POST WINDFARM INSTALLATION IMPACTS ON SOIL PROPERTIES AND CROP RESPONSE IN THE MIDWEST

by

Chelsea Emenhiser

A Thesis

Submitted to the Faculty of Purdue University
In Partial Fulfillment of the Requirements for the degree of

Master of Science

Department of Agronomy
West Lafayette, Indiana

December 2020

THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Jason Ackerson, Chair
School of Agronomy

Dr. Eileen Kladivko
School of Agronomy

Dr. Darrell Schulze
School of Agronomy

Approved by:
Dr. Ronald Turco

Dedicated to my Dad, Jason Emenhiser, for sharing his passion of agriculture and always supporting me.

ACKNOWLEDGMENTS

This study could not have been completed without the expertise of Dr. Jason Ackerson, my thesis adviser. I would also like to thank Drs. Kladivko and Schulze for being on my committee and taking time to read my thesis.

I extend my thanks to Jeff Bradford for sharing his knowledge of GIS technology, which proved vital for completing this study.

TABLE OF CONTENTS

LIST OF TABLES ... 7
LIST OF FIGURES ... 8
ABSTRACT ... 10
CHAPTER 1. LITERATURE REVIEW ... 11
1.1 Literature Review ... 11
1.1.1 Wind Energy Overview ... 11
1.1.2 Windfarm Site Selection and Leasing Contracts ... 12
1.1.3 Turbine Installation in Indiana ... 13
1.1.4 Soil Compaction – Soil Properties ... 14
1.1.5 Soil Compaction – Machine Factors ... 16
1.1.6 Soil Compaction – Weather Factors: Precipitation ... 17
1.1.7 Crop Response to Soil Compaction ... 18
1.1.8 Remote Sensing Technology in Soil Science ... 18
1.2 COVID-19 Pandemic Impacts on the Study ... 20
1.3 Objectives ... 20
1.3.1 Objective 1: Develop a method to quantify differences in crop response between former construction sites of turbines and adjacent, non-disturbed, agricultural land using remote sensing. ... 20
1.3.2 Objective 2: Evaluate the effect of soil and crop conditions on the persistence of impacts present in the turbine footprints caused by construction equipment. ... 20
1.3.3 Objective 3: Develop an application to rate soil organic matter in the state of Indiana. ... 21
CHAPTER 2. WIND TURBINE ANALYSIS ... 22
2.1 Introduction ... 22
2.2 Methods ... 24
2.2.1 Site Selection ... 24
2.2.2 Satellite Imagery ... 24
2.2.3 Image Processing and NDVI Calculation ... 25
2.2.4 Determining the NDVI Threshold ... 26

2.2.5 Calculating the Impacted Area for Each Turbine ... 27
2.2.6 Crop and Soil Data ... 27
2.2.7 Statistical Analysis ... 28
2.3 Results and Discussion ... 28
2.3.1 Windfarm Impacted Area ... 28
2.3.2 Potential Factors Affecting Crop Recovery ... 30
2.3.3 Impacted Area by Texture ... 31
2.3.4 Impacted Area by Drainage ... 33
2.3.5 Impacted Area by Crop ... 36
2.4 Conclusion ... 38
CHAPTER 3. SOIL ORGANIC MATTER RATING APPLICATION ... 40
3.1 Soil Organic Matter and its Importance ... 40
3.2 Role of Soil Organic Matter Agronomic and Ecosystem Functions ... 40
3.2.1 Cation Exchange Capacity (CEC) ... 41
3.2.2 Aggregation and Soil Structure ... 41
3.2.3 Biological Functions ... 42
3.2.4 Biogeochemical (i.e. N and C Pools) ... 42
3.2.5 Soil Water ... 42
3.3 Impacts of Management on Soil Organic Matter ... 43
3.3.1 Addition Mechanisms ... 43
3.3.2 Loss Mechanisms ... 44
3.4 Managing Soil Organic Matter ... 45
3.5 SOM Rating Application ... 47
APPENDIX A. ANALYSIS CODE ... 52
APPENDIX B. SOM RATING APPLICATION METHODS ... 55
REFERENCES ... 58

LIST OF TABLES

Table 2.1. Sentinel-2 image dates for each windfarm used in the analysis. 25

Table 3.1. Categorizes soil and crop management practices and lists the corresponding influence on soil organic matter (Magdoff & Weil, 2004). 46

LIST OF FIGURES

Figure 1.1. Wind turbines of the contiguous U.S. Turbines in the Midwest are highlighted in blue. (USWTDB Viewer, 2020) ....

Figure 1.2. Wind turbines in Indiana shown as blue outlined points..

