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Oil Extraction Infrastructure Development And Resulting Land-Cover Change In Mckenzie County, North Dakota, 2009 To 2014

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OIL EXTRACTION INFRASTRUCTURE DEVELOPMENT
AND RESULTING LAND-COVER CHANGE
IN MCKENZIE COUNTY, NORTH DAKOTA, 2009 to 2014

by

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This thesis, submitted by Eric F. Torgerson in partial fulfillment of the requirements for the Degree of Master of Science from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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This Thesis is being submitted by the appointed advisory committee as having met all of the requirements of the School of Graduate Studies at the University of North Dakota and is hereby approved.

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Dean of the School of Graduate Studies

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Title	Oil extraction infrastructure development and resulting land-cover change in McKenzie County, North Dakota, 2009 to 2014
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Eric F. Torgerson
4/12/2017

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ABSTRACT

Improved techniques and methods in directional drilling and hydraulic fracturing have allowed once inaccessible resources to become profitably accessible in the Bakken Region of North Dakota (Fershee 2011). This recent development has been rapid, and associated land-cover change can be described as spatially extensive (Baker et al. 2012). After an extensive literature review and to the best of my knowledge, little research has been conducted in the Bakken Region regarding land-cover change associated with oil development. Using high-spatial-resolution, four-band imagery from the National Agriculture Imagery Program (NAIP) in conjunction with Geographic Object-Based Image Analysis (GEOBIA) techniques, it is possible to identify narrow-linear and small-area features on the landscape associated with oil development.

The overall accuracy for McKenzie County was 41.2 percent, significantly lower than overall accuracies seen in similar studies. These results suggest this method is not entirely suitable for land-cover change analysis in the grassland biome without additional data analysis and/or editing. Further analysis of a selected smaller portion of the county displaying land-cover characteristics amenable for accurate classification found oil extraction infrastructure contributed to an expected but minimal decrease in grassland and agricultural land-cover.

CHAPTER I

INTRODUCTION

Oil extraction infrastructure, characterized by well pad sites, core holes, access roads, and pipelines, are primarily associated with the exploration and recovery of natural gas and oil (Baker et al. 2012, Salehi et al. 2014, Powers et al. 2015). Hydraulic fracturing, commonly referred to as fracking, hydrofracturing, or hydrofracking, has been the primary driving force in recent oil infrastructure development in several oil and gas producing regions of the U.S. (Prud'homme 2014). Improved techniques and methods in directional drilling and hydraulic fracturing have also allowed once inaccessible resources to be developed (Fershee 2011). As a result, new oil extraction infrastructure dots the landscape in areas such as the Bakken Shale Play of North Dakota. This recent development has been rapid, and associated land-cover change could be described as spatially extensive (Baker et al. 2012).

The Bakken Shale Formation lies within the larger Williston Basin, which covers an estimated area of 517,997 km^2 (200,000 mi^2) beneath parts of Montana, North Dakota and the Canadian provinces of Saskatchewan and Manitoba (Mason 2012, Prud'homme 2014). The North Dakota portion of the Bakken covers an estimated 30,981 km^2 (11,962 mi^2) (Mason 2012). This region has experienced oil booms during the early 1950s (Campbell et al. 1958) and the 1970s and 1980s.

Increased technology and demand for energy resources has allowed the Bakken to experience its largest boom over the last decade, starting in 2006 and continuing through the present day. This recent oil boom has led to an exponential increase in well-site development. December of 2006 saw only 289 oil producing wells in the Bakken region; 1,332 wells were producing oil by December 2009, and by January 2016 10,438 wells were producing oil in the North Dakota Bakken (North Dakota Department of Mineral Resources 2016).

To date, little research has been conducted in the Bakken Region regarding land-cover change resulting from oil development using remote sensing and Geographic Object-Based Image Analysis (GEOBIA). Related studies employing similar object-based image analysis methods using satellite or aerial imagery in other locations include Baker et al. (2012), Powers et al. (2014) and Salehi et al. (2014). Those studies specifically examined industrial disturbances, well-site extraction techniques, and associated land-cover change in the Marcellus Shale region of Pennsylvania (Baker et al. 2012), and in the oil sands region of Alberta, Canada (Powers et al. 2014, Salehi et al. 2014). Using GEOBIA methods provides a more efficient and time sensitive way to classify features associated with oil development across a large area or region, whereas manual digitization of the same features at the same scale would be time consuming.

Oil extraction infrastructure development in the Bakken Region and McKenzie County, like that seen in other oil and gas producing regions, can have significant and lasting impacts on the landscape and wildlife. With more than 404,600 ha (1 million ac) of public land containing unique ecosystems and landscapes such as the Badlands, found in western North Dakota, the state offers habitat for several important species of birds and mammals while providing numerous recreational opportunities such as hunting, hiking, biking, and bird watching (ND Stakeholder Assessment 2016). In a report compiled by Dyke et al. (2011) oil extraction infrastructure development was found to have varying levels of immediate or direct impacts on habitat loss among the species assessed. Increased traffic and more roads were found to contribute to some direct loss of wildlife and habitat fragmentation, while the increase in related oil development such as noise and drilling activity may lead wildlife to avoid or abandon former habitat (Dyke et al. 2011).

This research examined two central research questions: 1) is GEOBIA an effective tool for accurately mapping land-cover change associated with the development of oil extraction infrastructure in McKenzie County from 2009 to 2014?; and, if so 2) how much grassland and agricultural land-covers have been lost? With the use of object-based image analysis software, oil extraction infrastructure can be distinguished from other land-cover types. Grassland and agricultural land-cover can then be examined to determine any change in overall coverage as a result of oil development. In future studies, baseline data developed here may provide insight into impacts upon local wildlife, assist in monitoring environmental problems such as gas flaring and spills, and inform studies on social impacts of the oil boom.

CHAPTER II

LITERATURE REVIEW

2.1 Study Area

McKenzie County (Fig. 1) is located within the state of North Dakota above the Bakken Shale formation, which is a part of the larger Williston Basin. In 2014, the estimated population of McKenzie County was 10,996 and the county seat, Watford City, had a population of 4,206 (U.S. Census Bureau 2014). McKenzie County covers 7,149 km^2 (2,760 mi^2) (U.S. Census Bureau 2014). This makes it the largest county in North Dakota by area. The Missouri River lies to the north and defines the border between McKenzie and Williams counties. McKenzie County is also home to the North Unit of Theodore Roosevelt National Park (TRNP).

Topography is characterized by flat to rolling terrain interspersed with badlands and other rugged features, especially near TRNP and the Missouri and Little Missouri rivers. Grassland and agriculture are the dominant land-covers in McKenzie County. Native semi-arid grasslands constitute much of the land cover because of shallow shale and sandstone soils that are detrimental to crop production (Saylor 2011). More than 202,000 ha (500,000 ac) of the Little Missouri National Grassland are located in McKenzie County.

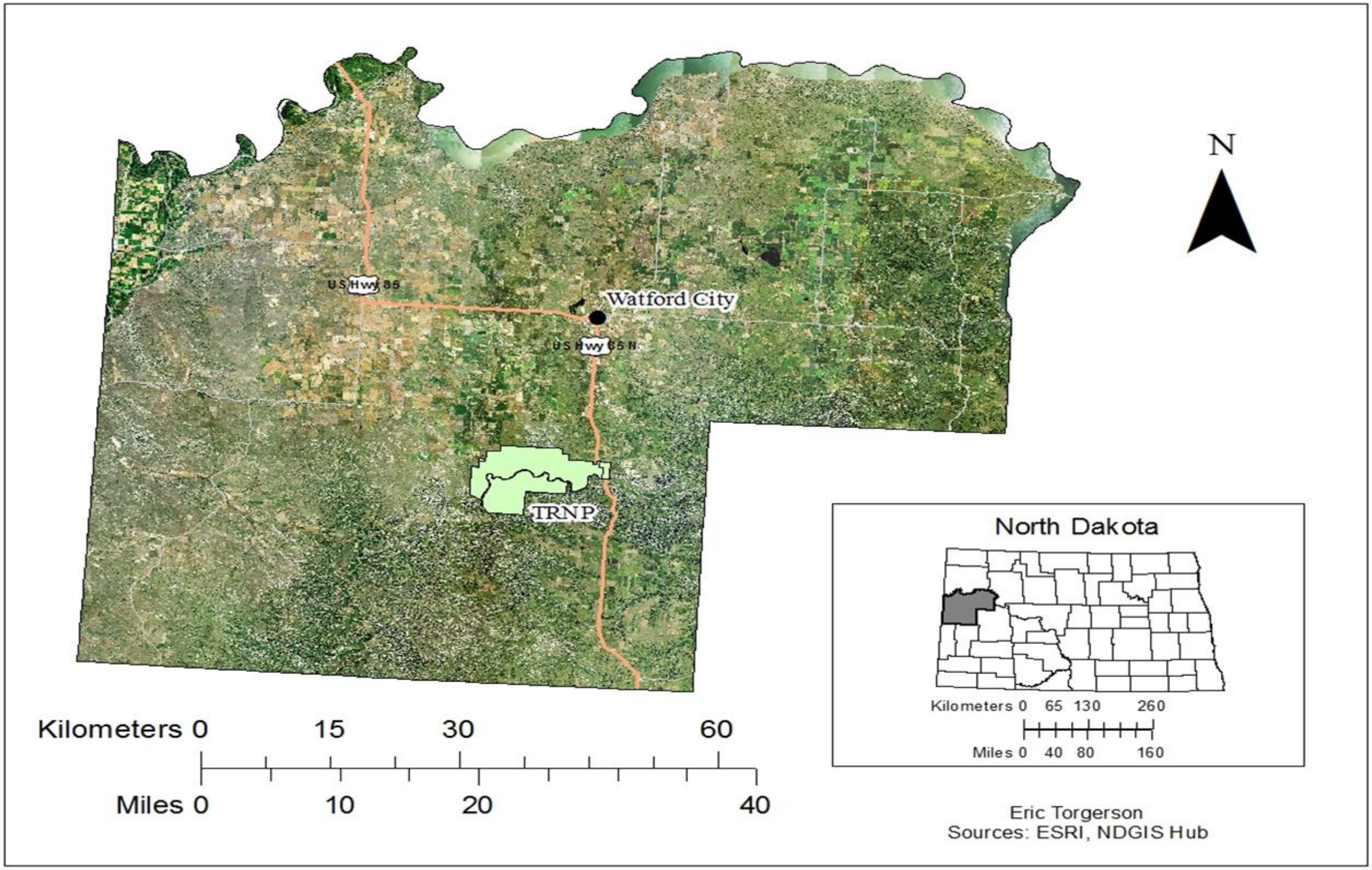


Figure 1. McKenzie County Location, with inset map showing its location within the state of North Dakota.

Agriculture is still important in the county but is not as prevalent today as it once had been. In 2007 McKenzie County had 492 farms that occupied 174,372 ha (430,884 ac) of land. Of these 492 farms, 419 harvested 133,606 ha (330,148 ac) of cropland (USDA 2012). In 2012 there were 466 farms that occupied 172,244 ha (425,625 ac) of land. Of these 466 farms, 386 harvested 137,877 ha (340,703 ac) of cropland (USDA 2012). Although there was an observed drop in total farms and total land occupied, harvested cropland increased in the county. The primary crops grown are spring wheat, durum wheat, and barley (USDA 2012).

Historically the Bakken region and McKenzie County have experienced oil boom cycles. Geologists and oilmen knew that this region was a potential source for oil since the 1920s, and in 1951 Amerada Petroleum Corporation successfully drilled and extracted 300 barrels of oil in 17 hours from a discovery well (Campbell et al. 1958). The resulting boom shares many similarities to the most recent boom of western North Dakota.

During the 1950s boom, the demand for housing to accommodate a large influx of people searching for oil and work was greater than the supply and demand for goods, which helped to spur economic and business growth in surrounding towns. Community services such as schools, transportation and communication systems became congested or strained, and cost of public services drastically rose. By 1955 conditions such as these could be described as stable or settled after the area had adjusted (Campbell et al. 1958).

Table 1: Top 5 oil producing counties in North Dakota, July 2009 (data from NDDMR).

Counties	Oil Produced in Barrels
Mountrail	2,742,397
Bowman	1,128,374
McKenzie	876,351
Dunn	797,360
Williams	480,084

Table 2: Top 5 oil producing counties in North Dakota, July 2014 (data from NDDMR).

Counties	Oil Produced in Barrels
McKenzie	11,478,438
Mountrail	8,302,943
Dunn	5,675,073
Williams	4,879,970
Divide	1,302,992

The county experienced enormous growth in oil development between 2009 and 2014 and is now the epicenter of oil development and production in western North Dakota (Figs. 2 and 3). In July of 2009 there were only 831 oil or gas producing wells in the county, and by July 2014 McKenzie County had 2,656 wells actually producing oil or gas, more than 600 more producing wells than the next county (NDDMR 2016). Oil production is much the same way. In July of 2009 McKenzie County wells produced 876,351 barrels of oil (Table 1), by July of 2014 wells produced 11,478,438 barrels of oil (Table 2), more than 3 million more barrels than the second leading county (NDDMR 2016).

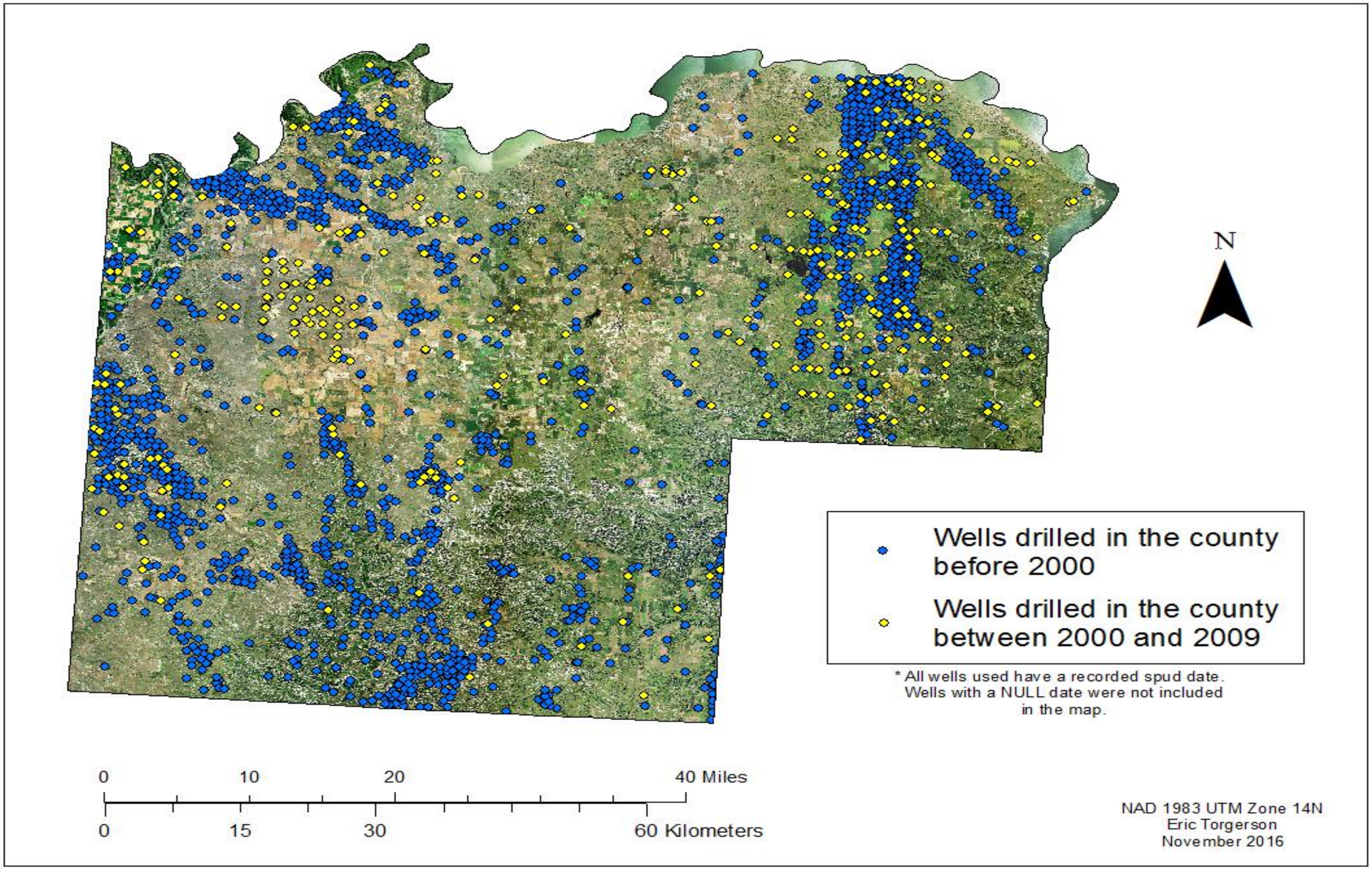


Figure 2: Wells in McKenzie County prior to 2000 and wells from 2000 through 2009. The majority of pre-2000 wells are a result of oil booms which occurred during the 1950s and the 1980s.

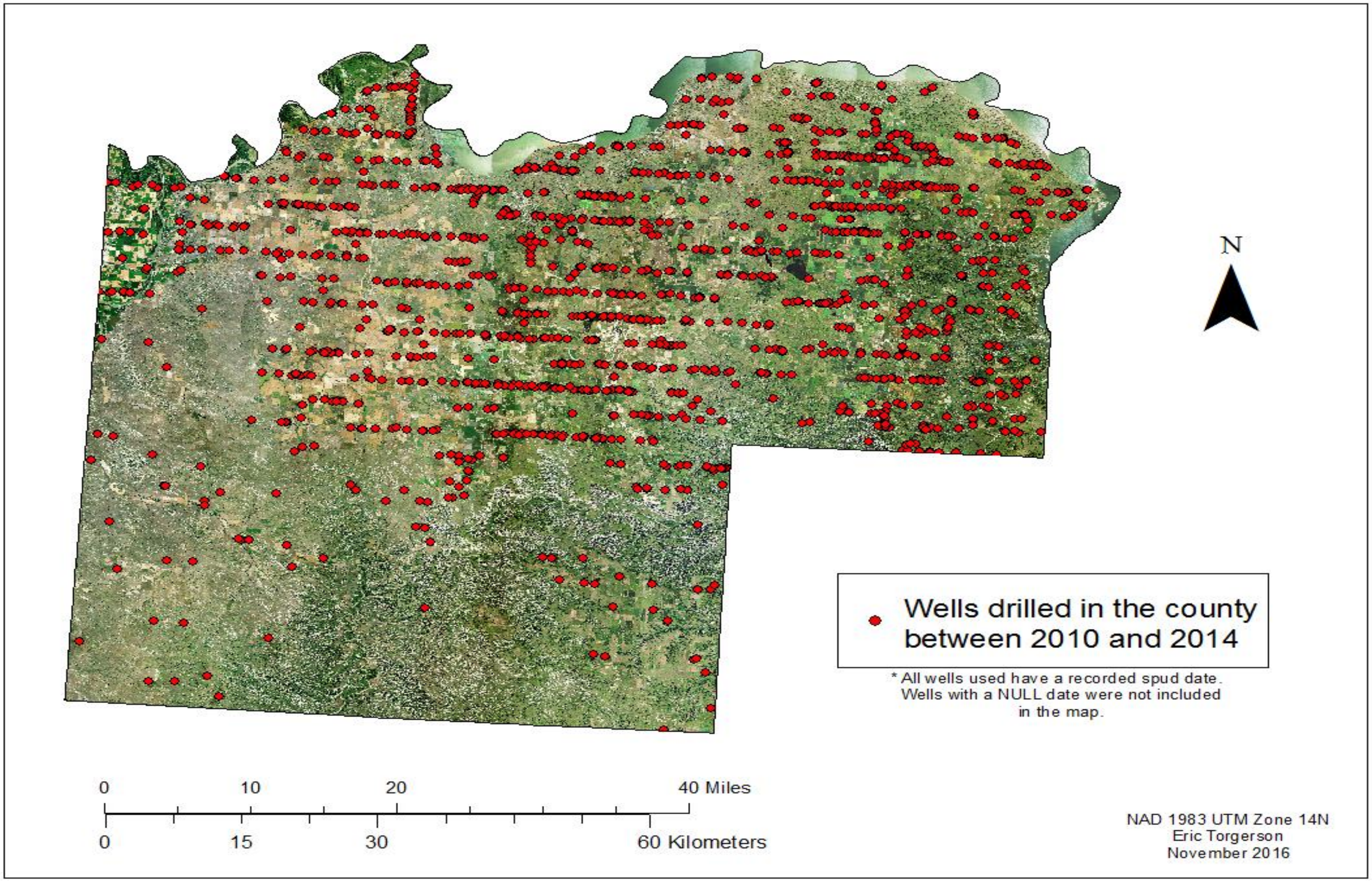


Figure 3: Wells drilled in McKenzie County from 2010 through 2014.

2.2 Oil Extraction Infrastructure

Oil extraction infrastructure (Fig. 4) is not limited to one outstanding feature but a host of small disturbances on the landscape that include well pads, roads, pipelines, seismic lines and core holes. These features are spatially, geometrically and temporally unique. He et al. (2009) grouped these disturbance features into two categories: narrow-linear disturbances and small-area disturbances. They characterize several narrow-linear and small-area disturbance features based upon spectral characteristics (surface, top), geometric characteristics (length, curvature, and width), and topological property.

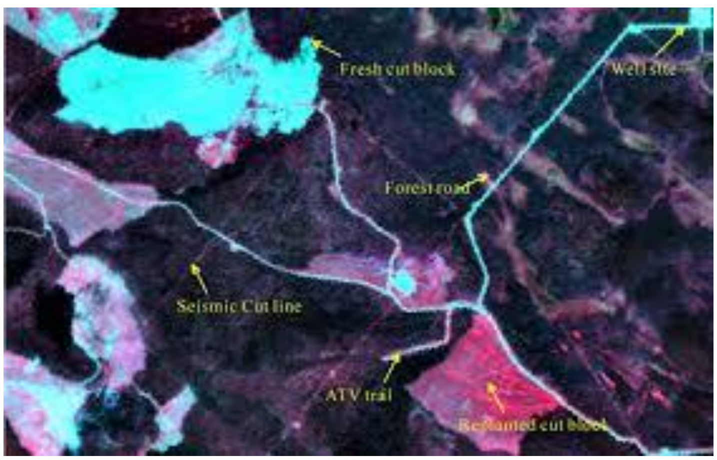


Figure 4: Narrow-linear and small-area disturbances associated with oil extraction infrastructure (He et al. 2009).

Narrow-linear disturbances include roads, trails, pipelines and seismic cut-lines. Previous studies by He et al. (2009, 2011) and Powers et al. (2015) examine the detection of narrow-linear forest disturbances in one Bear Management area (BMA) of the eastern foothills of the Rocky Mountains in Alberta, Canada, and the oil sands region of Alberta near Fort McMurray. These studies establish a solid framework for detecting, as well as characterizing, these features using high-spatial resolution imagery. Two linear features of increased interest in oil development areas are seismic cut-lines and roads because of their potential for widespread habitat fragmentation and ecosystem/environmental degradation.

Seismic cut-lines are the result of seismic surveys conducted to locate and evaluate oil and gas deposits (He et al. 2011, Powers et al. 2015). The result of these surveys is a patchwork of long, narrow parallel lines of cleared vegetation across the landscape (He et al. 2011). Typical of such a feature, seismic lines are long and very straight, but they tend to have a heterogeneous surface comprised of mixed gravel and grass or small shrub. Seismic lines have a constant width of ~5-10 m (16.4-32.8 ft) with little to no topological property (He et al. 2009, 2011).

Roads share similar characteristics to seismic lines. Similarities include having an exposed surface and their length can be described as long. Roads have a series of defining characteristics, however, that set them apart from other narrow-linear features such as seismic lines. Road surfaces are compact and uniform and are typically covered with gravel or dirt, their curvature is considered straight but conforms to the local curvature to account for any topographic barriers or impediments, and they are relatively wide with a constant width of ~20-30 m (~65-98 ft) (He et al. 2009). Roads experience constant use and maintenance so they become permanent features upon the landscape, whereas seismic lines may experience limited use as recreational paths or off-road vehicle trails after their initial use, leading to possible recovery over a much shorter time frame.

Small-area disturbances include features such as cut blocks and well-pad sites. Of the two, well-pad sites are the focus of this research. He et al. (2009) characterize well-pad sites as having a regular polygonal shape with a fixed size and uniform surface. One challenge though is that not all well-pads have a single fixed size, but rather a range in sizes. Baker et al. (2012) examined land-cover change associated with natural gas-well clearings in Pennsylvania, and found that well-pad sites range from 0.2 to 9.2 ha (0.4-22 ac), and averaged 0.9 ha (2 ac). In a similar study, Salehi et al. (2014) in the oil sands region of Alberta examined well pad locations and found that well pads had an approximate area of 1 ha (2.4 ac). Like roads, well-pad sites experience constant use and upkeep, allowing them to become established features.

Cut blocks are typically seen in conjunction with larger-scale anthropogenic activities such as expansive surface mining or logging in heavily forested areas. They have definable geometric characteristics but, unlike well pads, do not have a regular polygonal shape to them. Their surface is more similar to seismic lines, where it is heterogeneous and may include areas of exposed soil and experience possible vegetative re-growth over time (He et al. 2009). Because of limited use or reclamation of the site, cut blocks do not necessarily become distinguishable, permanent features upon the landscape. These are worth noting because of their impact in other regions where oil and gas exploration occur.

The cumulative impact of these narrow-linear and small-area disturbances upon the landscape is spatially extensive. Land-cover is permanently altered or may experience differing rates of regeneration depending upon the disturbance type (Powers et al. 2015). Depending on the resiliency of the affected ecosystem, native plants, wildlife, and other crucial ecosystem processes are at risk or irreversibly changed. As habitat becomes more fragmented many species experience increased difficulty in migrating between suitable habitat sites, which may lead to smaller population sizes or possible local extinction (He et al. 2009). Unique landscapes such as badlands and extensive grassland areas are found within McKenzie County. Being able to classify oil extraction infrastructure in the county may provide insight into habitat fragmentation, impacts on grassland ecosystems, and other localized impacts upon wildlife.

2.3 Mining and Mine Reclamation Classification

Observed oil extraction infrastructure for this study focused primarily on roads and well-pad sites because they are significant features on the landscape and are spatially expansive when observed at a county or regional scale. Similar studies have been conducted using GEOBIA and high-resolution imagery to classify land-cover change, industrial features, and mine reclamation associated with mountaintop removal mining methods (Maxwell et al. 2014, Maxwell and Warner 2015). Mountaintop removal is an extensive resource extraction method involving the mining of coal often seen in the Appalachian region of the U.S. Maxwell et al. (2014) identify it as the leading cause of land-cover change in coalfields of the eastern U.S., while also noting it is a faster but more pervasive method than traditional extraction practices.

Two studies were part of a larger, on-going project to examine the classification of mining and mine reclamation using GEOBIA and related image variables. First, Maxwell et al. (2014) used machine learning algorithms, light detection and ranging (LiDAR) data, and RapidEye imagery to perform a GEOBIA. Machine-learning algorithms used were: support vector machines (SVM), random forests (RF), boosted classification and regression trees (boosted CART), and *k*-nearest neighbor (*k*-NN). The use of ancillary data such as LiDAR generated an overall accuracy of the GEOBIA classification of 86.6 percent. When incorporated with LiDAR data, all four algorithms provided accuracies that were statistically comparable.

Maxwell and Warner (2015) provide further results using Digital Elevation Model (DEM)-derived terrain data compared with National Agriculture Imagery Program (NAIP) data to further distinguish between mine reclaimed and non-mining grasslands. The GEOBIA approach was combined with two machine-learning algorithms, RF and SVM, to help facilitate use of ancillary data used for classification. Results indicate mine reclaimed grasslands can be classified accurately with accuracies above 80 percent. GEOBIA used with the machine learning algorithms proved useful in exploiting non-spectral data such as DEM data and terrain shape variables.

These studies provide helpful insight as to working with complex machine-learning algorithms and working with ancillary data such as DEM or LiDAR data. Overall GEOBIA classification accuracy of reclaimed grassland areas can be significantly increased when incorporating ancillary data derived from DEM and LiDAR. Data sets like LiDAR and DEM could be applied to an area such as McKenzie County to observe grassland impacted by oil extraction infrastructure. Maxwell et al. (2014) note, however, object-oriented variables like object geometry and texture may in fact decrease or not improve overall accuracy when used in conjunction with ancillary terrain or elevation data.

2.4 Aerial image classification and GEOBIA

Remotely sensed satellite and aerial imagery is commonly used for the extraction of thematic information for the classification of land-cover. The objective of image classification is to cluster pixels within an image into groups that correspond to specific classes or categories. Traditional image classification methods classify aerial photography and satellite imagery on a pixel-by-pixel basis (Baker et al. 2012). As high-resolution aerial and satellite imagery has become increasingly available, the mapping of small-area and narrow-linear disturbance features has increased and allows for greater classification accuracy of these features. Traditional pixel-based classification methods cannot incorporate or capture the variation of high spatial resolution imagery as can newer object-based classification methods. GEOBIA exploits GIS functionality and incorporates spatial context and object shape in the classification (Blaschke 2010, Baker et al. 2012).

GEOBIA originates from remote sensing and related geospatial sciences. Hay and Castilla (2008) define GEOBIA as,

> A sub-discipline of Geographic Information Science (GIScience) devoted to developing automated methods to partition remote sensing imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scales, so as to generate new geographic information in GIS-ready format.

In short, it is a process that segments an image into individual objects based upon spectrally homogenous clusters of pixels. Supervised classification can be used to then classify these image objects (Maxwell et al. 2014). There are two significant advantages to object-based classification: 1) within-class spectral variation is reduced because of image pixels being converted to image objects, helping to remove any salt-and-pepper effect often seen with pixel-based classification; and 2) an object's spatial, textural, and contextual properties can be derived as complementing data related to spectral observations to improve classification accuracy (Liu and Xia 2010, Blaschke 2012). The user can further define object properties based upon object geometry and texture, mean, standard deviation, and median values for individual bands, and their association with neighboring objects (Blaschke 2012, Maxwell and Warner 2015, Maxwell et al. 2014, Salehi et al. 2014).

High-spatial resolution imagery allows for narrow-linear and small-area disturbances to be mapped with a high degree of accuracy. Geometric correction of high resolution imagery is often not needed to further distinguish linear or small-area disturbances on the landscape using object-based classification methods. Well pads and roads have bare surfaces and distinct geometric characteristics that allow for the use of object brightness, area, and shape index features during object classification (Salehi et al. 2014). Accuracies for classifying mining and oil extraction infrastructure using GEOBIA with moderate to high resolution imagery have had overall accuracies ranging from 70 to 98 percent. Supplementary data such as LiDAR and DEMs can be used to increase classification accuracy (Blaschke 2010, Maxwell et al. 2014, Maxwell and Warner 2015).

