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Mapping And Quantifying The Spatial Characteristics Of Agricultural Drainage Systems In Red River Valley Of The North

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MAPPING AND QUANTIFYING THE SPATIAL CHARACTERISTICS OF AGRICULTURAL DRAINAGE SYSTEMS IN RED RIVER VALLEY OF THE NORTH

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July 3, 2020

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I wish to express my sincere appreciation to the members of my advisory Committee for their guidance and support during my time in the master's program at the University of North Dakota.

ABSTRACT

The purpose of the study is to map agricultural drainage systems (ADS) at the watershed scale using remote sensing and GIS techniques and examine the effect of ADS. For achieving the purpose of the study, this study selected the Red River Valley (RRV) of the North in which agriculture is a primary industry at the region. Excessive nutrients, sediment, and pesticide from this agricultural area flow into the Red River throughout subsurface drainages. The ADS aims to remove excessed water from agricultural fields, and this ADS is divided into two systems - uncontrolled drainage system (UCDS) and controlled drainage system (CDS). While UCDS allows water flows to the stream or river through using pipes without controlling water table, CDS regulates water table by an equipped structure that controls the volume of water flows in the agricultural fields.

For mapping artificially drained tiles between UCDS and CDS fields in the RRV, this study used DEM to digitize linear, map slope, and to calculate surface area. This study digitized linear maps with eight UCDS and twenty CDS fields and the map contains a digitization of tile drainage locations, drainage system patterns, ADS types, and artificially drained surface areas. In the analysis of the two different ADS systems – i.e., UCDS and CDS, this study obtained the indexes by using NDVI, NDWI, and MSAVI2 provided by PlanetScope imagery. In testing the group difference between UCDS and CDS in the three different indexes is examined by computing Analysis of Variance Analysis (ANOVA). Also, this study postulated CDS is more effective to the healthiness of crops than UCDS does in the ADS system.

The results of ANOVA indicated that there is no difference in the spectral indexes analyzed by ADS type (i.e., NDVI, NDWI, and MSAVI2). This result implies that the healthiness of crops is not affected ADS type, at least for the year studied here. The causes of this result, as a limitation, is derived from missing information, which is that agricultural research should consider region-specific crop calendars that involve significant idiosyncratic information, such as crop types and cycles, and regional climates. Nonetheless, natural factors in the RRV in 2019 – e.g., weather – are, of course, things outside of the control of researchers and agricultural producers.

CHAPTER I

INTRODUCTION

1.1 Background

The Red River Valley of the North is the youngest major landscape in the U.S., because the valley is a residual landform of glacial Lake Agassiz that was the former floor and shorelines of a massive and prehistoric lake. There are two Red Rivers in the U.S., one in nation's south and one in the north (Red River of the North). This study focusses on the Red River Valley of the North, and I will simply refer to it as the "Red River" and the Red River Valley will be abbreviated "RRV" in this study. The Red River flows toward 550 miles from its source at the confluence of the Bois de Sioux and Otter Tail rivers in Wahpeton, ND, and Breckenridge, MN, to Lake Winnipeg in Manitoba, Canada. Along the river in the U.S. are the adjacent cities of Fargo, ND; and Moorhead, MN; and Grand Forks, ND; and East Grand Forks, MN, and other smaller cities and towns. The Red River forms the political boundary between the U.S. states of Minnesota and North Dakota.

Watersheds and water bodies in the RRV are dynamic and impacted by flooding, high levels of nutrients and sediments, habitat alteration, the introduction of invasive species, toxic pollutants, and land-use changes. Researchers in the region are taking an interest in the study of sustainable agricultural development such as water resource management, water quality, agricultural pollution, and tile drainage. One of these research areas is the impact of agricultural drainage systems (ADS), also known as "tile drainage," which helps us understand how water moving through landscapes affects crop production and surrounding environments. ADS serves to remove excess water from soil below the surface (Naz *et al.* 2009), with a goal to enhance agricultural production (Kross *et al.* 2015).

Geography is a scientific discipline, the practitioners of which describe and analyze features of the Earth such as landscapes, inhabitants, and phenomena, within the context of geographic space. Thus, geographic studies give us critical insights into global issues like the economy, health, policy, environment, and other public matters through geospatial analysis. To provide geographic perspectives, this study makes use of the geospatial analysis tools of remote sensing and Geographic Information Systems (GIS).

Remote sensors measure the interaction between electromagnetic radiation (EMR) and environmental surfaces of interest (Jensen, 1996). Remotely sensed data are acquired through satellite imaging, aerial photography, and hand-held sensors sensitive to various portions of the electromagnetic spectrum to obtain biophysical information about agricultural fields, lands, and water surfaces without contact between sensor and target. Thus, remote sensing provides researchers a tremendous amount of information, but because some forms are difficult to collect and analyze, some studies do not include remote sensing in combination with other types of spatial data.

Advancing technology has resulted in tremendous volumes of spatial information, making necessary new systems to store, retrieve, manipulate, analyze, and display spatial data. GIS are designed to handle large volumes of spatial data derived from a variety of sources (Jensen, 1996), including various forms of remote sensing.

1.2 Research Goals

Geography is sub-divided broadly into human geography and physical geography. It distinguishes each sub-field based on the study topic, whether it focusses most closely on people or the natural environment. A study of ADS is most closely related to physical geography because it concerns processes and patterns of biosphere and hydrosphere, but ADS also relates to human geography because it concerns people and their economics and interactions with the environment.

The goal is to use remote sensing and GIS techniques to map and analyze subsurface agricultural drainage infrastructure at the watershed scale. This contributes to the investigation of the potential of remote sensing for sustainable development research such as agricultural crop production, monitoring of vegetation, water resource management, water quality, and agricultural pollution. Through this study, subsequent tile drainage research can be narrowed down and focused on topics associated with how ADS affects crop yields and how the ADS changes the water quality.

To meet my research goals, Chapter 2 of my thesis contains a literature review describing ADS and how other researchers have examined it using remote sensing and GIS. Methodology in Chapter 3 provides a detailed procedure to evaluate ADS with remote sensing and GIS. Chapter 4 covers results and discussion, and conclusions are discussed in Chapter 5.

I expect to create maps of conventional and controlled fields drained by ADS. Then the created map indicates the density of drain tile and artificially drained land in the study area. I expect that remote sensing data is useful to distinguish conventional fields and controlled fields in ADS. Following the expectation, I determine the proportion of each type of drainage system in the study area. I also expect to find significant values between conventional fields and controlled fields in ADS in the RRV. I predict that this study will help to understand geographical features and regional agricultural industry. Furthermore, the data of this study provide valuable information to develop the local community.

1.3 Research Questions

The questions that this study examined are: 1) Can shallow subsurface agricultural drainage systems be mapped using remotely sensed data collected from high-resolution satellite platforms, and if so, what is the density of drain tile in the study area? What is the surface area of artificially drained lands?; and 2) Can conventional (uncontrolled) vs. controlled agricultural drainage systems be differentiated using remotely sensed data and, if so, what is the proportion of each type of drain tile in the study area?

1.4 Research Objectives

The objectives of this study are: 1) Produce maps of the study area depicting tile drainage locations (linear map), drainage system types, and surface areas artificially drained; and 2) Determine average spacing and density of tile drains in the study area.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

In this chapter, I review key publications in the area of mapping Agricultural Drainage Systems (ADS). Even though there are already several studies of ADS on crop yields in many states (*e.g.*, Green *et al*. 2006, Cicek *et al*. 2010, Sunohara *et al*. 2016, Gökkaya *et al*. 2017), the spatial and physical characteristics of ADS in the Red River of the North Valley (RRV) are unreported in the scientific literature. These characteristics include total length and proportion of different types of installed drain tiles, as well as the surface area drained (Naz *et al*. 2009). Previous ADS studies found a relationship between such characteristics and surface water pollution (*e.g.*, Green *et al*. 2006, Naz *et al*. 2009, Cicek *et al*. 2010, Kross *et al*. 2015, Sunohara *et al*. 2015, Gökkaya *et al*. 2017). To date, no systematic study of ADS mapping has occurred in the RRV, to my knowledge.

2.2 What is ADS?

The purpose of ADS is to remove excess water from agricultural fields, often using a system of ditches and subsurface drainage pipes (Verma *et al*. 1996). Commonly called "tile drainage," ADS was first used in the U.S. in 1838 (Palmer 1915, Pavelis 1987). Installing ADS usually requires digging of ditches and laying of pipes to move water off agricultural fields (Pavelis 1987). That is, concrete, clay, or plastic pipes installed a few feet below the ground surface convey water into adjacent ditches, or sometimes into natural streams (Fig. 1) (Naz *et al*. 2009).

Figure 1. Drainage ditch in HIGDEM Township, Polk County, MN, on May 13, 2019 (Photo taken by the Author).

Palmer (1915) notes that ADS has societal benefits because it increases crop yields, raises land values, improves public highways, reduces health risk from swamp gases, and reduces the risk of malaria. However, some ADS have resulted in water pollution. Water pollution from ADS is related primarily to high levels of nitrogen and phosphorous, as well as soil sediments, in adjacent drainage ditches, lakes, streams and rivers. According to the U.S. Environmental Protection Agency (EPA), watersheds and water bodies are generally threatened by high levels of nutrients, habitat loss, invasive species, toxic pollutants and land-use changes.

2.2.1 Uncontrolled (conventional) drainage system

An uncontrolled (conventional) drainage system (UCDS) (Fig. 2) is simply a system of plumbing. It involves installing perforated PVC pipes below the surface of an agricultural field (Tan *et al.* 2002, Sunohara *et al*. 2014). Through small perforations of PVC pipes, water is filtered from soil resulting in reduced soil erosion, surface runoff, and ponding in the field, but UCDS can result in massive inputs of nutrients into drainage ditches.

Figure 2. Uncontrolled or conventional drainage in ESTER Township, Polk County, MN, on May 13, 2019 (Photo taken by the Author).

2.2.2 Controlled drainage system

A controlled drainage system (CDS) (Fig. 3) is based on a conventional drainage system and uses the stop-log to control water flow. These systems are also known as "water flow control structures" (Kross *et al*. 2015, Gökkaya *et al*. 2017). The control structures regulate water loss from fields, and the system is highly flexible and helps farmers to retain water and nutrients in fields during the growing season to foster crop growth. Thus, the system can be effective in reducing agricultural pollutants delivered to ditches, lakes, streams, and rivers. As a result, CDS can increase crop yields and prevent pollution (*e.g.*, Drury *et al*. 1993, Tan *et al*. 2002, Green *et al*. 2006, Kross *et al*. 2015, Gökkaya *et al*. 2017, Khand *et al*. 2017).

Figure 3. Controlled drainage system in in ESTER Township, Polk County, MN, on May 13, 2019 (Photo taken by the Author).

2.2.3 ADS installation patterns

There are various patterns of agricultural drainages (Fig. 4), including herringbone, parallel, double-main, and targeted systems. For example, a herringbone system is in the shape of parallel tile laterals and is useful for draining long, narrow wet areas. Parallel, also called "gridiron," patterns are similar to herringbone without laterals and useful on flat areas. Double main is a modified gridiron pattern and is useful to drain depression areas or natural watercourses. Targeted, or "random," patterns are useful for draining isolated wet areas. A drainage pattern requires a match with the topography and groundwater conditions of the field (Hofstrand 2010). CDS and UCDS are not distinguished by installation patterns in agricultural fields. Most previous studies that have produced tile line maps use satellite imagery (Naz *et al.* 2009, Gökkaya *et al.* 2017). They recommend interpreting tile lines from images acquired about three days after a rainfall of 1 inch or greater (Iowaview.org 2018).

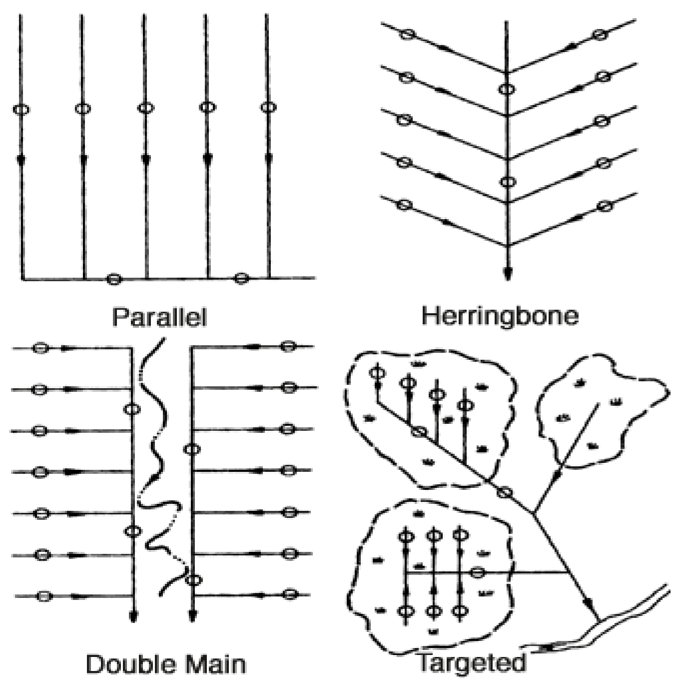

Figure 4. ADS installation patterns (Hofstand 2010).

2.3 ADS in the RRV

The installation of tile drainage in the RRV is intensive and extensive. The RRV (Fig. 5) is located on the edge of the U.S. Corn Belt (Fig. 6). The RRV has prolific soil, plentiful water resources, and ample solar radiation during the summer months to sustain a productive and profitable agricultural system. In addition to the natural resources found in the region, ADS is an artificial tool that farmers in the RRV can use to improve crop yields.

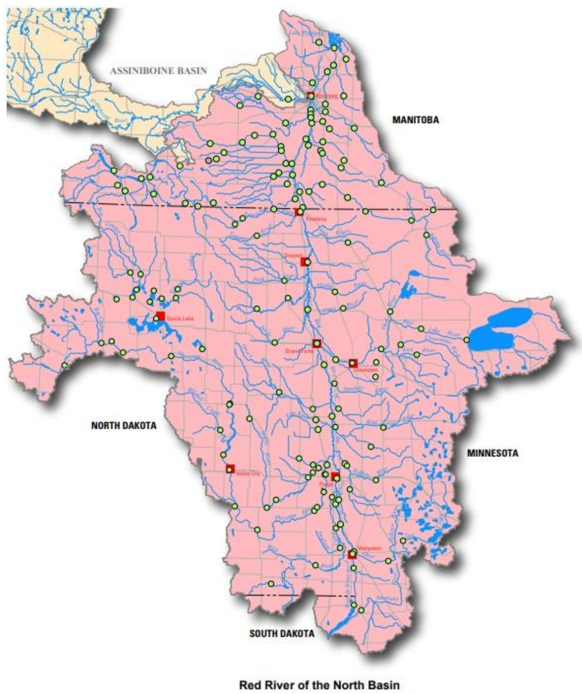

Figure 5. Drainage area of the Red River of the North. The Red River Basin is highlighted in pink. The Red River flows from south to north (Source: USGS).

The spatial and physical characteristics of ADS in the RRV are unknown. These characteristics include total length and proportion of different types of installed drain tiles, as well as the surface area drained. Farmers in the RRV have increasingly turned to tile drainage since the late 1990s as part of an overall strategy to increase crop production during times of high market prices.

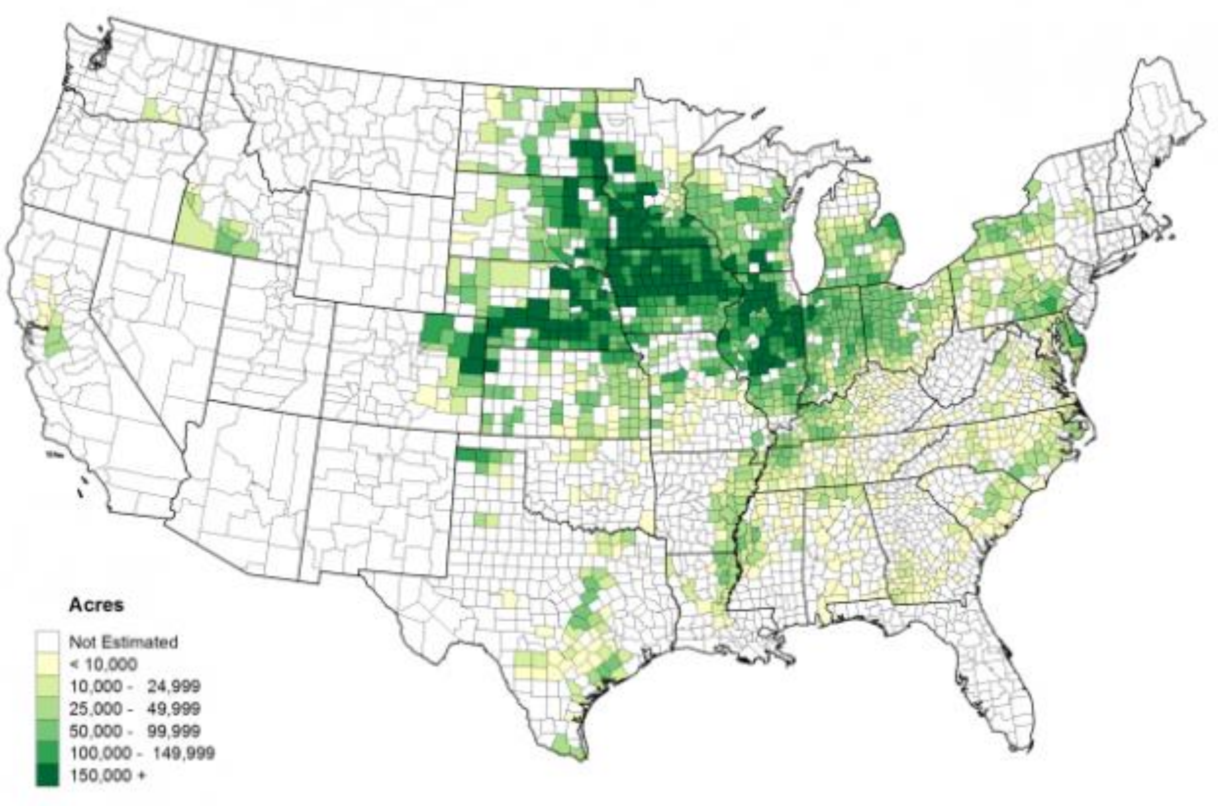

Figure 6. U.S. Corn Belt, showing acres planted in corn (Source: USDA).