Figure 2.1. Location of Meadow Lake V and Bluff Point windfarms as blue outlined points, respectively. ....

Figure 2.2 Turbine RStudio analysis flowchart. 28

Figure 2.3. Average turbine impact area for each year of the study for Meadow Lake V (MEADOW LAKE V) windfarm and Bluff Point (BLUFF POINT) windfarm, shown in black and white bars respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05...

Figure 2.4. Average turbine impact area by texture (m^2/turbine) for each year of the study for Bluff Point (BLUFF POINT) windfarm with silt loam and silty clay soils shown in black and white, respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05...

Figure 2.5 Average turbine impact area (m^2/turbine) by texture for each year of the study for Meadow Lake V (MEADOW LAKE V) windfarm with loamy and sandy soils shown in black and white, respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05. ....

Figure 2.6. Average turbine impact area by drainage (m^2/turbine) for each year of the study for Bluff Point (BLUFF POINT) windfarm with moderately well, poorly, and somewhat poorly drained soils shown in black, gray, and white, respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05..

Figure 2.7. Average turbine impact area (m^2/turbine) by drainage for each year of the study for Meadow Lake V (MEADOW LAKE V) windfarm with moderately well and somewhat poorly, poorly, and well drained soils shown in black, gray, and white, respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05. ....

Figure 2.8. Average turbine impact area by crop (m^2/turbine) for each year of the study for Bluff Point (BLUFF POINT) windfarm with corn and soybean shown in black and white, respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05. ....

Figure 2.9. Average turbine impact area (m^2/turbine) by crop for each year of the study for Meadow Lake V (MEADOW LAKE V) windfarm, with corn and soybean shown in black and white respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05...

Figure 3.1. Soil organic matter components illustration (Mani, 2014)...

Figure 3.2. Relationship between aggregate stability and organic matter content (Krull, et. al., 2004) ....

Figure 3.3. Soil pore space components illustration (University of Minnesota-Horticulture Follow, 2012) ....

Figure 3.4. Slope profile (i.e. landscape position) relevant to certain processes. The darkest part of the bars indicates high rates of the indicated process, and the lightest part of the bars indicate low rates of the indicated process (Reyes, 2016)... 44

Figure 3.5 Using the search bar to zoom to a specific address or place on the map. ....

Figure 3.6 The Select icon. ....

Figure 3.7 Clicking a specific area on the map to view that points data from the selected layer.....

Figure 3.8 Viewing the AOI selection and SOM data by soil type in the left-most information pane. ....

Figure 3.9 Using the ‘Select’ icon to draw the AOI. ....

Figure 3.10 Scrolling over the SOM data by soil type in the left-most information pane to see all selected area of the same soil type. ....

Figure 3.11 Accessing the layer attribute table and selecting a data row to view in the map. ....

Figure 3.12 Legend icon. ....

ABSTRACT

Throughout the United States, large windfarms, containing anywhere from 5 to 150 turbines, have been installed due to the increased demand for alternative energy. Since 2008, 1,264 turbines have been installed in Indiana, with the majority of installations occurring on agricultural fields. Despite the large number of turbine installations, impacts of these installations on soil and crop health is unknown. Turbine installation requires the traffic of heavy construction equipment within agriculture fields which may compact the soil altering its physical properties and negatively impact crop growth. To better understand the impact of turbine installation on soil and crop health, we developed a remote-sensing based method to quantify the areal extent of soil and crop impairment due to turbine installation. The method compares the normalized difference vegetation index (NDVI) from satellite images from areas of potential impairment to areas with no known impairment to determine statistical differences in NDVI between impaired and unimpaired areas and then calculates the area of potential impairment. We tested this methodology on two windfarms in Indiana. Our results showed that in the year following turbine installation, turbine installation was associated with an average impairment of 1.8 hectares per turbine and the area of impairment decreased approximately 15-30 percent in each subsequent year. Our results also suggest that soil texture and drainage have an effect on the magnitude and recovery rate of impairment. Coarse textured and/or well drained soils experienced very little to no impairment while fine textured and/or poorly drained soils experienced significant impairment and had not returned to pre-installation levels of impairment after three years. Our findings will allow landowners the opportunity to review current points of negotiation with windfarm developers as well as provide information regarding the potential loss of productivity in crops at these sites.