Multiple studies have justified the effectiveness of using high-spatial resolution aerial and satellite imagery combined with GEOBIA to classify small-scale industrial, narrow-linear and small-area disturbances related to oil development (e.g., He et al. 2009, 2010, Baker et al. 2012, Salehi et al. 2014, Powers et al. 2015). Using high-spatial-resolution imagery reduces or eliminates the need for image enhancement, mixed pixels are reduced and oil extraction infrastructure features are distinguishable on the landscape. Whereas with Landsat-5 TM imagery, well pad sites are described as occupying four to ten mixed pixels with only two pure pixels in the center, this results in decreased spectral contrast between wellsite pixels and surrounding pixels and well-pads may not even be detectable by visual interpretation (Salehi et al. 2014). This type of moderate resolution imagery would require geometric enhancement to effectively distinguish well pads.

Studies using GEOBIA for oil extraction infrastructure or related mining development have used the software eCognition Developer (Trimble Navigation, Sunnyvale, CA) for object segmentation and classification purposes (Baker et al. 2012, Maxwell et al. 2014, Maxwell and Warner 2015). Baker et al. (2013) tested the assumption GEOBIA is more accurate than pixel-based methods for classifying high-spatial-resolution imagery. They used 1-m imagery containing near-infrared bands from the USDA’s National Agriculture Imagery Program (NAIP) to classify forest clearings associated with natural gas drilling. Using eCognition Developer 8.0, a multi-resolution segmentation algorithm was run to segment the imagery into objects. Then, using image object features such as mean brightness, mean values of individual bands, and a normalized difference vegetation index (NDVI), they identified two classes: forest and non-forest. Their overall accuracy for object-based classification using 1-m NAIP was 87 percent. Their GEOBIA provides a good framework for identifying oil extraction infrastructure using high resolution NAIP data that could be applied to similar areas experiencing intense or significant oil development.

Once an image is classified an accuracy assessment is required. This involves the comparison between a classification map derived from aerial or satellite imagery and ground reference test information (Jensen 2005). An error matrix is then used to summarize the relationship between the two sets of information. It is necessary to report three measures of accuracy: overall accuracy, error of omission, and error of commission (Jensen 2005). Overall accuracy is determined by dividing the total amount of correctly classified pixels by the total number of pixels in the matrix. Error of omission is calculated by dividing the total number of correctly classified pixels by the total number of pixels in a given class from the reference data. Finally, error of commission is calculated by dividing the total number of correctly classified pixels by the total number of pixels in that class (Jensen 2005).

CHAPTER III

DATA AND METHODS

3.1 Acquisition and Preparation of 2009 and 2014 Imagery

I obtained free NAIP aerial imagery of McKenzie County for the years 2009 and 2014 from the USDA. Over this five-year period 1,825 new oil producing wells were completed in the county. The 4-band NAIP imagery has the standard visible (blue, green, and red) bands as well as a near-infrared band. Images for both 2009 and 2014 are high-spatial resolution, with a 1-by-1 m pixel size. The high spatial resolution assists in achieving a higher-level land-cover classification and allows for more accurate object identification.

I acquired aerial imagery from the State of North Dakota GIS server (ndgishub.nd.gov) through ArcGIS Desktop 10.4 (Environmental Systems Research Institute, Redlands, CA). I used an ArcGIS Model Builder model to extract McKenzie County from a statewide image. I then applied a 1.61-km (1-mi) buffer to a McKenzie County border to achieve a desired image extent when clipping the imagery to ensure all features in the county were included. I then "diced" the 2009 and 2014 images into 20 smaller sections using the ArcGIS 10.3 fishnet tool and Model Builder. I applied a 1.61-km (1-mi) overlap to all sides of each section in the fishnet to reduce any edge effect during the GEOBIA. This image dicing was done to allow for more efficient processing of the imagery and to avoid software crashes or computational hardware errors, resulting in faster processing times.

3.2 Geographic Object-based Image Analysis of McKenzie County

I performed the GEOBIA on the “diced” sections of the 4-band aerial imagery of McKenzie County for the years 2009 and 2014. These two time periods show land-cover and oil extraction infrastructure in the early stages and at the greatest height of the boom. This was based on methods from two prior studies examining oil extraction infrastructure. Using frameworks similar to Baker et al. (2012) and Salehi et al. (2014), I ran the GEOBIA to identify oil extraction infrastructure in the county. Baker et al. (2012) relied primarily upon spectral characteristics of image-objects for their study. But because oil extraction infrastructure possess specific geometric traits, I used the framework proposed by Salehi et al. (2014) which employed object features such as object area and shape index in developing the ruleset.

I performed the GEOBIA using the software eCognition Developer 9.1. I performed a multi-resolution segmentation algorithm to group image pixels into spectrally similar objects. I set the segmentation parameters to a scale of 25, a shape of 0.1, and a compactness of 0.5. These values were based on those used by Baker et al (2012). I then included a second segmentation, the spectral difference segmentation, and applied a maximum spectral difference of 5. In both segmentation algorithms Blue, Green, and NIR were given image layer weights of 1, and Red was given a weight of 2 (Appendix A). I further manipulated image objects by developing a ruleset using spectral features such as mean brightness, mean values of single bands (red, blue, green and NIR), NDVI, and geometry features such as asymmetry, area (pixel), density, length/width and shape index. Once ideal values for these features were achieved, I classified objects into a narrow-linear features class and small-area features class by executing the ruleset.

The developed ruleset was used to classify oil extraction infrastructure for both years. Because of possible differences in image spectral characteristics or other variables between the 2009 and 2014 images, ruleset feature values were adjusted accordingly to account for any difference.

These feature parameters represent different characteristics present in each object. Mean brightness and mean values of single bands differ little from each other; both of these features represent the mean intensity of all pixels forming an image-object, but are just used in different ways of identifying an image-object. The NDVI parameter needed to be calculated in eCognition Developer in order for it to be used for object identification. Asymmetry and length/width use similar characteristics of an object, the primary of which is length. Asymmetry describes the relative length of an image-object compared to a regular polygon, whereas length/width observes the length-to-width ratio of an object. Area (pixel) is the area of an image-object by the number of pixels one may contain; density labels the distribution in space of the pixels of an image-object, with the most "dense" shape being a square; and shape index describes the smoothness of an image-object border, with a smoother border resulting in a lower shape index (Trimble Documentation 2015).

Exceeding data limits for exporting shapefiles from eCognition Developer 9.1 required an alternate method to be taken for acquiring the final GEOBIA results. With the assistance of Prof. Jarlath O'Neil-Dunne of the University of Vermont, the imagery for 2009 and 2014 were processed on an eCognition server at the University of Vermont. Instead of processing each diced section individually, the original mosaicked image for both years were processed. To do this, additional algorithms were included into the original rule sets. The "create scene tiles" algorithm was added, which created tiled copies of the original images. Each tile becomes its own project yet still represents the complete scene before applying the algorithm (Trimble

Documentation 2015). Tile size parameters were applied within the algorithm, with parameters being a tile height of 5,000 pixels and a tile width of 5,000 pixels. The “submit scenes for analysis” algorithm was then added, and can only be executed if connected to an eCognition server. This algorithm allows any subroutines to be connected back to the main rule set (Trimble Documentation 2015), allowing the ruleset to then process imagery, in this case the image tiles that were created.

Each year was processed separately, with 2014 having a processing time of 1 hour, 22 minutes, and 2009 having a processing time of 3 hours, 14 minutes. Image processing was distributed to 20 cores on a hyper-threaded dual 8-core workstation with 3.12 GHz processors and 512 gigabytes (GB) of random-access memory (RAM).

3.3 Accuracy Assessment

An error matrix is the most appropriate method of analysis for remote sensing and aerial imagery land-cover classification but, I was interested in only two specific features upon the landscape, which left much of the imagery unclassified resulting in an error matrix being unsuitable for conducting the analysis. Instead, I used Microsoft Office Excel spreadsheets for conducting the accuracy assessment. On each I kept the total number of points, the assumed correct classification of each point, and the actual classification of the points for each class in 2009 and 2014. Minimal manual editing was done before carrying out the accuracy assessment, which consisted of removing all object-features that had been classified within the boundaries of the North Unit of TRNP. This was done since no oil development or resource extraction occurs within the park, and the objects removed consisted of bare earth features or roads.

I used ArcGIS Desktop 10.4 for conducting the accuracy assessment. To make the accuracy assessment more efficient the resulting output vector layers representing narrow-linear features and small area features for 2009 and 2014 were merged. This was done using the merge tool in ArcGIS Desktop 10.4 and resulted in four separate shapefiles; two for 2009 and 2014. To avoid potential bias during the assessment, I placed 200 random points within the narrow-linear features class for 2009 and 2014, and within the small-area features class for 2009 and 2014, so there was a total of 400 points for each year and each class. I used the Sampling Design Tool, which was downloaded into ArcGIS Desktop 10.4, to carry out the random point placement. I then visually interpreted each point in the classes for both years to determine if the point fell on a correctly classified narrow-linear feature or small-area feature, or to see if it fell on an incorrectly classified feature. Points falling on a correctly classified feature were labeled as a narrow-linear feature or small-area feature accordingly. If the point was found to fall on an incorrectly classified feature it was labeled according to what land-cover it fell on.

I compared further assessment of the narrow-linear features produced by the GEOBIA for both years by comparing them to existing land-cover datasets. I downloaded a National Agricultural Statistics Service (NASS) Cropscape Cropland Data Layer (CDL) of McKenzie County for 2009 and 2014. I downloaded these data layers as raster data files and loaded them into ArcGIS Desktop 10.4. I was interested in only four of the land-cover classifications comprising the cropland data layer; all considered developed to varying degrees of intensity that when combined included all roads in the county. To extract the desired classes I converted the raster datasets to polygons then dissolved this output to reduce the amount of polygons to those with only particular attributes. I then selected the developed land-covers and exported them to create a separate shapefile. Once this was completed I laid 200 random points on the developed data layers representing roads, and then compared where these points fell to the narrow-linear feature class I developed in the GEOBIA. As with the prior analysis I visually interpreted each point and whether it fell on the narrow-linear feature class or not, and recorded the assumed point classification and the correct point classification in an Excel spreadsheet. This was done for 2009 and 2014.

As with the narrow linear-features classification further assessment of my small-area features class was conducted; this was decided upon after the initial accuracy results proved to be lower than anticipated. To conduct this analysis I produced a slope classification of the county. I used five separate DEM's obtained from the U.S. Geological Survey's (USGS) National Elevation Dataset (NED) to make sure I covered all of McKenzie County. I mosaicked the five DEM's into a new raster using ArcGIS 10.4 and then used the extract by mask tool to match the DEM to the county boundary. I then converted the DEM to a slope raster to represent slope in degrees. A slope cut-off threshold for eliminating unwanted small-area features was found by overlaying the location of all existing wells in McKenzie County onto the slope layer and then extracting the slope value of each raster cell within which each well point fell.

These extracted slopes were then used to find an appropriate slope cut-off by using a box and whisker plot and observing the interquartile range. Of 7,796 well points, the median slope is 2.81 degrees. A lower quartile of 1.52 degrees and upper quartile of 4.79 degrees were determined to help identify any outliers in the data. By determining the lower inner fence to be -3.78 degrees, no low mild or extreme outliers are present. The upper inner fence, the boundary for mild outliers, of the plot was a value of 10.09 degrees, and the upper outer fence for the boundary of extreme outliers was 15.39 degrees. It was determined there were 335 upper-end mild outliers (values above 10.09) and 74 extreme outliers (values above 15.39). Using this information, a cut-off was set at 10.09 degrees, so all small-area features that overlapped a slope of 10.09 degrees were eliminated. I conducted the accuracy assessment like I had for the original classifications by randomly placing 200 points within the classification and visually interpreting each point.

While conducting previous assessments the accuracy of my small-area features classification have proven to be significantly influenced by misclassified features in areas where the topography is uneven and contains areas of bare earth. For this reason, an accuracy assessment was conducted on a selected north-eastern portion of the county (Fig. 5), occupying 339 km^2 (131 mi^2), where topography was level and bare earth at a minimum, and where land-cover consisted primarily of agriculture and areas of grassland. I digitized a new polygon to mark the boundary of this area and the small-area feature classifications for 2009 and 2014 were clipped to the extent of this boundary. I then generated 50 randomly placed points within each classification and visually interpreted each point to determine the accuracy within this area. With a suitable accuracy produced for 2014, I used the small-area feature classification within the selected area to determine how land-cover has been impacted by oil development. The 2014 small-area feature classification was overlaid on the 2009 CDL and used to eliminate corresponding land-covers, which were calculated to determine the total area and type of land-cover lost to oil development from 2009 to 2014.

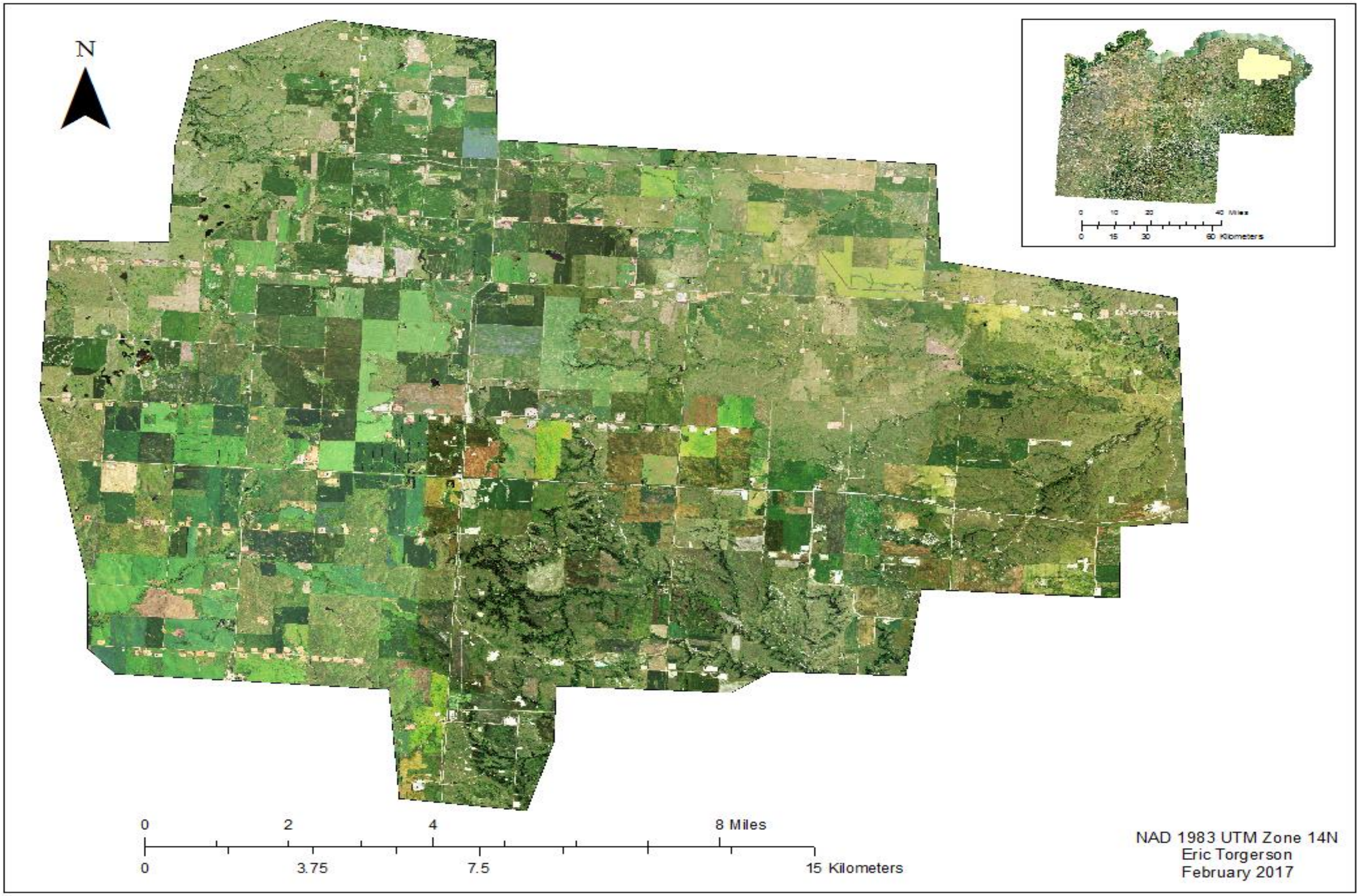


Figure 5: The selected portion of the county used to conduct land-cover change assessment and its location within McKenzie County.

CHAPTER IV

RESULTS

4.1 Land-cover Analysis and Change, 2009 to 2014

The classifications produced from the GEOBIA (Appendix B) indicate oil extraction infrastructure in McKenzie County experienced significant growth between 2009 and 2014 (Table 3). Small-area features nearly doubled in area from 2009 to 2014, where-as narrow-linear features experienced moderate but not significant growth over the same time period. Despite this growth seen between 2009 and 2014, further assessment proved these classifications were not accurate enough to confidently determine the impacts of oil development on grassland and agricultural land-covers. The classifications, however, do allude to the trends seen in the rapid development of oil extraction infrastructure in the county and region and its potential impact on land-cover.

Table 3: Growth of Oil extraction Infrastructure in McKenzie County.

	2009	2014
Small-Area Features	58 km^2 (22.3 mi^2)	104 km^2 (40 mi^2)
Narrow Linear Features	93 km^2 (36 mi^2)	120 km^2 (46.5 mi^2)

4.2 GEOBIA accuracy assessment

The overall accuracy of the GEOBIA for McKenzie County was 41.2 percent. A total of 330 out of 800 points were correctly classified as either a narrow linear feature or small area feature. This accuracy is significantly lower than the 73.5 to 93 percent overall accuracies reported in similar studies (e.g., Baker et al. 2012, Salehi et al. 2014, Powers et al. 2015). The GEOBIA also produced low to moderate accuracies for the individual years and classifications (Table 4). When observing the overall accuracies for the small-area and narrow-linear features classifications, assessment of the narrow-linear features resulted in a noticeably higher classification accuracy. The accuracy for each individual class within each year can explain the difference between overall classification accuracies, with the narrow-linear features producing a much higher accuracy than those of the small-area features. It is clear the GEOBIA produced more accurate feature classifications for 2014, resulting in a higher overall accuracy for that year over 2009.

Table 4: Overall and individual class and year accuracies.

	Small-Area Features	Narrow-Linear Features	Overall
2009	18.50%	52.00%	35.50%
2014	41.00%	53.50%	47.25%
Combined	29.75%	52.70%	NA

While conducting the accuracy assessment of the GEOBIA for 2009 and 2014, points that randomly fell on correctly classified features were recorded (Figs. 6 and 7), as well as those which fell on incorrectly classified land-cover features (Figs. 8 and 9) to see where error in the GEOBIA occurred. Unrelated bare-earth and agricultural land-covers were widely misclassified in the GEOBIA for both years in both the narrow-linear feature and small-area feature classifications (Table 5). Overall, unrelated bare-earth and agriculture accounted for nearly half of all features classified, with each accounting for about one-quarter of the nearly half of all features. The percentage of agricultural features classified remained consistent for the classifications within both years whereas unrelated bare-earth features varied amongst the individual classifications, with small-area features experiencing a higher percentage of unrelated bare-earth being classified compared to the narrow-linear feature classifications. The 2014 classifications also experienced lower percentages of misclassified features than 2009, with the exception of agriculture for the narrow-linear feature class.

Table 5: Percentage of the most prevalent misclassified land-covers. They are recorded by the percent each made up of the overall classification and individual yearly feature classifications.

	Unrelated Bare-earth	Agriculture
Overall Classification (both years, both classes)	22%	25%
Narrow-linear Feature (2009)	16.5%	25%
Small-area Feature (2009)	35%	24.5%
Narrow-linear Feature (2014)	10.5%	27%
Small-area Feature (2014)	26.5%	23.5%

The assessment of the narrow-linear feature classification compared to the CDL developed classes resulted in a higher rate of accuracy for the GEOBIA classification. The 2009 narrow-linear feature class compared to the selected 2009 CDL developed classification produced an accuracy of 59 percent, while the 2014 narrow linear feature class compared to the 2014 CDL developed classification produced an accuracy of 63.5 percent. The overall accuracy for both years combined was 61.3 percent, with 245 out of 400 randomly placed points falling on the CDL and then corresponding correctly to narrow-linear feature class.

Assessment of the small-area feature classification after incorporating slope to eliminate unwanted features resulted in a minimal to no increase in accuracy for the GEOBIA classification. The 2009 small-area feature class produced an accuracy of 22 percent after eliminating unwanted features, while the 2014 small-area feature class produced an accuracy of 40 percent. The overall accuracy for both years combined was 31 percent, with 124 out of 400 randomly placed points falling on features correctly classified as small-area features.

The assessment of the smaller selected portion of McKenzie County produced significantly higher accuracies for the small-area feature classifications than the original or the slope incorporated assessments. The 2009 small-area feature class had an accuracy of 50 percent, and the 2014 small-area feature class had an accuracy of 70 percent. A 70 percent accuracy was deemed suitable to conduct further analysis in determining the amount of agricultural and grassland land-cover lost to oil extraction infrastructure development between 2009 and 2014. Using the 2009 CDL, observed land-cover considered grassland covered noticeably more area than agriculture in the observed portion of the county (Table 6). Using the 2014 small-area feature class to eliminate underlying land-cover, the total area of agriculture and grassland were then determined for 2014. After calculating the difference, oil extraction infrastructure led to a minimal but expected drop in agricultural and grassland land-cover from 2009 to 2014, with agriculture losing more land-cover.

Table 6: Agriculture and grassland land-cover lost as a result of oil extraction infrastructure development.

Land-cover Type	**2009**	**2014**	**Area lost**
Agriculture	13,780.5 ha (34,052 ac)	13,534 ha (33,443 ac)	246.5 ha (609 ac)
Grassland	17,384 ha (42,957 ac)	17,188 ha (42,472 ac)	196 ha (485 ac)

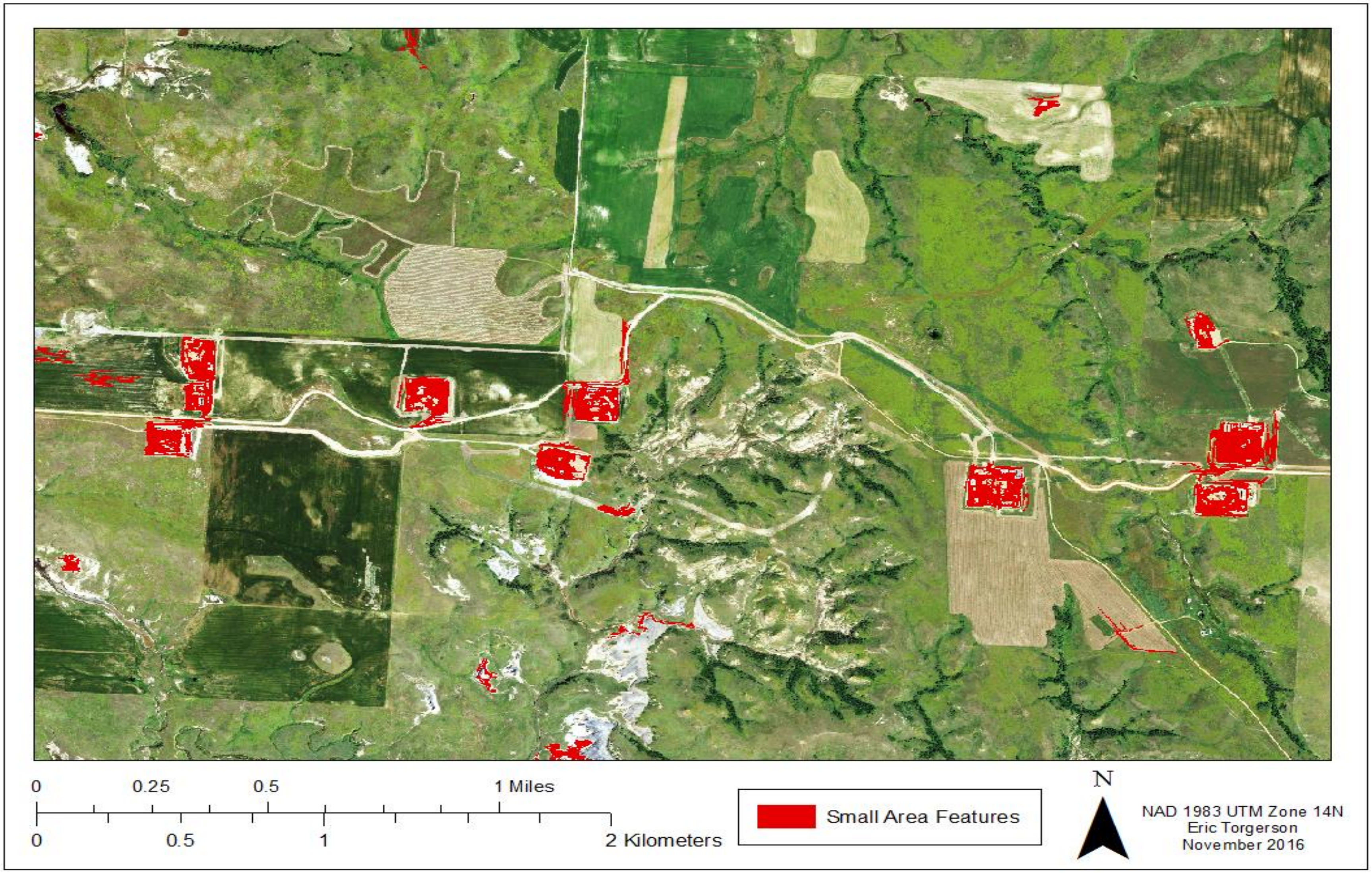


Figure 6: Correctly classified small-area feature image objects. Geometric features such as Shape Index, Area (pixel), and asymmetry were used in the ruleset to classify features such as well pads.

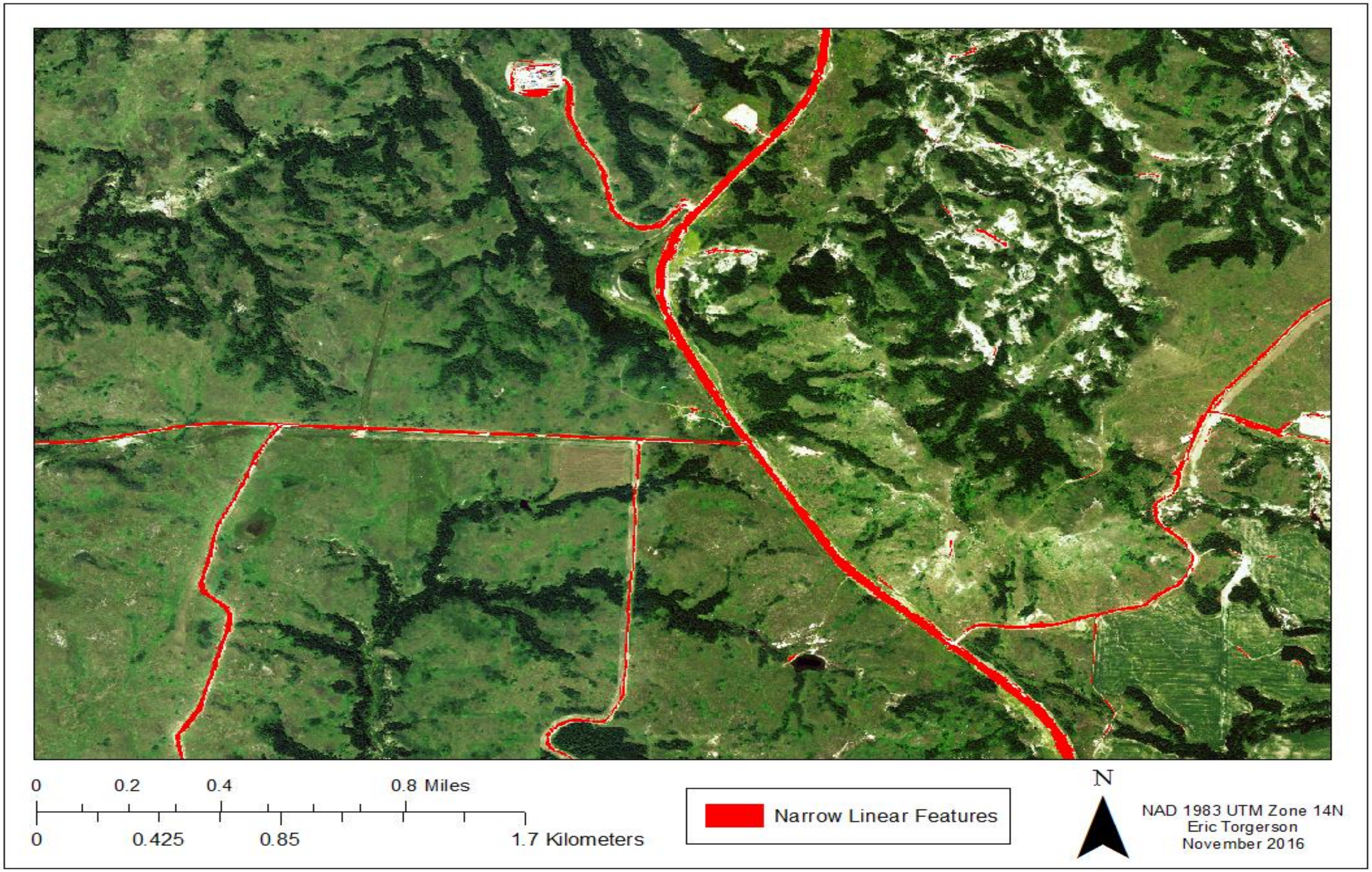


Figure 7: Correctly classified narrow-linear feature image objects. Geometric features such as Area (pixel), Asymmetry, and density were used to classify features such as roads.