2.3.1 Benefits of ADS

Tile drainage contributes to increased crop production by giving farmers a tool to control the water table; it allows them to drain excess water from snowmelt so spring planting can occur earlier than otherwise possible; it moves water from extreme rain events off the field, reducing drowned-out crops; and it reduces evaporation from the field, keeping soil salinity down (Sunohara *et al.* 2016). ADS allows farmers to retain soil water during dry spells. Increased bacterial action in ADS promotes water quality (Sunohara *et al.* 2016).

Environmentally speaking, through the appropriate operation of ADS, farmers can benefit from less soil compaction, better fertilizer usage, better aeration of the soil, and less agricultural pollutants moving into surrounding water bodies. Those factors all benefit the state and local economies and provide opportunities to protect the environment (North Dakota State Water Commission 2009, Hofstrand 2010).

2.3.2 Drawbacks of ADS

The major concerns about ADS are their environmental impacts and social costs when improperly managed. According to the EPA, excess fertilizer, erosion of excess sediments, pesticides, and high levels of chemicals result in water pollution. The harmful factors of water pollutants result from dilapidated tile lines and inappropriately controlled drainages. In other geographic regions, researchers have found positive relationships between tile drainage density, type, and area drained and levels of surface water pollution. In addition, there is some evidence that tile drainage has the potential to intensity flooding of rivers and streams. The environmental impacts extend to international concern because the water in the RRV flows northward, and so water quantity and quality issues associated with tile drainage are specific interest to Canada (North Dakota State Water Commission 2009, Hofstrand 2010).

2.3.3 Approval and cost of installing and operating ADS

The costs to install ADS depends on various factors such as soil type, soil condition, installation approaches, necessary equipment, and other factors. ADS installation involves a trencher (Ditch Witch), a mole plough, a backhoe, or other heavy equipment. For example, when a company installs tile in the fields, the cost average is $25 per foot depending on the depth and width of the drain (Kieser and Associates Environmental Sciences and Engineering 2020).

Before the installation of ADS, farmers need approval from the U.S. Department of Agriculture (USDA). Then a farmer needs to contact his or her designated county Farm Service Agency (FSA) agent with a description of the agricultural drainage plan (Hofstrand 2010). Also, the design must reveal the tile investment and a plan to improve drainage because designing usually results in high return and increased crop yields.

2.4 Remote sensing of ADS

Satellite remote sensing has proven to be a valuable tool in Earth science research since the early 1970s. Satellite sensors provide practical information about the Earth's land and water resources (Campbell and Wynne 2011). Remote sensing is useful to monitor vegetation conditions, soil moisture, and surface water.

There are numerous studies using remote sensing to investigate ADS in the Corn Belt states of Illinois, Iowa, Minnesota, and Indiana (Drury *et al*. 1993, Tan *et al*. 2002, Green *et al*. 2006, Naz *et al*. 2009, Cicek *et al*. 2010, Kross *et al*. 2015, Sunohara *et al*. 2016, Gökkaya *et al*. 2017, Khand *et al*. 2017). There are no such studies in the RRV, to my knowledge.

Recently, approaches to using high-resolution satellite imagery to study the effects of ADS on crop production have been developed (Cicek *et al*. 2010, Khand *et al*. 2017, Cooley *et al.* 2017). The satellite imagery provides a realistic and accurate classification of ADS (Kross *et al*. 2015). According to Ve (1996), ADS mapping is using high reflectance in the infrared (IR) region of remote sensing, and the IR range is sensitive variations in soil moisture.

Regarding remote sensing and agricultural study, previous research considered the crop calendar. The crop calendar is mostly used by farmers, and currently scientists, because it provides information of the cycle of crops grown for a year, and the calendar includes the regional climate, local practices, and economic incentives. Thus, scientists prepare their studies from various factors, and have to check specific sequencing of regional field conditions with the crop calendar. This is because traditional agriculture considered simply the seed, fertilizer, and pesticides following planting and growing stages. There are various factors considered such as soil, solar radiation, moisture, and drainage. Those vary markedly with agricultural fields (Campbell and Wynne 2011).

For instance, corn and soybean yields have been studied on fields using CDS. These studies estimate crop yields using the Normalized Difference Vegetation Index (NDVI) and Green Normalized Difference Vegetation Index (GNDVI) from satellite remote sensing (Cicek *et al.* 2010, Clevers and Gitelson 2013, Kross *et al.* 2015). Color-infrared orthophotos have been used to digitize tile drainage maps (Green *et al.* 2006). Normalized Difference Water Index (NDWI) uses two near-IR channels centered approximately at 0.86um and 1.24um for remote sensing of vegetation liquid water from space (Gao 1996). The Bare-Soil Index (BI or BSI) uses spectral bands to map built-up and bare areas in a dry climate from satellite (Rasul *et al.* 2018).

NDVI is derived from remote sensing measurements (Tucker 1977). NDVI indicates the difference between green plants, water, and soil using a simple graphical indicator. Thus, NDVI is well-known as an indicator of vegetation presence, abundance, and vigor. NDVI ratios the amount of NIR energy reflected by plant cell structures with the amount of red light absorbed by chlorophyll in plant cells. Researchers have established a strong correlation between NDVI and vegetation biomass and health (or vigor) of plants. NDVI has been correlated with crop yield for many different crop types (Jakubauskas *et al.* 2002, Mkhabela *et al.* 2011).

There are several studies of crop fields and the impact of ADS using NDVI. One such study compared NDVI and GNDVI for corn and soybean among CDS and UCDS fields. Cicek *et* *al.* (2010) used Landsat-5 Thematic Mapper (L5) and SPOT-4 (S4) multi-spectral satellite imagery. They analyzed satellite images through NDVI = (NIR – RED) / (NIR + RED) and GNDVI = (NIR – GREEN) / (NIR + GREEN). The interpretation of values is from -1.0 to +1.0. A value (close to zero) shows no vegetation, and a value close to +1 shows the highest density of green plants. As a result, NDVI and GNDVI indicate CDS did not adversely impact corn and soybean yields (Cicek *et al.* 2010).

NDWI is used for delineating and monitoring water content in plants. According to Gao (1996), NDWI can be used to assess changes in the water content of leaves using two near-infrared channels centered approximately at 0.86 um and 1.24 um for remote sensing of vegetation liquid water. He established (ρ(0.86 um) – ρ(1.24 um)) / (ρ(0.86um) + ρ(1.24um)) to define NDWI, and 'ρ' represents the radiance in reflectance units. He reported that NDWI is sensitive to change in liquid water of green plant canopies, and NDWI is less sensitive to atmospheric effects than NDVI.

McFeeters (1996) assessed water content using green and NIR bands. McFeeters used (green – nir) / (green + nir) to monitor water content. NDWI values are similar to NDVI, and the values from -1 to 0 refer to no vegetation or water content, then 0 to +1 represents water content. I will use McFeeters' (1996) approach to analyze the study sites because PlanetScope, my primary data set, has four bands (red, green, blue and near-infrared). NDWI has been developed to depict water features and improved their presence in the satellite imageries. Using green and NIR NDWI improved the accuracy of water feature and removing vegetation features. Therefore, NDWI often use to monitor turbidity water bodies. For example, NDWI used to study forecasting crop yield using remote sensing, and the study identify agricultural fields (Bolton and Fried 2013). They analyzed non-semi-arid counties and semi-arid counties using NDWI then each result is 0.67 and 0.69. Through the NDWI, they found the water index has important benefit for remote sensing-based study of crop yields (Bolton and Fried 2013).

The Modified Soil-Adjusted Vegetation Index (MSAVI2) is based on soil-adjusted vegetation index (SAVI). NDVI has unstable products including varying soil color, and SAVI compensates NDVI using a canopy background adjustment factor (L) with different red light and near-infrared light. SAVI uses 'L value' to minimize soil brightness variations. MSAVI2 refers to the modified SAVI method and tries to minimize the effect of bare soil on the SAVI. Using the formula $(1/2) * (2 * (NIR +1) - sqrt((2 * NIR + 1)^2-8(NIR - Red)))$, MSAVI2 calculates from a multiband raster object. Thus, this index can analyze plant growth, desertification, grassland, drought and erosion.

The preliminary study of BSI, which indicates relations to soil moisture, and it shows how much water is held in the spaces between soil particles. BSI requires shortwave-infrared (SWIR), and the PlanetScope satellite does not have SWIR. Regarding the MSAVI2 study, forecasting potato yields in Lebanon and Idaho used to MSAVI2, GNDVI, NDVI, and SAVI to analyze remotely sensed imagery (Abou Ali *et al.* 2020). They used PlanetScope satellite images for the growing state, and the imagery indicates validated yield forecasting model of potato in Idaho and Lebanon.

2.5 Summary

There are many studies relating remote sensing and ADS in Corn Belt states. There are no such studies in the RRV of North Dakota and Minnesota. The environment of the RRV is heavily impacted by subsurface tile drainage because agricultural fields comprise 90 percent of the landscape (Emerson *et al.* 2005). The North Dakota State Water Commission has proposed drainage systems on the fields because ADS play a role in water storage, and ADS potentially can reduce peak flood flows. ADS with control structures can control water on the surface and soil in late fall, winter, or early spring. ADS brings helps to mitigate severe weather in the RRV. This is because the major problem in the RRV is urban and agricultural flooding, and the flood causes the destructive and widespread damages. The damages and loss are not limited in the RRV between North Dakota and Minnesota because of flow to Canada. Thus, the concern of water quantity and quality issues are associated with ADS, and the issues have to be discussed internationally. Recently, thousands of miles of drain tiles have been installed in the RRV.

The purpose of ADS is the removal of excess water from fields through the use of ditches and subsurface pipes. Previous studies used various vegetation and water indexes with Sentinel2 satellite imagery to determine the relationship with ADS. Bare soil Index (BI) relates to soil moisture of ADS study, and BI required SWIR (Rasul *et al*. 2018). NDVI relates to biomass and health of crops in the study area. Also, NDWI has relates to liquid water. Gao's method is used to monitor changes in water content of leaves. McFeeter's method is used to monitor changes related to water content in water bodies.

CHAPTER 3

METHODOLOGY

3.1. Introduction

I used remote sensing and geographic information system (GIS) tools to examine agricultural drainage systems (ADS) in the Red River Valley (RRV). To do so, I needed a few “control” fields where I know the type of ADS used: uncontrolled (UCDS) or controlled (CDS). I identified control fields through a windshield survey, and I collected GPS points so that I could identify selected fields on satellite images. I used data from PlanetScope (planet.com), which provides free satellite images to students over small geographic areas. Satellite images were processed using ArcMap 10.6 (Environmental Systems Research Institute, Redlands, CA).

Agricultural research with remote sensing requires an understanding of farm practices and a region’s crop calendar provides important information on agricultural activities. The calendar is a kind of guideline for farming, because it describes the crop cycle such as when a crop should be planted, when a crop is expected to flower, and when a crop is ready to harvest. A crop calendar in a given region varies annually because of weather patterns, changing local practices, and economic incentives. According to the 2019 Minnesota Crop Progress Review of USDA Minnesota Field Office, the crop progress and yield was influenced by extreme weather events in 2019 (Fig. 7, 8, and 9). As a result, I struggled to design a study and to get data.

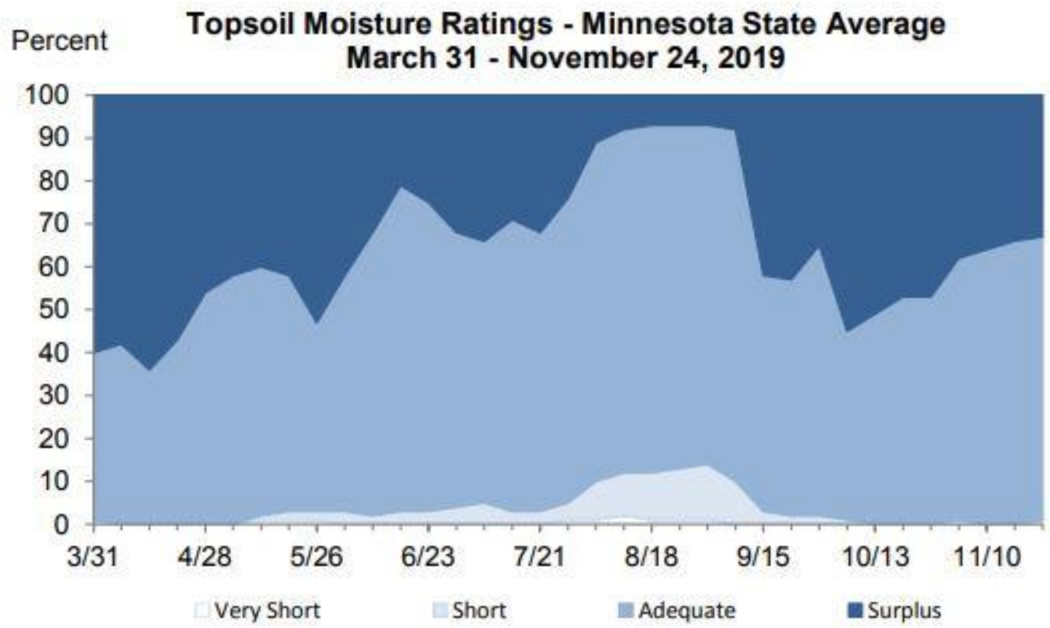

Figure 7. Topsoil moisture ratio of peculiar weather 2019 in Minnesota (Source: USDA - National Agricultural Statistics Service - Minnesota - Crop Progress and Condition Reports).

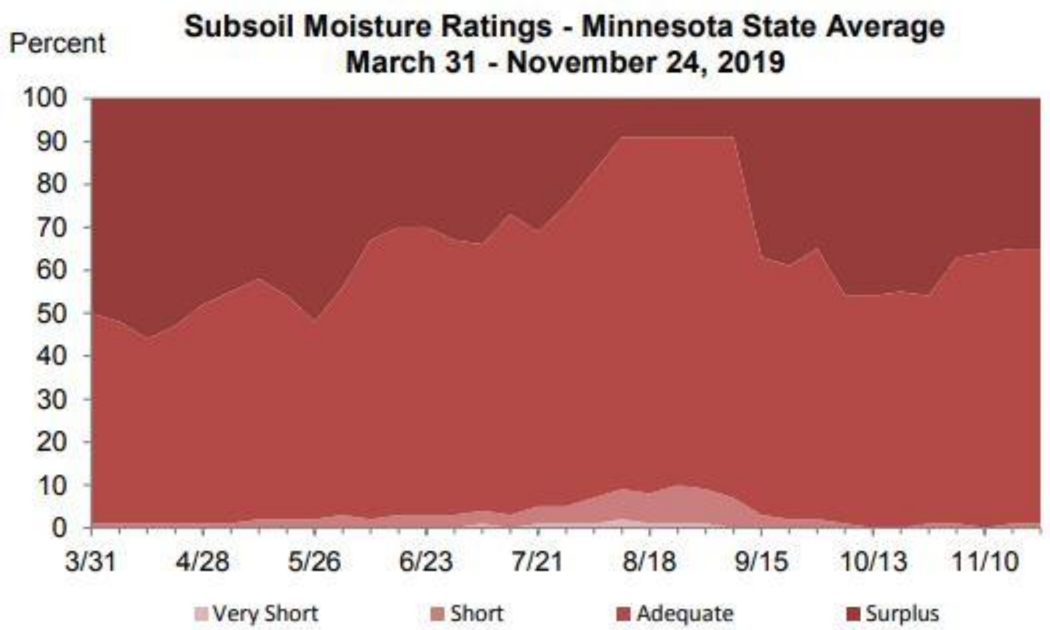

Figure 8. Subsoil moisture ratio of peculiar weather 2019 in Minnesota (Source: USDA - National Agricultural Statistics Service - Minnesota - Crop Progress and Condition Reports).

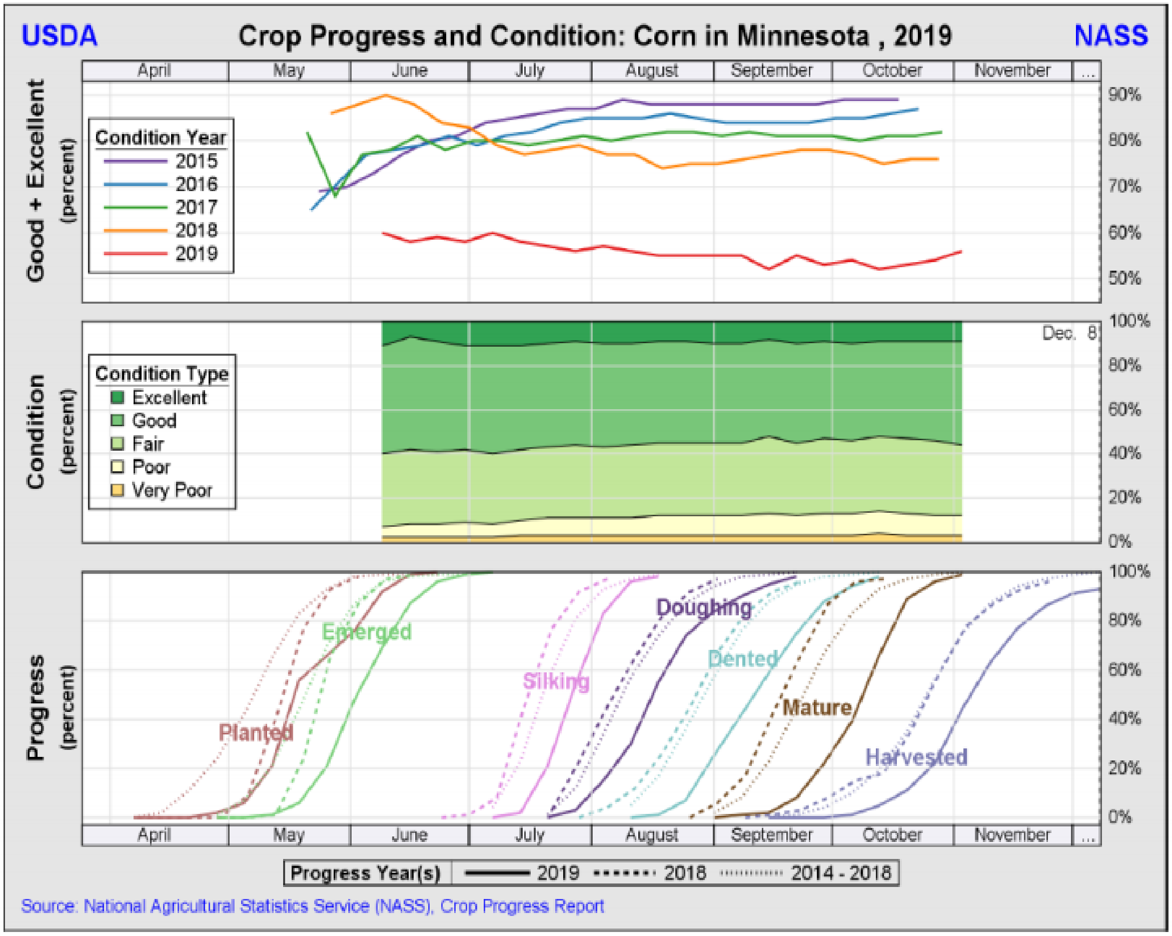

Figure 9. Comparison with annual corn progress and condition (Source: USDA - National Agricultural Statistics Service - Minnesota - Crop Progress and Condition Reports).

