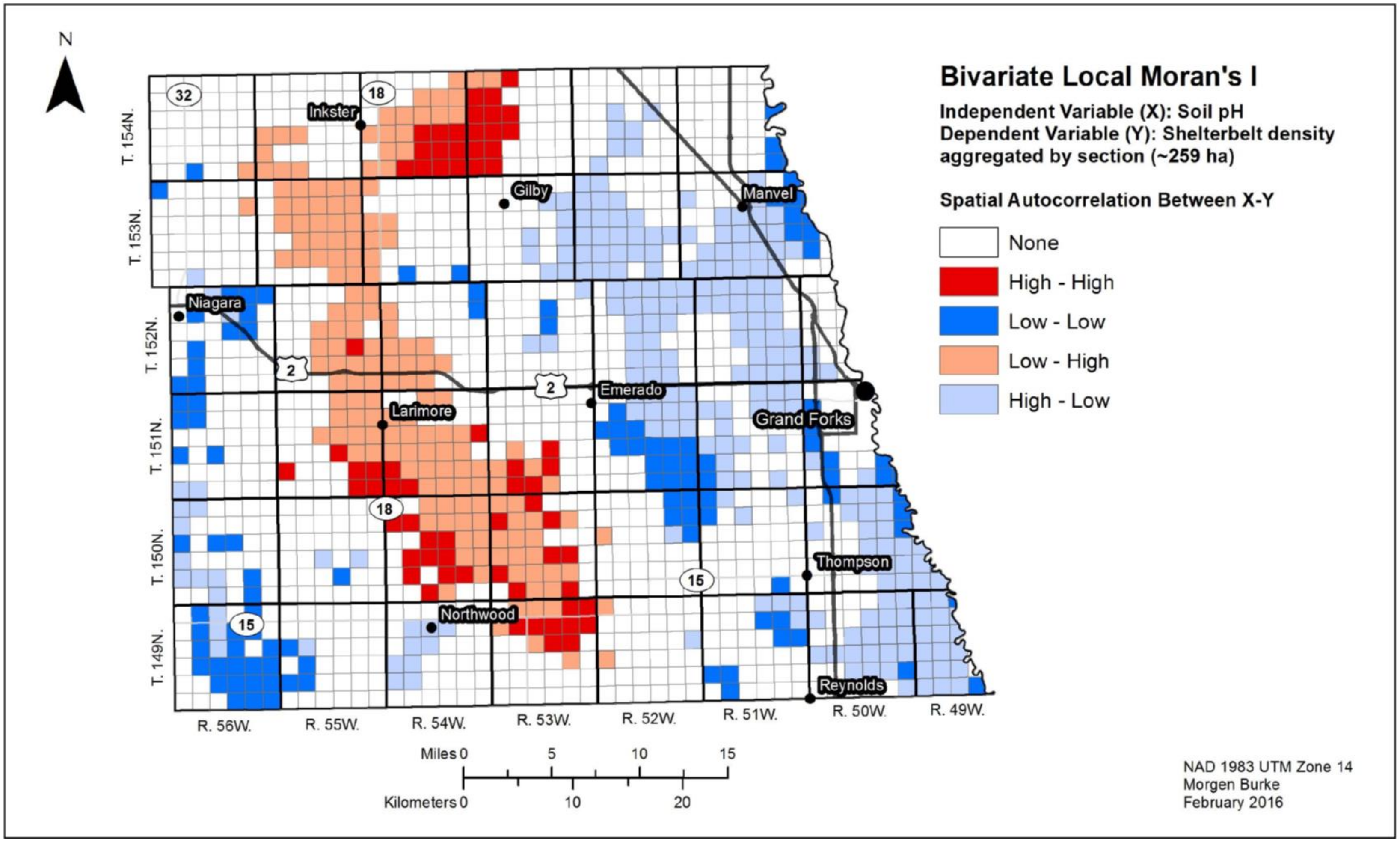

Figure 16: The Bivariate Local Moran's I for the 2014 shelterbelt polygons compared with soil pH. The analysis shows the spatial autocorrelation for areas of high or low soil pH as the independent variable, and areas of high or low shelterbelt density as the dependent variable. Significance is set at 95 percent with p = 0.05 and randomization was set at 999 permutations. Moran's I = -0.2467.

5.6 Surface geology

I examined the surface geology of Grand Forks County as another possible driving factor to explain the spatial arrangement of shelterbelts in the county. I found that the clustered shelterbelts seen in the hotspot analysis (Figures 9 and 10) did tend to run along features seen in the surface geology (Figure 17). The highest densities of shelterbelts occurred on the sand and cross-bedded sand sediments (Figure 18). However, I found till to contain the highest total area of shelterbelts (Figure 18), and the second highest was clay. Clay had the third highest density with till having the fourth highest density. All rankings of measurement in total area and density were found to be consistent between 1962 and 2014.