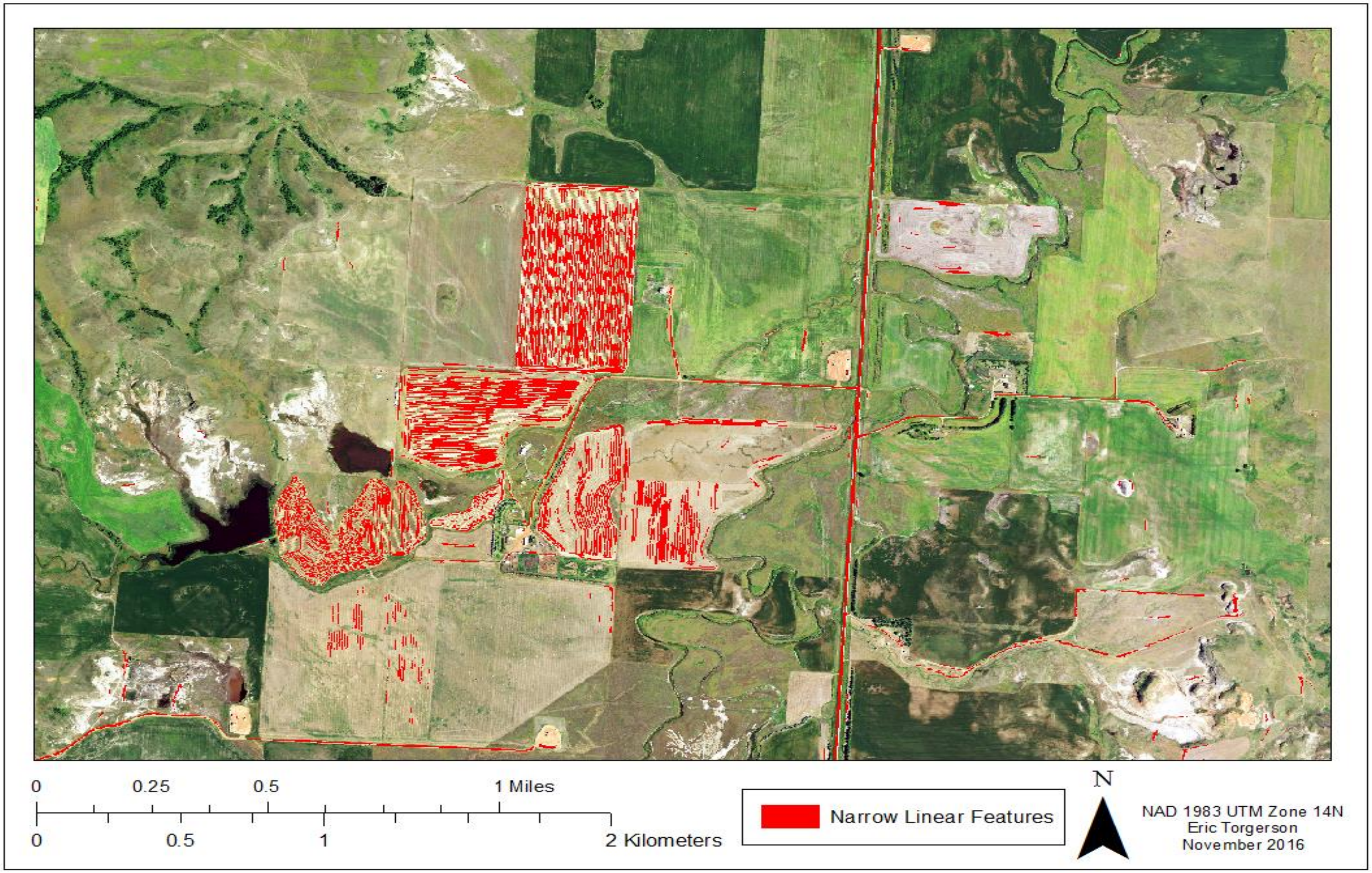


Figure 8: Misclassified narrow-linear feature image objects. Many other linear objects misclassified as narrow linear features include portions of fields where the linear pattern of row crops is evident and is noticed to be picked up more-so by using geometric features in the ruleset.

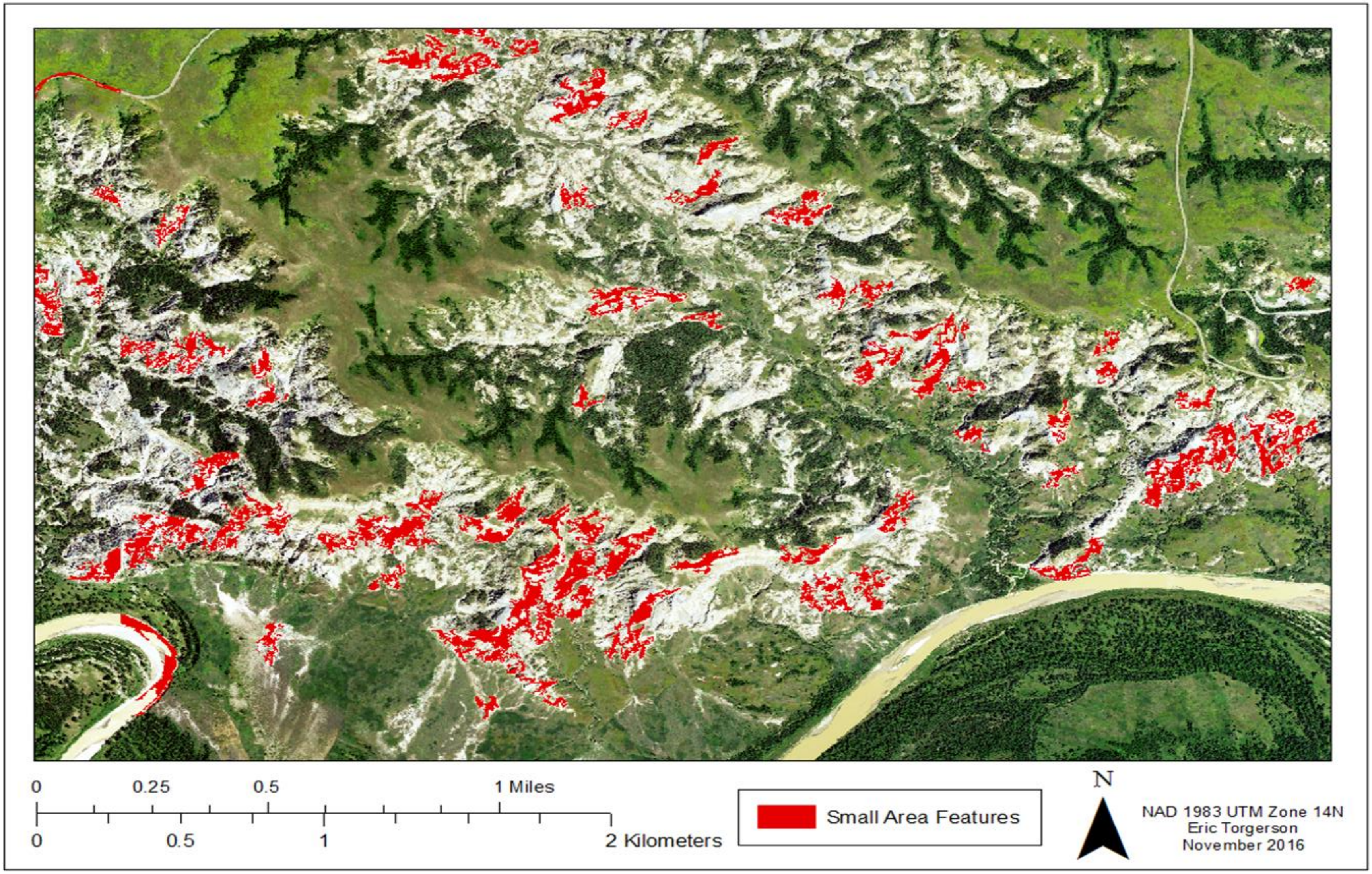


Figure 9: Misclassified small-area feature image objects. Much of this error is a result of these bare earth areas having similar spectral reflectance as that of other bare earth features such as well pads and could not be completely classified out of the final GEOBIA ruleset.

CHAPTER V

DISCUSSION & CONCLUSION

5.1 Discussion

Oil extraction infrastructure can be identified in McKenzie County using GEOBIA methods, although its effectiveness is in question because several accuracy assessments showed that the results of this study are not as accurate as similar published studies (e.g., Baker et al. 2012, Salehi et al. 2014, Powers et al. 2015). The accuracy of my results was significantly lower than anticipated. Because of these inaccuracies, impacts of oil development on agricultural and grassland land-cover could not be determined with confidence for the entire county. Rather, a small portion of the county with land-cover characteristics amenable to accurate classification was selected and assumed to be representative how the rest of the county has been impacted by oil development.

In Table 4 it is evident narrow linear features and the year 2014 had greater accuracies than small-area features and 2009. The narrow-linear feature classifications accuracies remained moderately low but consistent between both years, suggesting less impact from misclassified features identified by the GEOBIA. A noticeable difference is seen between the small-area features classifications between 2009 and 2014. For 2009 the accuracy fell below 20 percent, whereas 2014 had an accuracy of 41 percent. This noticeable increase in accuracy could be a result of the significant development that occurred from 2009 to 2014, with 2014 providing a larger number of correctly classified small-area features for randomly placed points to fall on during assessment.

The GEOBIA was successful in identifying oil extraction infrastructure in the county but also produced significant inaccuracies. Despite these significant inaccuracies I limited manually editing my classifications to prove if GEOBIA methods were effective or not. The natural landscape of the county contributed to many of these inaccuracies. The most significant inaccuracies resulted because bare-earth and other spectrally similar features are classified as small-area or narrow-linear features. These misclassified bare-earth features included agriculture and exposed hillsides associated with the badlands landscape seen along the banks of the Missouri and Little Missouri rivers and in much of the southern portion of the county in and around the North Unit of TRNP. The accuracy assessment produced an overall accuracy (across both classes and both years) of 41.2 percent, which is much lower than results reported in other studies. Bare-earth features made up 22 percent of all features observed during assessment of the classifications, while agriculture accounted for 25 percent of all features.

Similar studies also report classification errors and inaccuracies as a result of unrelated land-cover features, which share similar characteristics as the features being examined, influencing the classifications of their GEOBIA (Baker et al. 2012, Salehi et al. 2014, Powers et al. 2015). Baker et al. (2012) report inaccuracies of agricultural fields being classified as forest due to similar spectral reflectance of these features, and report a low producers accuracy for their "Forest to non-forest" GEOBIA classification of 29 percent when using 30 meter resolution imagery. Salehi et al. (2014) observe higher rates of misclassification in areas where land-covers share spectral similarities to those of oil development, such as areas of minimal vegetation and bare-earth, varied topography, and road and river boundaries; while Powers et al. (2015) record similar errors, where areas of extensive shrub cover and natural disturbances such as riverbank erosion and minor landslides may be misclassified as industrial features due to spectral similarities.

I limited manual editing only to the removal of classified image-object features within the borders of TRNP. I did this because oil development does not occur within the park. This excluded a small area of the county not experiencing land-cover change because of oil development, and including classified features within the park could have had the potential to slightly affect accuracies of the classifications. Other misclassified areas (primarily bare-earth) were removed with the use of DEMs to try to improve on initial accuracy results of the small-area feature classifications. The DEMs were used to create a slope layer for the county, which I then used to eliminate misclassified features falling at or above the calculated slope of 10.09 degrees. Using slope derived from the DEMs proved successful in eliminating misclassified features but only improved the accuracy of the small-area feature classifications slightly or not at all. These results suggest numerous misclassified features remained after applying the threshold of 10.09 degrees, with bare-earth and agriculture still being the most prevalent misclassified features. The date of the DEMs used also needs to be brought into consideration. The DEMs used were published in 2013, and this could have impacted the threshold calculated where well-pads built after 2013 are not present but slope values are still extracted when using points that represent well-pads in 2014, so some misclassified features may or may not have been eliminated due to this and some correctly classified features eliminated.

Determining impacts upon local land-covers using GEOBIA methods do not work well at the scale of a large county or region where there are significant areas of bare-earth as well as oil development. When focusing on a smaller area of McKenzie County covered predominantly by agriculture and grassland and few bare-earth features, accuracies for my small-area feature classifications significantly rose and impacts on agriculture and grassland could be more accurately determined. Focusing on areas that exhibit greater spectral contrast between land-cover types will likely produce more accurate results. Observing this smaller area also concluded that agricultural and grassland land-covers have been impacted by oil development, decreasing slightly within the observed area, and could be assumed the rest of the county has experienced similar land-cover loss. Table 6 shows agriculture experienced slightly more land-cover loss than grassland within this area. This could be due to federal and state agencies that manage public lands (i.e., Little Missouri National Grassland) have stricter regulations and reclamation standards to minimize impacts from oil development on them, while private landowners may not be aware to such standards or their rights to guarantee safe development and reclamation (ND Stakeholder Assessment 2016).

While developing the rulesets I used for the GEOBIA, I found spectral features like mean value for the red band and mean brightness to be of greatest importance when extracting small-area objects. Small-area features such as well-pads tended to have higher mean red and brightness values than the immediate surrounding landscape because of being devoid of vegetation. Powers et al. (2015) also found the mean value of the red band to be one of the most relevant descriptive attributes when performing their GEOBIA. However, other bare-earth features resulting from erosion and agricultural production were also extracted because they have similar spectral characteristics. For that reason, I incorporated geometric conditions such as area (pixels) and shape index into the rulesets since well-pads have distinct geometric characteristics.

Although area and shape indices were helpful in reducing the number of non-well-pad features, they did not eliminate all misclassifications. I encountered a threshold for both area and shape indices beyond which object-features representing well-pads were excluded from the classification. This limited the number of misclassified features that could be eliminated. The condition "asymmetry" was included in the ruleset and this also was useful in eliminating some, but not all, unwanted features because of their irregular shape.

Narrow-linear features relied primarily upon geometric conditions for classification, such as length/width, density and asymmetry and less upon spectral properties like small-area features. Length/width proved to be the most useful in identifying features like roads, and was able to extract a large majority of linear features in the county. Identifying narrow-linear features relied upon fewer conditions to classify them and resulted in higher accuracies than the small-area feature classifications. As with the small-area feature classifications, unwanted feature objects were extracted during the GEOBIA but did not result in as severe an impact upon final results for narrow-linear features. The inaccuracies most associated with classifying narrow-linear features were agricultural. Agricultural fields that contained row crops or linear patterns from previous harvest or plowing were extracted along with features like roads.

Manually digitizing small-area and narrow-linear features would have been time consuming given the size of McKenzie County and the detail that would have been needed to digitize each feature, so the GEOBIA proved effective in reducing the time identifying these features. Despite that advantage of the GEOBIA, manually digitizing these features would have resulted in a high accuracy and land-cover change between 2009 and 2014 could be confidently determined. I think manually digitizing small-area and narrow-linear features within the small portion of the county I examined would have been beneficial to the analysis. Although a small portion of the county, there would be a high degree of accuracy and determining land-cover change would have been much more exact.

I believe future studies can use the methods presented in this study to observe land-cover change in other western North Dakota counties that have experienced rapid oil development, and to observe continued development in McKenzie County. The GEOBIA can be further refined to be unique to grassland biomes and conducting future studies in regions that share similar land-cover characteristics as western North Dakota. A similar framework can be used to examine small-area or narrow-linear features associated with other types of industrial development, such as: urban sprawl, wind energy development, deforestation and logging activities, and mining development.

The methods presented in this study can also incorporate new types of data or techniques to further take advantage of certain characteristics displayed by oil development features. As seen in previous studies, elevation data can be used in conjunction with GEOBIA methods to identify land-cover change associated with large scale mining (Maxwell et al. 2014, Maxwell and Warner 2015). If given access to unlimited resources high-resolution LiDAR data could be attained, which could then be used to distinguish areas where land-cover changed between two time periods by identifying where elevation of the landscape has changed due to oil development, possibly making object identification easier. Different types of imagery could also be considered for future studies as well due to the spectral limitations of NAIP. Hyperspectral imagery would be ideal for observing features associated with oil development in McKenzie County due to distinct soils present. This imagery covers a wider range of the electromagnetic spectrum and divides it into many more bands, which can allow for numerous types of band ratios to be examined in order to extract features with particular spectral properties. An image processing technique that could be used in future studies is resolution merging, where the spectral and spatial resolutions of two different images are merged to take advantage of both images. This could be done with a high-resolution image such as NAIP and a high-spectral image like Landsat, and these advantages combined could result in more accurate identification of particular features associated with oil extraction infrastructure development.

5.2 Conclusion

The primary focus of this study was to determine if GEOBIA methods are effective at accurately mapping land-cover change associated with oil development in the county, followed by determining land-cover impacts to agriculture and grassland. Initial accuracy assessments and results of this study suggest that is not true, and GEOBIA methods are rather ineffective at identifying oil extraction infrastructure, which did not allow for accurate land-cover change analysis of agriculture and grassland for the whole county. Further analysis though proved features associated with oil extraction infrastructure development in McKenzie County can be identified using GEOBIA methods, and accuracies can be improved but only when limiting or observing areas with particular landscape characteristics present in the imagery. Limiting the amount of features that share similar spectral characteristics to small-area and narrow-linear features may result in higher accuracies of GEOBIA classifications, as evident from observing the small selected portion of McKenzie County, and could allow for accurate analysis of land-cover change. These methods could be applied to other counties in western North Dakota or similar regions with a grassland biome, but results will be dependent upon landscape characteristics present in that region.

Despite the recent decline in oil development and production in western North Dakota, McKenzie County in July of 2015 had 3,287 wells and July of 2016 had 3,504 wells actually producing oil and gas (NDDMR 2017), which are marked increases in active wells from the same time in 2014. This may be from a combination of wells previously drilled with the capability of producing being hydraulically fractured and new wells continually being drilled. Continuing to observe oil extraction infrastructure development in McKenzie County for recent years not examined in this study can also be a focal point for future studies. By observing the rate of growth in oil development over a span of several years and identifying where wells are drilled, trends in land-cover change can be analyzed and predictions of where expected growth may occur can be made.

APPENDICES

Appendix A

Geographic object-based image analysis rulesets

2009 Rule Set

1. Create Scene Subset
    1.1 Create Scene Tiles
        1.1.1 Tile Size Parameters
            1.1.1.1 Tile Height: 5000
            1.1.1.2 Tile Width: 5000
    1.2 Submit Scenes for Analysis
        1.2.1 Type of Scene Tiles: tiles
        1.2.2 Process Name: On Tiles
        1.2.3 Percent of Tiles to Submit: 100
2. Segmentation
    2.1 Multiresolution Segmentation
        2.1.1 Image Layer Weights: Blue 1, Green 1, Red 2, NIR 1
        2.1.2 Scale Parameter: 25
        2.1.3 Shape: 0.1
        2.1.4 Compactness: 0.5
        2.1.5 Number of cycles: 1
    2.2 Spectral Difference Segmentation
        2.2.1 Maximum Spectral Difference: 5
        2.2.2 Image Layer Weights: Blue 1, Green 1, Red 2, NIR 1
        2.2.3 Number of cycles: 1
3. Classification
    3.1 Narrow Linear Features
        3.1.1 Assign Class
            3.1.1.1 Class filter: Unclassified
            3.1.1.2 Use Class: Narrow Linear Features
            3.1.1.3 Number of cycles: 1
            3.1.1.4 Conditions:
                3.1.1.4.1 Length/Width > = 25
        3.1.2 Assign Class
            3.1.2.1 Class filter: Unclassified
            3.1.2.2 Use Class: Narrow Linear Features
            3.1.2.3 Number of cycles: 1
            3.1.2.4 Conditions:
                3.1.2.4.1 Asymmetry > = 0.95
        3.1.3 Assign Class
            3.1.3.1 Class filter: Unclassified
            3.1.3.2 Use Class: Narrow Linear Features
            3.1.3.3 Number of cycles: 1
            3.1.3.4 Conditions
                3.1.3.4.1 Density < = 0.8
        3.1.4 Assign Class

        3.1.4.1 Class filter: Narrow Linear Features
        3.1.4.2 Use Class: Undefined
        3.1.4.3 Number of cycles: 1
        3.1.4.4 Conditions:
            3.1.4.4.1 Mean Red < = 145
    3.1.5Assign Class
        3.1.5.1 Class filter: Narrow Linear Features
        3.1.5.2 Use Class: Undefined
        3.1.5.3 Number of cycles: 1
        3.1.5.4 Conditions:
            3.1.5.4.1 Mean Red > = 230
    3.1.6 Assign Class
        3.1.6.1 Class filter: Narrow Linear Features
        3.1.6.2 Use Class: Undefined
        3.1.6.3 Number of cycles: 1
        3.1.6.4 Conditions:
            3.1.6.4.1 Mean Green < 151
    3.1.7 Merge Region
        3.1.7.1 Class filter: Narrow Linear Features
        3.1.7.2 Number of cycles: 1
3.2 Small Area Features
    3.2.1 Assign Class
        3.2.1.1 Class filter: Unclassified
        3.2.1.2 Use Class: Small Area Features
        3.2.1.3 Number of cycles: 1
        3.2.1.4 Conditions:
            3.2.1.4.1 Brightness > = 140
            3.2.1.4.2 Mean Red > = 180
    3.2.2 Assign Class
        3.2.2.1 Class filter: Small Area Features
        3.2.2.2 Use Class: Undefined
        3.2.2.3 Number of cycles: 1
        3.2.2.4 Conditions:
            3.2.2.4.1 Area (pixels) < = 500
            3.2.2.4.2 Shape Index < = 2.5
    3.2.3 Assign Class
        3.2.3.1 Class filter: Small Area Features
        3.2.3.2 Use Class: Undefined
        3.2.3.3 Number of cycles: 1
        3.2.3.4 Conditions:
            3.2.3.4.1 NDVI < = -0.12
    3.2.4 Assign Class
        3.2.4.1 Class filter: Undefined
        3.2.4.2 Use Class: Small Area Features
        3.2.4.3 Number of cycles: 1
        3.2.4.4 Conditions:

3.2.4.4.1 Shape Index < = 7
3.2.4.4.2 Shape Index > = 2.6
3.2.5 Merge Region
3.2.5.1 Class filter: Small Area Features
3.2.5.2 Number of cycles: 1
3.2.6 Merge Region
3.2.6.1 Class filter: Undefined
3.2.6.2 Number of cycles: 1
3.2.7 Assign Class
3.2.7.1 Class filter: Unclassified
3.2.7.2 Use Class: Small Area Features
3.2.7.3 Number of cycles: 1
3.2.7.4 Conditions:
3.2.7.4.1 Mean Red > = 170
3.2.7.4.2 Mean Red < = 200
3.2.8 Assign Class
3.2.8.1 Class filter: Small Area Features
3.2.8.2 Use Class: Undefined
3.2.8.3 Number of cycles: 1
3.2.8.4 Conditions:
3.2.8.4.1 Shape Index > = 16
3.2.9 Assign Class
3.2.9.1 Class filter: Small Area Features
3.2.9.2 Use Class: Undefined
3.2.9.3 Number of cycles: 1
3.2.9.4 Conditions:
3.2.9.4.1 Area (pixels) < = 2500
3.2.10 Assign Class
3.2.10.1 Class filter: Small Area Features
3.2.10.2 Use Class: Undefined
3.2.10.3 Number of Cycles: 1
3.2.10.4 Conditions:
3.2.10.4.1 Area (pixels) > = 50000
3.2.11 Assign Class
3.2.11.1 Class filter: Undefined
3.2.11.2 Use Class: Unclassified
3.2.11.3 Number of cycles: 1
3.2.12 Merge Region
3.2.12.1 Class filter: Small Area Features
3.2.13.2 Number of cycles: 1
3.2.13 Assign Class
3.2.13.1 Class filter: Small Area Features
3.2.13.2 Use Class: Unclassified
3.2.13.3 Number of cycles: 1
3.2.13.4 Conditions:
3.2.13.4.1 Asymmetry > = 0.75

4. Export to Polygon
    4.1 Export vector layer
        4.1.1 Class filter: Narrow Linear Features
    4.2 Export vector layer
        4.2.1 Class filter: Small Area Features

2014 Rule Set

1. Create Scene Subset
    - 1.1 Create Scene Tiles
        - 1.1.1 Tile Size Parameters
            - 1.1.1.1 Tile Height: 5000
            - 1.1.1.2 Tile Width: 5000
    - 1.2 Submit Scenes for Analysis
        - 1.2.1 Type of Scene Tiles: tiles
        - 1.2.2 Process Name: On Tiles
        - 1.2.3 Percent of Tiles to Submit: 100
2. Segmentation
    - 2.1 Multiresolution Segmentation
        - 2.1.1 Image Layer Weights: Blue 1, Green 1, Red 2, NIR 1
        - 2.1.2 Scale Parameter: 25
        - 2.1.3 Shape: 0.1
        - 2.1.4 Compactness: 0.5
        - 2.1.5 Number of cycles: 1
    - 2.2 Spectral Difference Segmentation
        - 2.2.1 Maximum Spectral Difference: 5
        - 2.2.2 Image Layer Weights: Blue 1, Green 1, Red 2, NIR 1
        - 2.2.3 Number of cycles: 1
3. Classification
    - 3.1 Narrow Linear Features
        - 3.1.1 Assign Class
            - 3.1.1.1 Class filter: Unclassified
            - 3.1.1.2 Use Class: Narrow Linear Features
            - 3.1.1.3 Number of cycles: 1
            - 3.1.1.4 Conditions:
                - 3.1.1.4.1 Length/Width > = 30
        - 3.1.2 Assign Class
            - 3.1.2.1 Class filter: Unclassified
            - 3.1.2.2 Use Class: Narrow Linear Features
            - 3.1.2.3 Number of cycles: 1
            - 3.1.2.4 Conditions:
                - 3.1.2.4.1 Asymmetry > = 0.95
        - 3.1.3 Assign Class
            - 3.1.3.1 Class filter: Unclassified
            - 3.1.3.2 Use Class: Narrow Linear Features
            - 3.1.3.3 Number of cycles: 1
            - 3.1.3.4 Conditions
                - 3.1.3.4.1 Density < = 0.7
        - 3.1.4 Assign Class
            - 3.1.4.1 Class filter: Narrow Linear Features
            - 3.1.4.2 Use Class: Undefined
            - 3.1.4.3 Number of cycles: 1

3.1.4.4 Conditions:
3.1.4.4.1 Mean Red < = 155
3.1.5Assign Class
3.1.5.1 Class filter: Narrow Linear Features
3.1.5.2 Use Class: Undefined
3.1.5.3 Number of cycles: 1
3.1.5.4 Conditions:
3.1.5.4.1 Mean Red > = 254
3.1.6 Assign Class
3.1.6.1 Class filter: Narrow Linear Features
3.1.6.2 Use Class: Undefined
3.1.6.3 Number of cycles: 1
3.1.6.4 Conditions:
3.1.6.4.1 Mean Green < 170
3.1.7 Merge Region
3.1.7.1 Class filter: Narrow Linear Features
3.1.7.2 Number of cycles: 1
3.2 Small Area Features
3.2.1 Assign Class
3.2.1.1 Class filter: Unclassified
3.2.1.2 Use Class: Small Area Features
3.2.1.3 Number of cycles: 1
3.2.1.4 Conditions:
3.2.1.4.1 Brightness > = 150
3.2.1.4.2 Mean Red > = 190
3.2.2 Assign Class
3.2.2.1 Class filter: Small Area Features
3.2.2.2 Use Class: Undefined
3.2.2.3 Number of cycles: 1
3.2.2.4 Conditions:
3.2.2.4.1 Area (pixels) < = 500
3.2.2.4.2 Shape Index < = 2.5
3.2.3 Assign Class
3.2.3.1 Class filter: Small Area Features
3.2.3.2 Use Class: Undefined
3.2.3.3 Number of cycles: 1
3.2.3.4 Conditions:
3.2.3.4.1 NDVI < = -0.12
3.2.4 Assign Class
3.2.4.1 Class filter: Undefined
3.2.4.2 Use Class: Small Area Features
3.2.4.3 Number of cycles: 1
3.2.4.4 Conditions:
3.2.4.4.1 Shape Index < = 7
3.2.4.4.2 Shape Index > = 2.6
3.2.5 Merge Region

3.2.5.1 Class filter: Small Area Features
3.2.5.2 Number of cycles: 1
3.2.6 Merge Region
3.2.6.1 Class filter: Undefined
3.2.6.2 Number of cycles: 1
3.2.7 Assign Class
3.2.7.1 Class filter: Unclassified
3.2.7.2 Use Class: Small Area Features
3.2.7.3 Number of cycles: 1
3.2.7.4 Conditions:
3.2.7.4.1 Mean Red > = 200
3.2.7.4.2 Mean Red < = 205
3.2.8 Assign Class
3.2.8.1 Class filter: Small Area Features
3.2.8.2 Use Class: Undefined
3.2.8.3 Number of cycles: 1
3.2.8.4 Conditions:
3.2.8.4.1 Shape Index > = 16
3.2.9 Assign Class
3.2.9.1 Class filter: Small Area Features
3.2.9.2 Use Class: Undefined
3.2.9.3 Number of cycles: 1
3.2.9.4 Conditions:
3.2.9.4.1 Area (pixels) < = 3000
3.2.10 Assign Class
3.2.10.1 Class filter: Small Area Features
3.2.10.2 Use Class: Undefined
3.2.10.3 Number of Cycles: 1
3.2.10.4 Conditions:
3.2.10.4.1 Area (pixels) > = 80000
3.2.11 Assign Class
3.2.11.1 Class filter: Undefined
3.2.11.2 Use Class: Unclassified
3.2.11.3 Number of cycles: 1
3.2.12 Merge Region
3.2.12.1 Class filter: Small Area Features
3.2.13.2 Number of cycles: 1
3.2.13 Assign Class
3.2.13.1 Class filter: Small Area Features
3.2.13.2 Use Class: Unclassified
3.2.13.3 Number of cycles: 1
3.2.13.4 Conditions:
3.2.13.4.1 Asymmetry > = 0.85