3.2 Study Sites and Periods

The study sites are: In Minnesota, Polk County, HIGDEM Township (Section 14 NW ¼, Section 15 NW 80, and Section 17 NE ¼), ESTER Township (Section 2 NE ¼ and Section 12 SW ¼), and SANDSVILLE Township (Section 31 NW ¼ and Section 20 SE ¼). Marshall County has OAK PARK Township (Section 2 SW ¼). In North Dakota, Traill County has BINGHAM Township (Section T147N R49W 35 SW ¼), (Section T147N R49W, T147N R50W, T147N R51W, and T147N R52W), (Section T148N R49W, T147N R50W, and T147N R51W), and (Section T150N R50W).

The study period is 2019 sorted by planting season (May ~ June), growing season (August ~ September), and harvesting season (October ~ November).

3.3 Data Collection

3.3.1 GPS with application program

GPS is useful to find the location of an agricultural field on a satellite image. In this study, I used a Garmin GPSMAP 64st (Garmin Ltd., Olathe, KS) to gather an accurate location, and Garmin BASEMAP application software to process GPS data. My GPS point collection protocol is as follows. First, I visited each study site with the GPS unit and determined whether I had a good connection to GPS satellites. If I did, I marked the drained field with a waypoint, which includes essential information such as altitude, latitude, height, and connected satellite information. After gathering all waypoints for each control field, the data displays using BASEMAP, and the application transfers information between the GPS unit and the computer. Then, I used the waypoints to ArcMap to analyze satellite imagery.

3.3.2 Digital Elevation Model (DEM)

A Digital Elevation Model (DEM) is a digital representation of elevation variation across the Earth's surface (Ghuffar 2018). That is, DEM data are used to represent the characteristics of a topographic surface of the Earth. DEM data are raster files comprised of individual cells containing a value indicating elevation above mean sea level. DEMs have been used extensively to extract terrain parameters for geomorphology (Fabrikant 2000). I acquired the DEM raster files from Minnesota Geospatial Commons (https://gisdata.mn.gov/) and from North Dakota LiDAR Dissemination Map services (https://lidar.swc.nd.gov/). The downloaded file from the Minnesota site is LiDAR Elevation, Red River of the North Basin, 2008–2010, UTM Zone 15.

The DEM data can be downloaded in 3.25 square mile blocks based on 1/16 of USGS 1:24,000 quadrangle. The Horizonal positional accuracy is 1m RMSE, and vertical positional accuracy is 15cm RMSE. The DEM file of North Dakota site is Red River Basin Mapping Initiative 2008 – 2010, UTM Zone 14. The Horizonal positional accuracy is 1.35m RMSE, and vertical positional accuracy is 15cm RMSE.

In this study, I created slope maps from the DEM layer. Slope consists of gradient or rate of maximum change in z-value from each cell of the DEM raster file. The DEM can be transformed into a slope map using slope tool in ArcGIS. To create slope map, I used slope function in toolbox in ArcGIS, and I selected the output of the Topo to Raster tool as the input raster (Chang 2006; Zhu 2016). Then I set pathway to save the output raster and choose the output measurement.

3.3.3 Linear and spacing map

There are patterns of ADS; herringbone, parallel or gridiron, double-main, and targeted (Hofstrand 2010). The study sites have combined ADS patterns without distinguishing CDS from UCDS.

In this study, I used PlanetScope (planet.com) satellite imagery acquired in April or May 2019 to draw ADS lines. The RRV had seen a lot of snow during winter and spring, then the snow melted in April and May, providing good contrast on the imagery between wet tile lines and drier conditions across the fields. I digitized lines using satellite image on the ArcMap after the period indicates drainage lines on the surface.

Regarding to surface volume calculation, I used the surface volume tool in the ArcMap 10.6. to calculate agricultural drainage volume for my control fields, I input a raster file of the

ADS set below in reference plane, specified the elevation of the reference, and used the tool to calculate surface volume.

3.3.4 Satellite imagery collection

In this study, I choose PlanetScope satellite imagery. Planet data are available for free to students over limited geographic areas for non-commercial purpose. The images from PlanetScope are easy to find and download using a web-based application. Through the PlanetScope webpage, selected imagery can be processed by various formats to analyze ADS with mapping. PlanetScope is one of sensors in Planet. The spatial resolution is 3.7 m and temporal resolution is daily. PlanetScope operates to get Earth images, and the images are acquired by four bands as a split-frame with a RGB (Red, Green, and Blue) half and a near-infrared (NIR) half. PlanetScope uses 590 to 670 nm wavelength and provides three product lines: basic scene, ortho scene, and ortho tile. I used the ortho tile product to study ADS because ortho tile products provide multiple orthorectified scenes in a single strip. Also, the scenes can be merged and divided when I defined a grid in ArcMap 10.6.

The data selection and download procedure for PlanetScope is as follows: 1) draw study area with a geometry tool, and 2) select filter results using satellite constellations and environmental conditions. I chose 4-band PlanetScope in the satellite constellation section and applied area coverage 80–100 %, cloud cover 0–10 %, ground sample distance 0.1– 30 m, off-nadir angle negative -60 degrees–+60 degrees, Sun azimuth 0–360 degrees, and Sun elevation -90 degrees– +90 degrees in the environmental conditions section. Then I edited the acquisition date ranges. Lastly, items selected were ordered (at no cost).

3.3.5 Image management and analysis formula

ArcMap 10.6 is well-known as a geospatial processing application. Most geospatial data is edited, created, and analyzed by ArcMap. To analyze PlanetScope satellite images, I applied the appropriate vegetation index formula to PlanetScope in ArcGIS. Normalized Difference Vegetation Index (NDVI) used (NIR – RED) / (NIR + RED) (Tucker 1977). Normalized Difference Water Index (NDWI) used (GREEN – NIR) / (GREEN + NIR) (McFeeters 1996). Modified Soil-Adjusted Vegetation Index (MSAVI2) used (1/2) * (2 * (NIR +1) – square root ((2 * NIR + 1)^2 - 8 (NIR - Red))) (Cooley *et al.* 2017; Hoa 2017; Baloloy *et al.* 2018; Mudereri *et al.* 2019; Abou Ali *et al.* 2020). Image analysis window in ArcMap 10.6 used to analyze NDVI. Map algebra in ArcMap 10.6 used to calculate NDWI and MSAVI2.

All analyzed values of three different indexes between UCDS and CDS in the study were run by SPSS statistics software (SPSS, version 23). For examining a group difference between UCDS and CDS fields related to NDVI, NDWI, and MSAVI2 in the Red River Valley (UCDS = 0 and CDS =1), one-way ANOVA was conducted for each index through using the SPSS statistic program (SPSS, version 23).

CHAPTER 4

RESULTS

4.1 Linear maps and slope with surface volume

Using remotely sensed data collected from a high-resolution satellite platform, I mapped shallow subsurface agricultural drainage systems (ADS). Most agricultural fields in my study areas used ADS on fields of cultivated crops. Through a field trip to distinguish uncontrolled, or conventional, drainage systems (UCDS) from controlled drainage systems (CDS), I found no preference for the agricultural areas in Minnesota and North Dakota that I focused on. That is, the linear and slope maps that I produced with surface volume show that UCDS and CDS are mixed.

I found the herringbone pattern on two of the fields that I sampled, and the double main patterns on four fields, in Minnesota. I found the parallel pattern on five fields in MN and ND, and the targeted pattern on six fields. The herringbone pattern for UCDS drainage (Fig. 10) and its slope (Fig. 10) were found in Polk County, MN. The herringbone pattern for CDS (Fig. 11) (Fig. 11) were also found in Polk County. Parallel patterns and slope maps of conventional (Fig. 12) is in Polk County, MN. Parallel patterns and slope maps of CDS (Fig. 13) is in Traill County, ND. Fig. 14 and 15 show double main pattern of both agricultural drainage types in Polk County, MN. The slope maps of double main pattern are Figs. 14 and 15. Fig. 16 shows targeted pattern of UCDS in Traill County, ND, and Fig. 16 is its slope of the targeted pattern. The agricultural field in Polk County, MN, is targeted pattern (Fig. 17). Most slope maps in Polk County, MN, indicate that drains or ditches have angle to irrigate water as well as tiles or pipelines in the flat fields, while slope maps of Traill County, ND, show that agricultural fields are plowed.

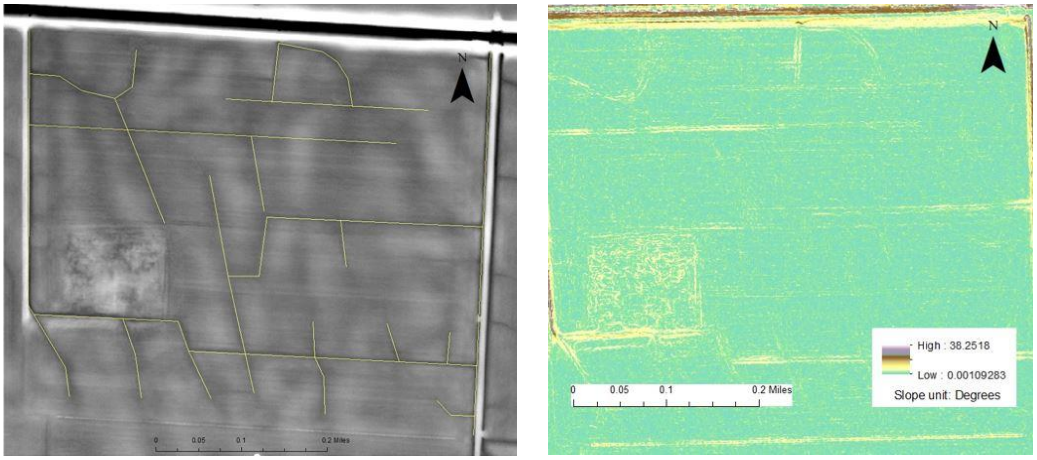

Figure 10. Herringbone pattern of conventional drainage and its slope in Polk County, MN.

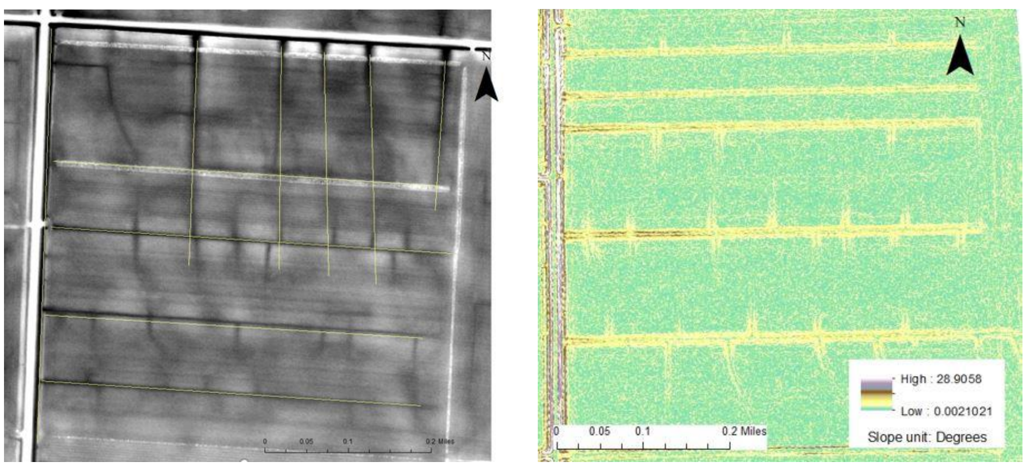

Figure 11. Herringbone pattern of controlled drainage and its slope in Polk County, MN.

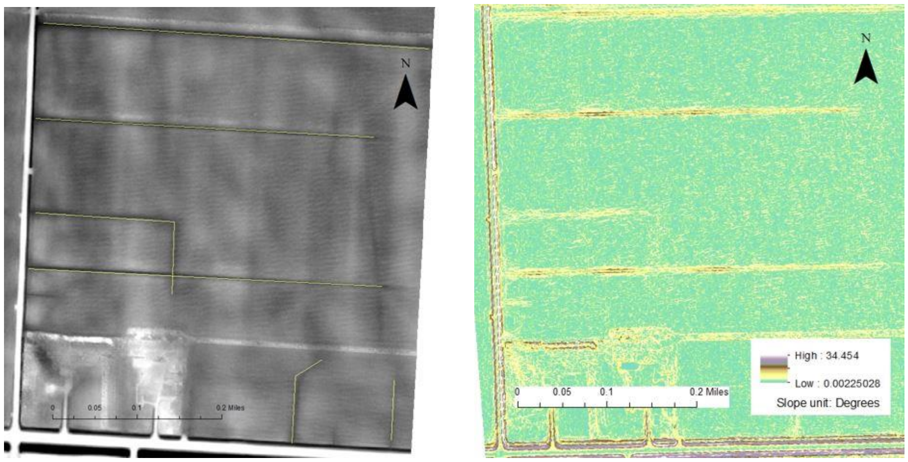

Figure 12. Parallel pattern of conventional drainage and its slope in Polk County, MN.

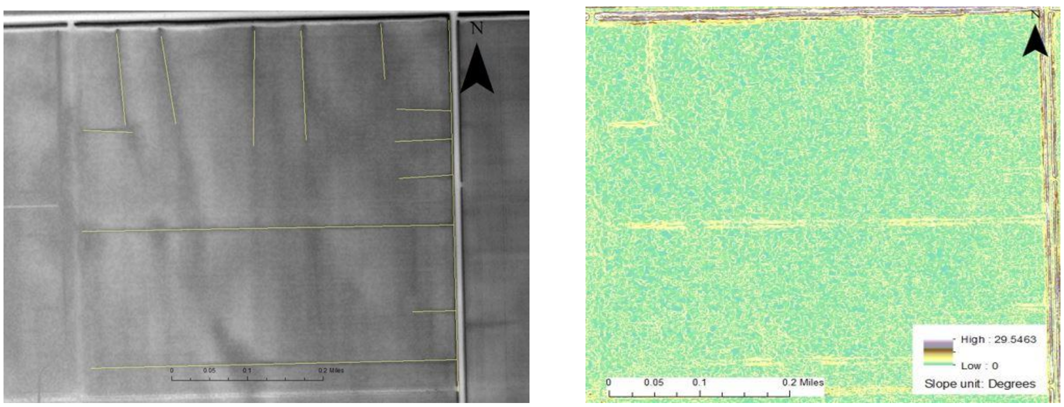

Figure 13. Parallel pattern of controlled drainage and its slope in Traill County, ND.

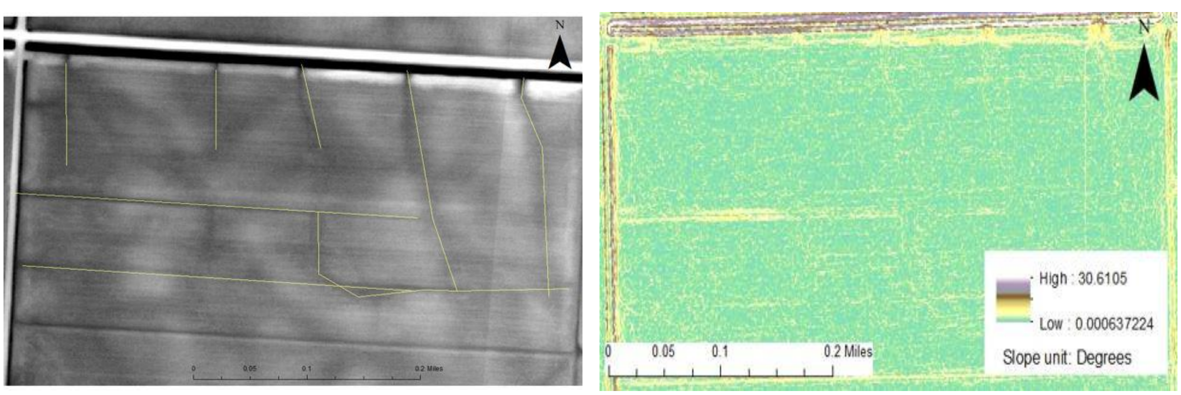

Figure 14. Double main pattern of conventional drainage and its slope in Polk County, MN.

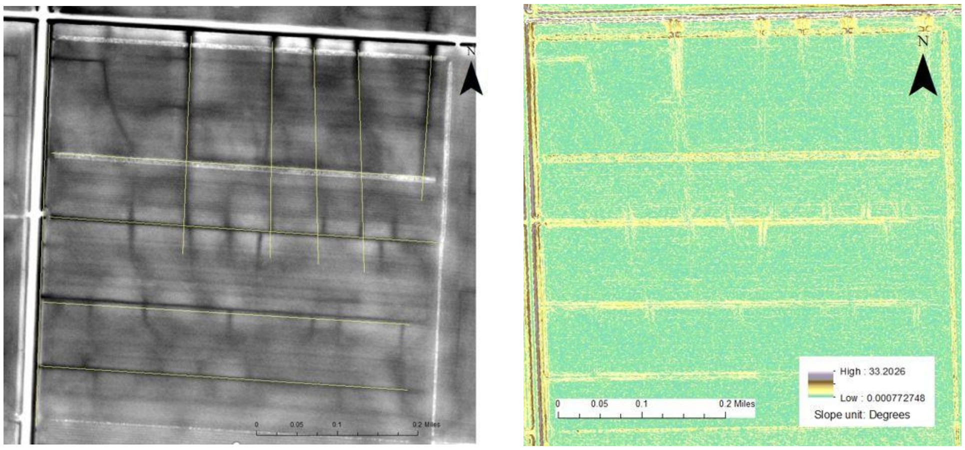

Figure 15. Double main pattern of controlled drainage and its slope in Polk County, MN.