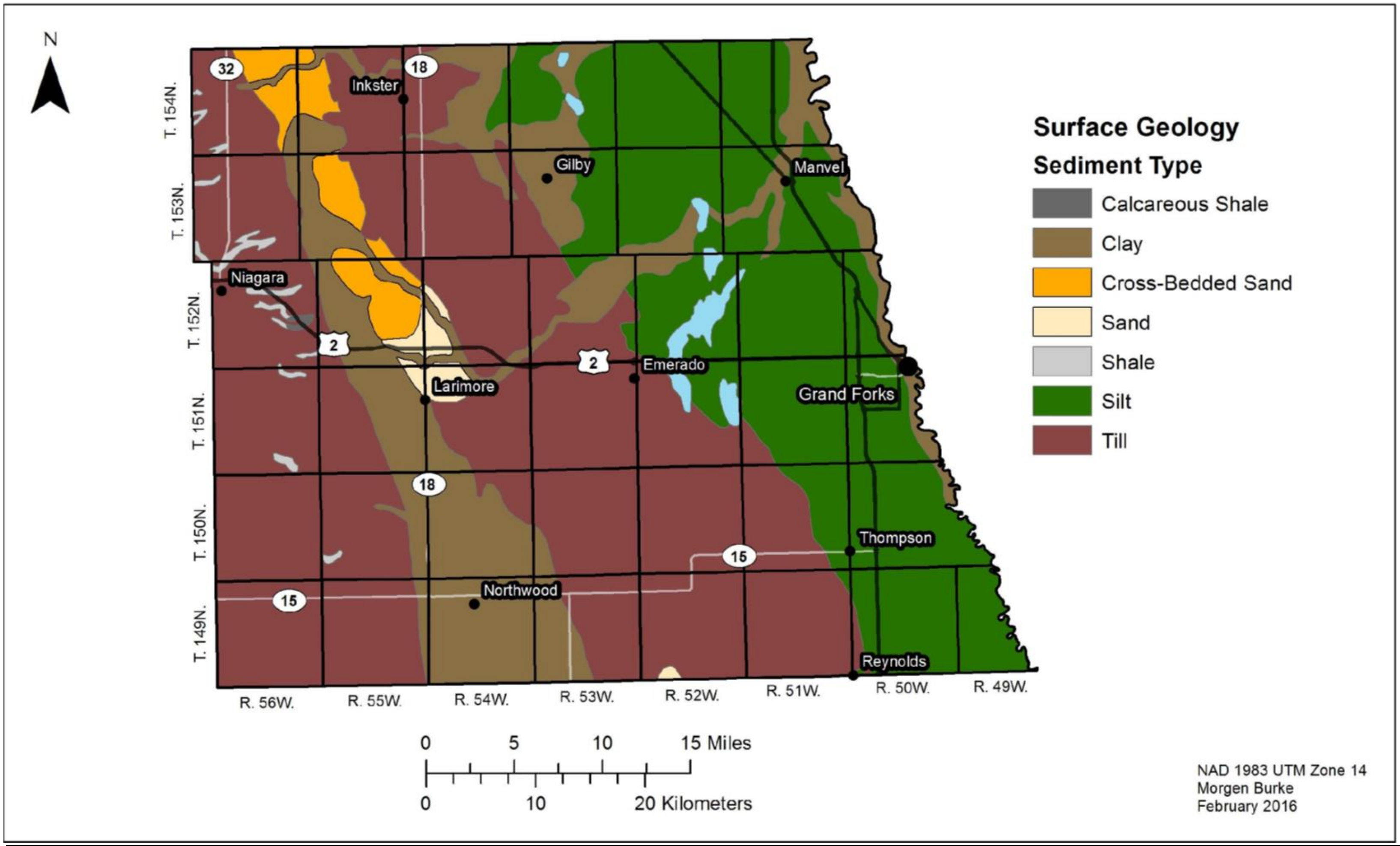

Figure 17: The surface geology for Grand Forks County. Data acquired from the North Dakota Geological Survey (NDGS).