4. Export to Polygon
4.1 Export vector layer
4.1.1 Class filter: Narrow Linear Features

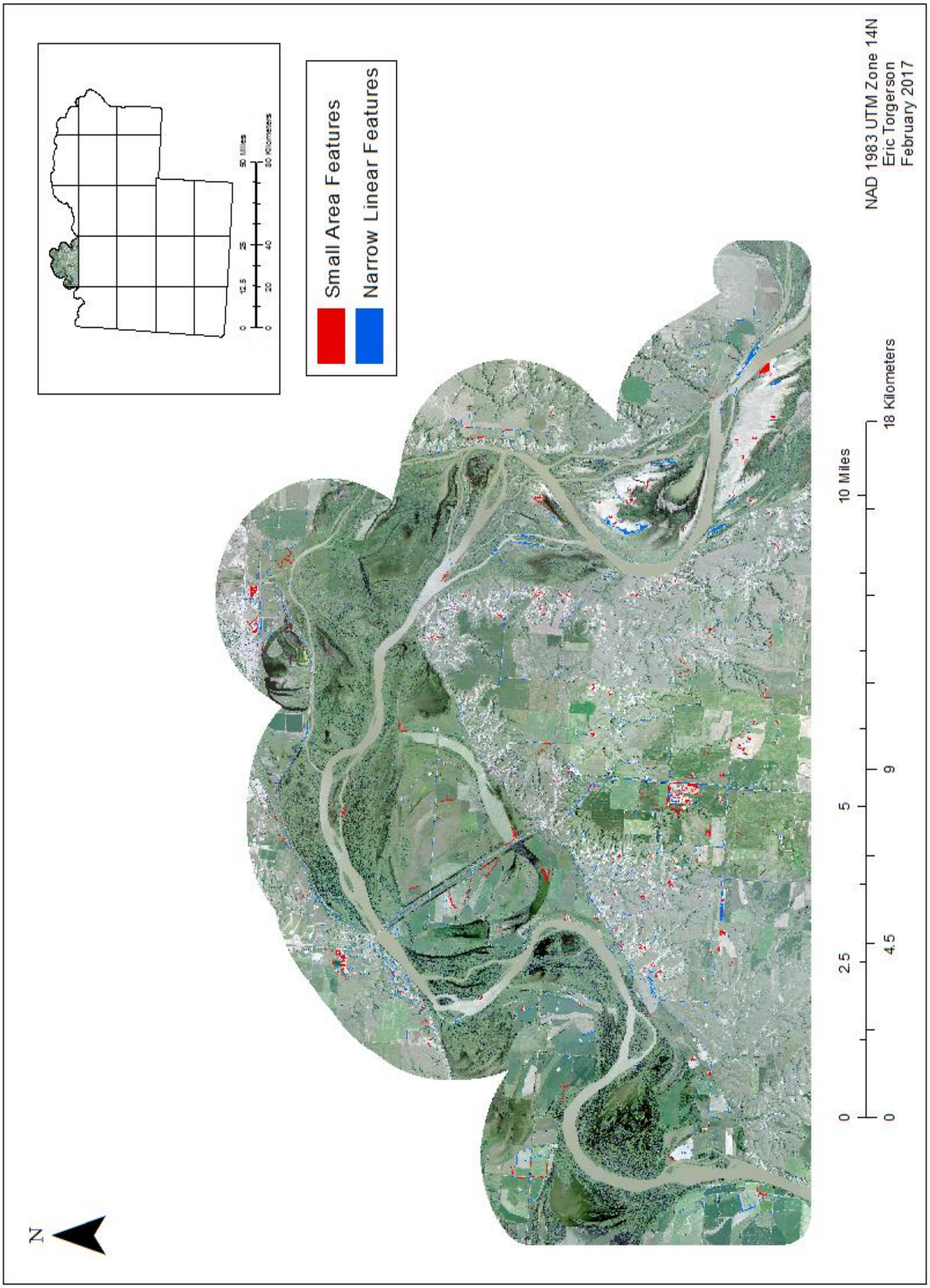
4.2 Export vector layer

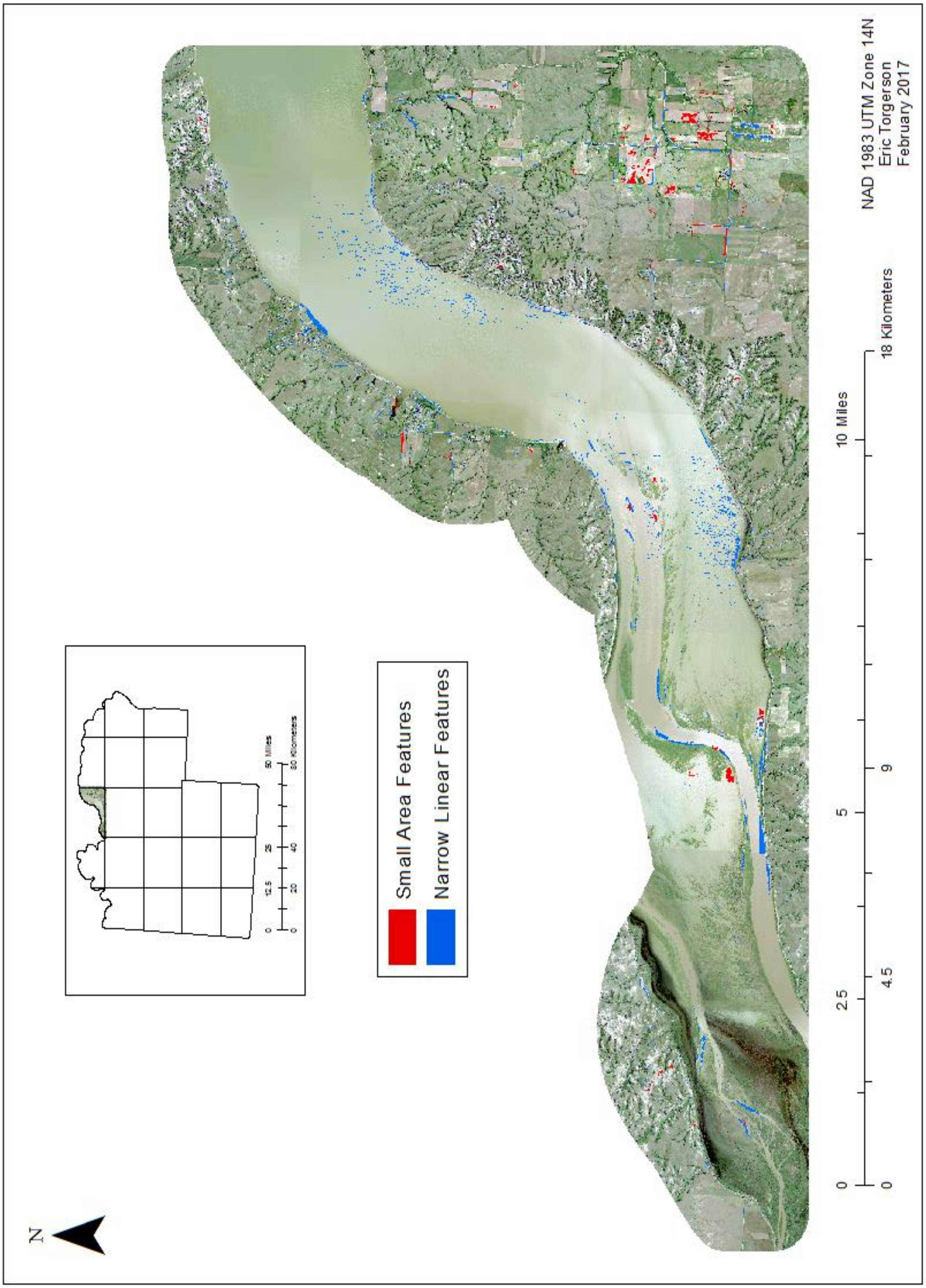
4.2.1 Class filter: Small Area Features

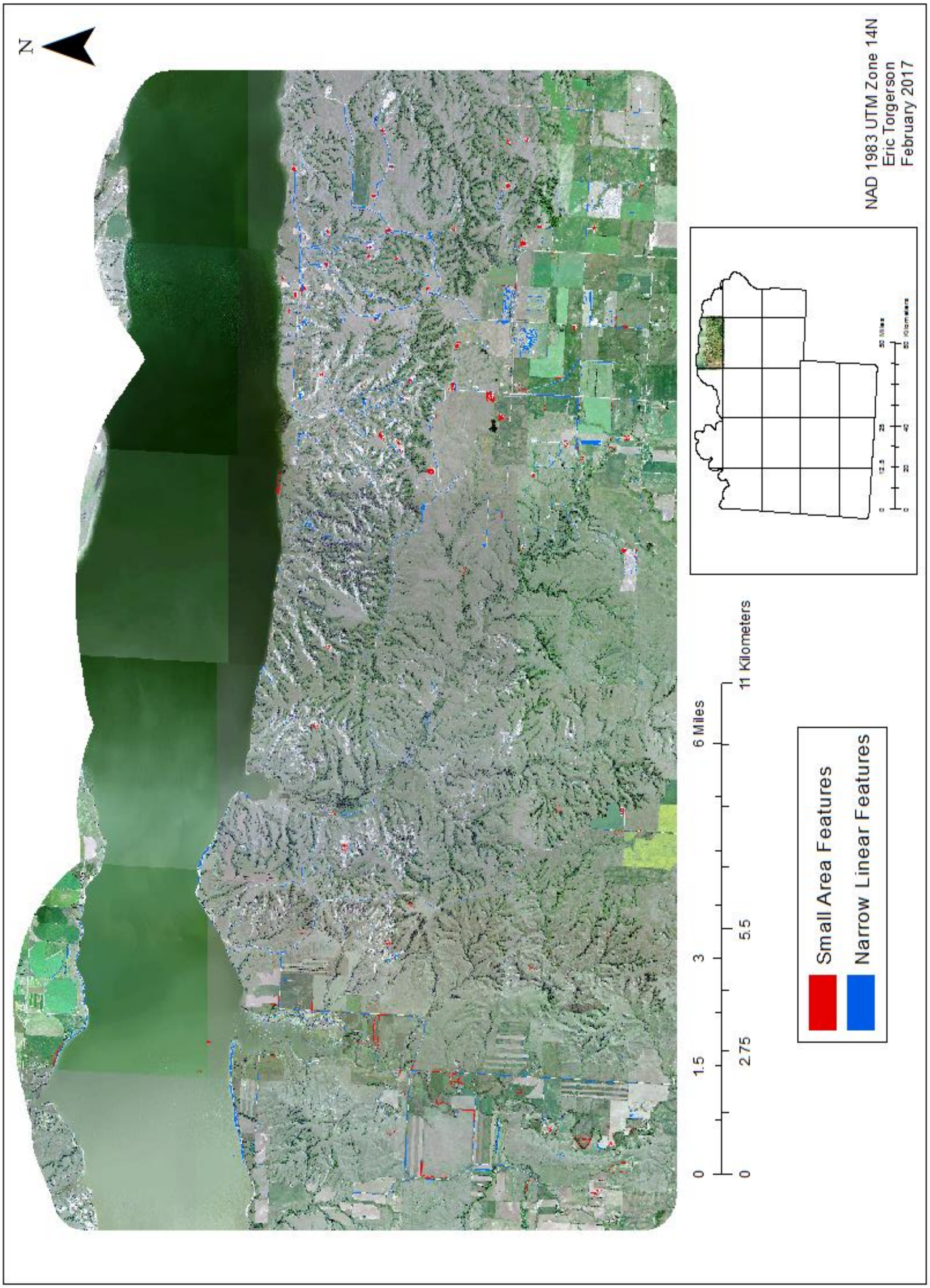
Appendix B

Classification Results

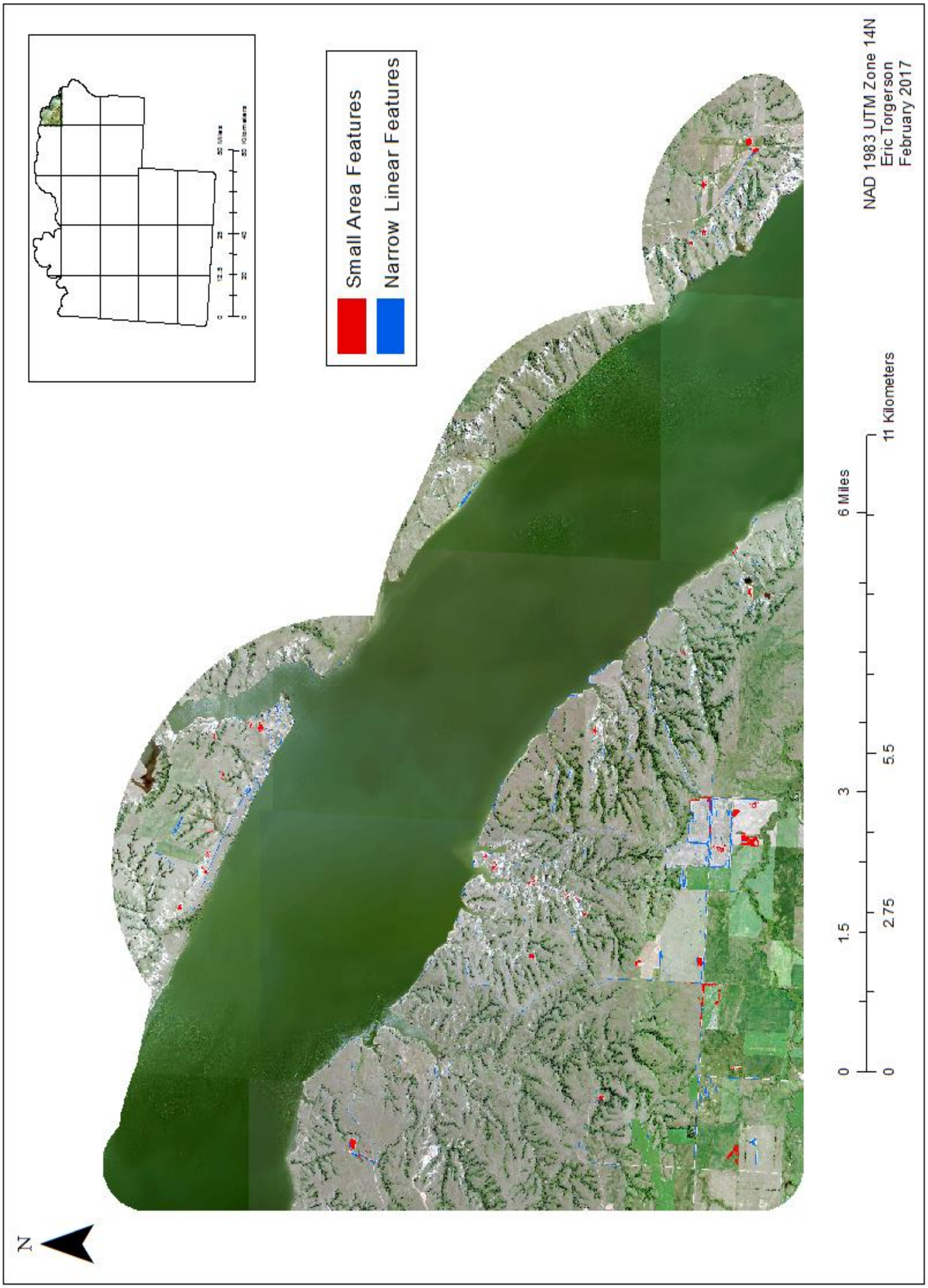
2009 GEOBIA Classifications


Small Area Features
Narrow Linear Features
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 2.5 5 10 Miles
0 4.5 9 18 Kilometers
N


N
Small Area Features
Narrow Linear Features
0 12.5 25 50 Miles
0 20 40 80 Kilometers
0 2.5 5 10 Miles
0 4.5 9 18 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017



N
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 1.5 3 6 Miles
0 2.75 5.5 11 Kilometers
Small Area Features
Narrow Linear Features


Small Area Features
Narrow Linear Features
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
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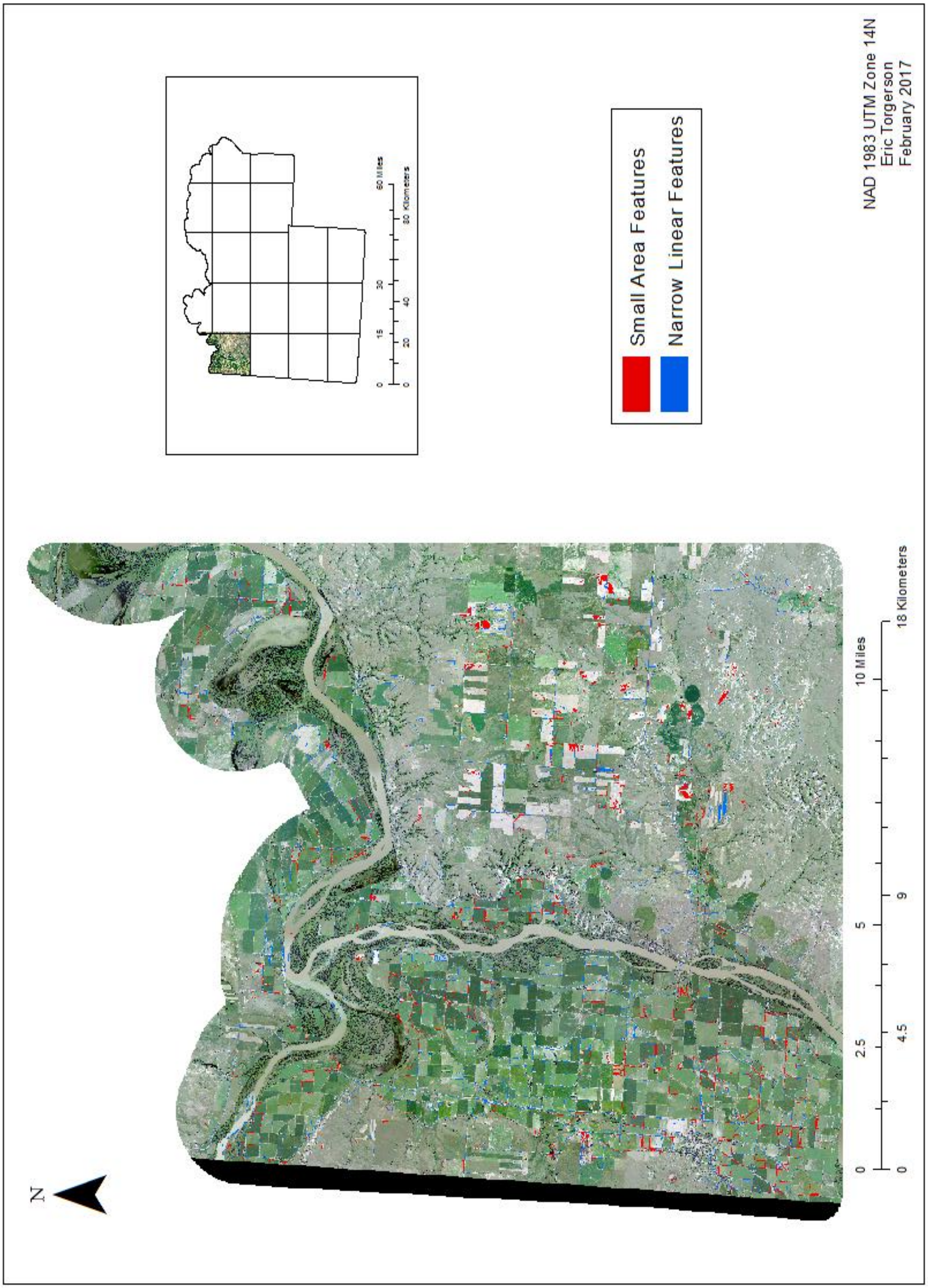
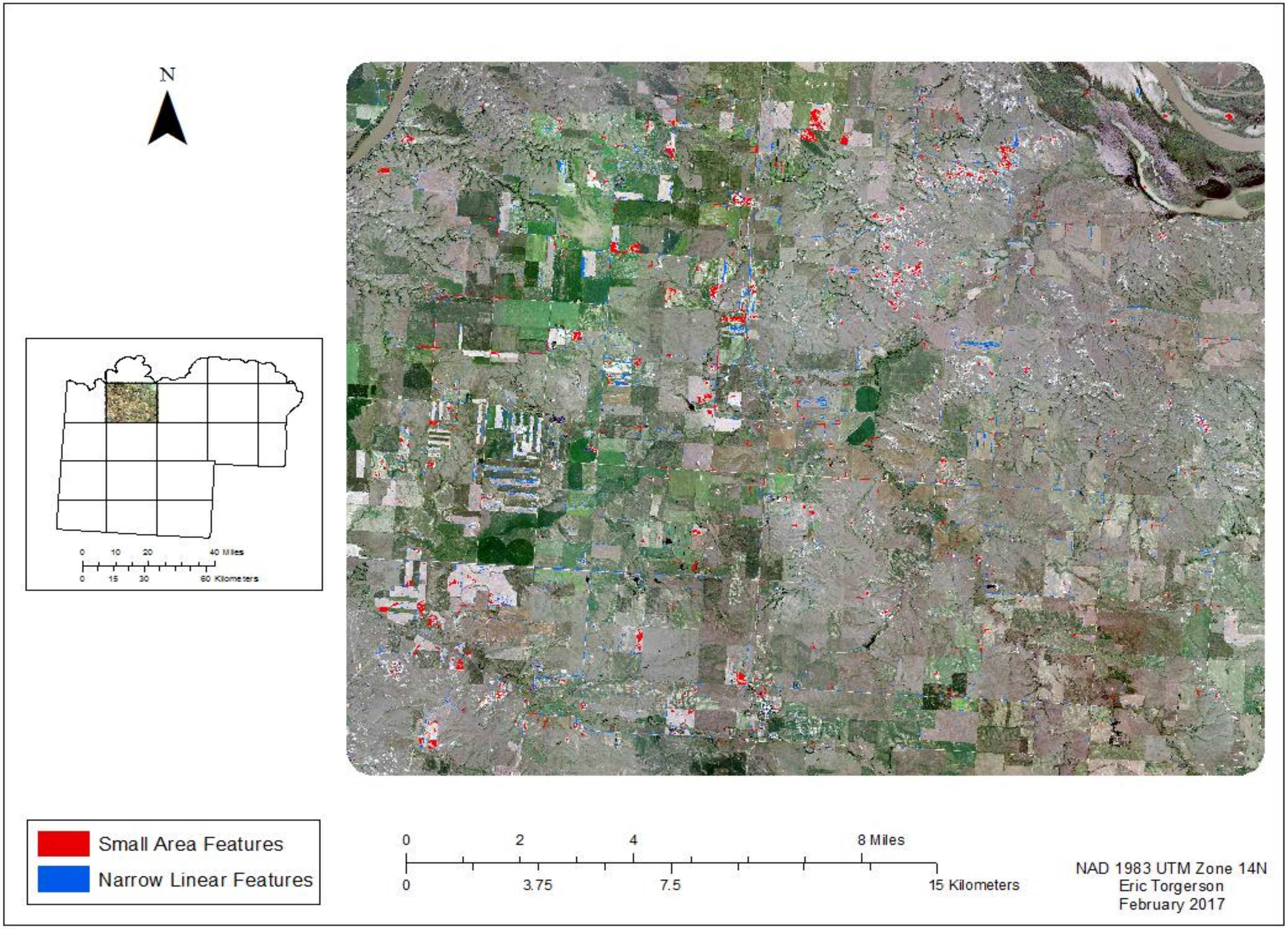
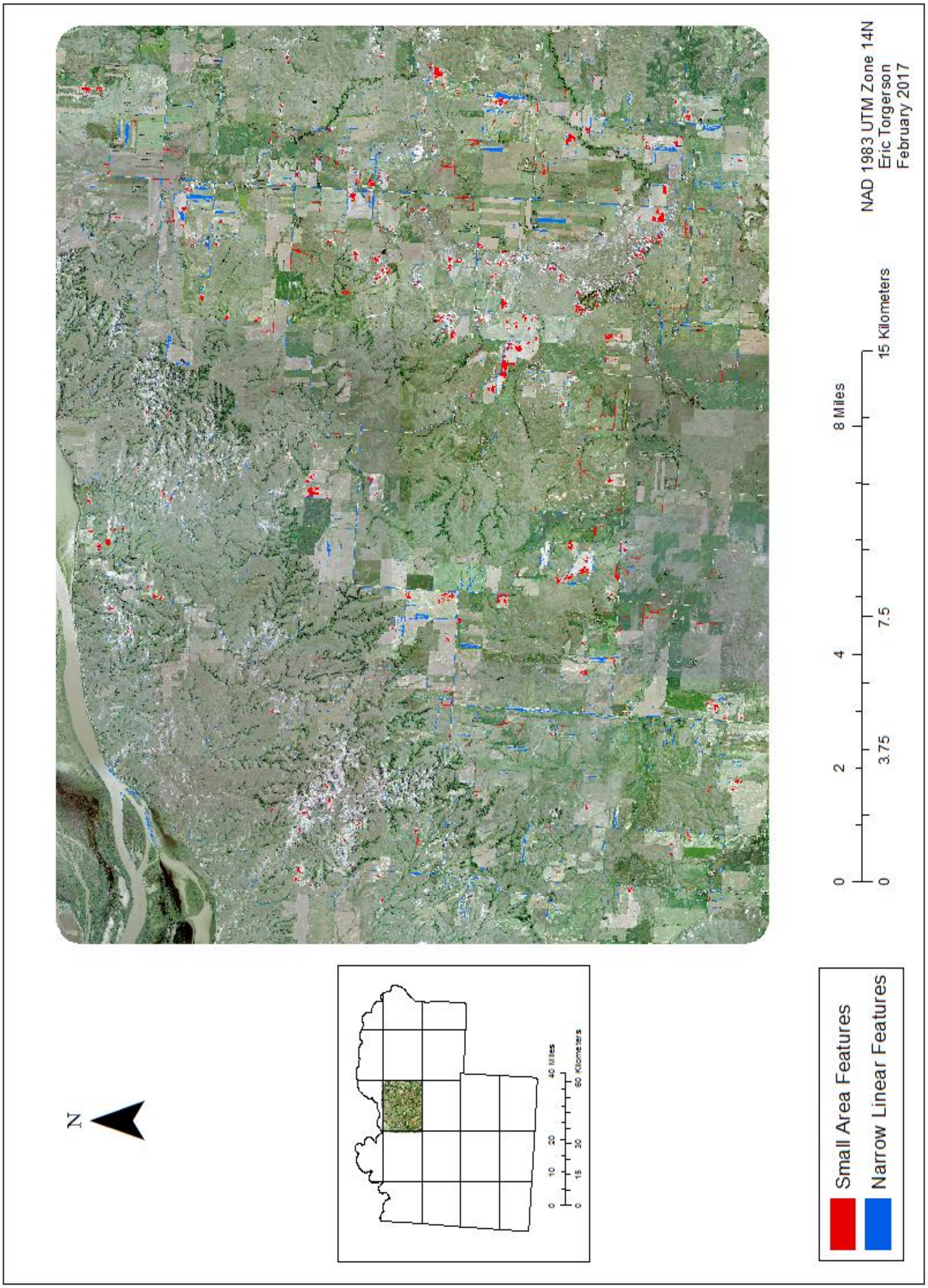
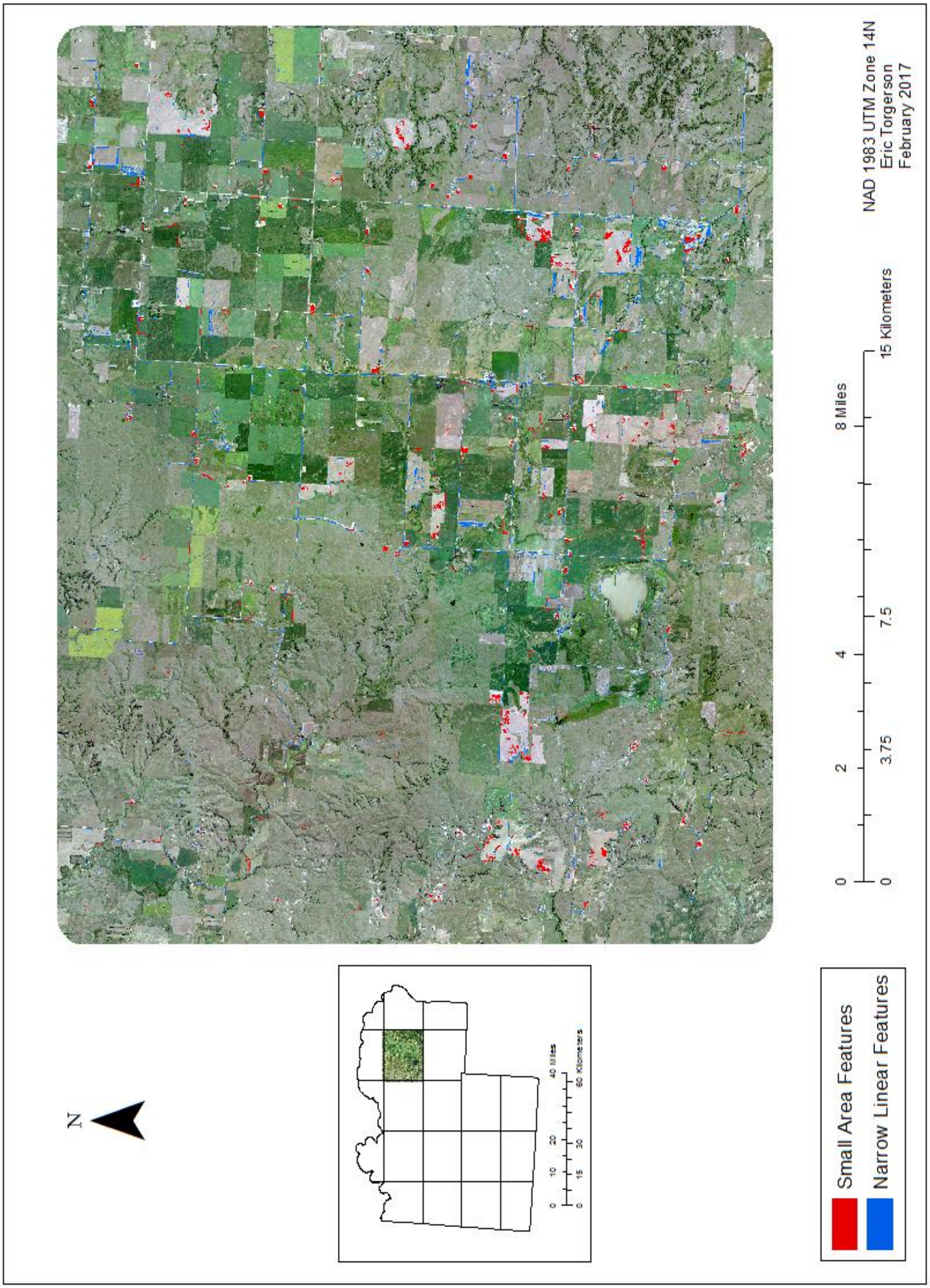
0 2.75 5.5 11 Kilometers
N