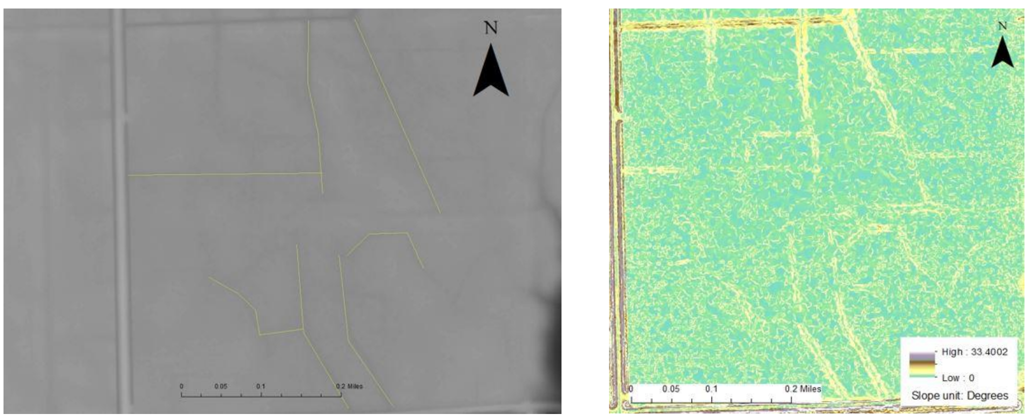

Figure 16. Targeted pattern of conventional drainage and its slope in Traill County, ND.

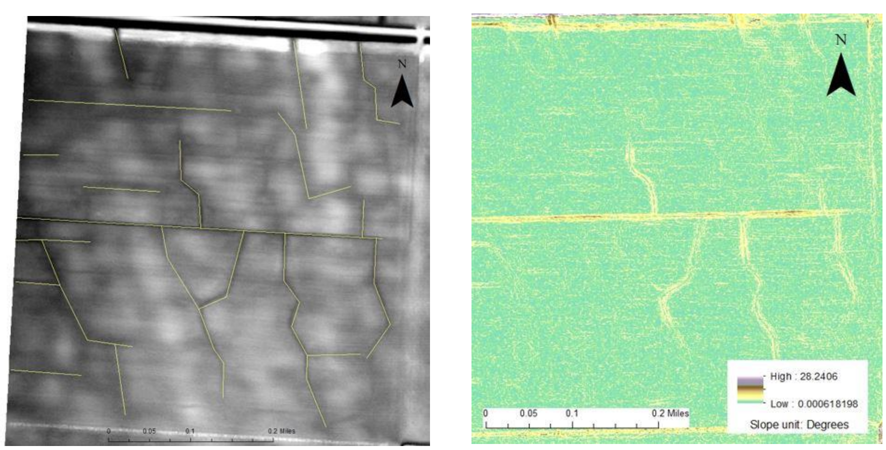

Figure 17. Targeted pattern of controlled drainage and its slope are in Polk County, MN.

Table 1 gives the results of the surface area of artificially drained lands in Minnesota. Most plane heights are similar but surface volume is different depending on agricultural field size. The surface volume of agricultural fields in North Dakota is shown in Table 2.

Table 1. Surface area of study sites in Minnesota

Study site	Plane Height (meters)	Area 2D (sq. meters)	Area 3D (sq. meters)	Volume (cu. meters)
UCDS 1	245	852,012	854,159	2,579,313
UCDS 2	245	756,540	757,598	1,749,894
UCDS 3	245	455,184	456,093	918,510
UCDS 4	246	852,822	854,989	1,348,212
UCDS 5	246	843,586	845,323	1,406,698
UCDS 6	244	816,282	818,412	1,934,543
UCDS 7	247	737,590	739,045	1,500,351
CDS 1	227	839,055	842,151	1,749,796
CDS 2	247	927,085	928,492	1,326,816
CDS 3	246	851,904	853,162	1,268,250
CDS 4	244	876,060	878,439	3,348,500
CDS 5	243	891,136	892,291	1,341,425
CDS 6	241	912,016	912,853	2,219,420
CDS 7	242	218,988	219,630	509,887
CDS 8	243	855,456	857,413	1,898,595
CDS 9	243	464,849	466,054	971,529
CDS 10	247	854,281	856,003	1,135,626

Table 2. Surface area of study sites in North Dakota

Study site	Plane Height (meters)	Area 2D (sq. meters)	Area 3D (sq. meters)	Volume (cu. meters)
UCDS 1	259	724,201	725,346	1,115,166
CDS 1	264	738,698	740,268	1,188,497
CDS 2	282	1,519,848	1,521,309	5,374,633
CDS 3	257	741,320	742,505	1,454,728
CDS 4	267	743,850	745,127	1,177,401
CDS 5	266	374,781	375,186	1,066,901
CDS 6	280	758,637	759,703	1,169,965
CDS 7	283	149,668	149,996	600,916
CDS 8	282	874,264	875,600	4,764,747
CDS 9	277	657,465	658,599	4,223,745
CDS 10	275	724,201	725,346	1,115,166

4.2 Analysis of Remotely Sensed Data

To compare UCDS and CDS crop biomass and health, I used PlanetScope satellite imagery. I explored eight UCDS and 20 CDS in MN and ND. Through results of analysis of vegetation indexes for UCDS and CDS fields, there is no apparent difference in Minnesota or North Dakota.

Normalized Difference Vegetation Index (NDVI) shows that the study sites in Minnesota have a maximum value of 0.57 and minimum value of -0.18 in June 2019 (Fig. 18). North Dakota sites a maximum value of 0.63 and a minimum value of -0.24 also in June 2019 (Fig. 19). NDVI analysis in September 2019 indicates a maximum value 0.66 and a minimum value of -0.17 in Minnesota (Fig. 20) and a maximum value of 0.55 and a minimum value of -0.46 in North Dakota (Fig. 21). Minnesota study sites in October 2019 have a maximum value of 0.58 and minimum value of -0.47 (Fig. 22). North Dakota study sites in November 2019 have a maximum value of 0.33 and a minimum value of -0.37 (Fig. 23).

The results revealed that there is no significance between UCDS and CDS for all indexes as shown in Table 9 and Table 10 (i.e., p-values were not smaller than .05). That is, the series of results indicated that the assumption of this study (the null hypothesis denoted H0: UCDS = CDS while alternative hypothesis denoted H1: UCDS ≠ CDS) was not supported. It implies that the healthiness of crops does not affected by whether the CDS is equipped on the sites or not.

Table 3. Spectral index values for study sites in Minnesota

Field ID	Month	NDVI min	NDVI max	NDVI mean	NDWI min	NDWI max	NDWI mean	MSAVI2 min	MSAVI2 max	MSAVI2 mean
UCDS1	June	-0.105	0.372	0.134	-0.408	0.501	0.047	-0.233	0.542	0.154
	Sept.	-0.045	0.644	0.300	-0.501	0.096	-0.202	-0.094	0.783	0.345
	Nov.	-0.257	0.492	0.118	-0.344	0.391	0.023	-0.690	0.660	-0.015
UCDS2	June	-0.107	0.407	0.150	-0.254	0.201	-0.026	-0.239	0.578	0.170
	Sept.	-0.097	0.634	0.269	-0.491	0.203	-0.144	-0.215	0.776	0.281
	Nov.	-0.215	0.308	0.046	-0.206	0.367	0.080	-0.548	0.471	-0.039
UCDS3	June	-0.105	0.331	0.113	-0.171	0.202	0.015	-0.235	0.497	0.131
	Sept.	-0.014	0.630	0.308	-0.484	0.108	-0.188	-0.028	0.772	0.372
	Nov.	-0.220	0.269	0.024	-0.130	0.363	0.116	-0.565	0.423	-0.071
UCDS4	June	-0.111	0.506	0.198	-0.360	0.190	-0.085	-0.250	0.672	0.211
	Sept.	-0.031	0.618	0.293	-0.463	0.145	-0.159	-0.064	0.764	0.350
	Nov.	-0.220	0.277	0.029	-0.150	0.355	0.103	-0.563	0.434	-0.065
UCDS5	June	-0.110	0.570	0.230	-0.427	0.199	-0.114	-0.247	0.726	0.240
	Sept.	-0.169	0.614	0.223	-0.464	0.257	-0.104	-0.406	0.761	0.177
	Nov.	-0.337	0.574	0.118	-0.322	0.390	0.034	-1.018	0.729	-0.144
UCDS6	June	-0.123	0.443	0.160	-0.291	0.227	-0.032	-0.280	0.614	0.167
	Sept.	-0.055	0.631	0.288	-0.487	0.148	-0.170	-0.117	0.773	0.328
	Nov.	-0.412	0.344	-0.034	-0.203	0.513	0.155	-1.397	0.512	-0.442
UCDS7	June	-0.175	0.502	0.163	-0.351	0.187	-0.082	-0.425	0.668	0.122
	Sept.	-0.164	0.566	0.201	-0.425	0.211	-0.107	-0.392	0.723	0.166
	Nov.	-0.249	0.466	0.109	-0.327	0.394	0.033	-0.662	0.636	-0.013
CDS1	June	-0.153	0.454	0.151	-0.300	0.205	-0.048	-0.362	0.625	0.132
	Sept.	-0.090	0.631	0.271	-0.491	0.191	-0.150	-0.197	0.774	0.289
	Nov.	-0.257	0.325	0.034	-0.213	0.403	0.095	-0.691	0.490	-0.100
CDS2	June	-0.107	0.472	0.183	-0.343	0.214	-0.064	-0.240	0.642	0.201
	Sept.	-0.105	0.590	0.243	-0.433	0.253	-0.090	-0.234	0.742	0.254
	Nov.	-0.259	0.495	0.118	-0.342	0.388	0.023	-0.699	0.662	-0.018
CDS3	June	-0.116	0.451	0.168	-0.302	0.190	-0.056	-0.262	0.622	0.180
	Sept.	-0.080	0.661	0.290	-0.519	0.217	-0.151	-0.175	0.796	0.311
	Nov.	-0.211	0.455	0.122	-0.327	0.373	0.023	-0.534	0.625	0.046
CDS4	June	-0.112	0.474	0.181	-0.332	0.205	-0.064	-0.251	0.644	0.196
	Sept.	-0.052	0.645	0.297	-0.501	0.200	-0.151	-0.109	0.784	0.338
	Nov.	-0.262	0.460	0.099	-0.318	0.415	0.048	-0.709	0.630	-0.040
CDS5	June	-0.142	0.330	0.094	-0.191	0.218	0.014	-0.331	0.497	0.083
	Sept.	-0.060	0.574	0.257	-0.445	0.104	-0.170	-0.128	0.729	0.301
	Nov.	-0.402	0.558	0.078	-0.412	0.528	0.058	-1.343	0.716	-0.314
CDS6	June	-0.109	0.345	0.118	-0.206	0.200	-0.003	-0.245	0.514	0.134
	Sept.	-0.075	0.640	0.282	-0.497	0.186	-0.155	-0.163	0.780	0.309
	Nov.	-0.471	0.447	-0.012	-0.314	0.571	0.129	-1.778	0.618	-0.580
CDS7	June	-0.108	0.292	0.092	-0.164	0.191	0.013	-0.242	0.452	0.105

	Sept.	-0.049	0.648	0.299	-0.507	0.181	-0.163	-0.103	0.786	0.342
	Nov.	-0.217	0.086	-0.065	0.024	0.362	0.193	-0.555	0.159	-0.198
CDS8	June	-0.110	0.429	0.160	-0.276	0.174	-0.051	-0.248	0.601	0.177
	Sept.	-0.064	0.574	0.255	-0.433	0.162	-0.136	-0.136	0.729	0.297
	Nov.	-0.203	0.234	0.015	-0.129	0.337	0.104	-0.510	0.379	-0.065
CDS9	June	-0.113	0.480	0.184	-0.330	0.193	-0.069	-0.255	0.649	0.197
	Sept.	-0.103	0.570	0.233	-0.417	0.199	-0.109	-0.230	0.726	0.248
	Nov.	-0.184	0.325	0.070	-0.189	0.302	0.056	-0.451	0.491	0.020
0CDS10	June	-0.122	0.517	0.197	-0.368	0.225	-0.071	-0.279	0.682	0.201
	Sept.	-0.089	0.613	0.262	-0.460	0.202	-0.129	-0.195	0.761	0.283
	Nov.	-0.178	0.401	0.112	-0.273	0.312	0.019	-0.432	0.573	0.070

Table 4. Spectral index values for study sites in North Dakota

Field ID	Month	NDVI min	NDVI max	NDVI mean	NDWI min	NDWI max	NDWI mean	MSAVI2 min	MSAVI2 max	MSAVI2 mean
UCDS1	June	-0.113	0.405	0.146	-0.221	0.180	-0.021	-0.256	0.576	0.160
	Sept.	-0.070	0.371	0.151	-0.235	0.129	-0.053	-0.151	0.542	0.195
	Nov.	-0.142	0.179	0.019	-0.068	0.233	0.082	-0.331	0.304	-0.013
CDS1	June	-0.104	0.470	0.183	-0.267	0.194	-0.037	-0.233	0.640	0.203
	Sept.	-0.064	0.492	0.214	-0.365	0.169	-0.098	-0.136	0.660	0.262
	Nov.	-0.256	0.081	-0.088	0.018	0.396	0.207	-0.689	0.150	-0.270
CDS2	June	-0.126	0.621	0.248	-0.422	0.230	-0.096	-0.289	0.767	0.239
	Sept.	-0.138	0.546	0.204	-0.380	0.203	-0.089	-0.319	0.707	0.194
	Nov.	-0.135	0.326	0.095	-0.196	0.284	0.044	-0.312	0.491	0.090
CDS3	June	-0.047	0.630	0.291	-0.404	0.135	-0.134	-0.099	0.772	0.337
	Sept.	-0.093	0.491	0.199	-0.343	0.187	-0.078	-0.205	0.659	0.227
	Nov.	-0.217	0.092	-0.063	0.010	0.339	0.174	-0.553	0.168	-0.193
CDS4	June	-0.112	0.601	0.245	-0.376	0.204	-0.086	-0.253	0.751	0.249
	Sept.	-0.080	0.551	0.236	-0.401	0.161	-0.120	-0.174	0.710	0.268
	Nov.	-0.262	0.257	-0.003	-0.136	0.386	0.125	-0.708	0.408	-0.150
CDS5	June	-0.069	0.543	0.237	-0.336	0.146	-0.095	-0.148	0.704	0.278
	Sept.	-0.006	0.543	0.269	-0.401	0.146	-0.128	-0.012	0.701	0.345
	Nov.	-0.169	0.079	-0.045	-0.001	0.284	0.142	-0.405	0.146	-0.129
CDS6	June	-0.087	0.451	0.182	-0.273	0.185	-0.044	-0.191	0.622	0.216
	Sept.	-0.095	0.512	0.209	-0.376	0.264	-0.056	-0.209	0.677	0.234
	Nov.	-0.195	0.072	-0.062	0.005	0.283	0.144	-0.485	0.134	-0.176
CDS7	June	-0.241	0.546	0.152	-0.364	0.344	-0.010	-0.635	0.706	0.036
	Sept.	-0.457	0.496	0.020	-0.379	0.424	0.023	-1.681	0.664	-0.509
	Nov.	-0.366	0.325	-0.021	-0.181	0.407	0.113	-1.157	0.791	-0.183
CDS8	June	-0.106	0.585	0.240	-0.363	0.172	-0.096	-0.236	0.738	0.251
	Sept.	-0.093	0.492	0.199	-0.362	0.148	-0.107	-0.204	0.659	0.228
	Nov.	-0.172	0.231	0.030	-0.083	0.298	0.108	-0.415	0.375	-0.020
CDS9	June	-0.132	0.533	0.200	-0.323	0.191	-0.066	-0.305	0.695	0.195
	Sept.	-0.160	0.469	0.154	-0.324	0.199	-0.062	-0.380	0.638	0.129
	Nov.	-0.179	0.106	-0.037	-0.028	0.266	0.119	-0.435	0.191	-0.122
CDS10	June	-0.113	0.405	0.146	-0.221	0.180	-0.021	-0.256	0.576	0.160
	Sept.	-0.070	0.371	0.151	-0.235	0.129	-0.053	-0.151	0.542	0.195
	Nov.	-0.142	0.179	0.019	-0.068	0.233	0.082	-0.331	0.304	-0.013

Table 5. Visual interpretation of crop cover on study sites in Minnesota

Field ID	Month	Field Status
UCDS1	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested
UCDS2	June	Crop
	Sept.	Bare Soil
	Nov.	Bare Soil
UCDS3	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested
UCDS4	June	Bare Soil
	Sept.	Bare Soil
	Nov.	Bare Soil
UCDS5	June	Crop
	Sept.	Forest
	Nov.	Harvested
UCDS6	June	Bare Soil
	Sept.	Bare Soil
	Nov.	Bare Soil
UCDS7	June	Bare Soil
	Sept.	Bare Soil
	Nov.	Bare Soil
CDS1	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested
CDS2	June	Bare Soil
	Sept.	Bare Soil
	Nov.	Bare Soil
CDS3	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested
CDS4	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested
CDS5	June	Crop
	Sept.	Bare Soil
	Nov.	Bare Soil
CDS6	June	Crop
	Sept.	Bare Soil
	Nov.	Crop
CDS7	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested
CDS8	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested
CDS9	June	Crop
	Sept.	Bare Soil
	Nov.	Bare Soil
CDS10	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested

Table 6. Visual interpretation of crop cover of study sites in North Dakota

Field ID	Month	Field Status
UCDS1	June	Crop
	Sept.	Crop
	Nov.	Harvested
CDS1	June	Bare Soil
	Sept.	Crop
	Nov.	Bare Soil
CDS2	June	Crop
	Sept.	Crop
	Nov.	Harvested
CDS3	June	Crop
	Sept.	Bare Soil
	Nov.	Bare Soil
CDS4	June	Bare Soil
	Sept.	Bare Soil
	Nov.	Bare Soil
CDS5	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested
CDS6	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested
CDS7	June	Crop
	Sept.	Bare Soil
	Nov.	Crop
CDS8	June	Bare Soil
	Sept.	Crop
	Nov.	Harvested
CDS9	June	Crop
	Sept.	Bare Soil
	Nov.	Crop