CHAPTER 1. LITERATURE REVIEW

1.1 Literature Review

The following literature review will discuss the installation of wind turbines built as an alternative energy source on agricultural land put back into production, and what impacts this may have on soil properties directly correlated with crop response and productivity. Specifically, it focuses on subsoil compaction causes, persistence, and effect on crop growth, the use of remote sensing (RS) technology to analyze any potential effect on soil quality, and the history of harnessing wind energy including present-day concerns. The next section will address the factors surrounding the installation of the wind turbines as well as the three major components involved in soil compaction formation including: soil properties, weather conditions, and machine/traffic factors (Soane and van Ouwerkerk, 1994). The role of construction equipment in compacting the soil and any concerns there are regarding wind turbine installation will be discussed. The review will conclude with a discussion of the role in which remote sensing is used to assess soil conditions with regards to crop response.

1.1.1 Wind Energy Overview

Historically, windmills were used for grinding grain and pumping water. Harnessing the wind for energy has been in practice since the 70's and 80's, and since then tremendous improvements have been made regarding the efficiency of the process. Wind energy entails creating electricity using the wind and is conducted by wind turbines which have blades that collect the wind's kinetic energy when they rotate and turn it into mechanical energy which is then transferred to the grid. A windfarm refers to a grouping of turbines which are constructed close together and function as a single power plant (American Wind Energy Association, 2020). Between 1992 and 2007 global wind power increased by more than 25% and has been considered fully commercial ever since (van Steen & Zervos, 2009). As of 2019, nearly 60,000 turbines have been installed in the United States (Figure 1.1) with a combined energy generating capacity of 105,583 megawatts (MW). Over the past decade, wind power in the U.S. has more than tripled making it the largest source of renewable energy in the country accounting for about 6.5 percent of the nation’s electricity in 2018 (American Wind Energy Association, 2020). Wind energy has been shown to create few environmental impacts (van Steen & Zervos, 2009), and the wind industry has provided thousands of jobs nationwide with projects paying over one billion dollars to state and local governments and private landowners every year (American Wind Energy Association, 2020).

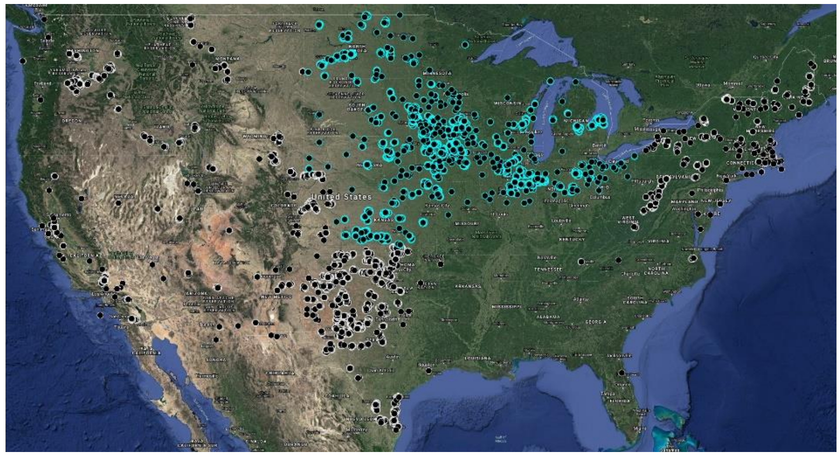

Figure 1.1. Wind turbines of the contiguous U.S. Turbines in the Midwest are highlighted in blue. (USWTDB Viewer, 2020)

1.1.2 Windfarm Site Selection and Leasing Contracts

Site selection is important as it has huge impacts on the development of a windfarm. Multiple constraints must be considered before any leasing contracts can be drafted, including maximum installed capacity, set back (i.e. distance from roads, dwellings, overhead lines, ownership boundaries, etc.) environmental constraints, location of visually sensitive viewpoints, and turbine minimum spacing which is defined by the supplier.. All these things are subject to change during the negotiation process. Typical factors affecting wind turbine location within windfarms include the optimization of energy production, visual influence, noise, and turbine loads. Spacing between turbines depends largely on the nature of the terrain and the wind rose, a diagram showing the relative frequency of wind directions at a certain location (van Steen & Zervos, 2009). About one acre of land is required to physically locate a turbine, but 40 to 60 acres of unobstructed land is required for efficient access to the wind. Most land on which windfarms are built may be used for other, usually agricultural, purposes without interfering with the wind energy collection process (Reid, 2016).

Before the turbines are installed, a leasing contract must be made between the wind energy developer and landowners with desirable locations. Leasing contracts typically contain two components. The first describes the part of the agreement concerning the physical land rent in acres. These leases usually only last between three and five years and offers the landowner an annual payment of two to ten dollars per acre covered by the lease. The second explains the agreement concerning the actual tower and other related development like access roads. This lease lasts much longer than the first because it allows the developer the opportunity to recover their investment cost and make a return on the investment. This usually spans 15 to 20 years, so the lease is written for 20 to 25 years.