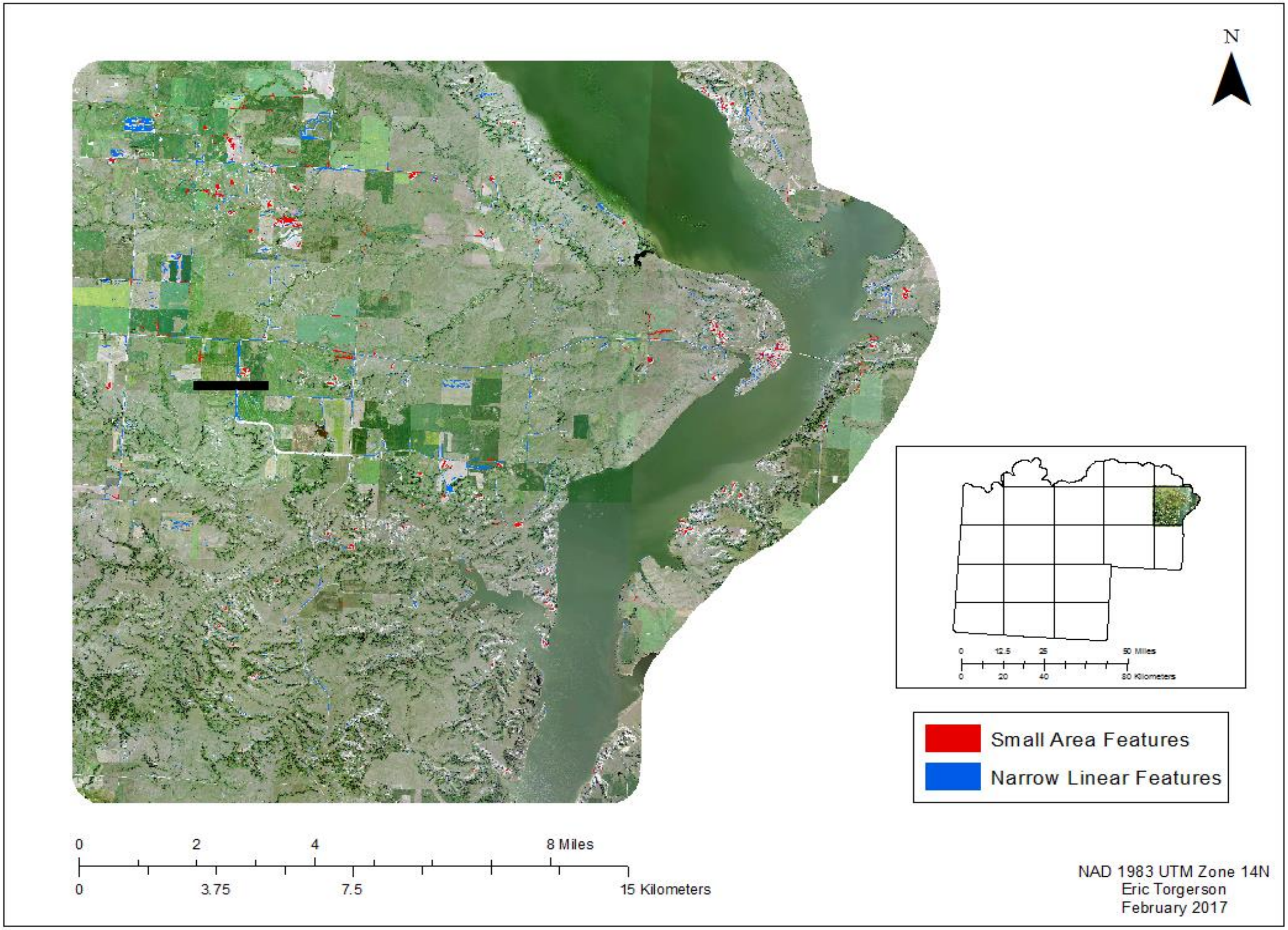

N
0
2.5
5
10 Miles
0
4.5
9
18 Kilometers
0
15
30
60 Miles
0
20
40
80 Kilometers
Small Area Features
Narrow Linear Features
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017

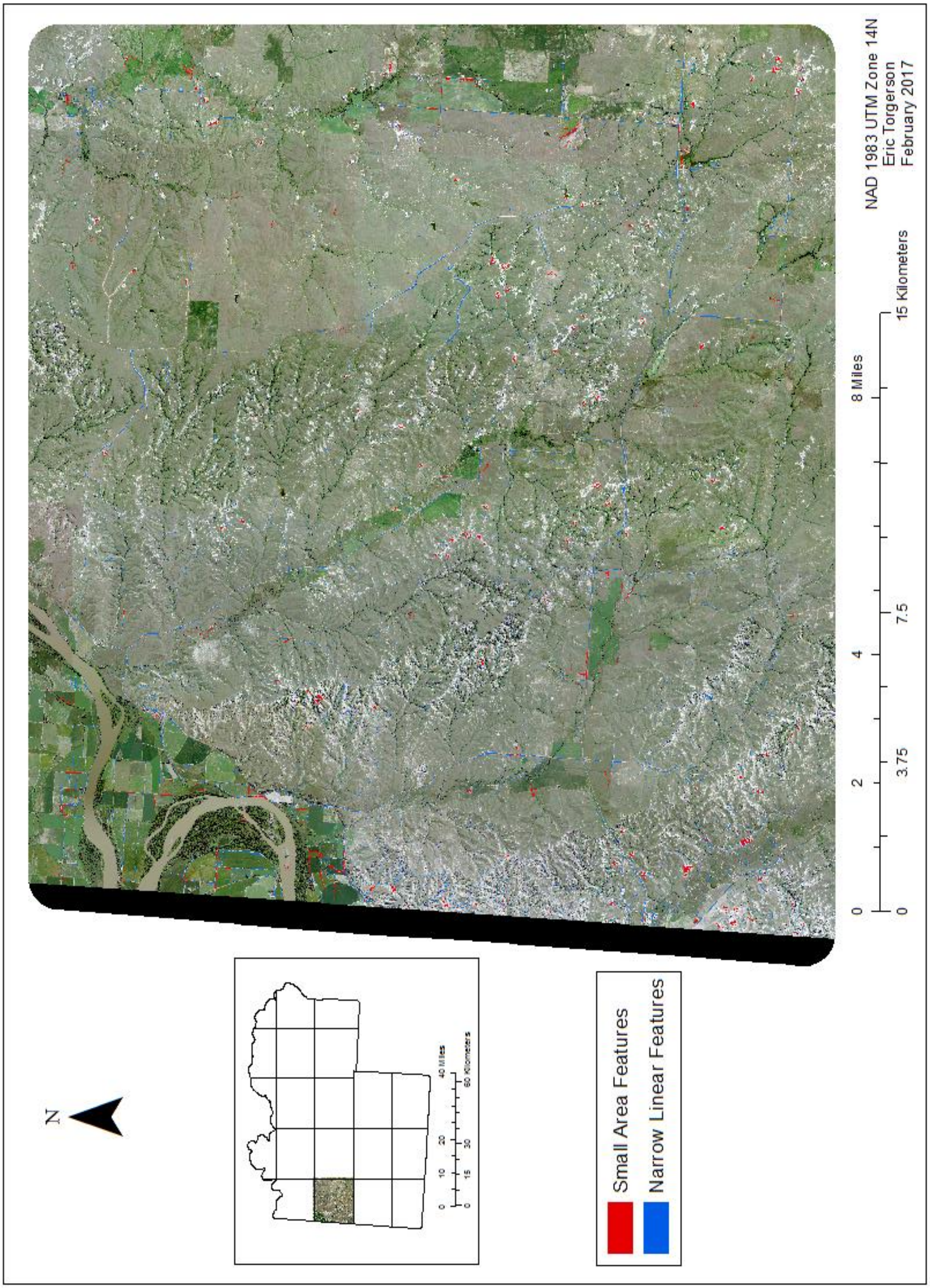

N
0 10 20 40 Miles
0 15 30 60 Kilometers
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017



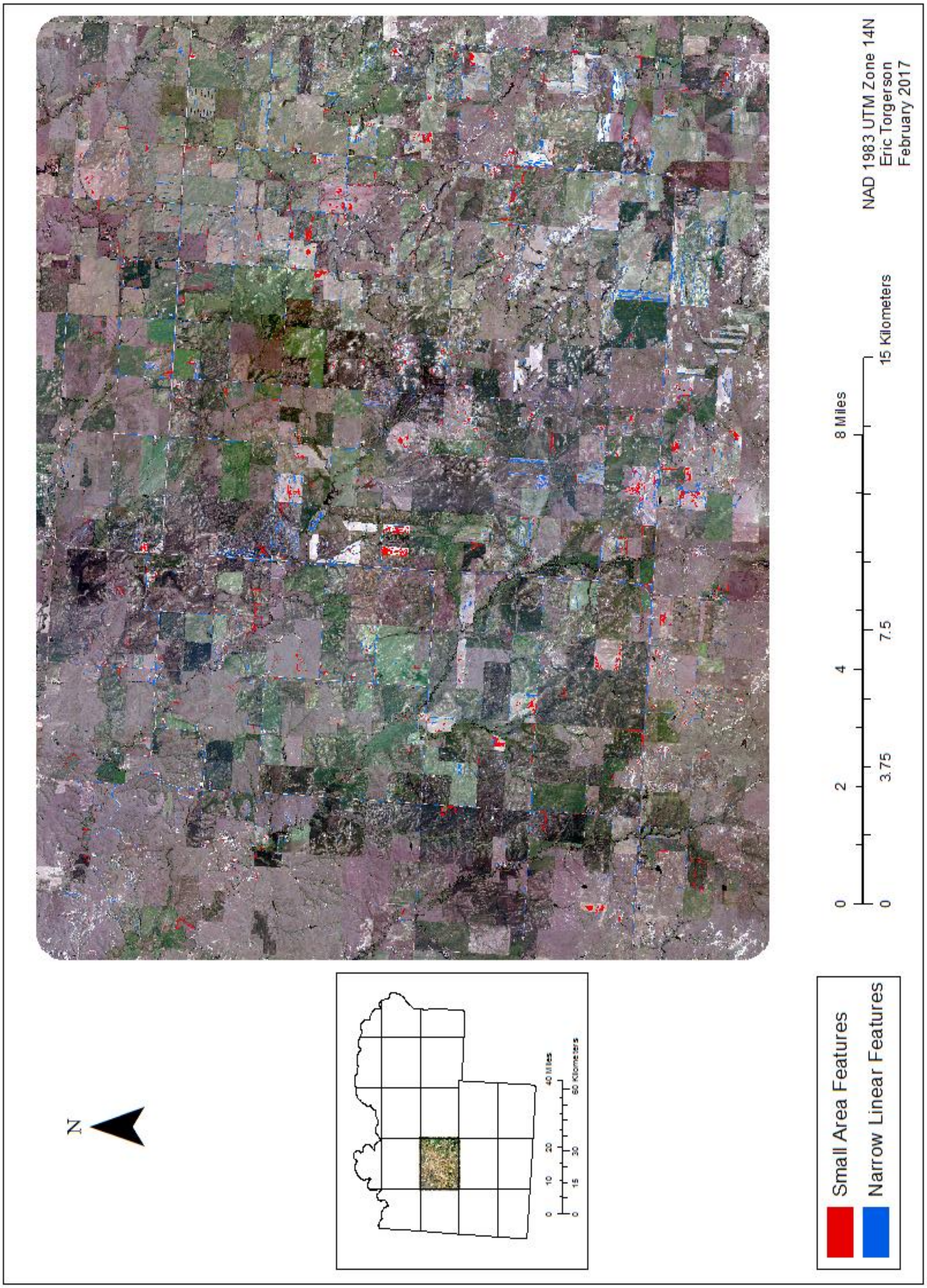
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
N
0 10 20 40 Miles
0 15 30 60 Kilometers
Small Area Features
Narrow Linear Features

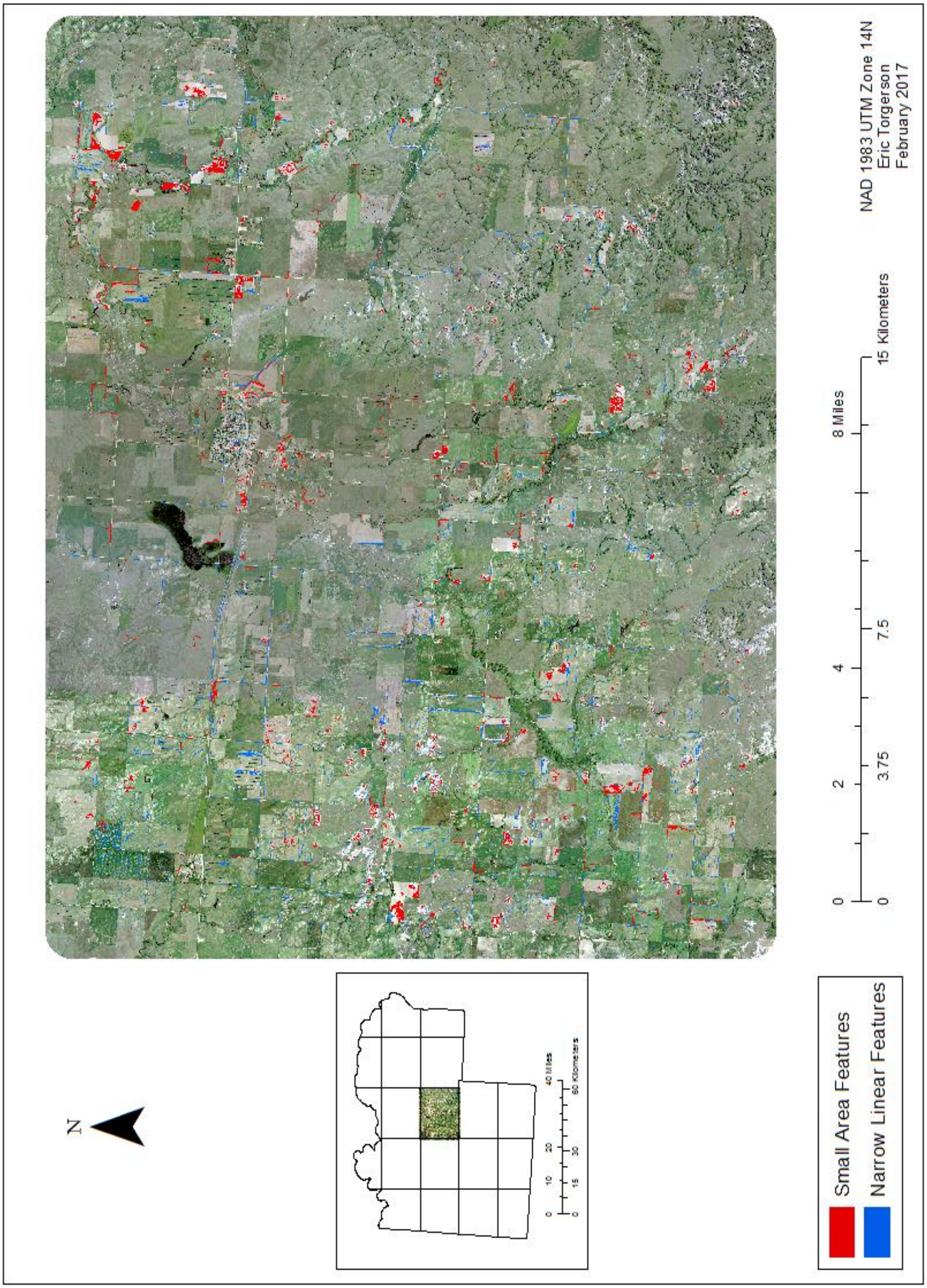

NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
N
0 10 20 40 Miles
0 15 30 60 Kilometers
Small Area Features
Narrow Linear Features


N
Small Area Features
Narrow Linear Features
0 12.5 25 50 Miles
0 20 40 80 Kilometers
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017



NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
N
Small Area Features
Narrow Linear Features


N
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 10 20 40 Miles
0 15 30 60 Kilometers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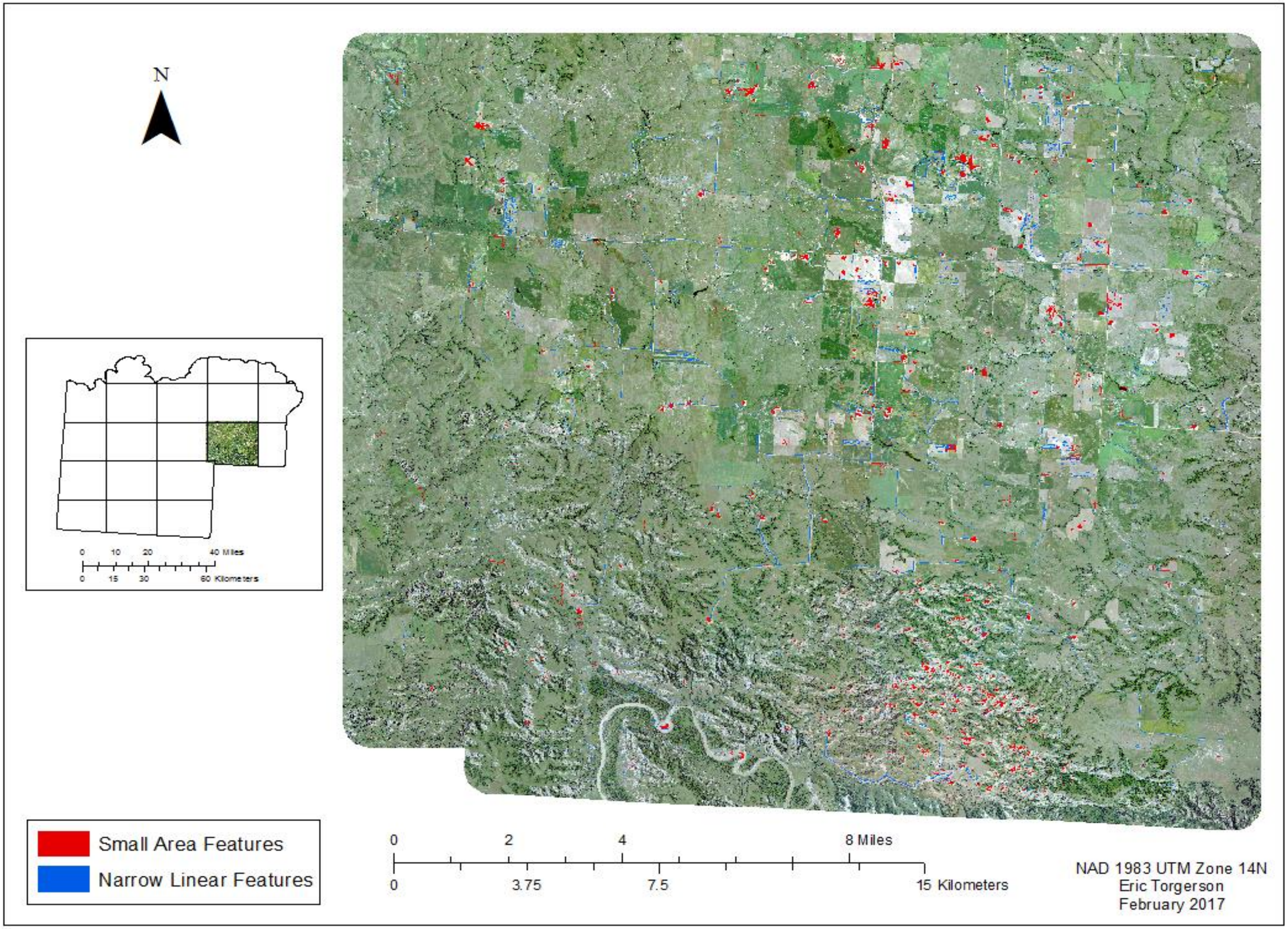
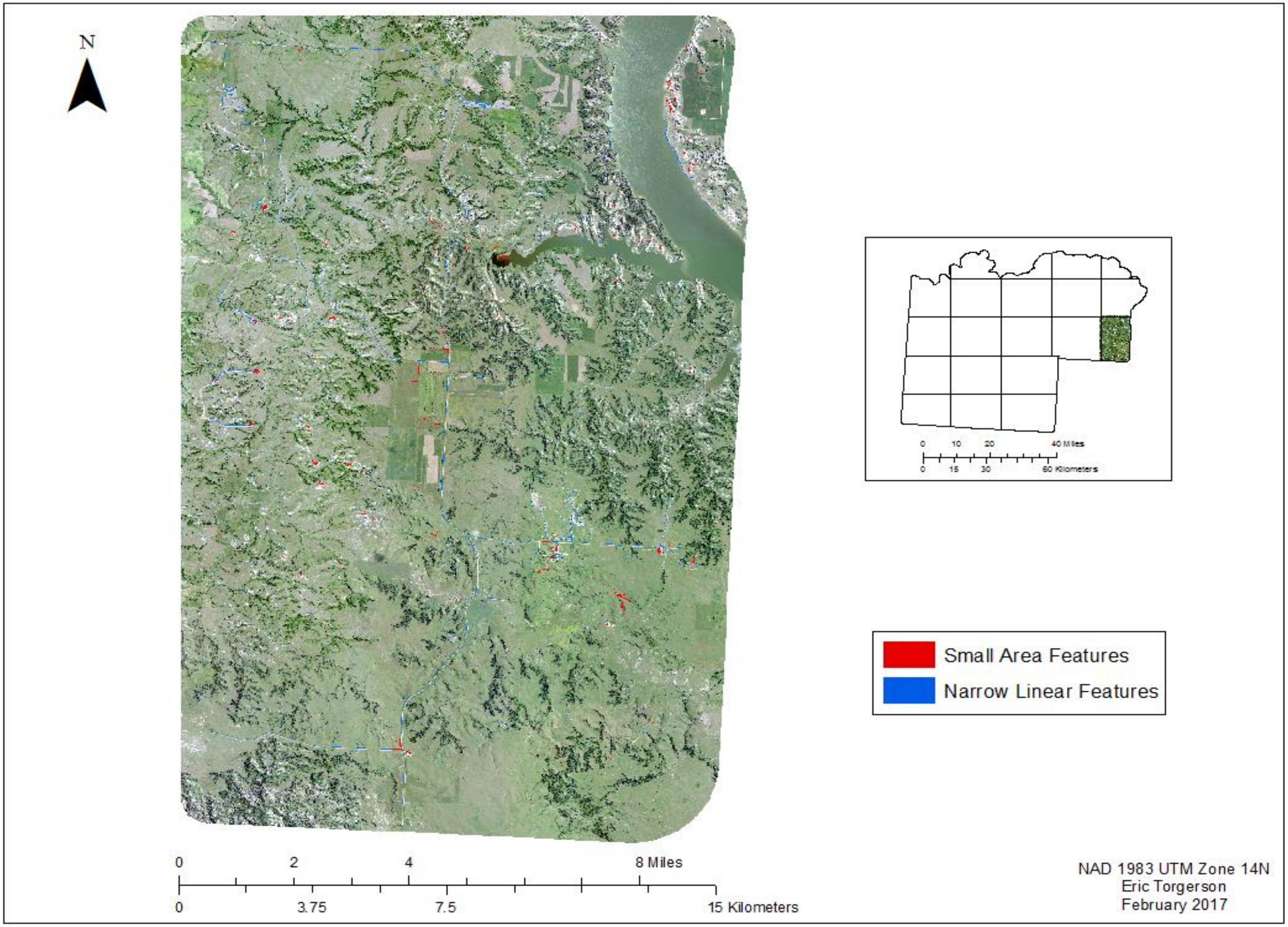
Eric Torgerson
February 2017
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
N
Small Area Features
Narrow Linear Features


N
0 10 20 40 Miles
0 15 30 60 Kilometers
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017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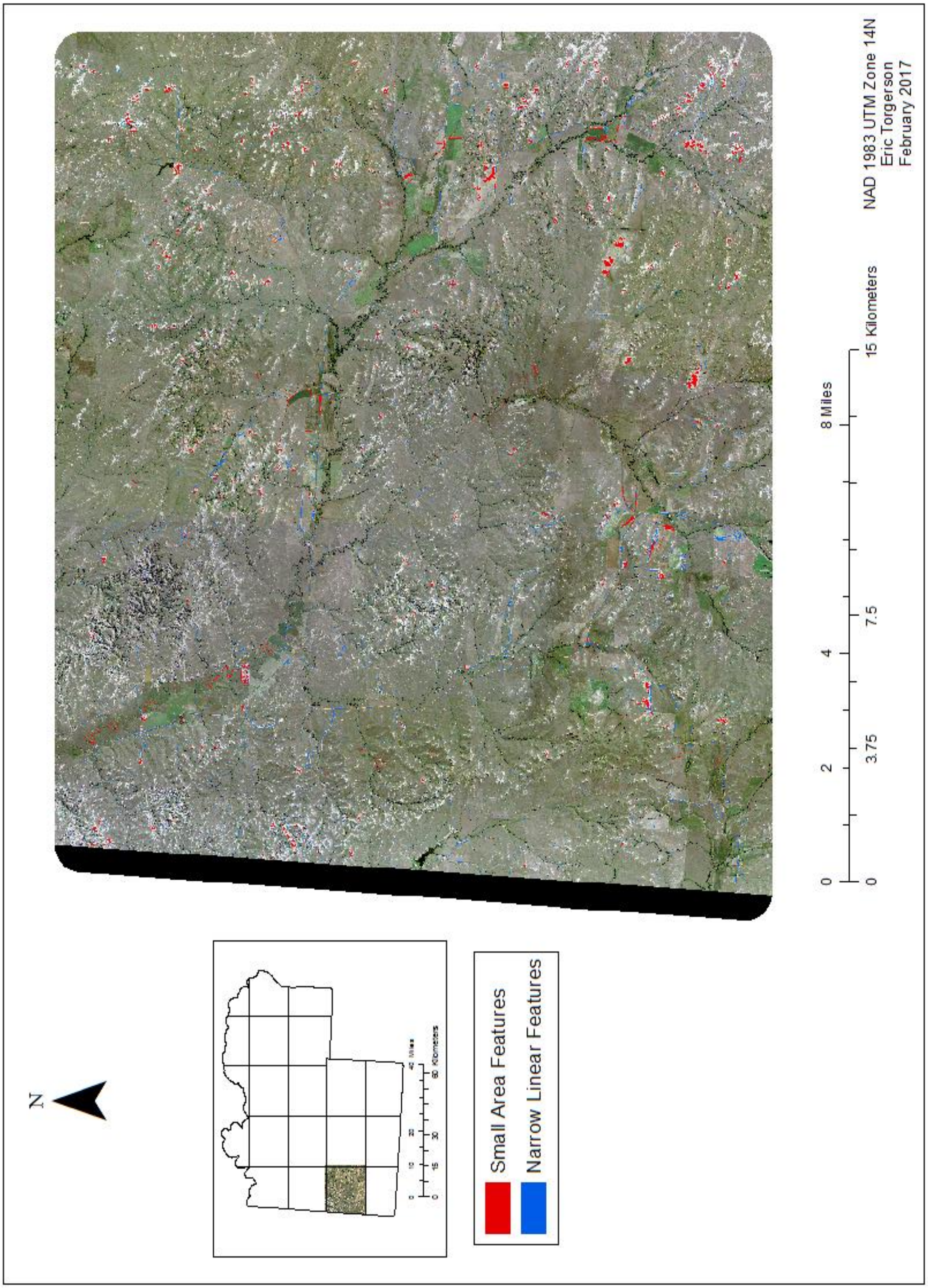
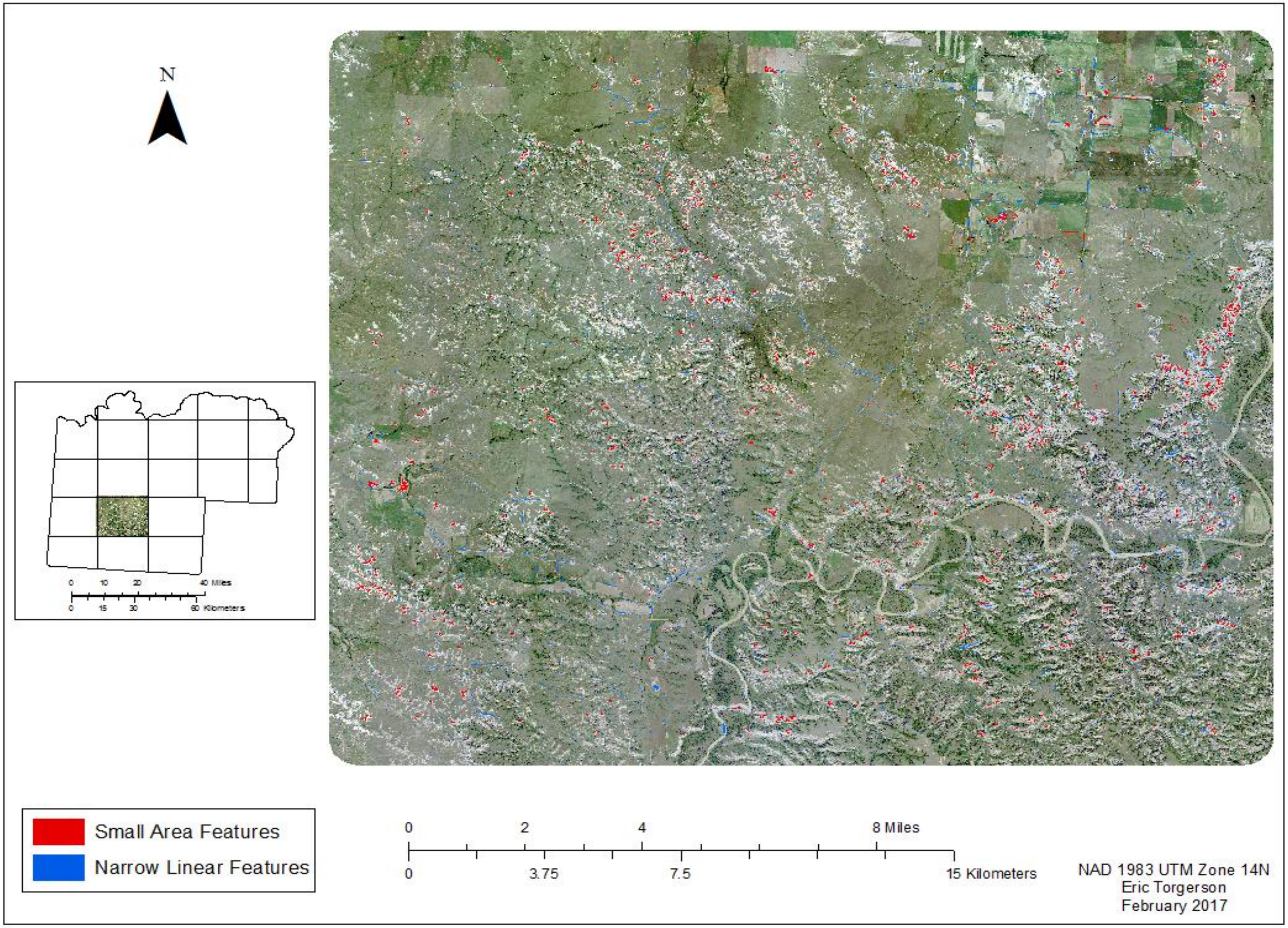
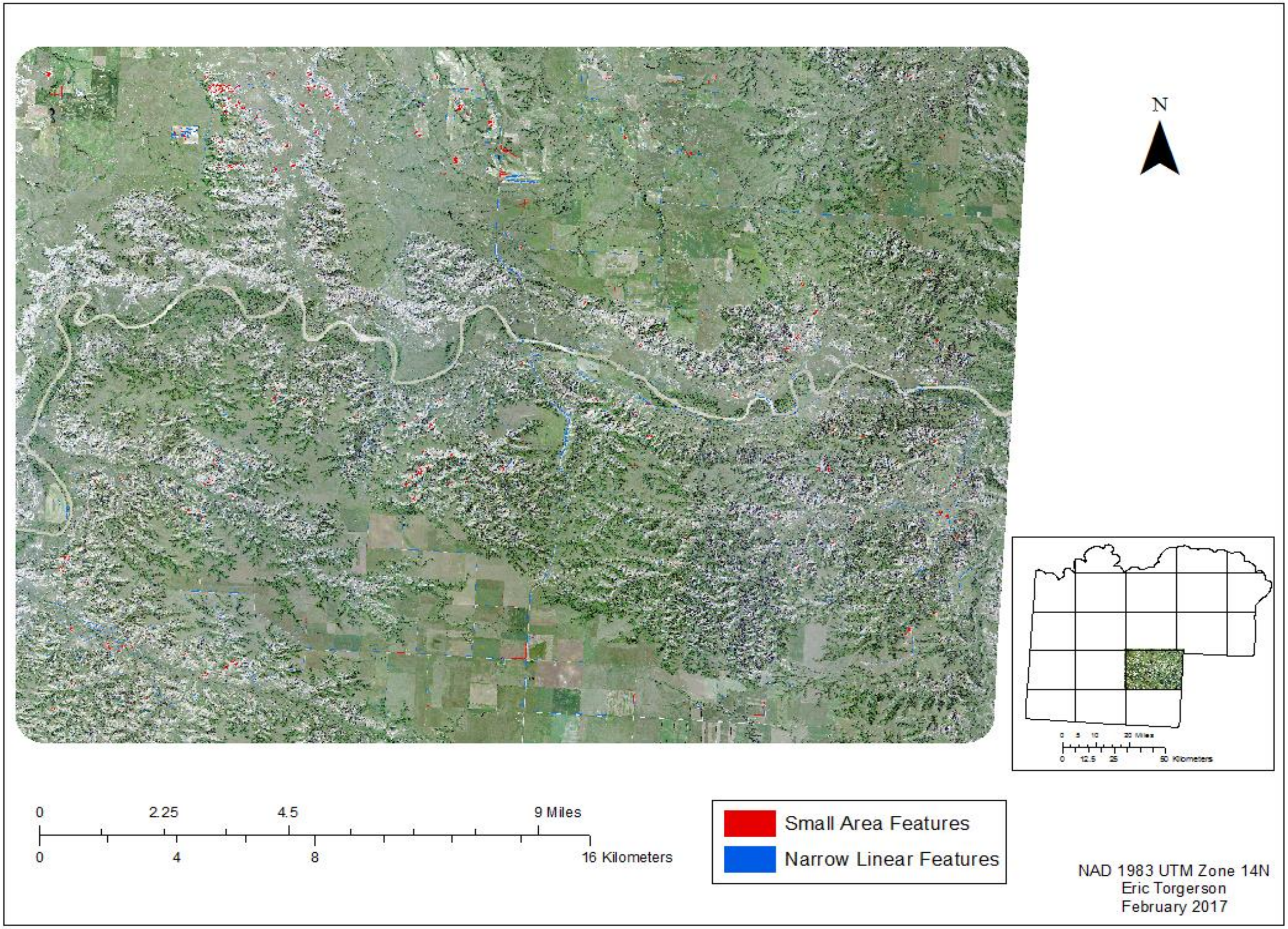
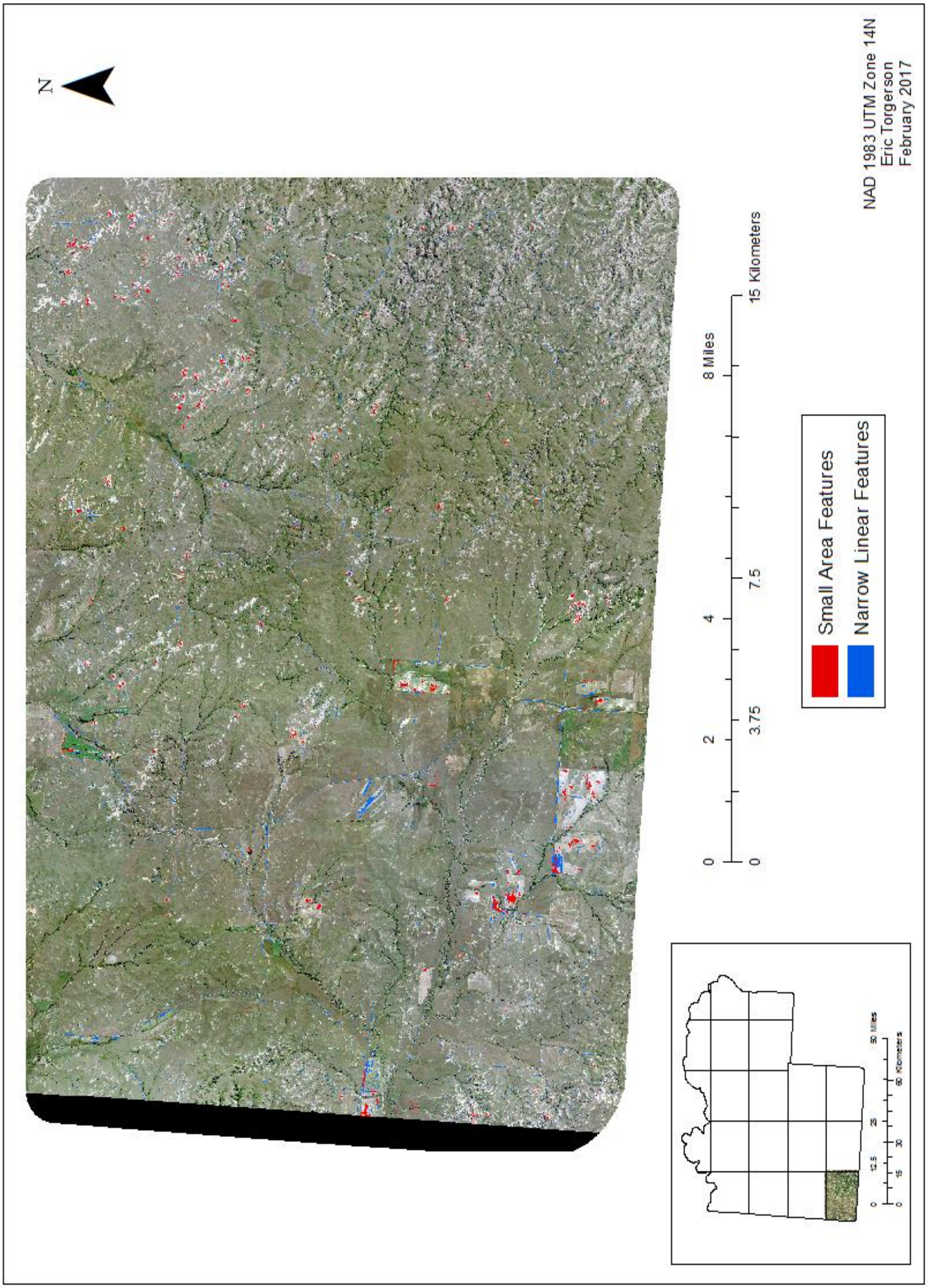
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
0 10 20 40 Miles
0 15 30 60 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017