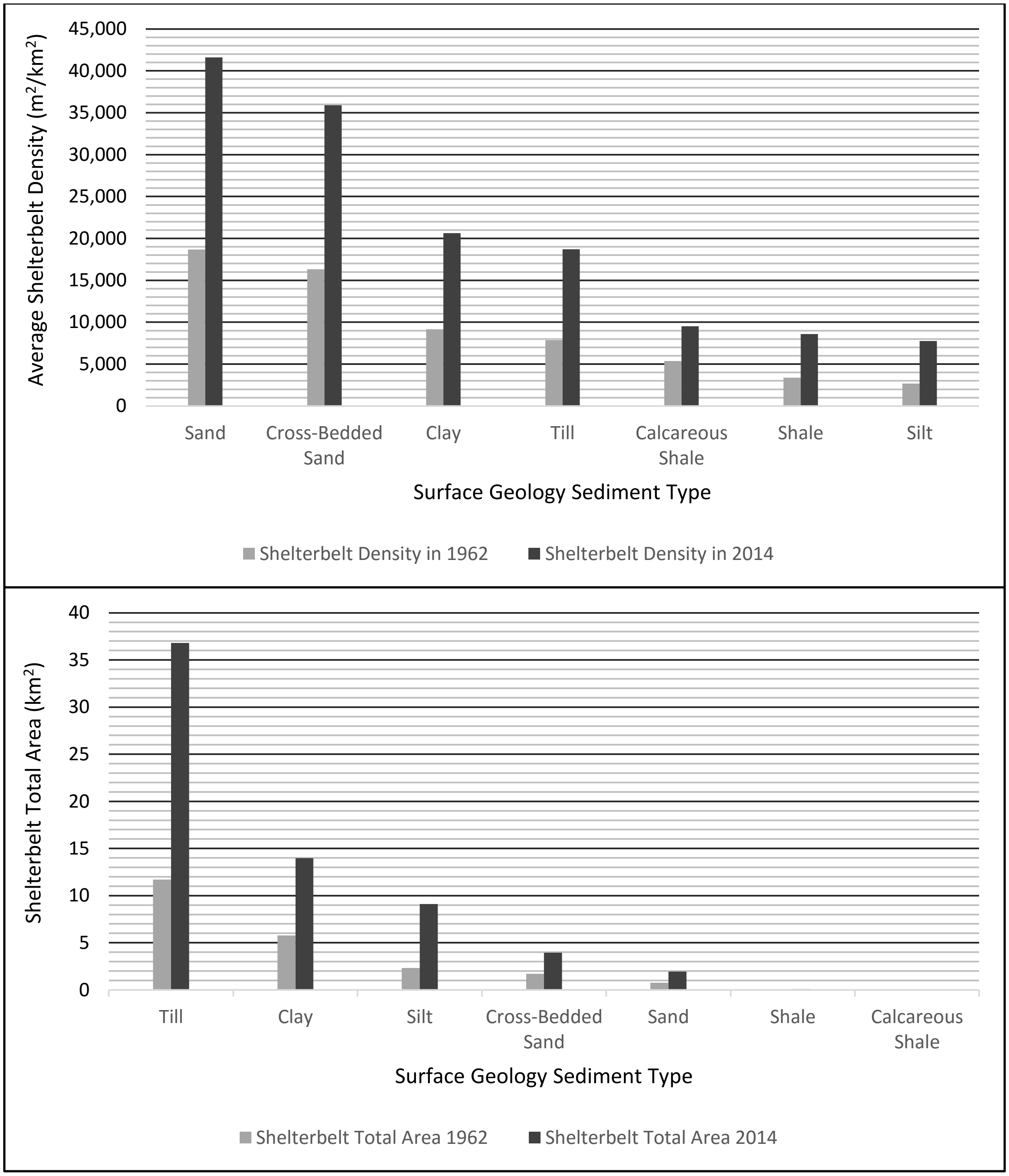

Figure 18: Comparing surface geology and shelterbelts in Grand Forks County. Surface geology compared with shelterbelt density for both 1962 and 2014 (top). Surface geology compared with total area covered by shelterbelts in both 1962 and 2014 (bottom).

CHAPTER VI

DISCUSSION

Shelterbelt density changed in Grand Forks County between 1962 and 2014. The change was the opposite of what I originally hypothesized, as density increased by 89.5 percent over the 52 years. Secondly, reports of shelterbelt removal in the county (Knutson 2011, Knutson 2014, Wachenheim 2013) are not consistent with the results of this study.

I successfully digitized shelterbelts using the 1962 imagery. Manually georeferencing and digitizing the imagery was a significant time investment, however the final results were also assumed to have a high level of accuracy versus results obtain through image classification in which an accuracy assessment would be needed. Using these results, shelterbelt density for the county was calculated as well as density per section of land.