Table 7. Image ID and acquisition date of study sites in Minnesota

Field ID	Month	Image ID	Image Acquisition Date
UCDS1	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170310_1035_3B_AnalyticMS	2019-09-04T17:03:10+00:00
	Nov.	20191024_170337_1025_3B_AnalyticMS	2019-10-24T17:03:37+00:00
UCDS2	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170310_1035_3B_AnalyticMS	2019-09-04T17:03:10+00:00
	Nov.	20191024_170336_1025_3B_AnalyticMS	2019-10-24T17:03:36+00:00
UCDS3	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170310_1035_3B_AnalyticMS	2019-09-04T17:03:10+00:00
	Nov.	20191024_170336_1025_3B_AnalyticMS	2019-10-24T17:03:36+00:00
UCDS4	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170310_1035_3B_AnalyticMS	2019-09-04T17:03:10+00:00
	Nov.	20191024_170336_1025_3B_AnalyticMS	2019-10-24T17:03:36+00:00
UCDS5	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170310_1035_3B_AnalyticMS	2019-09-04T17:03:10+00:00
	Nov.	20191024_170336_1025_3B_AnalyticMS	2019-10-24T17:03:36+00:00
UCDS6	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170310_1035_3B_AnalyticMS	2019-09-04T17:03:10+00:00
	Nov.	20191024_170336_1025_3B_AnalyticMS	2019-10-24T17:03:36+00:00
UCDS7	June	20190614_170046_0f17_3B_AnalyticMS	2019-06-14T17:00:46+00:00
	Sept.	20190904_170311_1035_3B_AnalyticMS	2019-09-04T17:03:11+00:00
	Nov.	20191024_170337_1025_3B_AnalyticMS	2019-10-24T17:03:37+00:00
CDS1	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170310_1035_3B_AnalyticMS	2019-09-04T17:03:10+00:00
	Nov.	20191024_170336_1025_3B_AnalyticMS	2019-10-24T17:03:36+00:00
CDS2	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170310_1035_3B_AnalyticMS	2019-09-04T17:03:10+00:00
	Nov.	20191024_170336_1025_3B_AnalyticMS	2019-10-24T17:03:36+00:00
CDS3	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170310_1035_3B_AnalyticMS	2019-09-04T17:03:10+00:00
	Nov.	20191024_170336_1025_3B_AnalyticMS	2019-10-24T17:03:36+00:00
CDS4	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170310_1035_3B_AnalyticMS	2019-09-04T17:03:10+00:00
	Nov.	20191024_170336_1025_3B_AnalyticMS	2019-10-24T17:03:36+00:00
CDS5	June	20190614_170043_0f17_3B_AnalyticMS	2019-06-14T17:00:43+00:00
	Sept.	20190904_170309_1035_3B_AnalyticMS	2019-09-04T17:03:09+00:00
	Nov.	20191024_170335_1025_3B_AnalyticMS	2019-10-24T17:03:35+00:00
CDS6	June	20190614_170043_0f17_3B_AnalyticMS	2019-06-14T17:00:43+00:00
	Sept.	20190904_170308_1035_3B_AnalyticMS	2019-09-04T17:03:08+00:00
	Nov.	20191024_170334_1025_3B_AnalyticMS	2019-10-24T17:03:34+00:00
CDS7	June	20190614_170043_0f17_3B_AnalyticMS	2019-06-14T17:00:43+00:00
	Sept.	20190904_170308_1035_3B_AnalyticMS	2019-09-04T17:03:08+00:00
	Nov.	20191024_170334_1025_3B_AnalyticMS	2019-10-24T17:03:34+00:00
CDS8	June	20190614_170043_0f17_3B_AnalyticMS	2019-06-14T17:00:43+00:00
	Sept.	20190904_170308_1035_3B_AnalyticMS	2019-09-04T17:03:08+00:00
	Nov.	20191024_170334_1025_3B_AnalyticMS	2019-10-24T17:03:34+00:00
CDS9	June	20190614_170043_0f17_3B_AnalyticMS	2019-06-14T17:00:43+00:00
	Sept.	20190904_170308_1035_3B_AnalyticMS	2019-09-04T17:03:08+00:00
	Nov.	20191024_170334_1025_3B_AnalyticMS	2019-10-24T17:03:34+00:00
CDS10	June	20190614_170045_0f17_3B_AnalyticMS	2019-06-14T17:00:45+00:00
	Sept.	20190904_170311_1035_3B_AnalyticMS	2019-09-04T17:03:11+00:00
	Nov.	20191024_170337_1025_3B_AnalyticMS	2019-10-24T17:03:37+00:00

Table 8. Image ID and acquisition date of study sites in North Dakota

Field ID	Month	Image ID	Image Acquisition Date
UCDS1	June	20190605_171004_00_1057_3B_AnalyticMS	2019-06-05T17:10:04+00:00
	Sept.	20190923_170142_1013_3B_AnalyticMS	2019-09-23T17:01:42+00:00
	Nov.	20191031_170408_0f22_3B_AnalyticMS	2019-10-31T17:04:08+00:00
CDS1	June	20190605_171004_00_1057_3B_AnalyticMS	2019-06-05T17:10:04+00:00
	Sept.	20190923_170140_1013_3B_AnalyticMS	2019-09-23T17:01:40+00:00
	Nov.	20191107_170247_0f28_3B_AnalyticMS	2019-11-07T17:02:47+00:00
CDS2	June	20190605_171004_00_1057_3B_AnalyticMS	2019-06-05T17:10:04+00:00
	Sept.	20190923_170142_1013_3B_AnalyticMS	2019-09-23T17:01:42+00:00
	Nov.	20191107_170248_0f28_3B_AnalyticMS	2019-11-07T17:02:48+00:00
CDS3	June	20190605_171004_00_1057_3B_AnalyticMS	2019-06-05T17:10:04+00:00
	Sept.	20190923_170140_1013_3B_AnalyticMS	2019-09-23T17:01:40+00:00
	Nov.	20191107_170247_0f28_3B_AnalyticMS	2019-11-07T17:02:47+00:00
CDS4	June	20190605_171004_00_1057_3B_AnalyticMS	2019-06-05T17:10:04+00:00
	Sept.	20190923_170142_1013_3B_AnalyticMS	2019-09-23T17:01:42+00:00
	Nov.	20191107_170248_0f28_3B_AnalyticMS	2019-11-07T17:02:48+00:00
CDS5	June	20190605_171006_04_1057_3B_AnalyticMS	2019-06-05T17:10:06+00:00
	Sept.	20190923_170142_1013_3B_AnalyticMS	2019-09-23T17:01:42+00:00
	Nov.	20191107_170249_0f28_3B_AnalyticMS	2019-11-07T17:02:49+00:00
CDS6	June	20190605_171006_04_1057_3B_AnalyticMS	2019-06-05T17:10:06+00:00
	Sept.	20190923_170142_1013_3B_AnalyticMS	2019-09-23T17:01:42+00:00
	Nov.	20191107_170248_0f28_3B_AnalyticMS	2019-11-07T17:02:48+00:00
CDS7	June	20190605_171004_00_1057_3B_AnalyticMS	2019-06-05T17:10:04+00:00
	Sept.	20190923_170140_1013_3B_AnalyticMS	2019-09-23T17:01:40+00:00
	Nov.	20191107_170247_0f28_3B_AnalyticMS	2019-11-07T17:02:47+00:00
CDS8	June	20190605_171004_00_1057_3B_AnalyticMS	2019-06-05T17:10:04+00:00
	Sept.	20190923_170139_1013_3B_AnalyticMS	2019-09-23T17:01:39+00:00
	Nov.	20191107_170246_0f28_3B_AnalyticMS	2019-11-07T17:02:46+00:00
CDS9	June	20190605_171004_00_1057_3B_AnalyticMS	2019-06-05T17:10:04+00:00
	Sept.	20190923_170139_1013_3B_AnalyticMS	2019-09-23T17:01:39+00:00
	Nov.	20191107_170246_0f28_3B_AnalyticMS	2019-11-07T17:02:46+00:00

Table 9. Comparison between UCDS and CDS computed by SPSS 23

	CDS	N	Mean	Std. Deviation	Std. Error Mean
NDVI-CDS_min	UCDS	24	-.151888	.0962076	.0196383
	CDS	57	-.153748	.0977942	.0129532
NDVI-CDS_max	UCDS	24	.464650	.1376466	.0280970
	CDS	57	.444211	.1642868	.0217603
NDWI-CDS_min	UCDS	24	-.324353	.1302240	.0265819
	CDS	57	-.299318	.1443099	.0191143
NDWI-CDS_max	UCDS	24	.257885	.1202442	.0245447
	CDS	57	.255201	.1010078	.0133788
MSAVI2I-CDS_min	UCDS	24	-.391884	.3156292	.0644275
	CDS	57	-.402733	.3543720	.0469377
MSAVI2-CDS_max	UCDS	24	.622314	.1346016	.0274754
	CDS	57	.600020	.1846647	.0244594

Table 10. Statistics of ADS in the study sites by One-way ANOVA of SPSS 23

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
NDVI-CDS_min	Between Groups	.000	1	.000	.006	.938
	Within Groups	.748	79	.009		
	Total	.749	80			
NDVI-CDS_max	Between Groups	.007	1	.007	.286	.594
	Within Groups	1.947	79	.025		
	Total	1.954	80			
NDWI-CDS_min	Between Groups	.011	1	.011	.537	.466
	Within Groups	1.556	79	.020		
	Total	1.567	80			
NDWI-CDS_max	Between Groups	.000	1	.000	.011	.918
	Within Groups	.904	79	.011		
	Total	.904	80			
MSAVI2I-CDS_min	Between Groups	.002	1	.002	.017	.897
	Within Groups	9.324	79	.118		
	Total	9.326	80			
MSAVI2-CDS_max	Between Groups	.008	1	.008	.285	.595
	Within Groups	2.326	79	.029		
	Total	2.335	80			

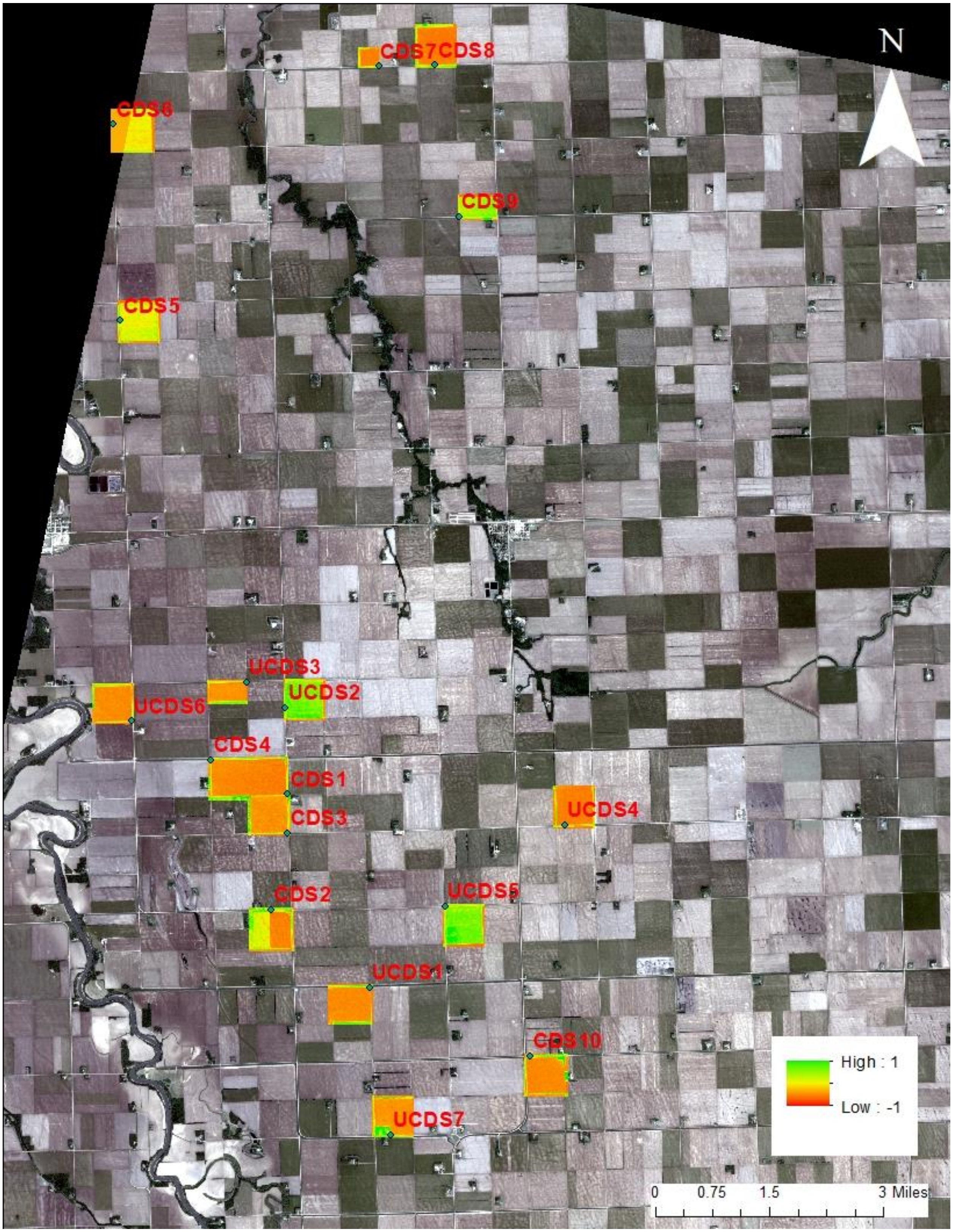

Figure 18 NDVI in June 2019 over sampled fields in Minnesota.

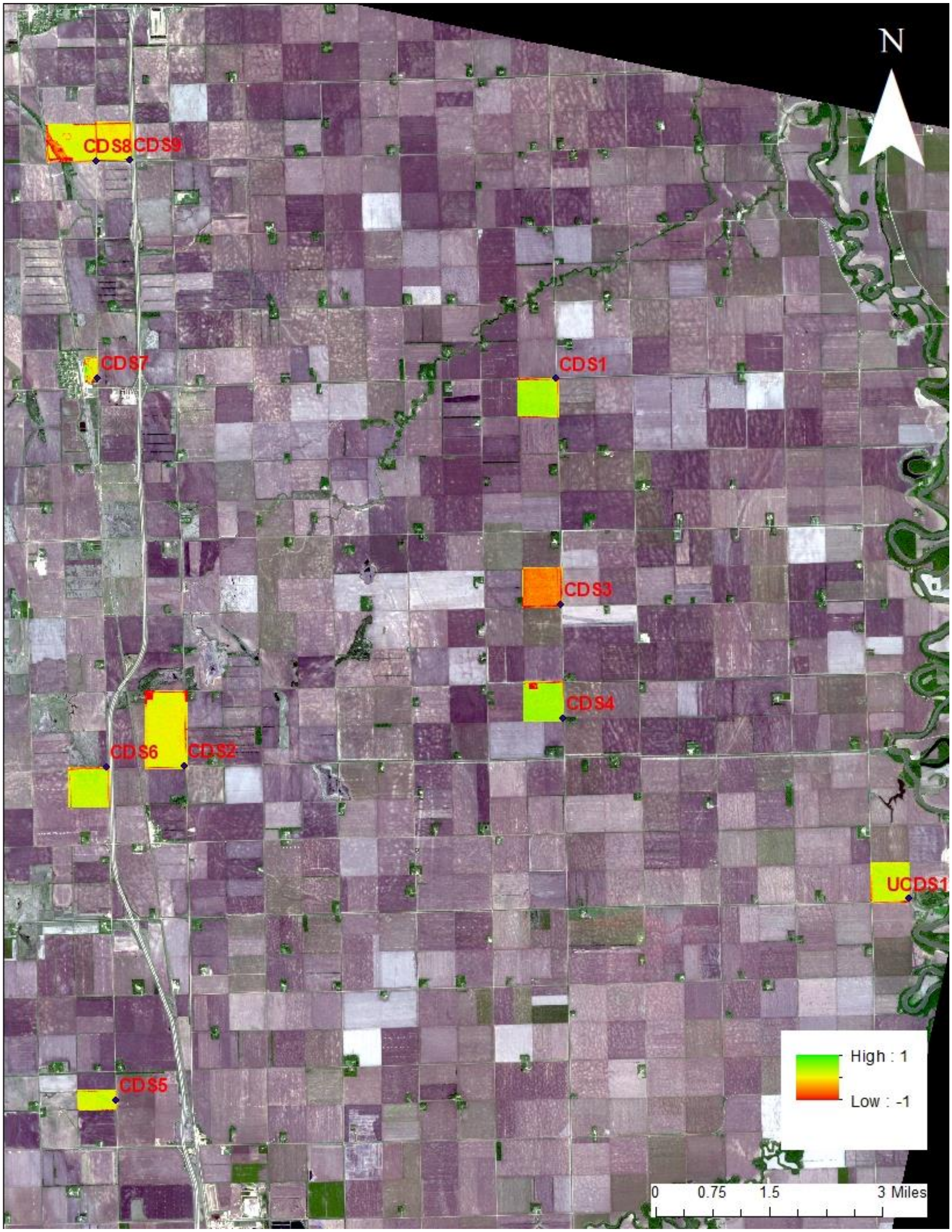

Figure 19. NDVI in June 2019 over sampled fields in North Dakota.