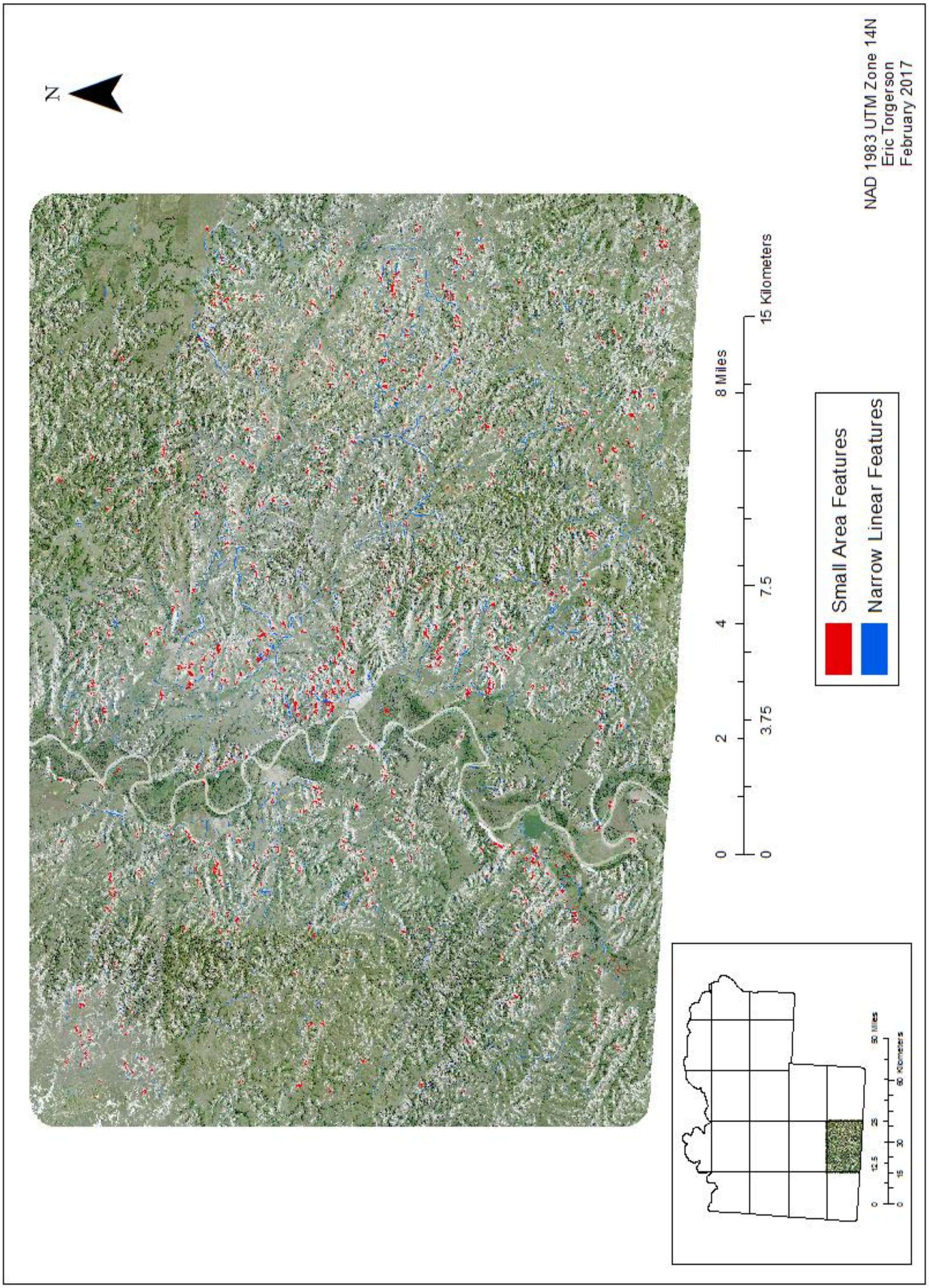


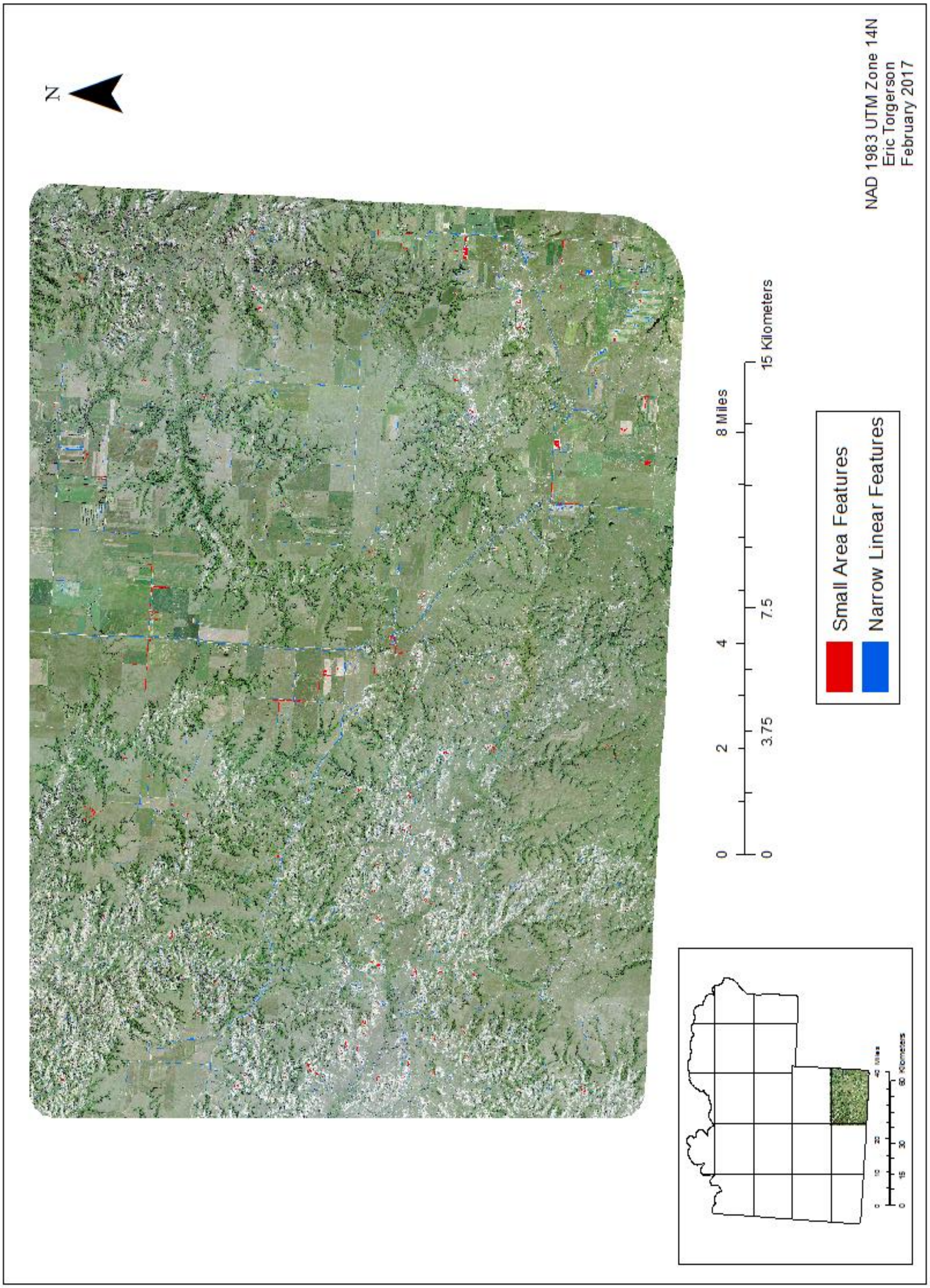
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
N
Small Area Features
Narrow Linear Features


N
0 10 20 40 Miles
0 15 30 60 Kilometers
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017

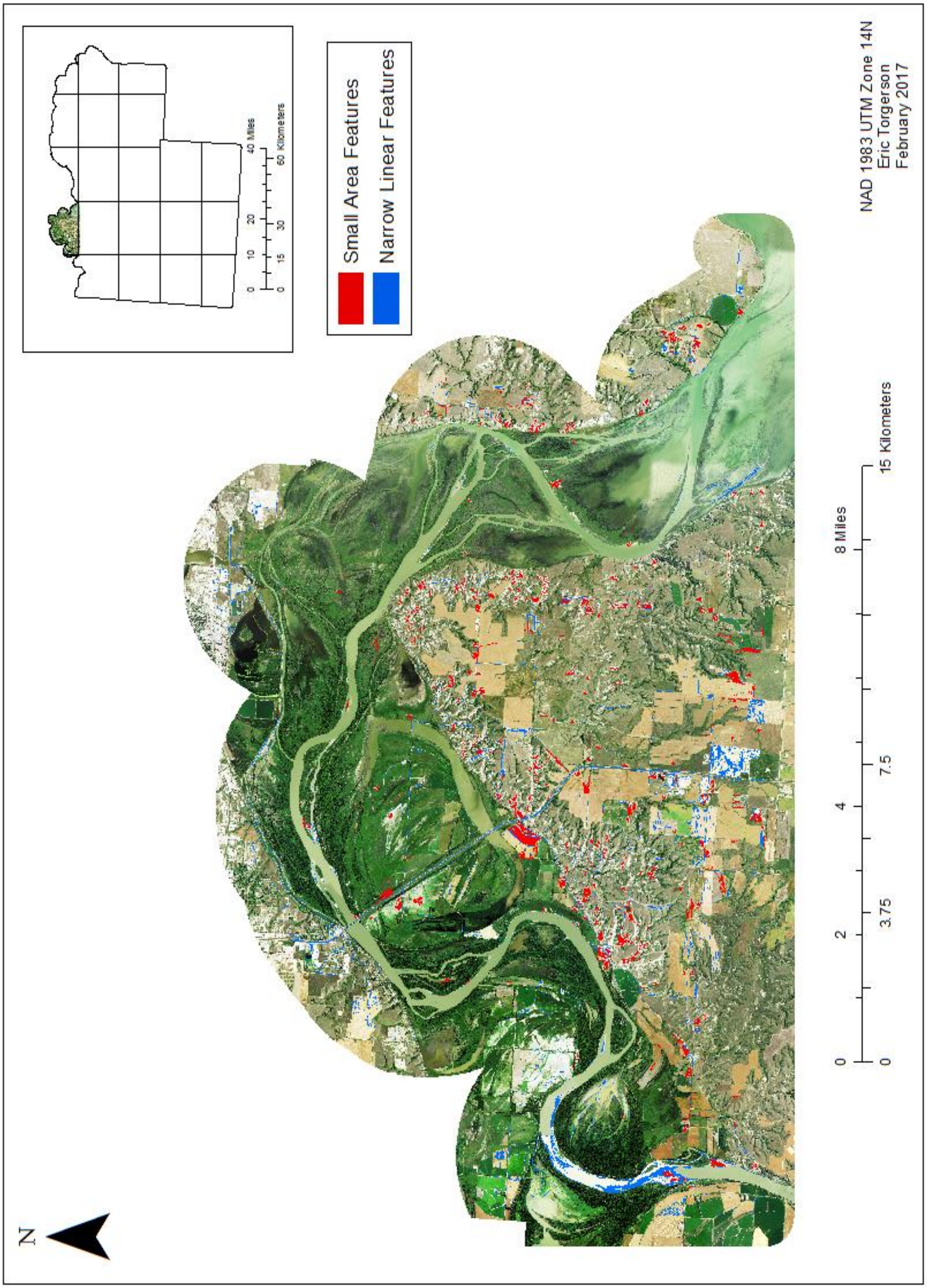

N
0 5 10 20 Miles
0 12.5 25 50 Kilometers
0 2.25 4.5 9 Miles
0 4 8 16 Kilometers
Small Area Features
Narrow Linear Features
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017


N
Small Area Features
Narrow Linear Features
0
2
4
8 Miles
0
3.75
7.5
15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017

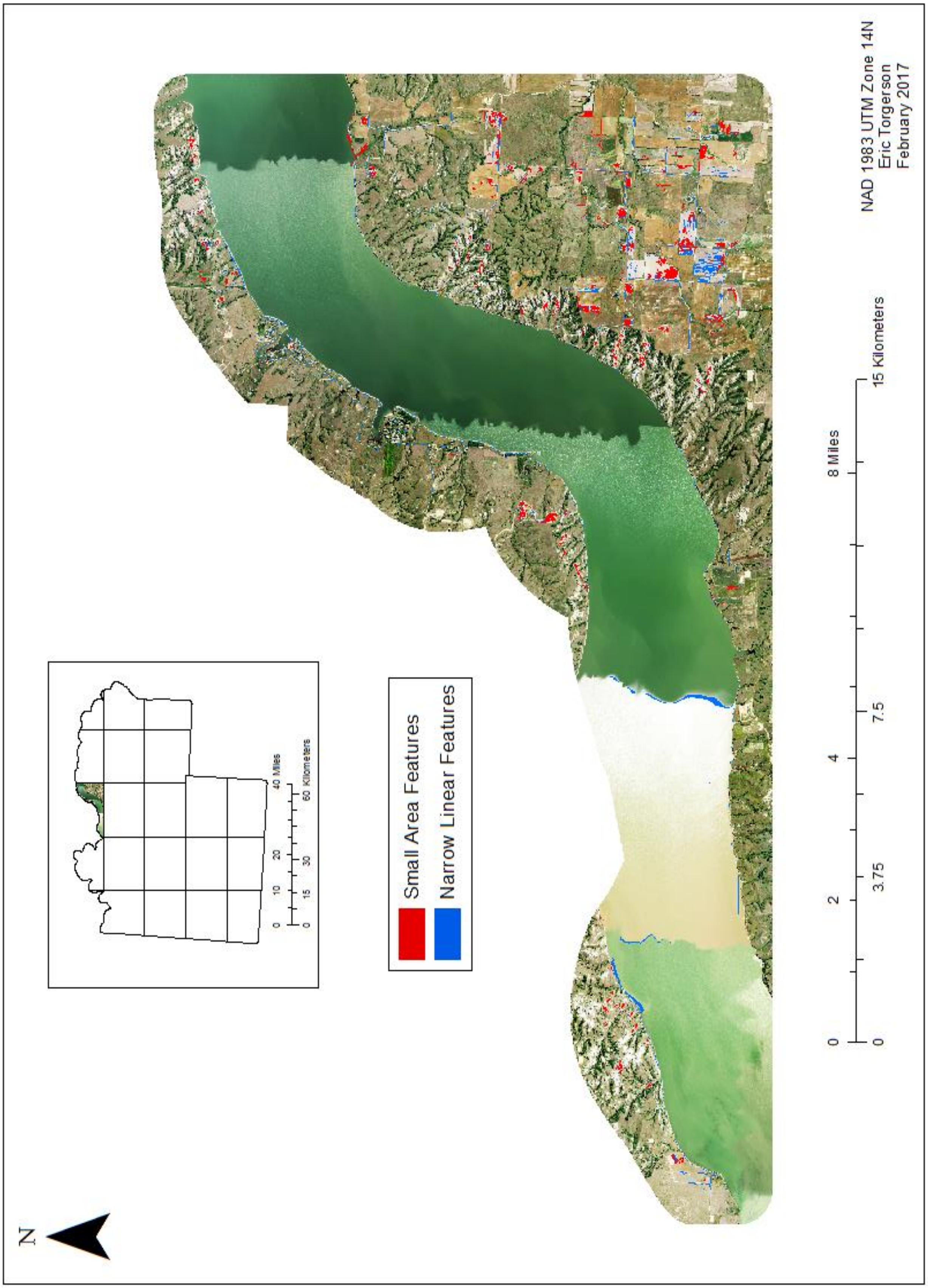

N
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers

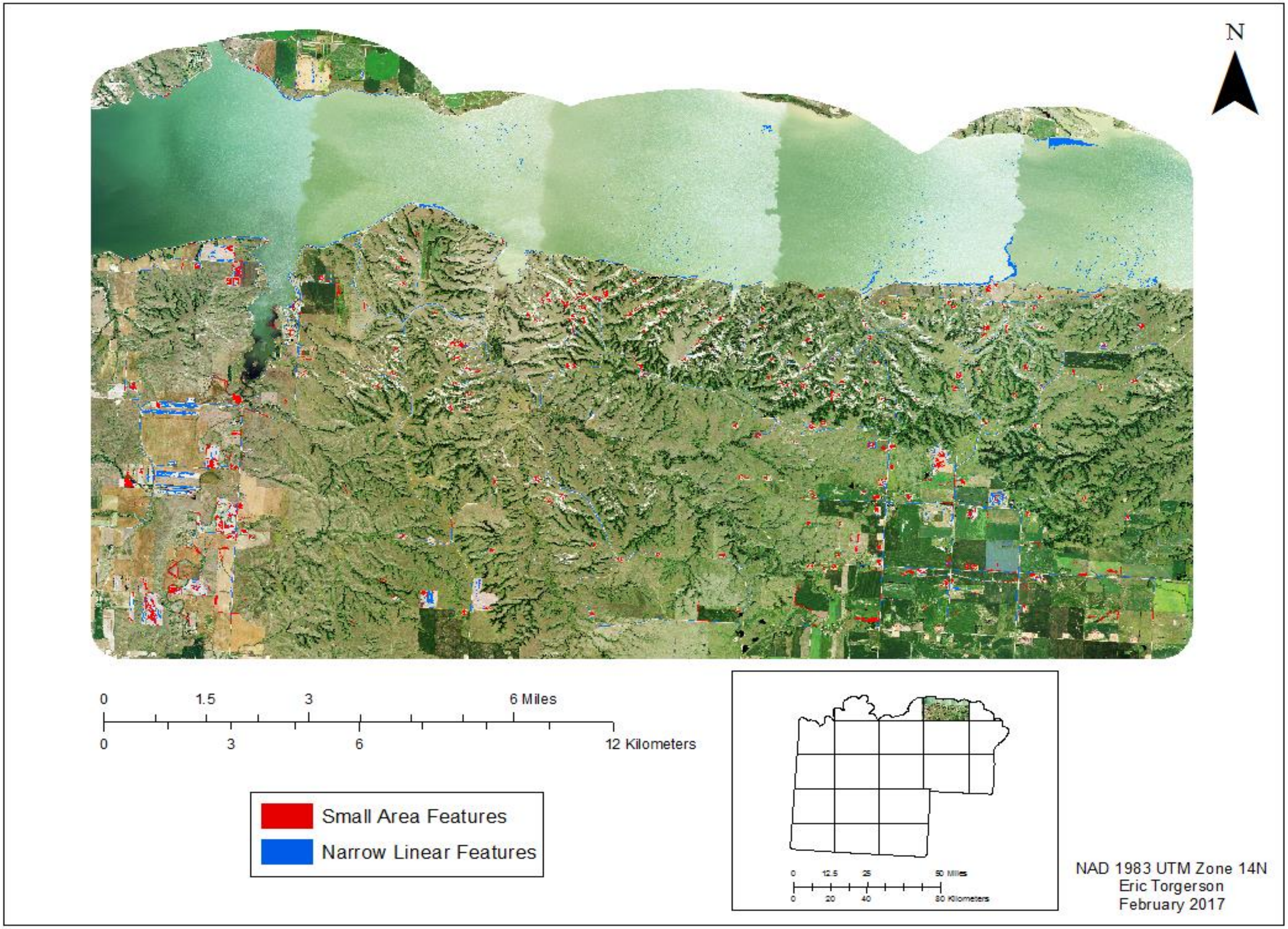

N
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers

2014 GEOBIA Classifications



Small Area Features
Narrow Linear Features
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
N
0 10 20 40 Miles
0 15 30 60 Kilometers