The GEOBIA allowed successful digitization of shelterbelts in the county using the 4-band NAIP imagery. However, after carrying out the GEOBIA I manually edited the resulting shelterbelt polygons to clean out any large inaccuracies. These inaccuracies consisted mostly of trees that were not shelterbelts being digitized resulting in an error of commission. This included trees around homesteads and running along-side riparian areas. In total 9,703 polygons were removed from the GEOBIA created shelterbelt polygons, leaving 6,854 polygons that I visually interpreted as actually being shelterbelts. After the shelterbelt polygons were cleaned, I carried out the accuracy assessment. The accuracy assessment found overall accuracy to be only 59.8 percent, which I considered relatively low. However, I found that 35.8 percent of the inaccuracies were caused by misalignment in digitized polygons resulting in small polygon fragments being left around the edge of shelterbelt polygons that existed in both the 1962 and the 2014 imagery (Figure 3). I thought that the misalignment was caused by the 2014 shelterbelts having matured over the years which increased the tree canopy area, which does not create an actual increase in density. I removed this error by decreasing the shelterbelt area values by 35.8 percent across all 2014 shelterbelts before I conducted the density calculations. I found that the remaining 4.4 percent of inaccuracies in the GEOBIA were caused through classification errors in which a shelterbelt was digitized in an area in which a shelterbelt did not actually exist in the 2014 imagery. I considered the 4.4 percent classification inaccuracy acceptable.

While it would have been ideal for the GEOBIA results to have required no manual editing, the ruleset that I produced in eCognition Developer digitized many trees that were not shelterbelts. In some cases, groups of tree objects were merged together that contained trees planted as shelterbelts and trees that were not part of a shelterbelt. This occurred when a shelterbelt was found to extend perpendicular to a riparian area that also contained trees. The point at which the shelterbelt and the riparian area met would cause the two objects to merge together and make it difficult to separate using the GEOBIA. The manual editing of the GEOBIA produced polygons required 15 percent less time than did the manually digitized 1962 shelterbelt polygons. Therefore, using the GEOBIA settings (Appendix A) to classify future 4-band NAIP imagery, or for classifying 4-band

NAIP imagery in other counties would be more time efficient, even with the manual cleanup of polygons, versus digitizing all shelterbelts manually.

The ruleset that I developed by the GEOBIA used a combination of image object properties to help extract tree objects from the imagery. I found texture to be of great use when extracting tree objects. eCognition Developer has prebuilt algorithms for texture with measurements such as homogeneity, contrast, dissimilarity, and entropy that were all found to improve the extraction of tree objects. However, I found that measures of texture greatly increased computing time to complete the imagery classification. I assessed the usefulness of various image object properties using eCognition Developer's graphic user interface (GUI) which allows the user to examine how each variable compares across select sample locations within imagery. Users can then determine if a given variable helps to extract image objects for a given classification.

I found tree shadows to be a useful feature to improve tree object classification. Using a combination of the NIR and the overall object brightness across all four bands, I found that tree shadows could be successfully extracted from the image objects. Then using rules of association, objects next to tree shadows tended to be tree objects. Using this method other rules for extracting tree objects could be broadened while using association to tree shadow to ensure a more accurate classification of trees.

Once tree objects were classified in the GEOBIA, I sorted them as being either a shelterbelt or a non-shelterbelt object. To do this I merged the tree objects together so that I could use measures of geometry on entire areas of trees. These measurements include the length-to-width ratio, and compactness of tree objects. Because I found that shelterbelts often merged with non-shelterbelt objects, I kept these rules fairly broad so they would not exclude shelterbelt objects that had merged with non-shelterbelt objects. However, this also resulted in many non-shelterbelt objects being classified as shelterbelts, which is why manual cleaning of the resulting polygons was needed.

To help strengthen the resulting change in density found between 1962 and 2014, I manually digitized shelterbelts using imagery taken between 1995-1997. Only 10.2 percent of the sections in the 1995-1997 were digitized, however this was used to help interpret the density of shelterbelts at this point in time. Examining Figure 7 it is apparent that the density found in the 1995-1997 imagery is consistent with the increase found between 1962 and 2014 with the data point falling slightly below a linear line between the 1962 and 2014 densities. However, because this data point only represents 10.2 percent of sections, the true density value could differ, and completely digitizing the 1995-1997 imagery would verify this result.

Tillage data for Grand Forks County was limited temporally to cover only 1989 to 2004. The data gathered in the CRM survey by the CTIC for the county do not appear to show a shift in conservation tillage practice over time. I expected that conservation tillage would increase over the years as has been seen on average for the entire U.S. However, Figure 8 shows conservation tillage is used on only 14 percent of cropland in 2004 when it started at 22 percent in 1989, and reached a peak of 59 percent in 1997. A higher temporal resolution of conservation tillage in the county would be needed to better understand how this practice might be influencing other soil management practices such as the use of shelterbelts within Grand Forks County.