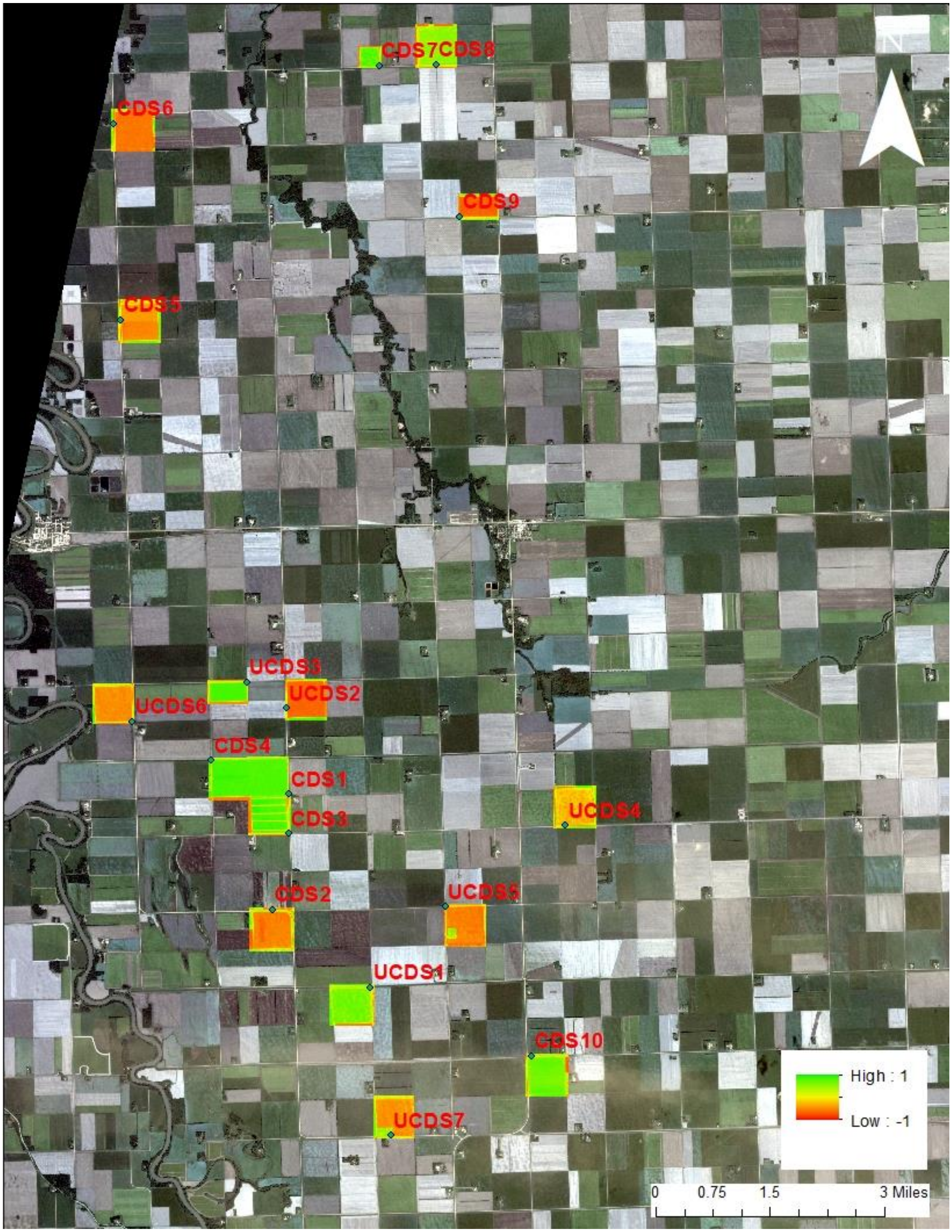

Figure 20. NDVI in September 2019 over sampled fields in Minnesota.

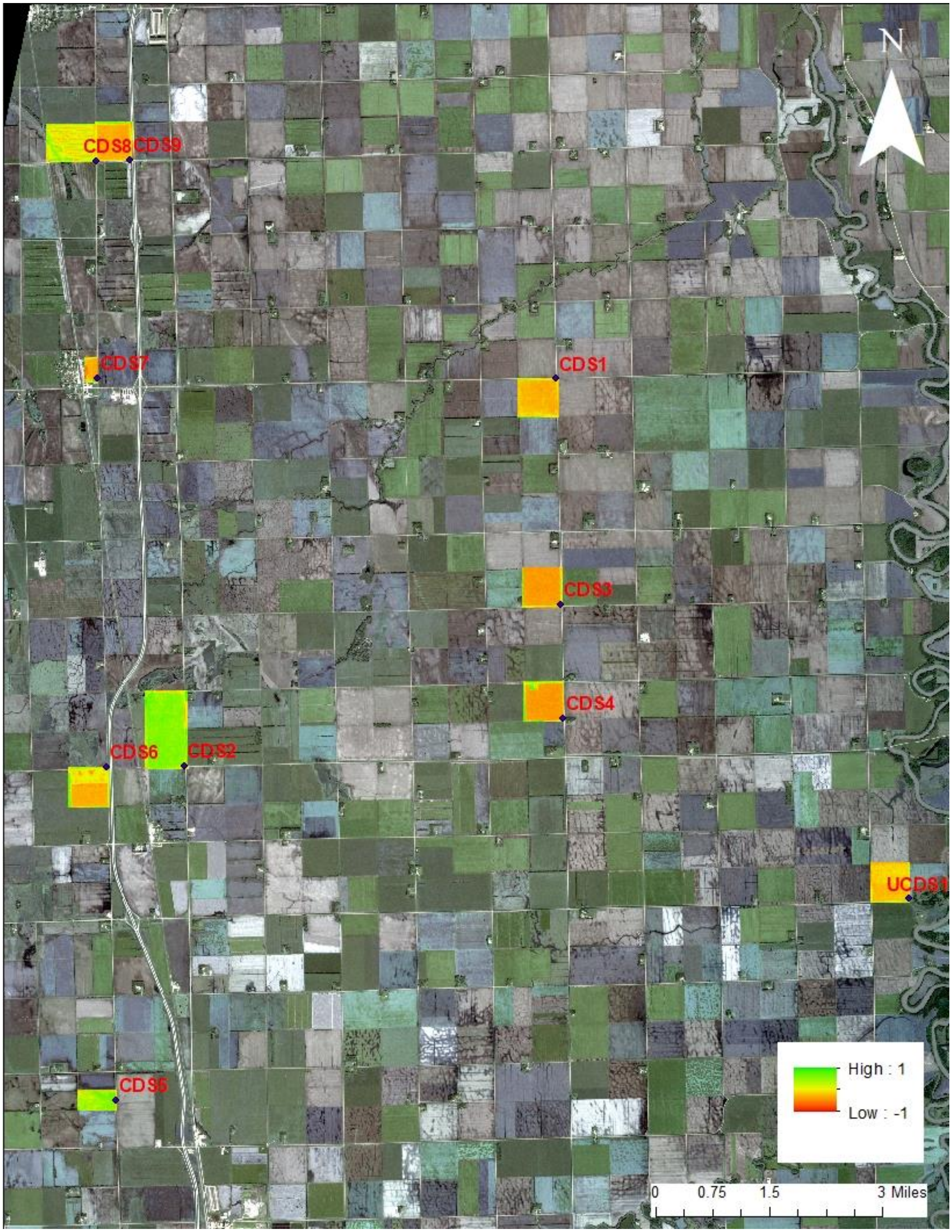

Figure 21. NDVI in September 2019 over sampled fields in North Dakota.

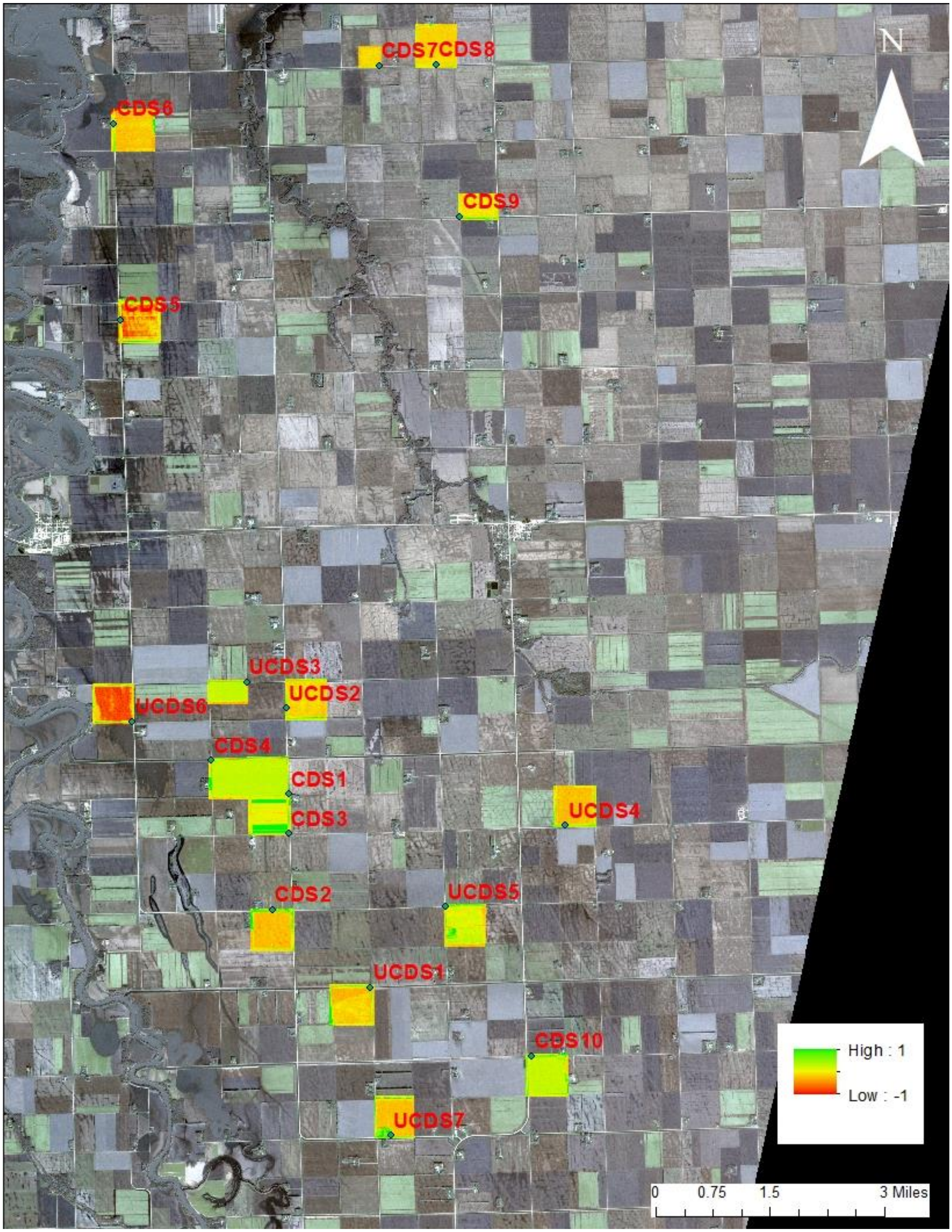

Figure 22. NDVI in October 2019 over sampled fields in Minnesota.

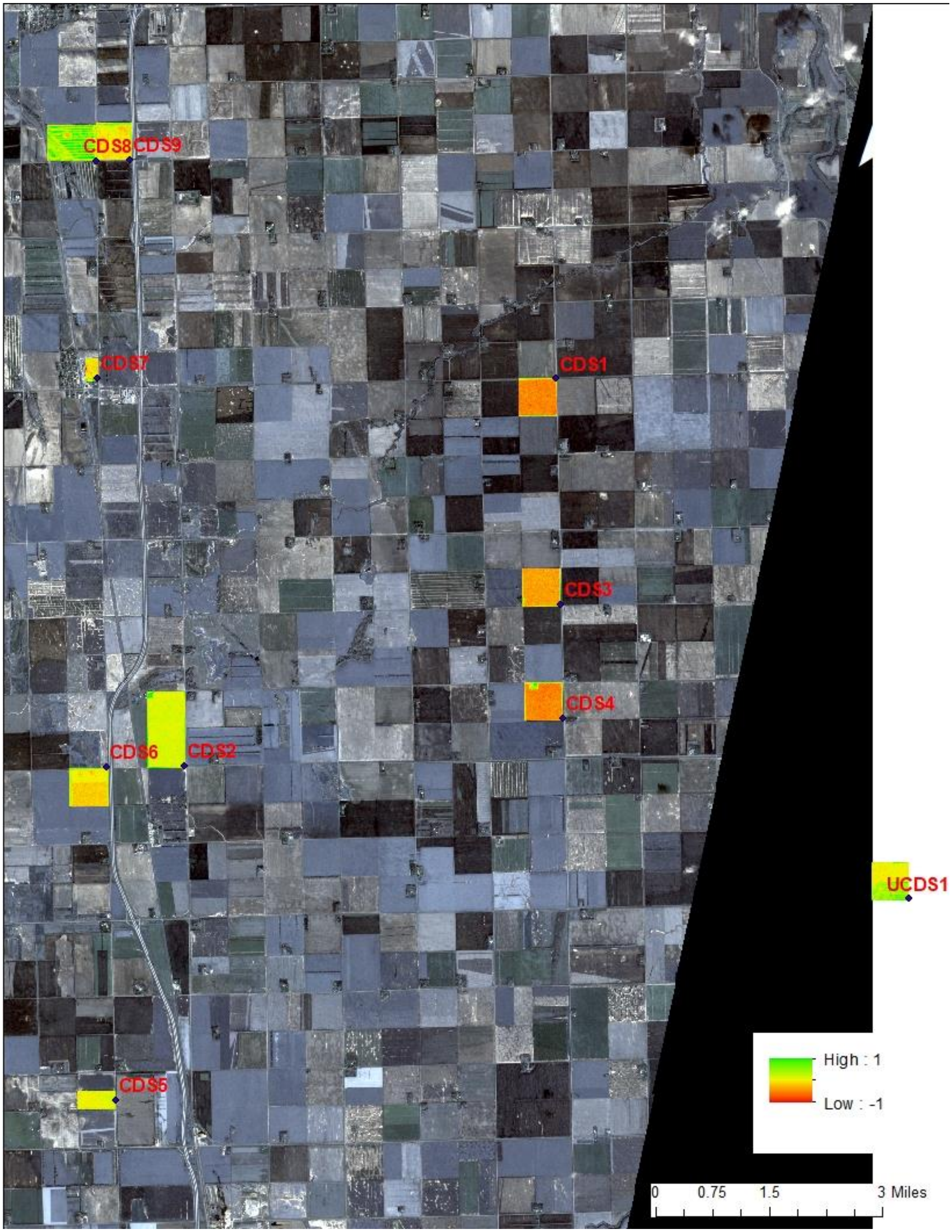

Figure 23. NDVI in November 2019 over sampled fields in North Dakota.

Normalized Difference Water Index (NDWI) shows that the study sites in Minnesota have a maximum value 0.50 and a minimum value of -0.42 in June 2019 (Fig. 24). North Dakota sites have a maximum value of 0.62 and a minimum value of -0.24 also in June 2019 (Fig. 25). NDWI analysis in September 2019 indicates a maximum value of 0.25 and a minimum value of -0.51 in Minnesota (Fig. 26) and maximum value of 0.42 and minimum value of -0.40 in North Dakota (Fig. 27). Minnesota study sites in October 2019 have high value of 0.57 and low value of -0.41 (Fig. 28). North Dakota study sites in November 2019 have a maximum value of 0.40 and a minimum value of -0.19 (Fig. 29).

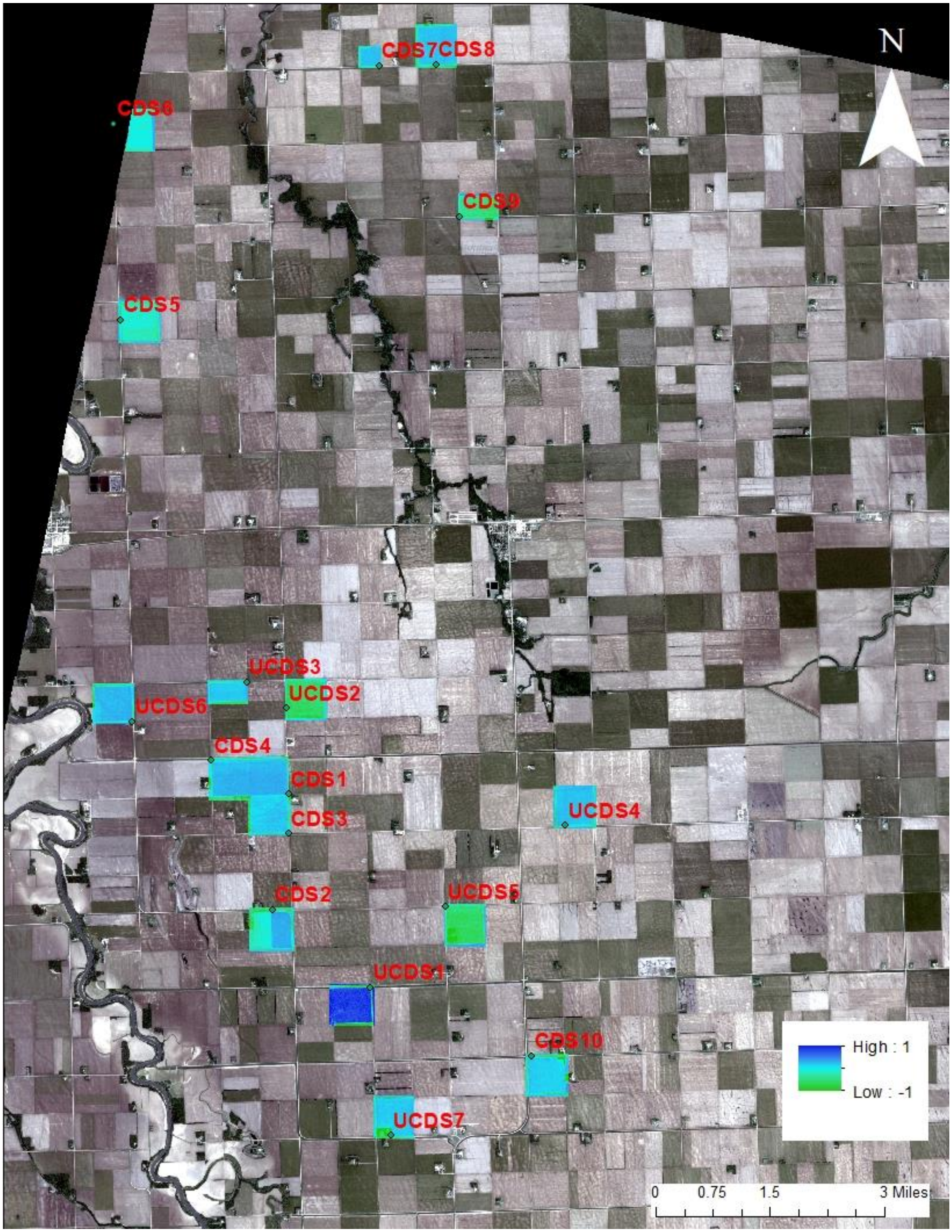

Figure 24. NDWI in June 2019 over sampled fields in Minnesota.