N
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017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0
1.5
3
6 Miles
0
3
6
12 Kilometers
Small Area Features
Narrow Linear Features
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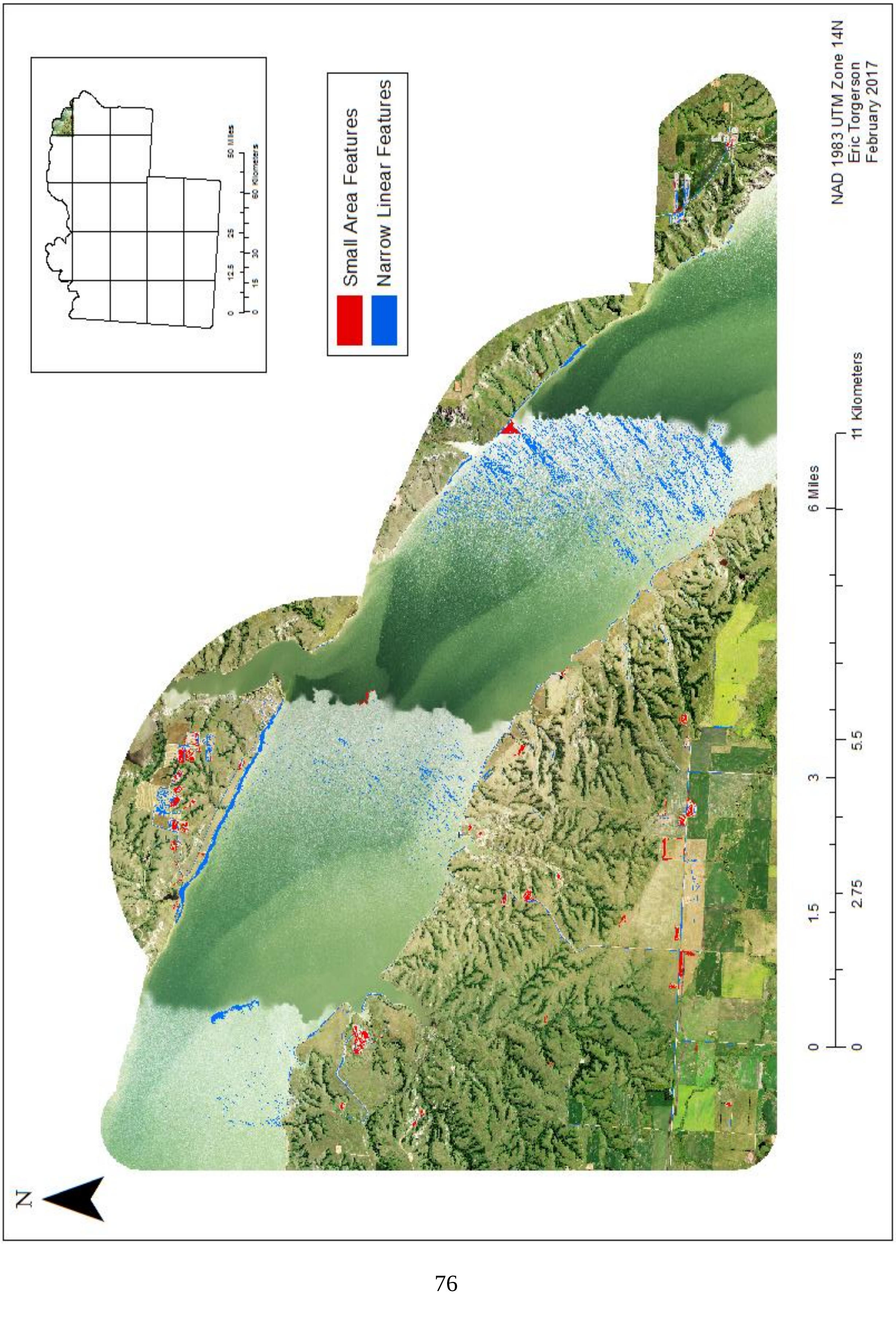
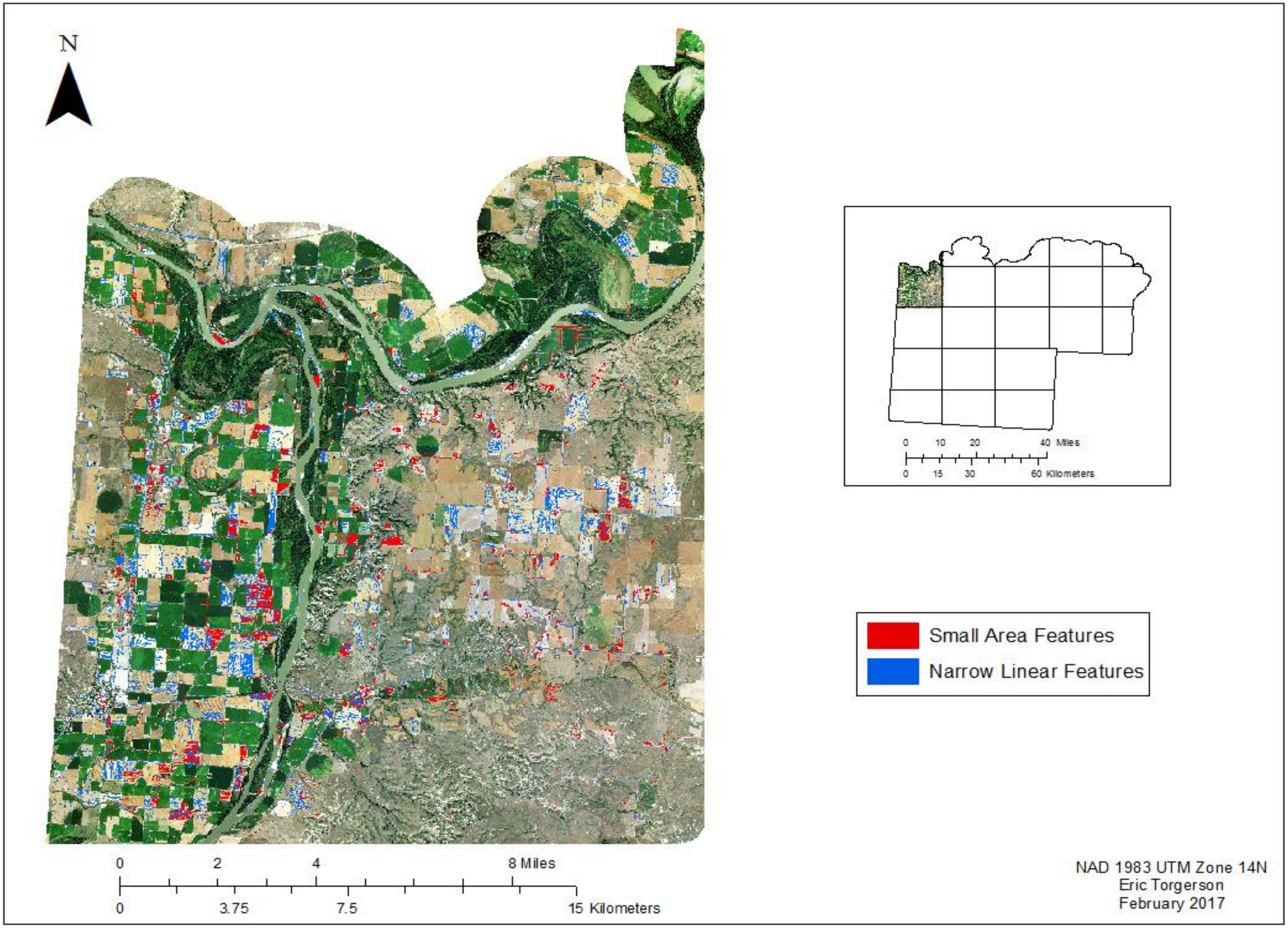
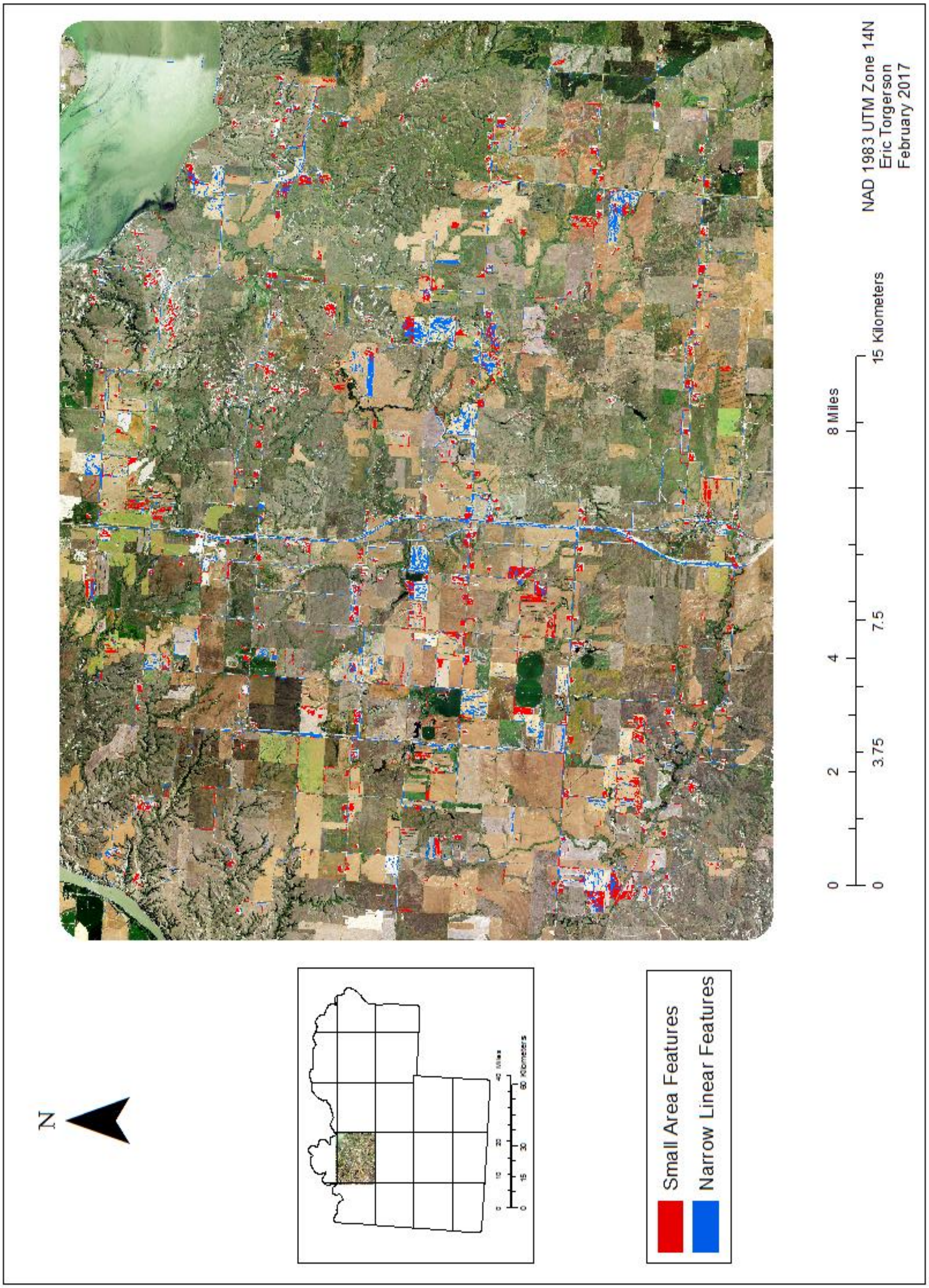
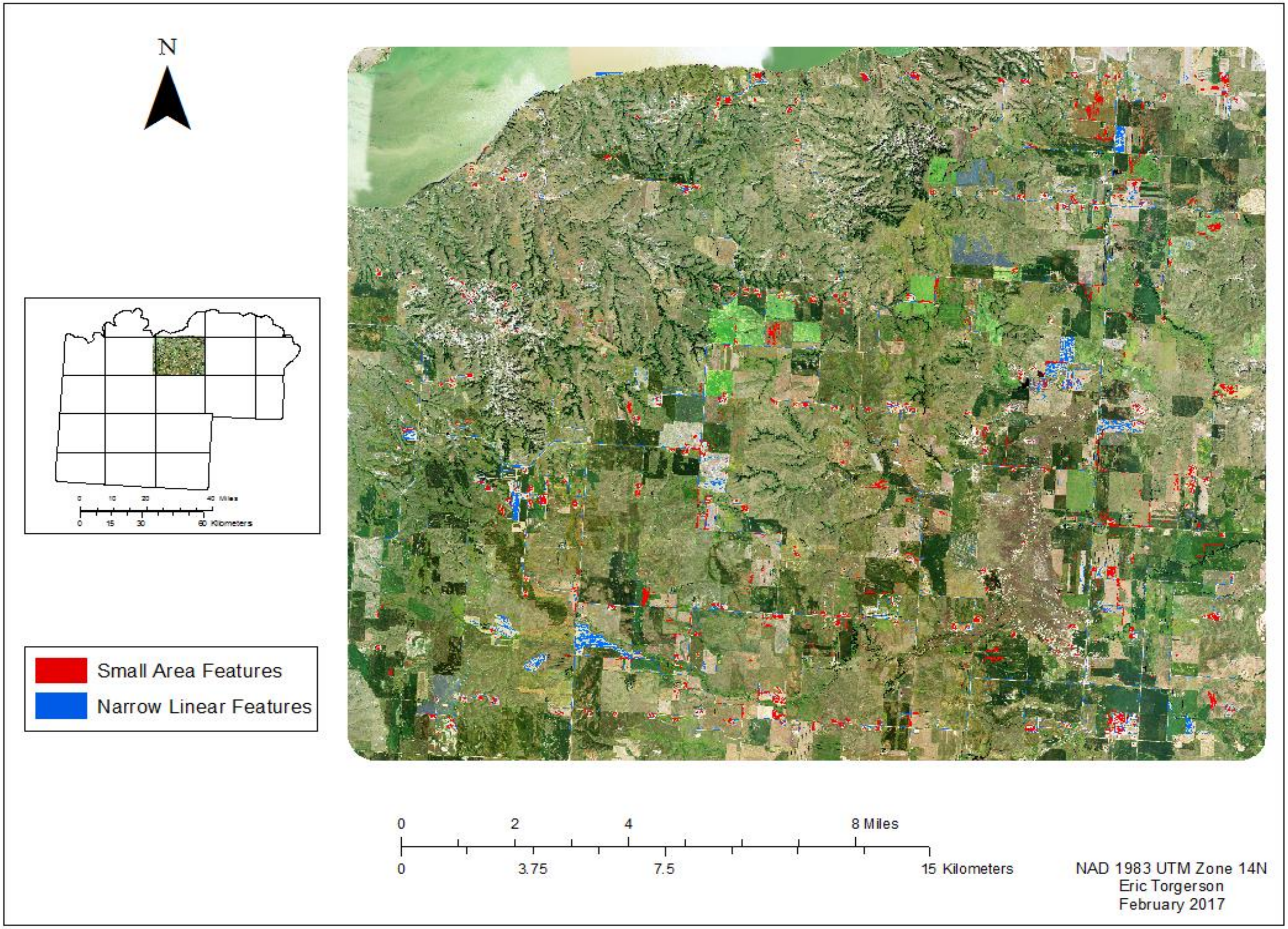
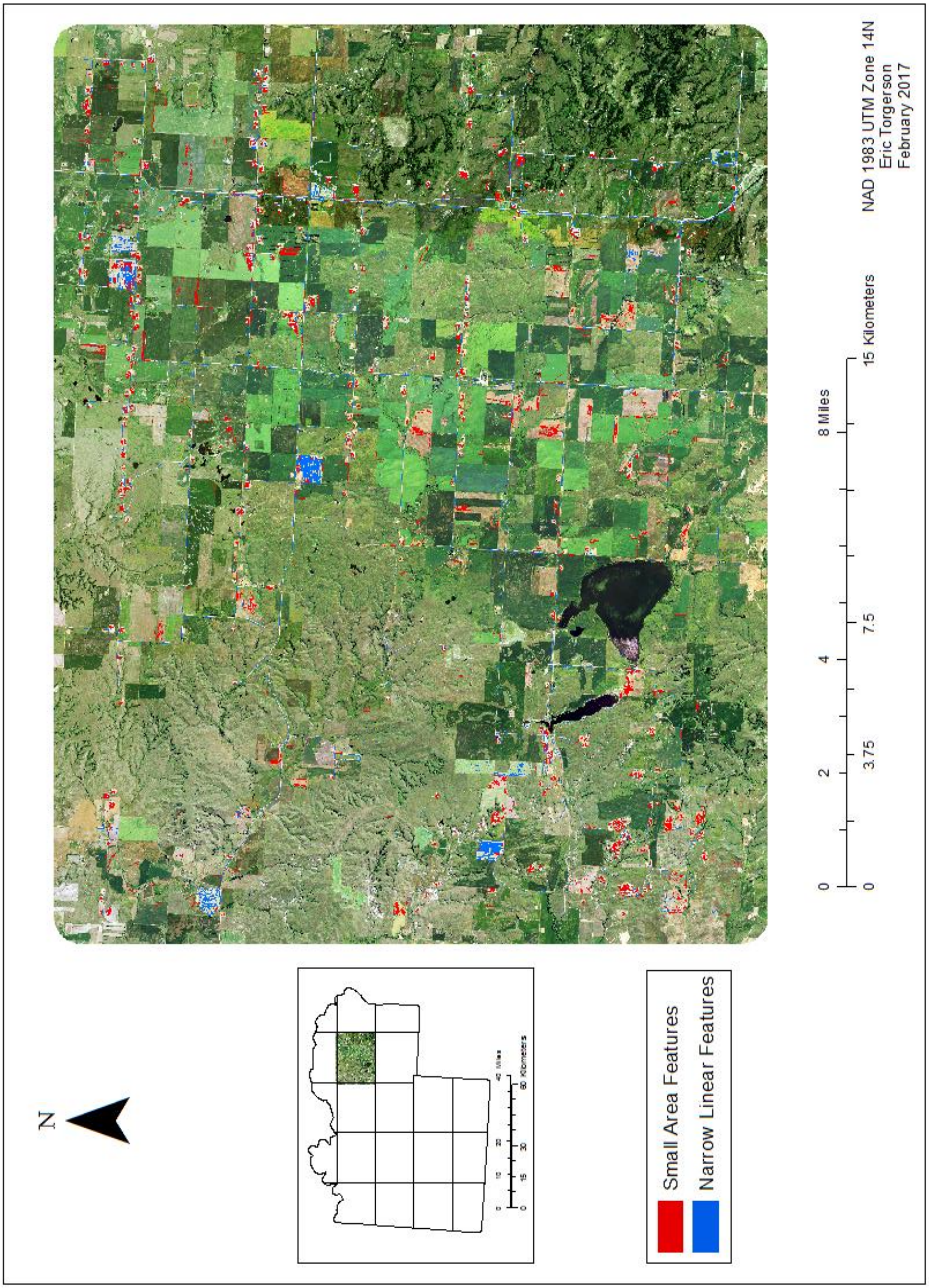
12.5
25
50 Miles
0
20
40
80 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017


Small Area Features
Narrow Linear Features
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0
1.5
3
6 Miles
0
2.75
5.5
11 Kilometers
N

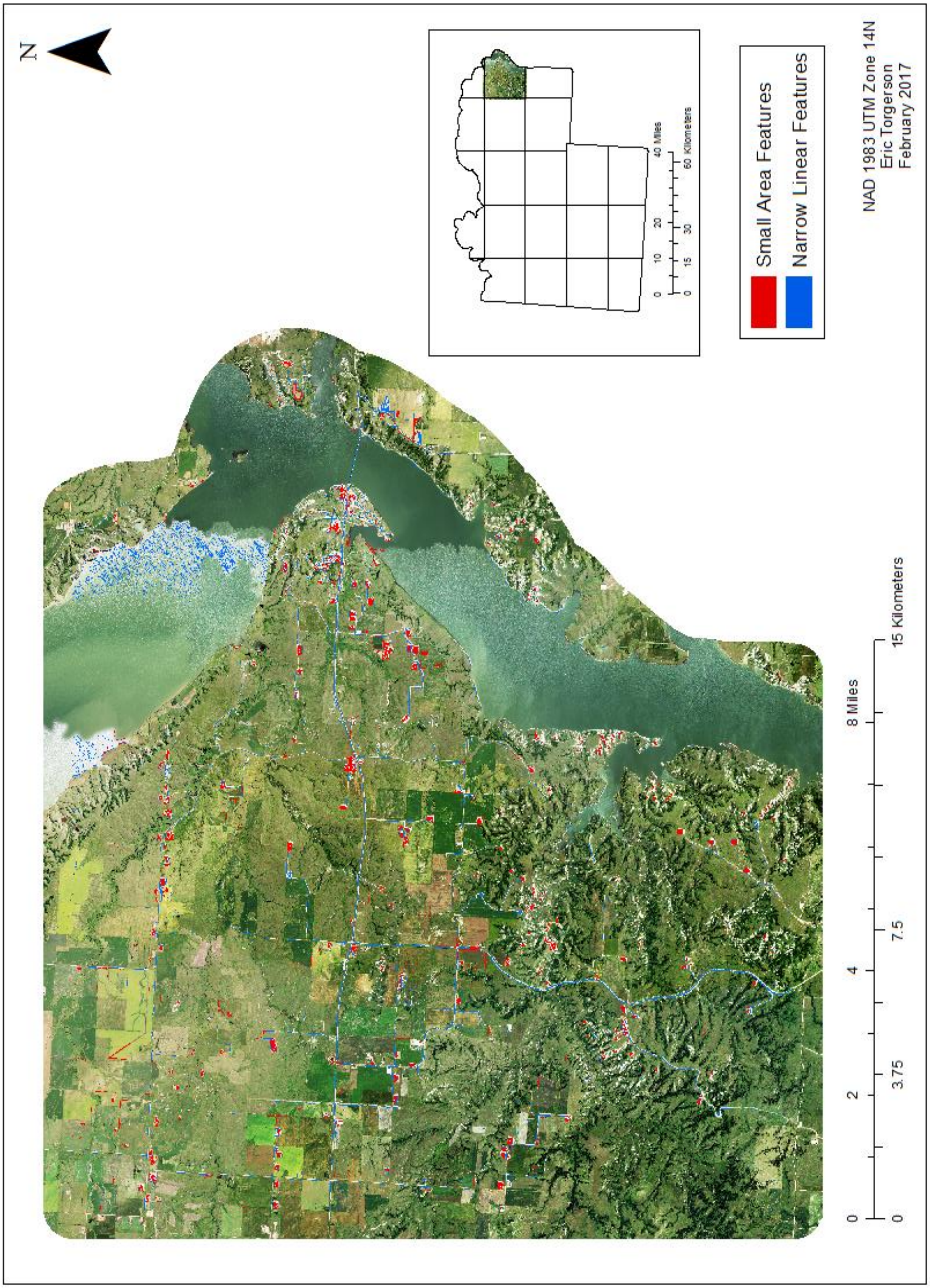

N
0 10 20 40 Miles
0 15 30 60 Kilometers
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017

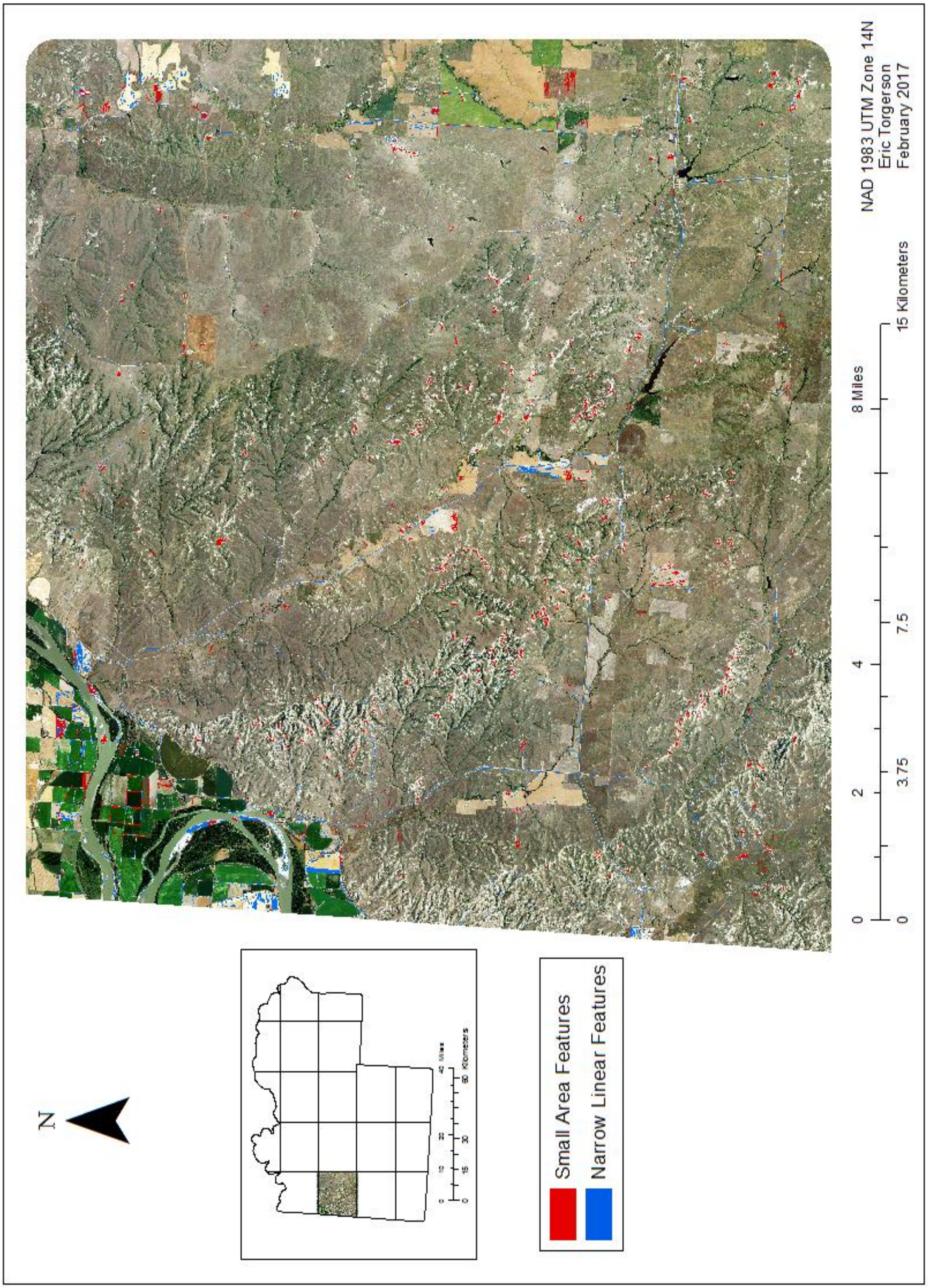

N
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017

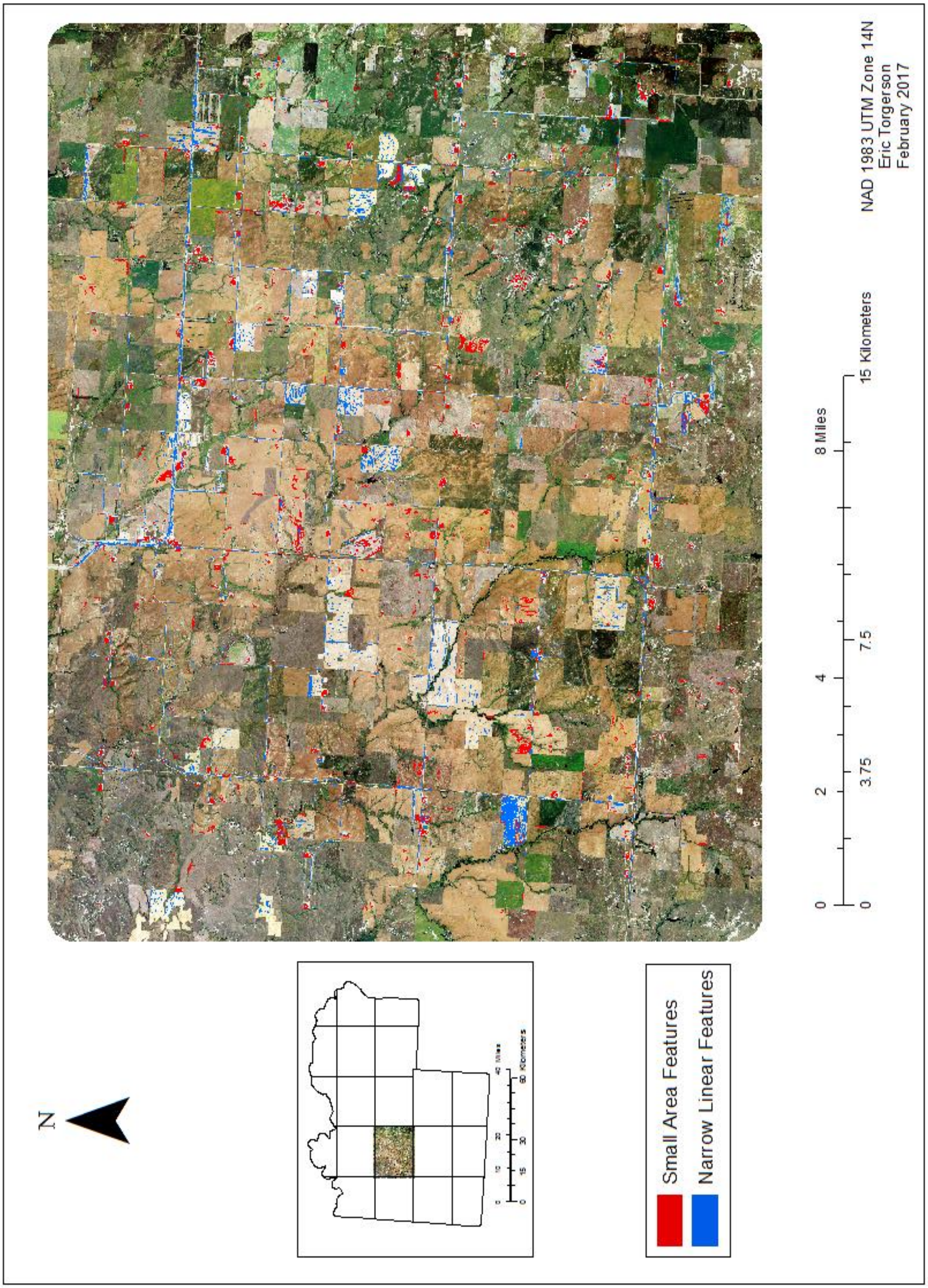

N
0 10 20 40 Miles
0 15 30 60 Kilometers
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017

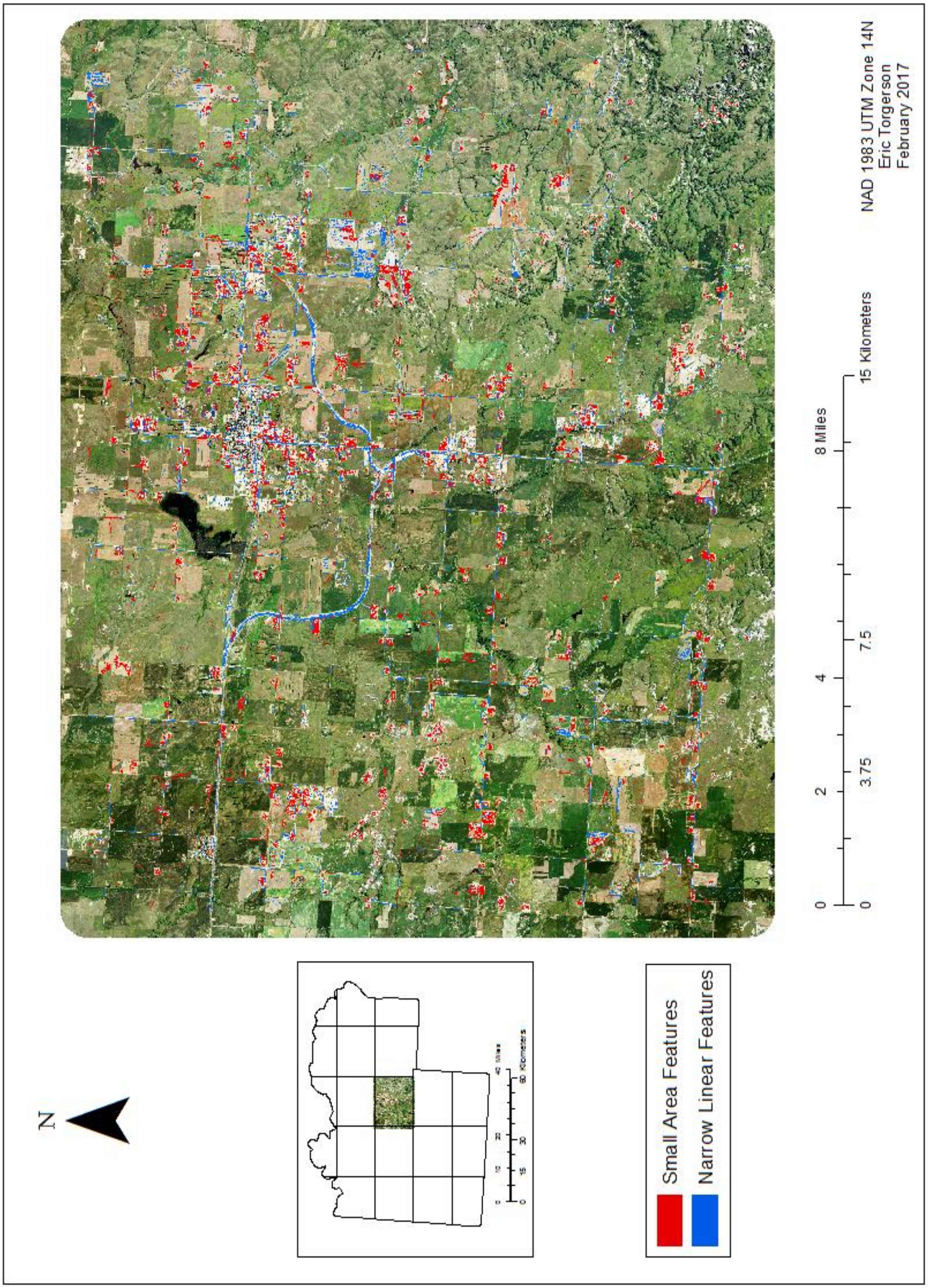


NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
N
Small Area Features
Narrow Linear Features