Using the hotspot analysis shown in Figures 9 and 10, I found that shelterbelt densities in Grand Forks County have a significant spatial pattern in both 1962 and 2014.

The hotspots for the 1962 and 2014 shelterbelt densities remained fairly consistent, with 16.1 percent of sections in 1962 and 15.8 percent of sections in 2014 having a significant Getis-Ord Gi* p value. The location and spatial arrangement of the hotspots also do not appear to differ greatly between the two time periods. I conducted the hotspot analysis to determine if the planting of shelterbelts in the county was random, or if there are driving factors that determine their placement. The results of the hotspot analysis suggest that something is driving the placement of the shelterbelts, and therefore I conducted further analysis. The factors that I examined are the wind erodibility index, the soil pH, and the surface geology.

I used the Bivariate Local Moran's I to test for significance in both the wind erodibility index and the soil pH variables. Examining Figures 12 and 13 the wind erodibility index values appear to have no relationship with shelterbelt density as both figures have a Moran's I value close to 0. This suggests that agricultural producers are not necessarily planting shelterbelts in locations in which wind erosion is of concern. Figure 13 also shows the locations in the county for 2014 in which low shelterbelt densities and high wind erodibility index values are found. With this information, future efforts in the county to increase shelterbelts could target these areas.

The results of running the Bivariate Local Moran's I on the soil pH variable are seen in Figures 15 and 16. Unlike the wind erodibility index variable, the soil pH produced a Moran's I of -0.2145 for the 1962 shelterbelt densities and a value of -0.2467 for 2014 shelterbelt densities. This suggest that there is a slight inverse relationship between alkaline soils and shelterbelt densities. This relationship may exist because soils with a more neutral pH close to 7.0 tend to increase the survivability of shelterbelts, while more alkaline soils reduce the survivability of shelterbelts (Hussain *et al.* 1994).

Surface geology was the last factor that I examined as a possible driving factor influencing the spatial arrangement of shelterbelt densities in the county. Comparing surface geology (Figure 17) with the hotspot maps (Figures 9 and 10) shows that the highest shelterbelts densities are found in the regions in which sand, cross-bedded sand, clay, and till are dominant sediment types, with shelterbelt densities being lowest in the silt sediments found closest to the Red River of the North on the east side of the county. The small region of sand sediment found north of Larimore contained the highest density of shelterbelts, while the much larger region of till sediment running north to south along the west side of the county contained the highest total area of shelterbelts. This correlation suggests that shelterbelts tend to be planted in regions with sand, till, or clay based soils, while at the same time shelterbelts also tend to be located in soils with low pH.

CHAPTER VII

CONCLUSION

Using the methods that I have presented in this study, future aerial imagery of Grand Forks County can be used to monitor change in shelterbelt density. Secondly, these methods can be applied to other counties and states. By examining both current shelterbelt densities and the wind erodibility index (Figure 13) areas with high wind erodibility index values that have low shelterbelt densities can be identified, and can be used to focus future shelterbelt planting efforts. Knutson (2014) reported that in 2002 the Lincoln-Oakes Nursery located in Bismarck, ND sold approximately 5 million trees, while in 2013 their sales declined to 1.5 million trees. Unpublished data provided by the USDA Natural Resources Conservation Service (NRCS) shows continued tree planting in the county from 1981 to 2011 with a gradual decline over time (Figure 19). However, these data also show that it was not until the early 2000s that shelterbelt planting in the county had greatly declined. Future studies on shelterbelt density in North Dakota could focus on more recent years and examine if shelterbelt density correlates with the reported decline in nursery sales, and the reduced number of tree plantings during this smaller time period.