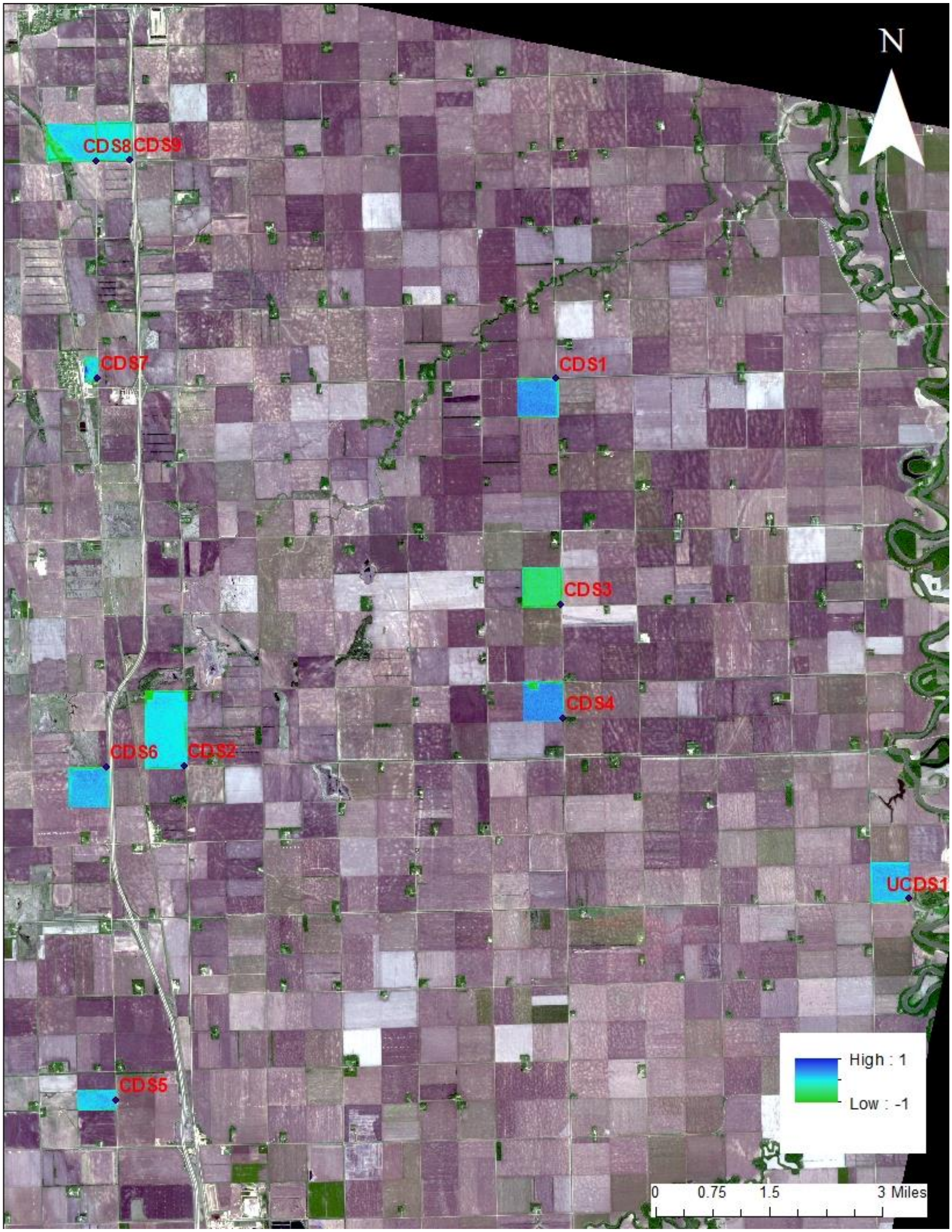

Figure 25. NDWI in June 2019 over sampled fields in North Dakota.

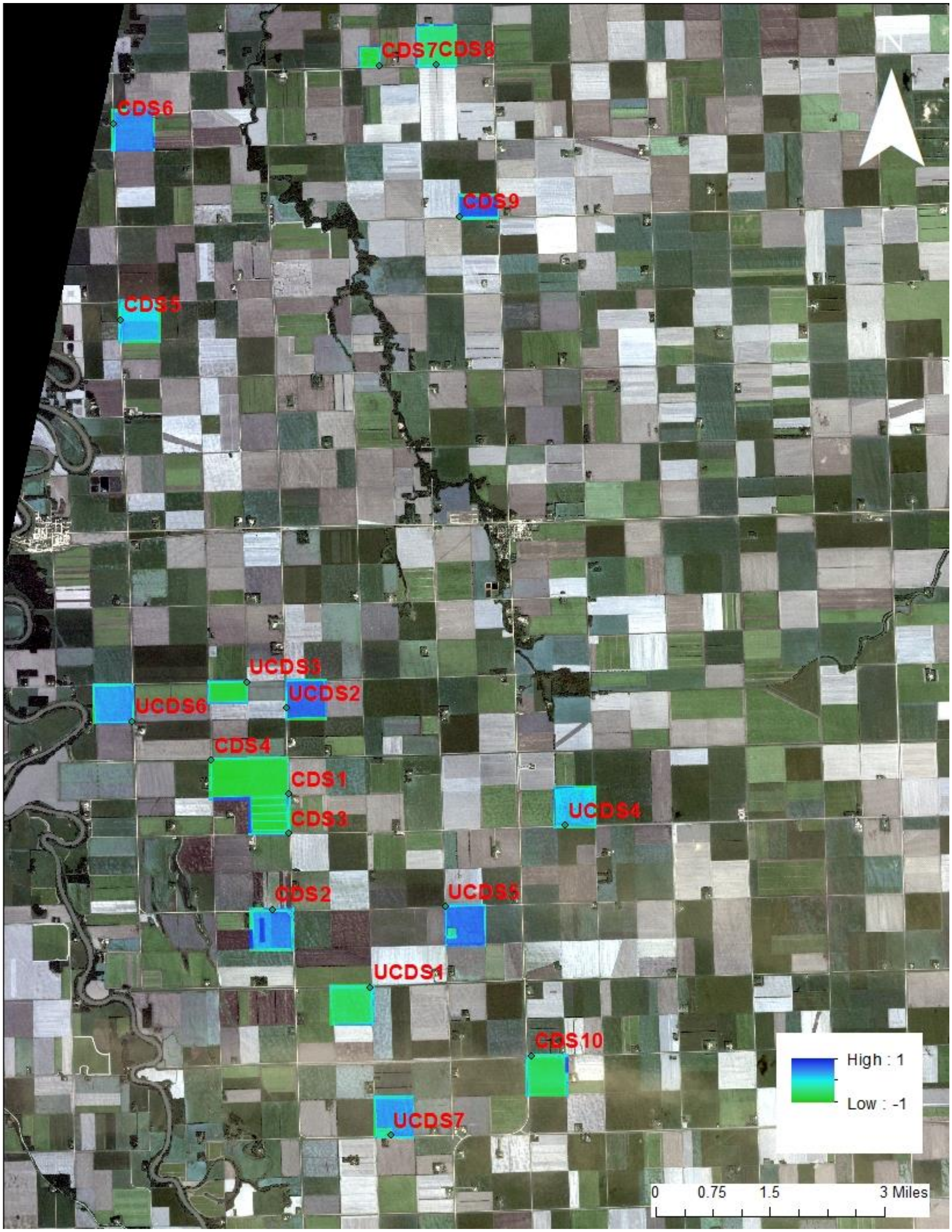

Figure 26. NDWI in September 2019 over sampled fields in Minnesota.

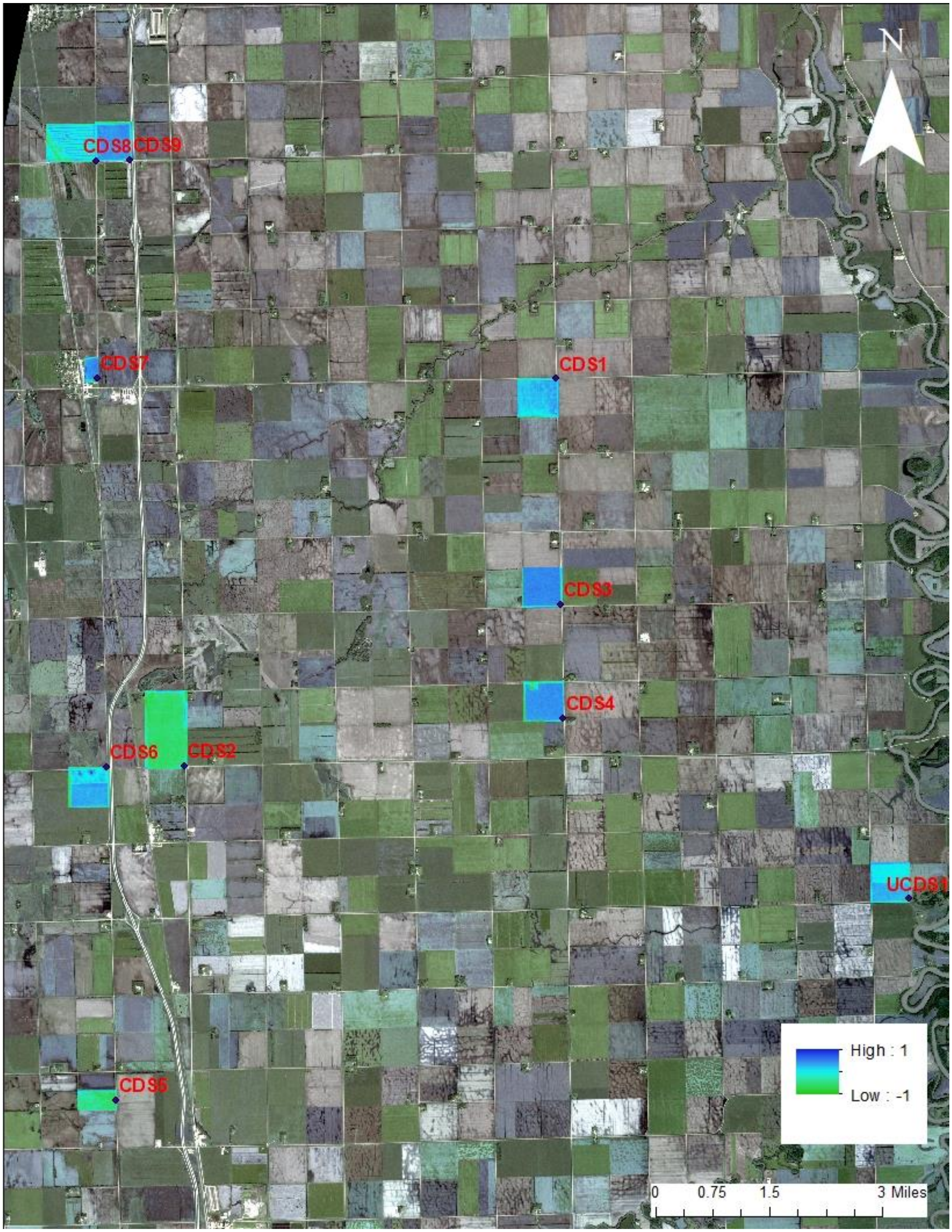

Figure 27. NDWI in September 2019 over sampled fields in North Dakota.

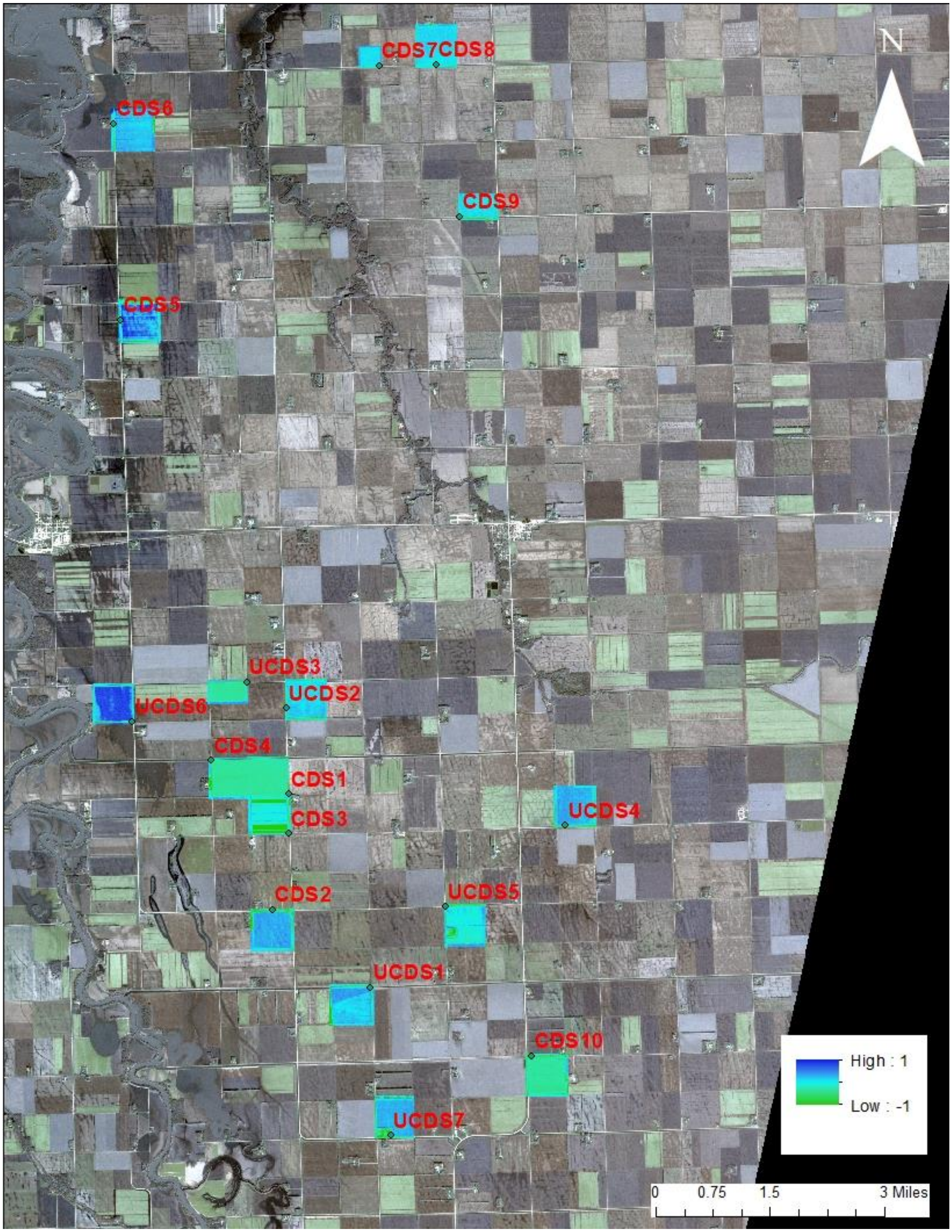

Figure 28. NDWI in October 2019 over sampled fields in Minnesota.

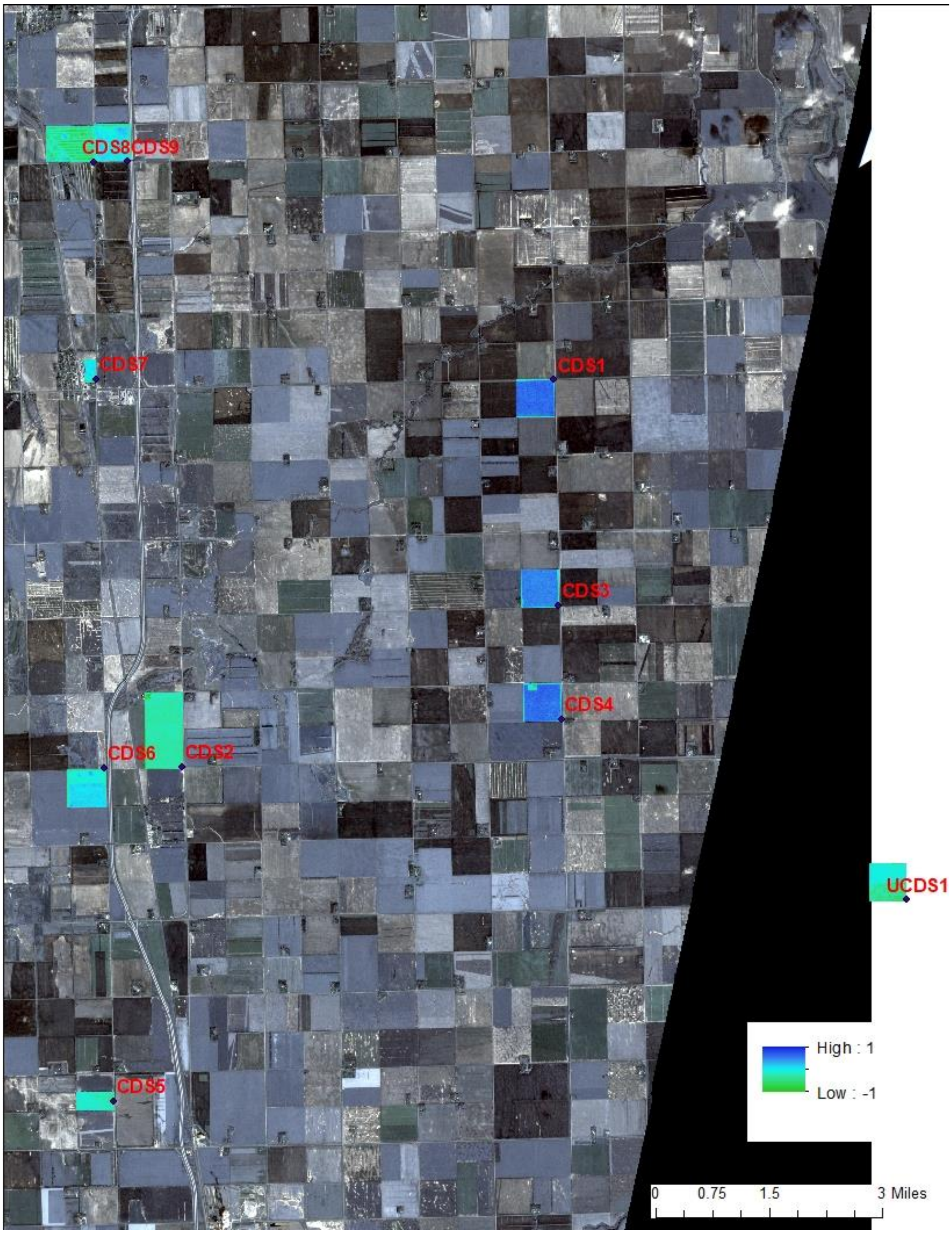

Figure 29. NDWI in November 2019 over sampled fields in North Dakota.

Modified Soil-Adjusted Vegetation Index 2 (MSAVI2) shows that the study sites in Minnesota have a maximum value of 0.72 and a minimum value of -0.42 in June 2019 (Fig. 30). North Dakota sites have a maximum value of 0.77 and minimum value of -0.63 also in June 2019 (Fig. 31). MSAVI2 analysis in September 2019 indicates a maximum value of 0.79 and a minimum value of -0.40 in Minnesota (Fig. 32) and maximum value of 0.70 and minimum value of -1.68 in North Dakota (Fig. 33). Minnesota study sites in October 2019 have a maximum value of 0.72 and a minimum value of -1.77 (Fig. 34). North Dakota study sites in November 2019 have a maximum value of 0.49 and a minimum value of -0.16 (Fig. 35).