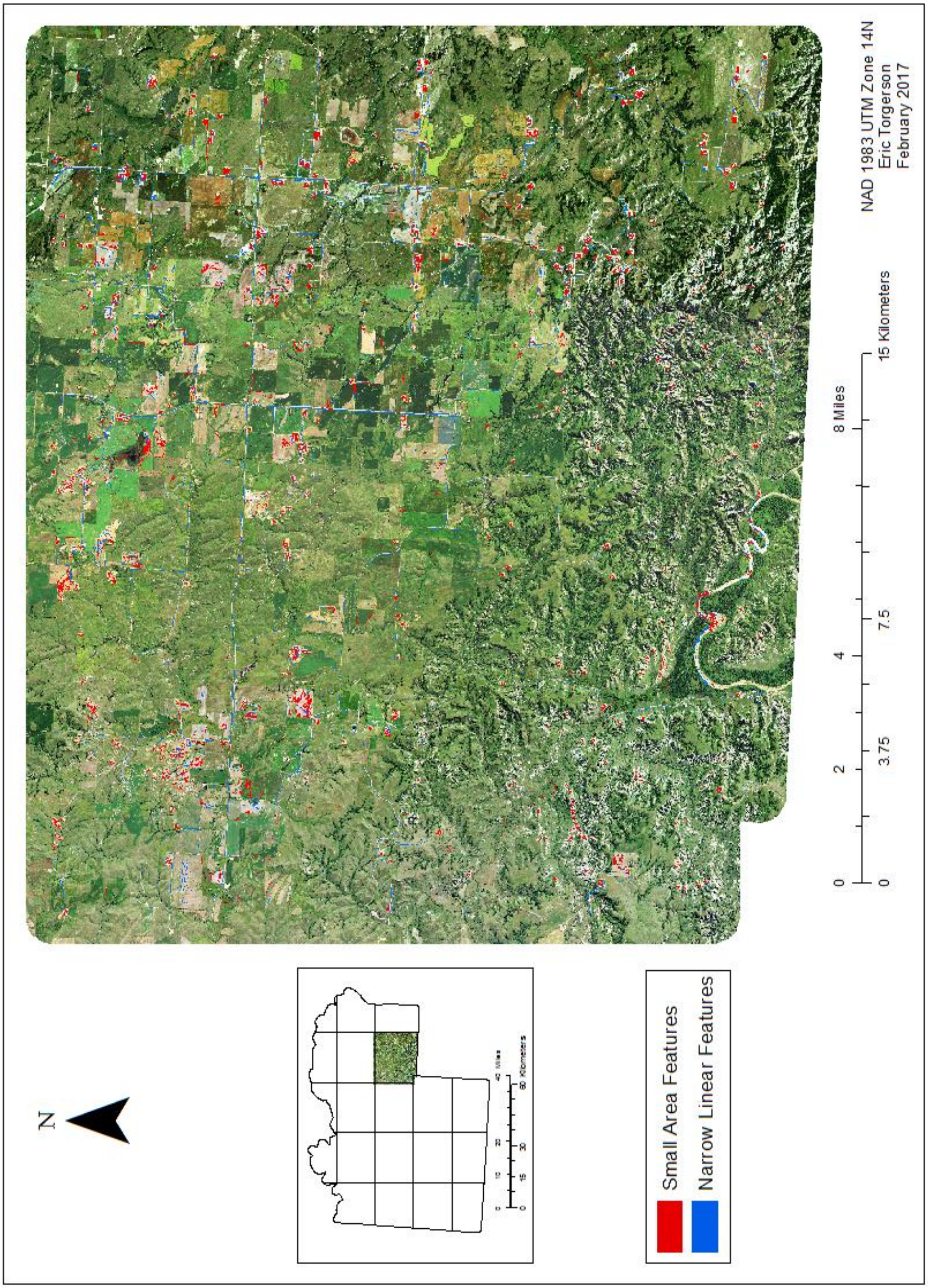

N
Small Area Features
Narrow Linear Features
0 10 20 40 Miles
0 15 30 60 Kilometers
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017


NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
N
Small Area Features
Narrow Linear Features

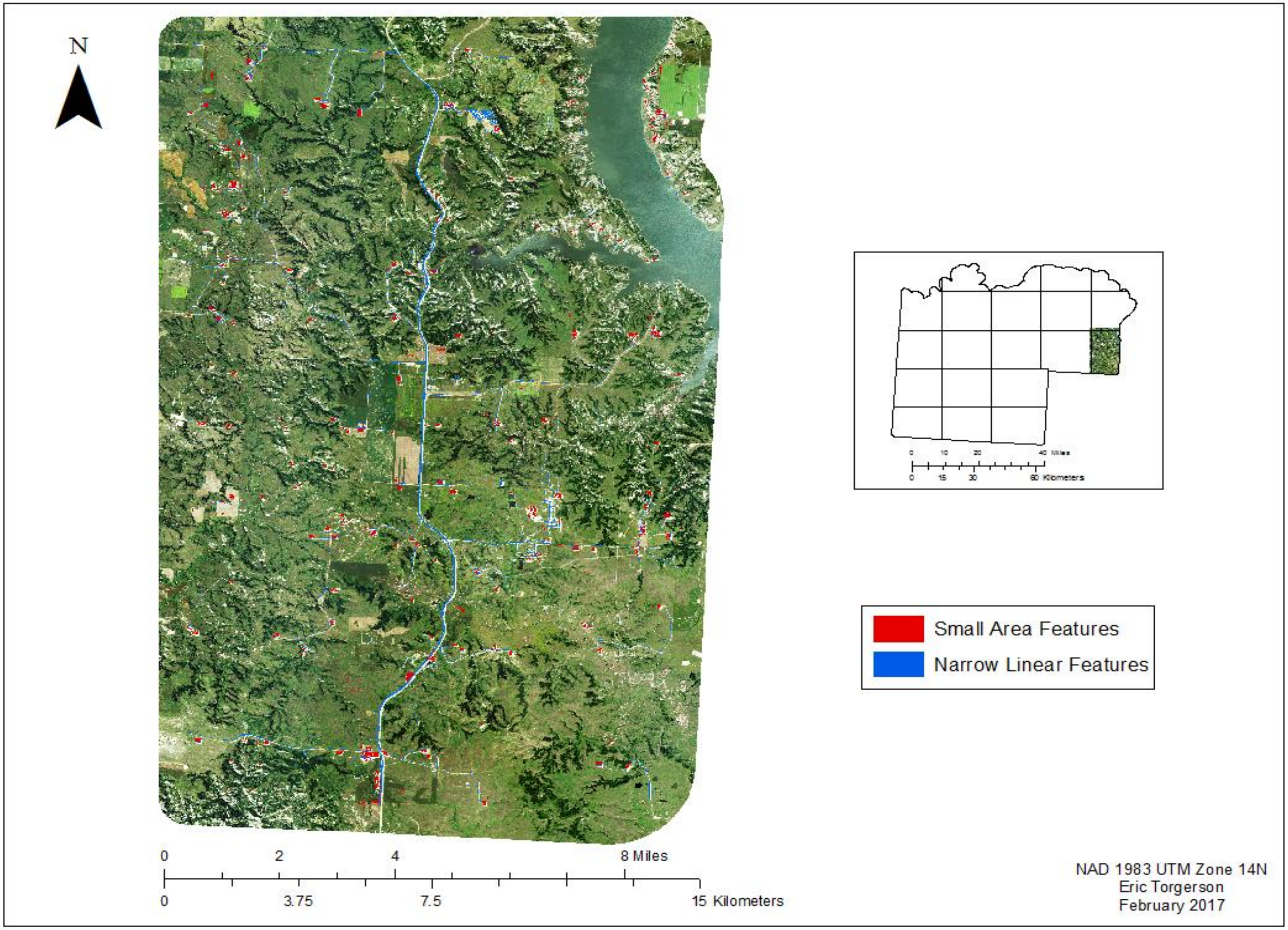

N
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017

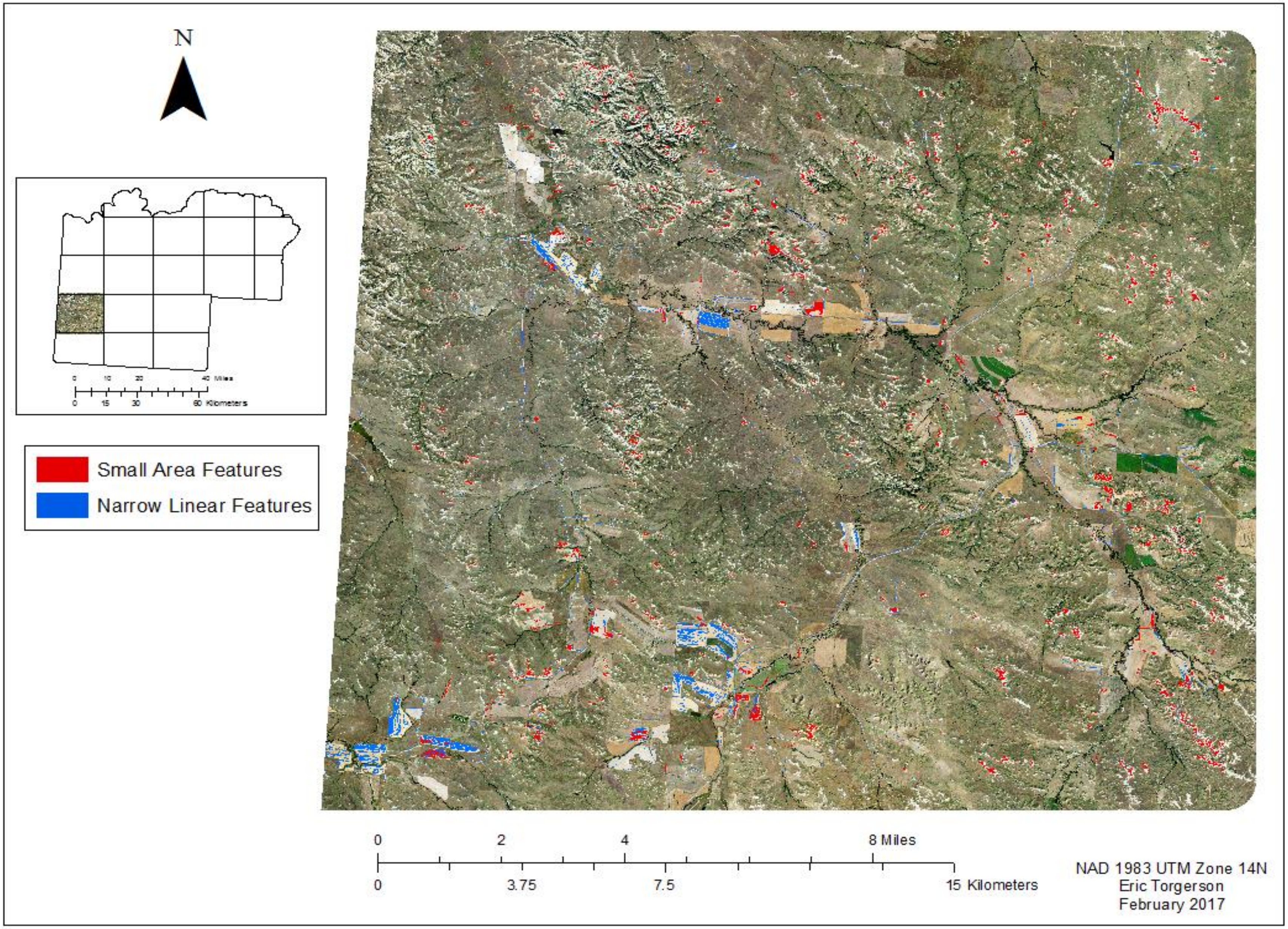


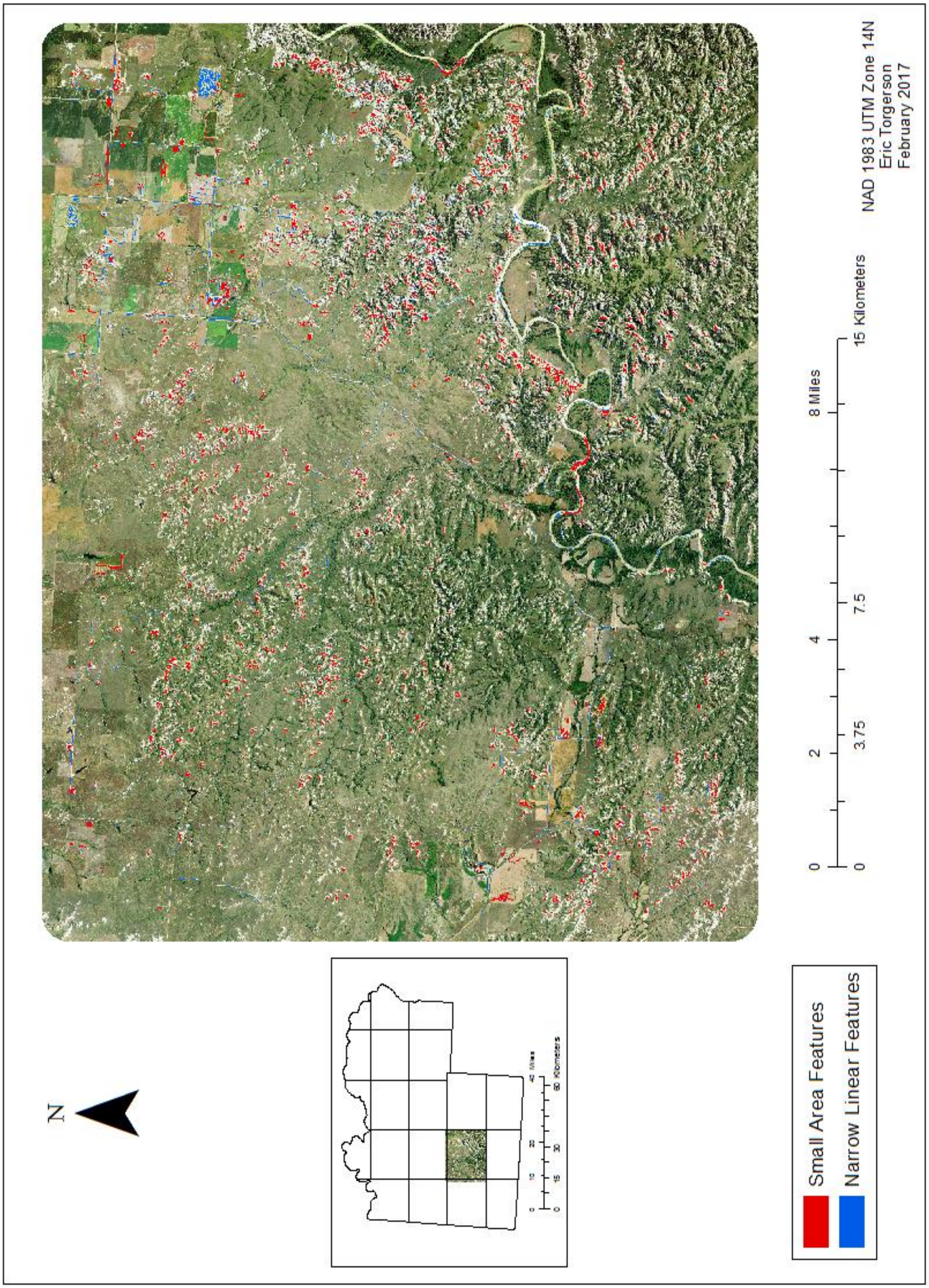
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
N
Small Area Features
Narrow Linear Features

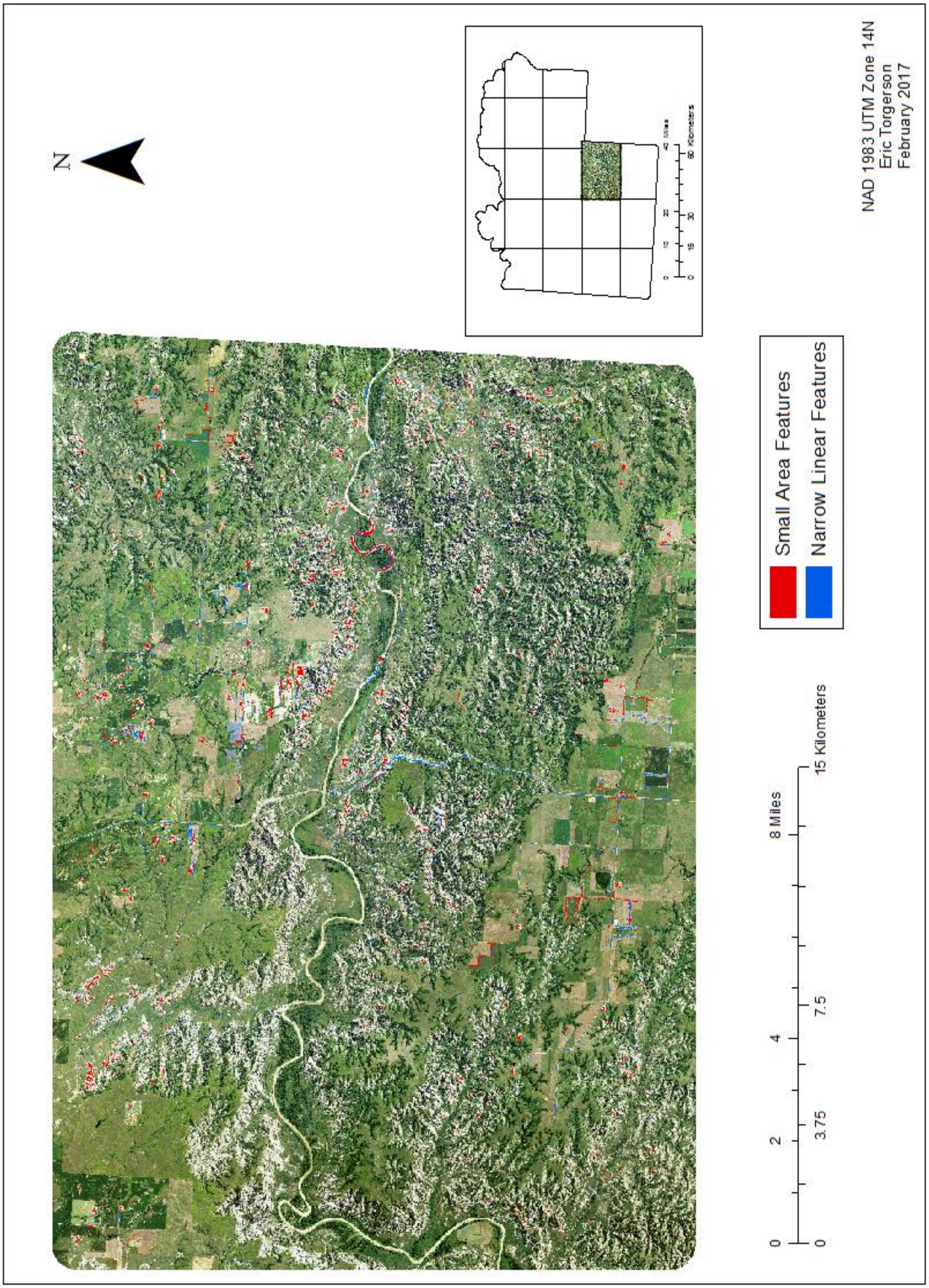


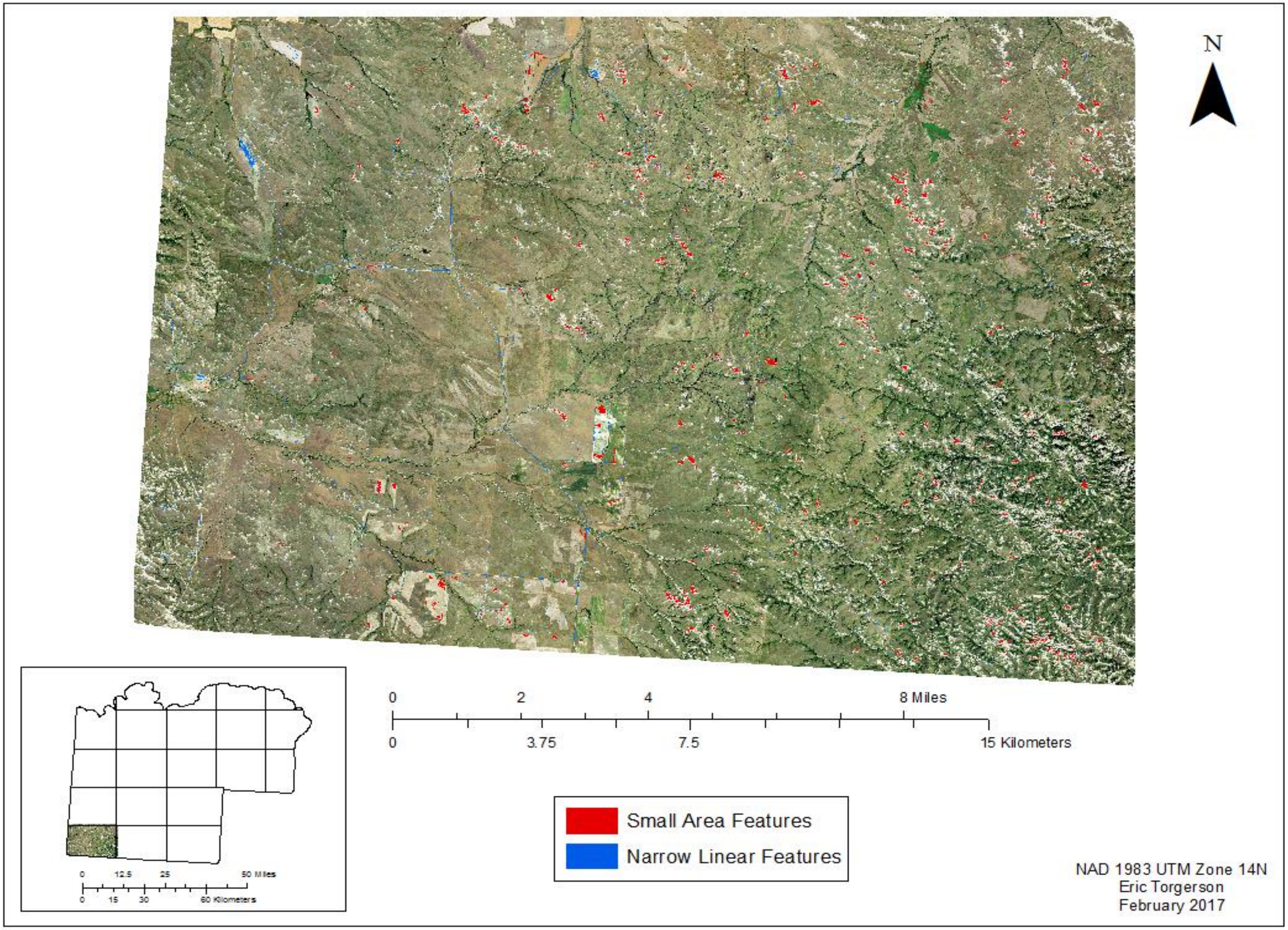
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017
0
2
4
8 Miles
0
3.75
7.5
15 Kilometers
N
Small Area Features
Narrow Linear Features

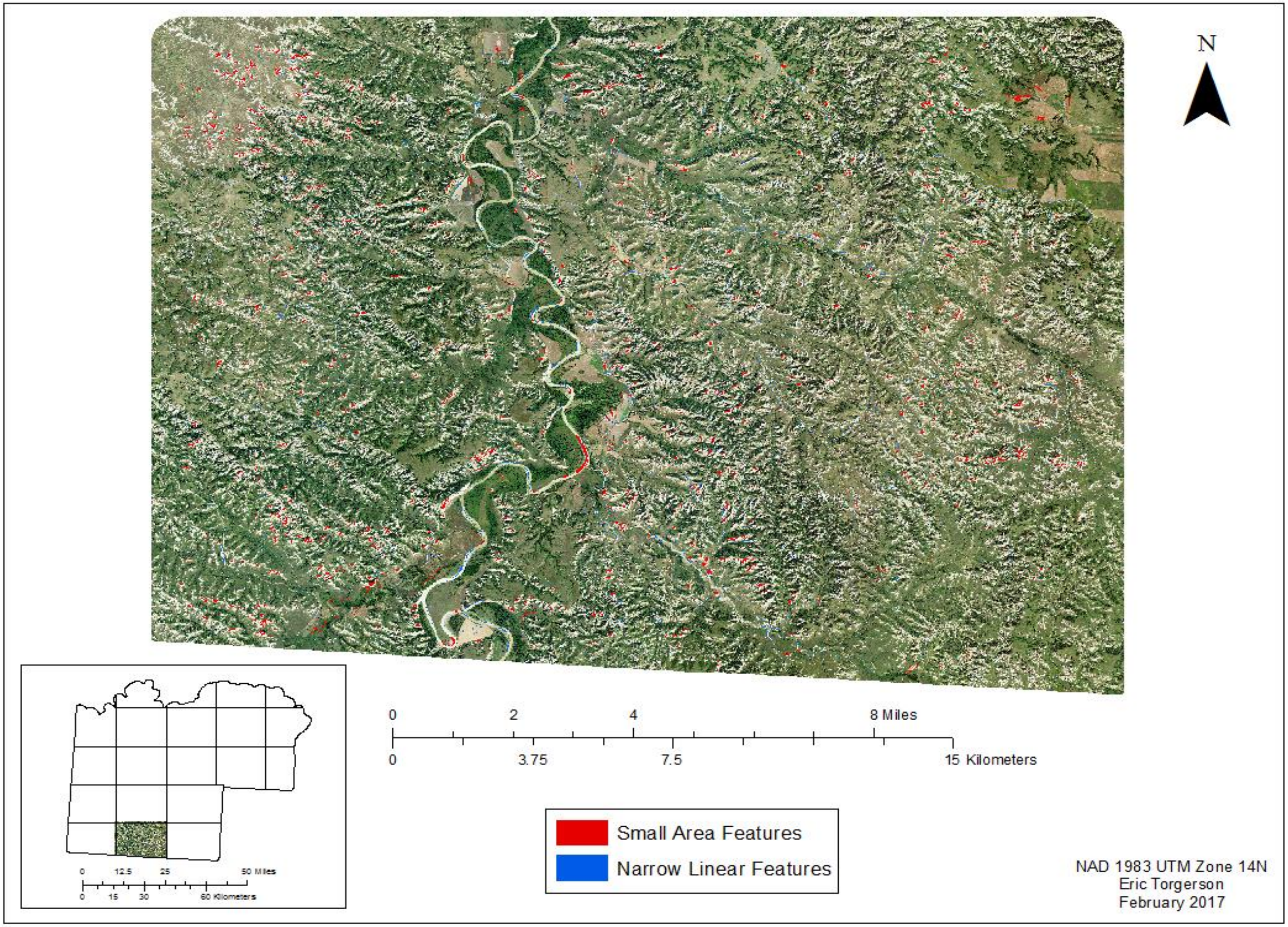

N
Small Area Features
Narrow Linear Features
0
2
4
8 Miles
0
3.75
7.5
15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017


N
Small Area Features
Narrow Linear Features
0
2
4
8 Miles
0
3.75
7.5
15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017


N
Small Area Features
Narrow Linear Features
0 2 4 8 Miles
0 3.75 7.5 15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017


N
Small Area Features
Narrow Linear Features
0
2
4
8 Miles
0
3.75
7.5
15 Kilometers
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017


N
0
2
4
8 Miles
0
3.75
7.5
15 Kilometers
Small Area Features
Narrow Linear Features
NAD 1983 UTM Zone 14N
Eric Torgerson
February 2017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8 Miles
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3.75
7.5
15 Kilometers
Small Area Features
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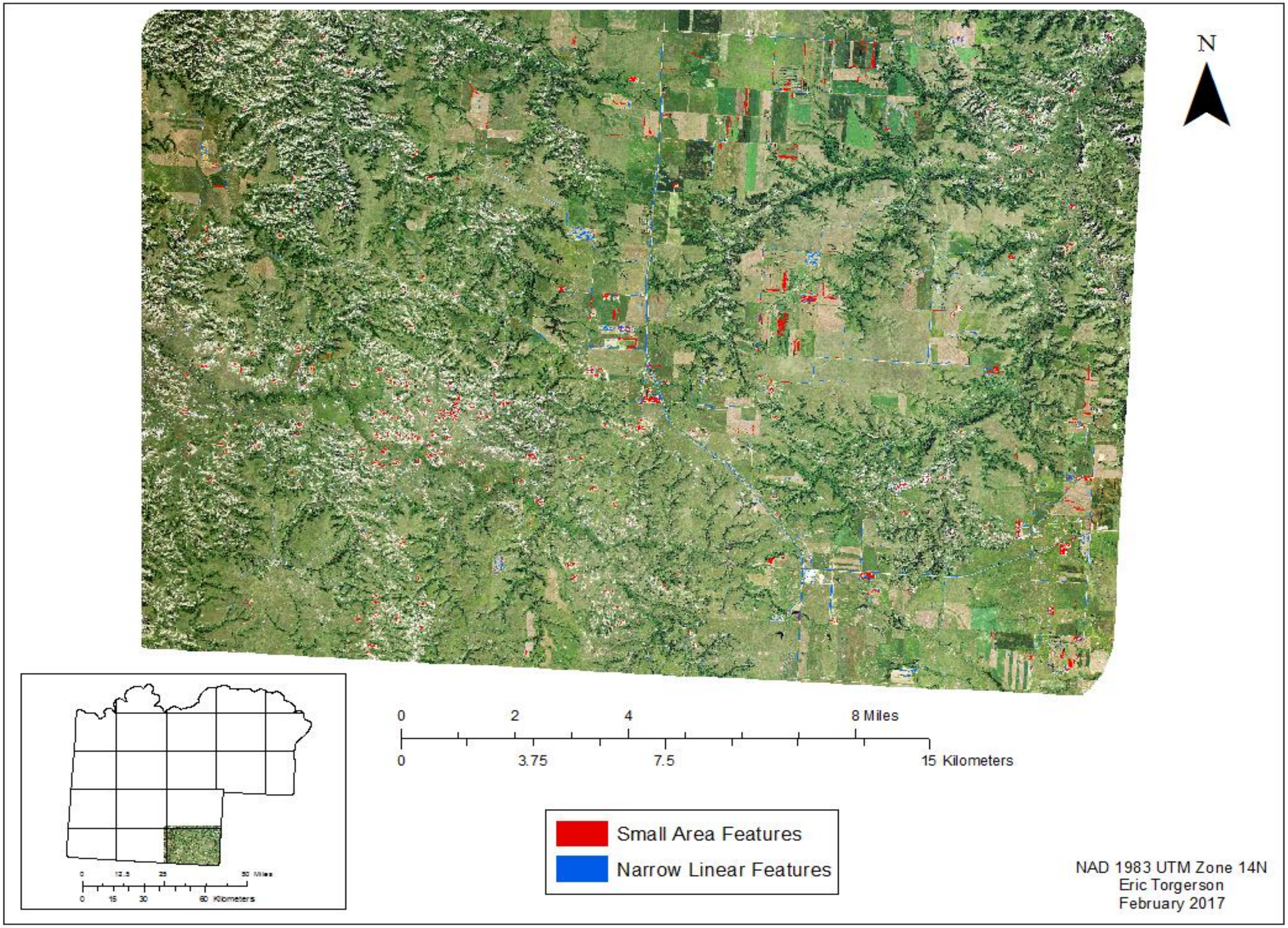

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