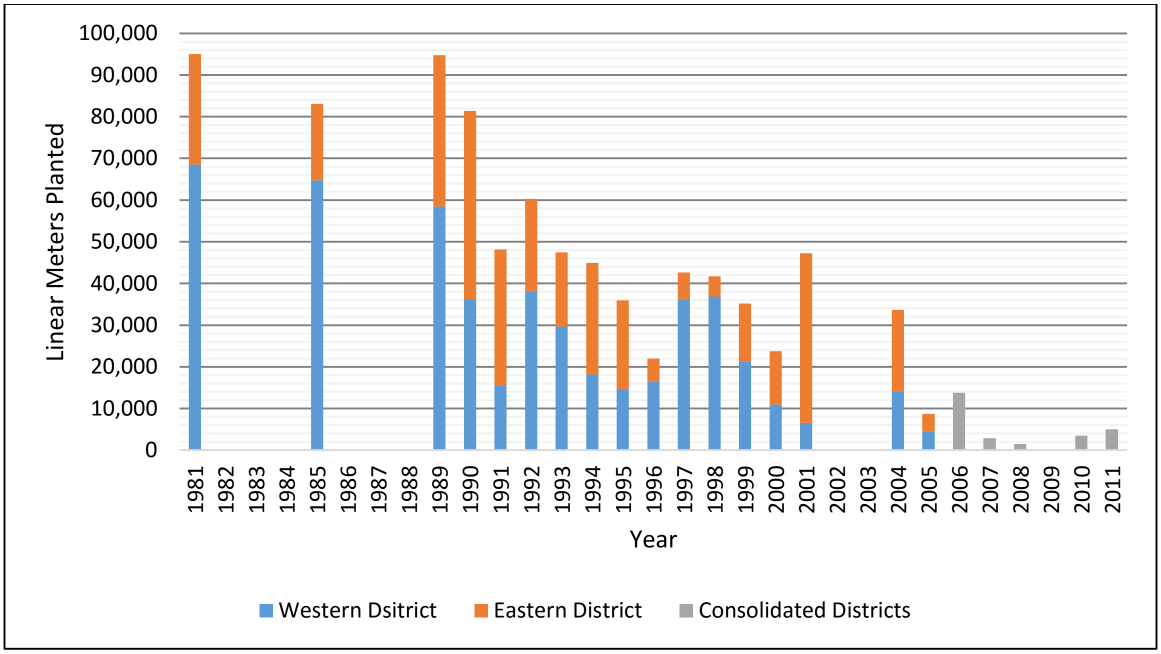

Figure 19: Grand Forks County Soil Conservation District (GFSCD) tree planting in linear meters. Unpublished data provided by the USDA NRCS office located in Grand Forks, ND. Years without data represent years in which the number of shelterbelts planted is unknown, and not years in which no trees were planted.

Knutson (2011) reported that shelterbelt density is declining in Grand Forks County. However, Knutson (2011) also reported that the USDA NRCS, the Grand Forks County Soil Conservation District (GFSCD), and the Continuous Conservation Reserve Program (CCRP) continue to encourage and provide subsidies for agricultural producers who choose to plant shelterbelts on their land. The results of this study suggest that programs supporting shelterbelt planting in Grand Forks County have increased the total number of shelterbelts when compared with the number of shelterbelts in 1962. However, the decline in tree plantings in more recent years (Figures 19) may become prevalent in future studies of shelterbelt densities in Grand Forks County if the number of trees planted does not match or exceed the number of trees being removed.

APPENDIX

Appendix A

Geographic object-based image analysis ruleset

1. Segmentation
    - 1.1 Multiresolution Segmentation
        - 1.1.1 Image Layer Weights: Blue 1, Green 1, Red 1, NIR 3
        - 1.1.2 Scale Parameter: 10
        - 1.1.3 Shape: 0.7
        - 1.1.4 Compactness: 0.2
        - 1.1.5 Number of Cycles: 10
    - 1.2 Spectral Difference Segmentation
        - 1.2.1 Maximum Spectral Difference: 2
        - 1.2.2 Image Layer Weights: Blue 1, Green 1, Red 1, NIR 3
        - 1.2.3 Number of Cycles: 10
2. Classification
    - 2.1 Vegetation
        - 2.1.1 Assign Class
            - 2.1.1.1 Class filter: Unclassified
            - 2.1.1.2 Use Class: Vegetation
            - 2.1.1.3 Number of Cycles 1
            - 2.1.1.4 Conditions
                - 2.1.1.4.1 Mean NDVI < = 0.65
                - 2.1.1.4.2 Mean NDVI > = -0.2
                - 2.1.1.4.3 Mean GNDVI < = 0.63
                - 2.1.1.4.4 Mean GNDVI > = -0.2
                - 2.1.1.4.5 Mean Red < = 189
                - 2.1.1.4.6 Mean Red > = 26
                - 2.1.1.4.7 Mean Green < = 200
                - 2.1.1.4.8 Mean Green > = 23
                - 2.1.1.4.9 Mean Blue < = 172
                - 2.1.1.4.10 Mean Blue > = 39
                - 2.1.1.4.11 Mean NIR < = 226
                - 2.1.1.4.12 Mean NIR > = 0
        - 2.1.2 Assign Class
            - 2.1.2.1 Class filter: Unclassified
            - 2.1.2.2 Use Class: Vegetation
            - 2.1.2.3 Number of Cycles: 1
            - 2.1.2.4 Conditions
                - 2.1.2.4.1 Min pixel value Blue < = 75
                - 2.1.2.4.2 Min pixel value Green < = 125
                - 2.1.2.4.3 Area (pixels) < = 12000
                - 2.1.2.4.4 GLCM Homogeneity (quick 8/11)(all dir.) > = 0.1