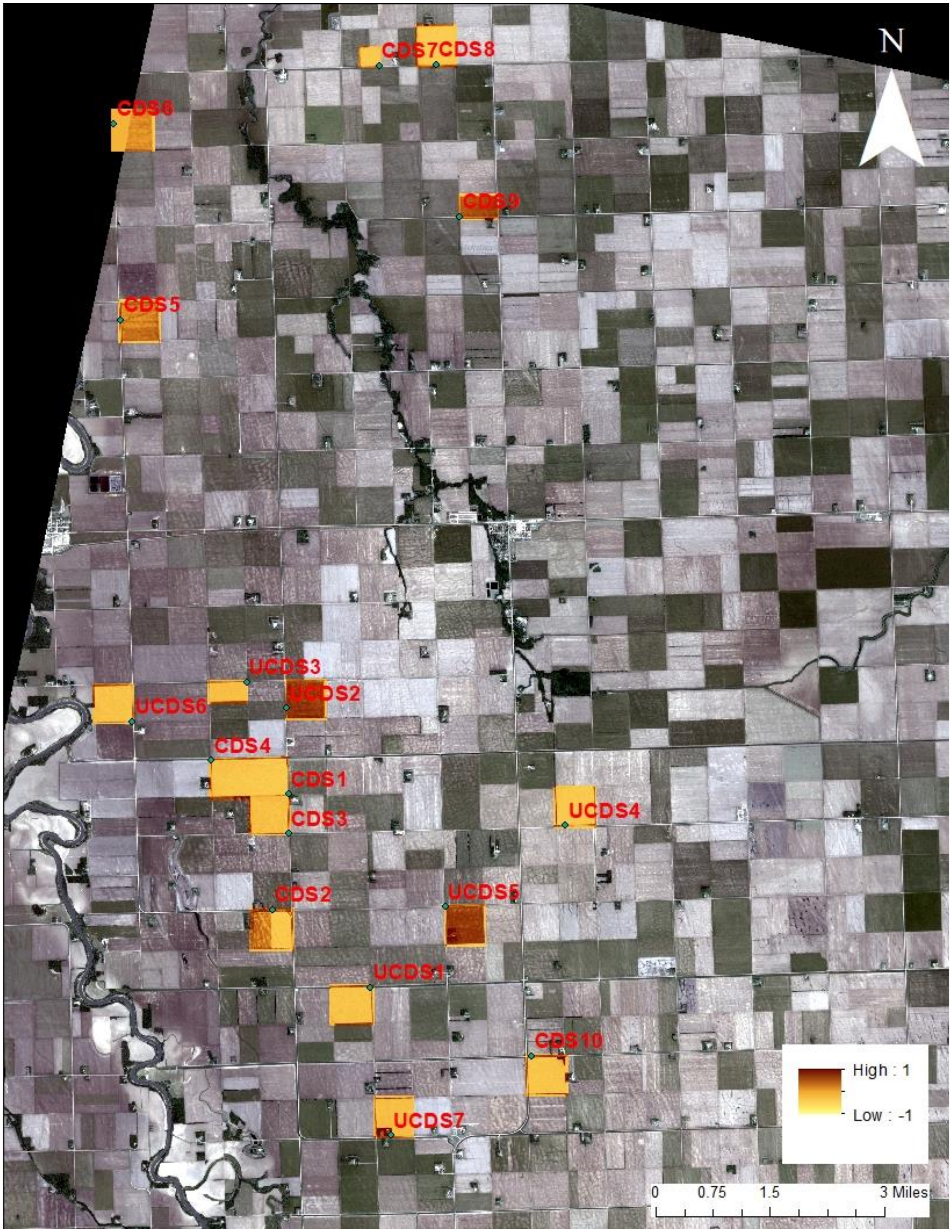

Figure 30. MSAVI2 in June 2019 over sampled fields in Minnesota.

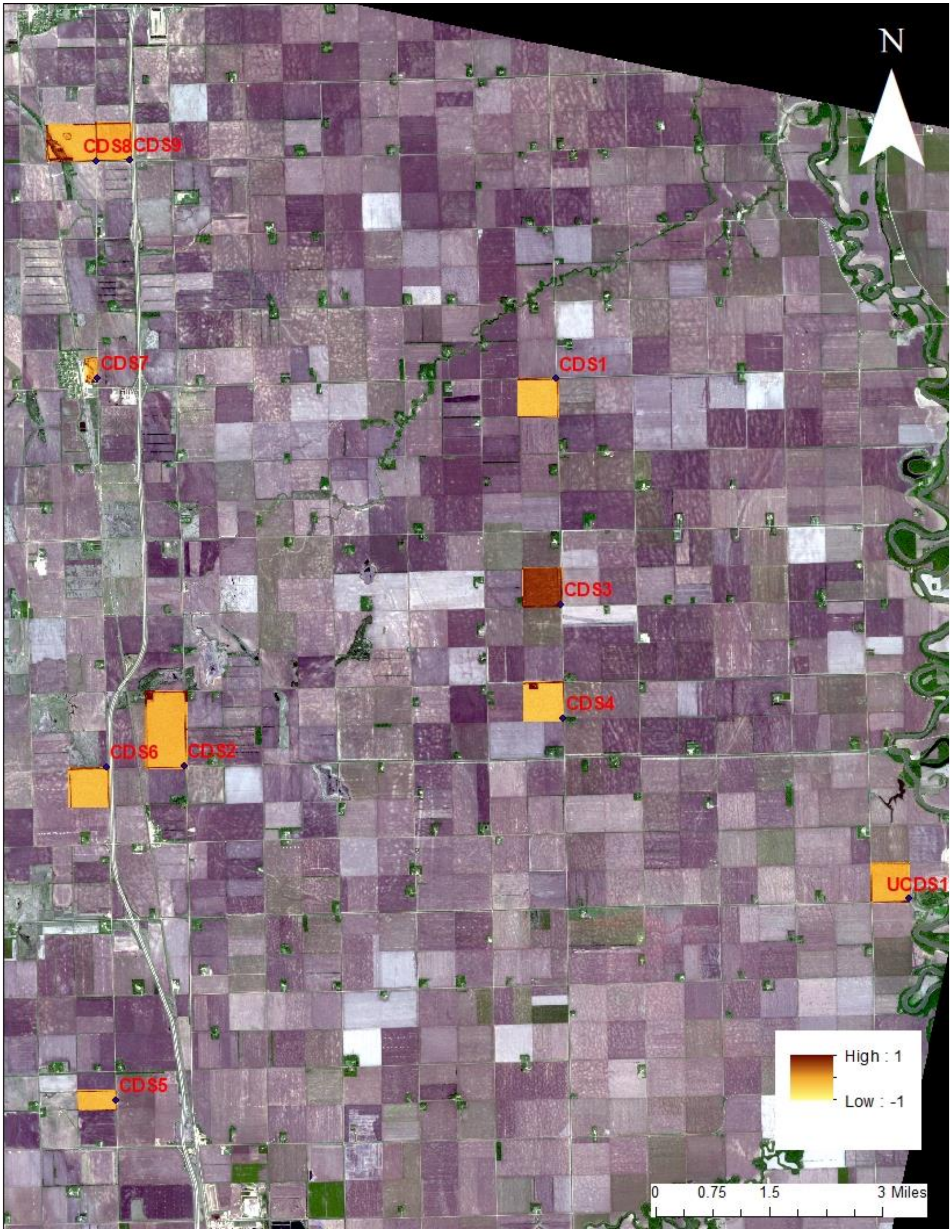

Figure 31. MSAVI2 in June 2019 over sampled fields in North Dakota.

Figure 32. MSAVI2 in September 2019 over sampled fields in Minnesota.

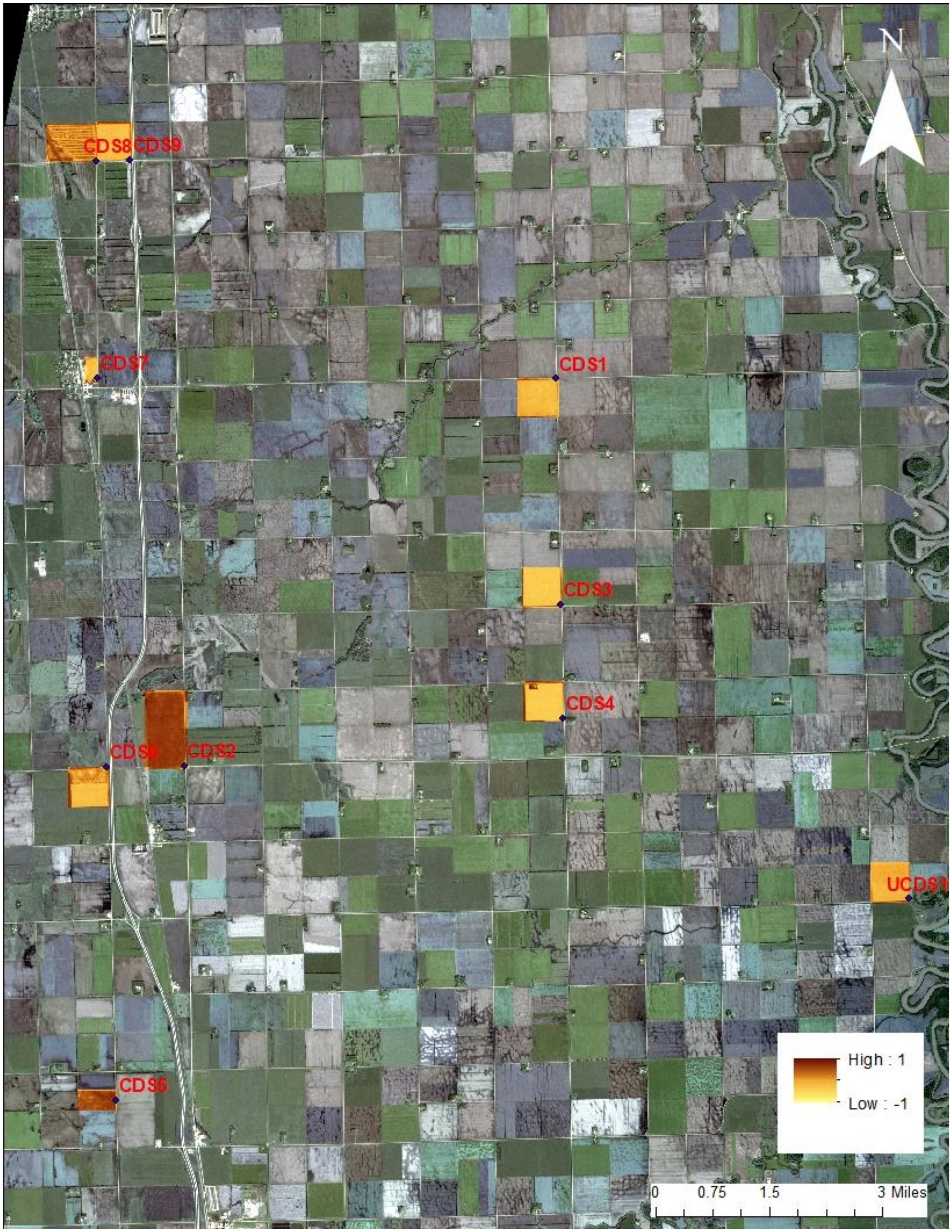

Figure 33. MSAVI2 in September 2019 over sampled fields in North Dakota.

Figure 34. MSAVI2 in October 2019 over sampled fields in Minnesota.

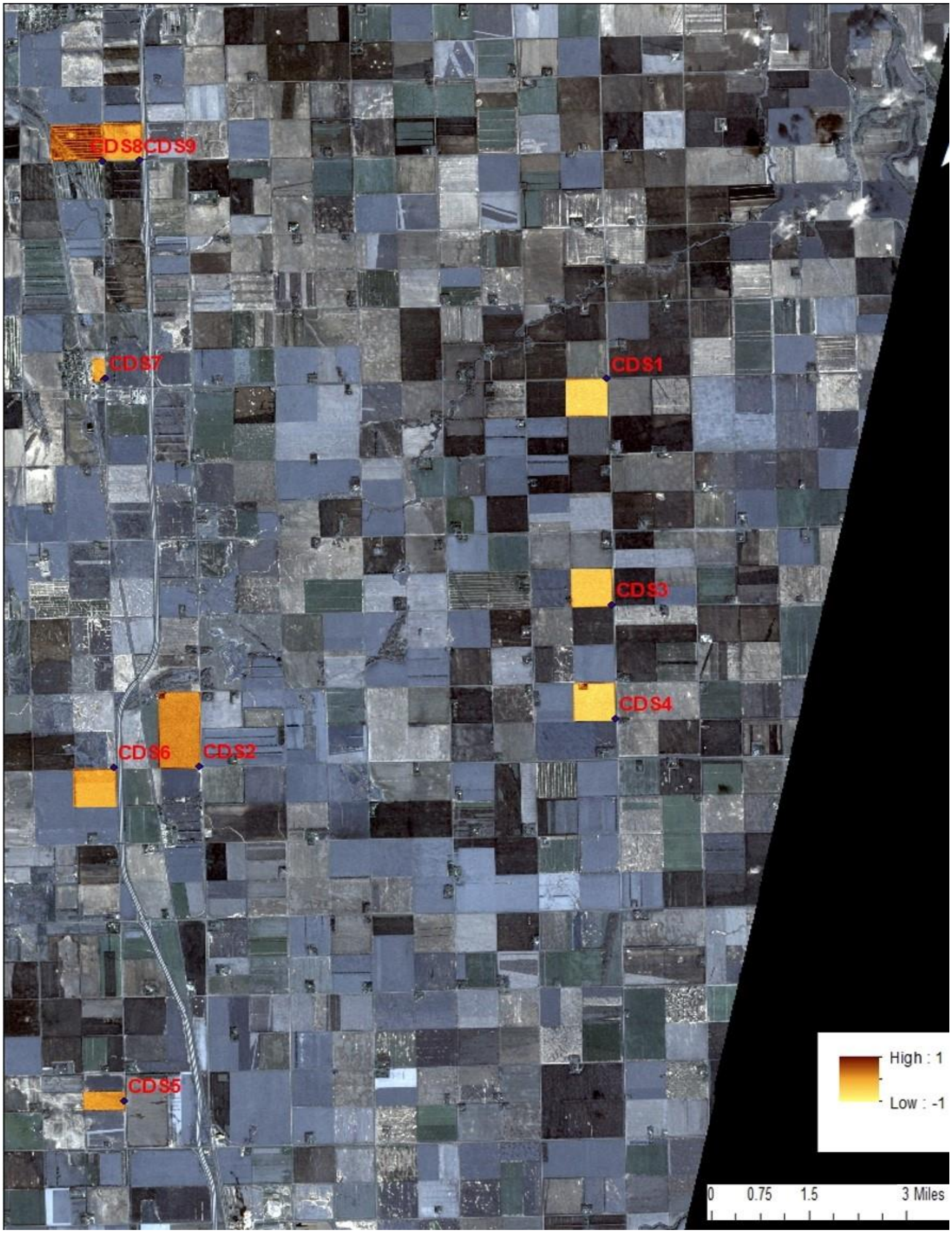

Figure 35. MSAVI2 in November 2019 over sampled fields in North Dakota.

CHAPTER 5

DISCUSSION AND CONCLUSIONS

5.1 Limitations and assumptions

My methods are considered the most appropriate for analyzing differences in crop conditions between fields with different types of agricultural drainage systems (ADS) using remotely sensed data. The results of my remote sensing analysis did not yield the results that I expected. That is, I found no difference between crop condition, measured by vegetation and soil moisture indexes, between uncontrolled drainage systems (UCDS) and controlled drainage systems (CDS).

I speculate that dry condition on the agricultural fields would be best for this study, because agricultural drainage systems (ADS) have an effect on moisture in soil, and the water table below surface correlates highly with root system of crops. In general, crop requires abundant water to grow during the growing season. With CDS farmers can regulate the amount of water in the growing season, while with UCDS they cannot. Once agricultural fields were dried, the difference between CDS and UCDS was measured by crop health. I would expect crops to be healthier on CDS fields because of the ability for farmers to retain moisture using those systems.

One challenge was collecting images when there were actually crops on the fields that I sampled. I looked at images early in the growing season and later in the growing season, and some crops either had not been planted or were already harvested when the images were acquired. In addition, 2019 was an unusual year for weather in the study area, with many fields inundated by excessive rains, which harmed crop health.

Generally, agricultural research must follow regional crop calendars because the calendar contains information or features of crop type, crop cycle, and regional climate. However, weather could not be controlled and influences to crop cycle and crop yields. Another challenge was that although satellite data used is free for study, the quota of each user and I was unable to obtain data for the entire growing season.

5.2 Linear and Slope maps with surface volume

Linear maps for eight UCDS fields and 20 CDS fields were developed to depict tile drainage locations, drainage system patterns, ADS types, and surface areas artificially drained. The vertical resolution of DEM potentially impacted the values of slope maps in the study sites because vertical precision related to large number of sharply sloping Through the surface area (square meter) the study had the density of drain tile in the study area. Installation of ADS patterns is mixed between UCDS and CDS in the RRV.

Satellite imagery analysis

NDVI, NDWI, and MSAVI2 all yield values ranging from +1 to -1. The interpretation of the three indexes is the same such that near +1 means good crop health in NDVI and high moisture in soil in NDWI. MSAVI2 minimizes the effect of soil brightness in areas where vegetative cover is low. So +1 refers to good conditions and -1 means poor conditions. Eight UCDS and 20 CDS in the study sites show differences between ADS type, but I found similarities between NDVI and MSAVI2 because comparison of the three index values for all three months studied shows that when NDVI values are high, MSAVI2 values are high. While

NDVI and MSAVI2 values are high, NDWI values are low. It can be interpreted that germinated crop or growing crop use water in soil while the crops are healthy.

In general, radiometric correction is to avoid radiometric errors or distortions in any image, and the correction is significant because radiometric correction changes digital numbers to either at-satellite radiance, top-of-atmosphere reflectance, or surface reflectance. The metadata associated with the images used in the study, and it indicates whether the data are radiometrically correct or not. The metadata used the study has been corrected because when comparing images between dates or across geographic areas, they were matched.

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