2.1.2.4.5 GLCM Homogeneity (quick 8/11)(all dir.) < = 0.8
2.1.2.4.6 GLCM Contrast (quick 8/11)(all dir.) > = 0.75
2.1.2.4.7 GLCM Dissimilarity (quick 8/11)(all dir.) > = 0.7
2.1.2.4.8 Brightness > 53

2.2 Trees
2.2.1 Assign class
2.2.1.1 Class filter: unclassified
2.2.1.2 Use Class: Tree Shadow
2.2.1.3 Number of cycles: 1
2.2.1.4 Conditions:
2.2.1.4.1 Brightness < = 53
2.2.1.4.2 NIR/Brightness > = 0.5
2.2.2 Merge region
2.2.2.1 Class filter: Tree Shadow
2.2.2.2 Number of cycles: 1
2.2.3 Assign class
2.2.3.1 Class filter: Vegetation
2.2.3.2 Use Class: Trees
2.2.3.3 Number of cycles: 1
2.2.3.4 Conditions:
2.2.3.4.1 Min pixel value Blue < = 75
2.2.3.4.2 Min pixel value Green < = 125
2.2.3.4.3 Min pixel value Red < = 74
2.2.3.4.4 Shape index > = 1
2.2.3.4.5 Shape index < = 6
2.2.3.4.6 Area (pixels)< = 12000
2.2.3.4.7 Length of longest edge (polygon) < = 165
2.2.3.4.8 GLCM Homogeneity (quick 8/11)(all dir.) > = 0.3
2.2.3.4.9 GLCM Homogeneity (quick 8/11)(all dir.) < = 0.7
2.2.3.4.10 Texture ADD* > = 6
2.2.4 Assign class
2.2.4.1 Class filter: Vegetation
2.2.4.2 Use Class: Trees
2.2.4.3 Number of cycles: 1
2.2.4.4 Conditions:
2.2.4.4.1 Min pixel value Blue < = 75
2.2.4.4.2 Min pixel value Green < = 125
2.2.4.4.3 Min pixel value Red < = 74
2.2.4.4.4 Texture ADD* > = 9.2
2.2.5 Assign class
2.2.5.1 Class filter: Trees
2.2.5.2 Use Class: Vegetation
2.2.5.3 Number of cycles: -Infinite-

2.2.5.4 Conditions:
2.2.5.4.1 Related border to Trees < 0.2
2.2.5.4.2 Min pixel value Red > = 40
2.2.6 Assign class
2.2.6.1 Class filter: Vegetation, unclassified
2.2.6.2 Use Class: Trees
2.2.6.3 Number of cycles: -Infinite-
2.2.6.4 Conditions:
2.2.6.4.1 Related Border to Trees > = 0.9
2.2.7 Assign class
2.2.7.1 Class filter: Vegetation
2.2.7.2 Use Class: Trees
2.2.7.3 Number of cycles: 3
2.2.7.4 Conditions:
2.2.7.4.1 Min pixel value Blue < = 75
2.2.7.4.2 Min pixel value Green < = 125
2.2.7.4.3 Shape index > = 1
2.2.7.4.4 Shape index < = 6
2.2.7.4.5 Area (pixels) < = 12000
2.2.7.4.6 Length of longest edge (polygon) < = 165
2.2.7.4.7 Related border to Trees > = 0.5
2.2.8 Assign class
2.2.8.1 Class filter: Vegetation, unclassified
2.2.8.2 Use Class: Trees
2.2.8.3 Number of cycles: -Infinite-
2.2.8.4 Conditions:
2.2.8.4.1 Related border to Trees > = 0.8
2.2.9 Assign class
2.2.9.1 Class filter: Vegetation
2.2.9.2 Use Class: Trees
2.2.9.3 Number of cycles: -Infinite-
2.2.9.4 Conditions:
2.2.9.4.1 Min pixel value Blue < = 75
2.2.9.4.2 Min pixel value Green < = 125
2.2.9.4.3 Shape index > = 1
2.2.9.4.4 Shape index < = 6
2.2.9.4.5 Area (pixels) < = 12000
2.2.9.4.6 Length of longest edge (polygon) < = 165
2.2.9.4.7 Related border to Trees > = 0.1
2.2.9.4.8 Related border to Tree Shadow > = 0.1
2.2.10 Assign class
2.2.10.1 Class filter: Vegetation
2.2.10.2 Use Class: Trees

- 2.2.10.3 Number of cycles: 3
- 2.2.10.4 Conditions:
  - 2.2.10.4.1 Min pixel value Blue < = 75
  - 2.2.10.4.2 Min pixel value Green < = 125
  - 2.2.10.4.3 Shape index > = 1
  - 2.2.10.4.4 Shape index < = 6
  - 2.2.10.4.5 Area (pixels) < = 12000
  - 2.2.10.4.6 Length of longest edge (polygon) < = 165
  - 2.2.10.4.7 Related border to Trees > = 0.5

2.2.11 Merge region
- 2.2.11.1 Class filter: Trees
- 2.2.11.2 Number of cycles: 1

2.2.12 Assign class
- 2.2.12.1 Class filter: Trees
- 2.2.12.2 Use Class: Vegetation
- 2.2.12.3 Number of cycles: 1
- 2.2.12.4 Conditions:
  - 2.2.12.4.1 Related border to Tree Shadow < 0.01

2.2.13 Assign class
- 2.2.13.1 Class filter: Tree Shadow
- 2.2.13.2 Use Class: Trees
- 2.2.13.3 Number of cycles: 1
- 2.2.13.4 Conditions:
  - 2.2.13.4.1 Mean NIR > = 35
  - 2.2.13.4.2 Related border to Trees > = 0.5

2.2.14 Assign class
- 2.2.14.1 Class filter: Tree Shadow
- 2.2.14.2 Use Class: Trees
- 2.2.14.3 Number of cycles: 1
- 2.2.14.4 Conditions:
  - 2.2.14.4.1 Mean NIR > = 40

2.2.15 Merge region
- 2.2.15.1 Class filter: Trees
- 2.2.15.2 Number of cycles: 1

2.2.16 Assign class
- 2.2.16.1 Class filter: Tree Shadow, Vegetation, unclassified
- 2.2.16.2 Use Class: Trees
- 2.2.16.3 Number of cycles: 1
- 2.2.16.4 Conditions:
  - 2.2.16.4.1 Related border to Trees 0.6

2.2.17 Assign class
- 2.2.17.1 Class filter: Vegetation
- 2.2.17.2 Use class: Trees

2.2.17.3 Number of cycles: -Infinite-

2.2.17.4 Conditions:

2.2.17.4.1 Min pixel value Blue < = 75

2.2.17.4.2 Min pixel value Green < = 125

2.2.17.4.3 Shape index > = 1

2.2.17.4.4 Shape index < = 6

2.2.17.4.5 Area (pixels) < = 12000

2.2.17.4.6 Length of longest edge (polygon) < = 165

2.2.17.4.7 Maximum difference > = 0.5

2.2.17.4.8 Related border to Trees > = 0.4

2.2.17.4.9 GLCM Homogeneity (quick 8/11)(all dir.) > = 0.3

2.2.17.4.10 GLCM Homogeneity (quick 8/11)(all dir.) < = 0.7

2.2.17.4.11 GLCM Contrast (quick 8/11)(all dir.) > = 1

2.2.17.4.12 GLCM Dissimilarity (quick 8/11)(all dir.) > = 0.8

2.2.17.4.13 GLCM Angle 2nd moment (quick 8/11)(all dir.) < = 0.1

2.2.18 Assign class

2.2.18.1 Class filter: Tree Shadow, Vegetation

2.2.18.2 Use Class: Trees

2.2.18.3 Number of cycles: 1

2.2.18.4 Conditions:

2.2.18.4.1 Related Border to Trees + Related Border to Tree Shadow > = 1

2.3 Shelterbelts

2.3.1 Merge Region

2.3.1.1 Class filter: Trees

2.3.1.2 Number of cycles: 1

2.3.2 Assign class:

2.3.2.1 Class filter: Trees

2.3.2.2 Use class: Shelterbelts

2.3.2.3 Number of cycles: 1

2.3.2.4 Conditions:

2.3.2.4.1 Border index > = 1

2.3.2.4.2 Border Length / Width > = 4.8

2.3.2.4.3 Compactness (polygon) < = 0.4

3. Export to Polygon

3.1 Export vector layer

3.1.1 Class filter: Shelterbelts

* Texture ADD = GLCM Dissimilarity (quick 8/11) (all dir.) + GLCM Contrast (quick 8/11) (all dir.) + GLCM Entropy (quick 8/11) (all dir.) + Max. diff.

Class Hierarchy

1. Vegetation
   1.1 Trees
      1.1.1 Shelterbelts
2. Tree Shadow

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