Landowner compensation can come in multiple forms. Payments could be per tower, per MW produced, a percent of the gross revenue produced, or a combination of the three. There are usually four compensation packages for landowners to choose from, including fixed payments, royalty or percentage of revenue, combinations, and equity partnership (Aakre and Haugen, 2009). Ensuring that compensation remains adequate throughout the duration of the leasing contract is crucial for landowners.

All energy lease provisions are subject to negotiation, and therefore landowners have the ability to request compensation for the loss of value in previous activities, and to make sure there are provisions providing mandatory release of unused land. The landowner will want to ensure their right to use the land for the same practices it was under before the wind turbine was constructed. This includes a broad set of retained rights including farming, ranching, hunting and recreational uses, etc. Landowners should ask for copies of the surveys of turbine placement and may also want to restrict the developer's uses of the premises (Reid, 2016). It is encouraged to negotiate the positioning of access roads to the wind turbines. These roads will disrupt agricultural practices resulting in a loss of efficiency, but these effects can be minimized by building them parallel to field operations. The construction of wind turbines can also cause sizable amounts of land to be impacted in excess of acreage needed for the tower and access road. Contracts should include compensation for all crop damage that occurs during the construction phase to cover any losses in yield (Aakre and Haugen, 2009). With all these factors, and more, involved with leasing contracts for windfarms it is advised to consult professional legal and engineering help (Reid, 2016).

1.1.3 Turbine Installation in Indiana

Indiana is one of the fastest growing states for wind energy development in the U.S. Currently, there are 1,264 turbines in Indiana (Figure 1.2) making the state's installed wind capacity 2,317 MW, and ranking Indiana as twelfth in installed wind capacity. Due to the state's attractive investment potential, Indiana could likely be a national leader in the wind energy industry, currently providing around 14 million dollars in annual state and local tax payments and 5 to 10 million dollars in annual land lease payments (American Wind Energy Association, 2020).

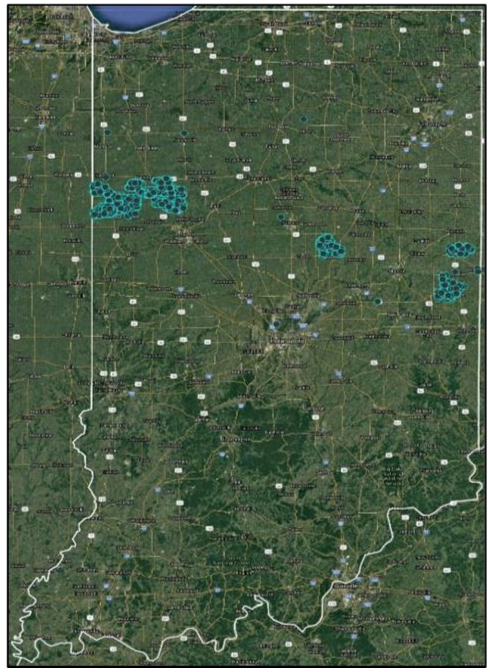

Figure 1.2. Wind turbines in Indiana shown as blue outlined points.

Northwest Indiana has one of the largest concentrations of wind turbines, in density of turbines per land area, in the world. Support for windfarms in this area is primarily financial and environmental. Windfarms are seen as a way to protect farmland from urban sprawl because of economic benefits to farmers (Mulvaney, Woodson, and Stalker Prokopy, 2013). Less than 5% of windfarm area is occupied by turbines, electrical equipment, and access roads and leaves plenty of space for farming operations to continue (Kaldellis, Kavadias, and Paliatsos, 2003). In contrast, views of wanting to protect the landscape do not necessarily support windfarms (Mulvaney, Woodson, and Stalker Prokopy, 2013). The most common negative views of windfarms include interference with habitats, noise pollution, aesthetic degradation, and interference with bird flight paths (Abbasiand Abbasi, 1999).

1.1.4 Soil Compaction – Soil Properties

Soil compaction is most commonly defined as a process in which the soil is deformed (Kilic, Özgöz, and Akbas, 2004; Soane and van Ouwerkerk, 1994; Keller, Lamandė, and Peth et al., 2013). This process alters soil structure, reduces saturated hydraulic conductivity and water infiltration, which can lead to surface runoff and soil erosion by water, and reduces soil aeration and air permeability (Keller, Lamandė, and Peth et al., 2013; Whalley, Dumitru, and Dexter, 1995; Soane and van Ouwerkerk, 1994; Horn, Domialb, and Slowihka-jurkiewiczb et al., 1995). Compaction is primarily affected by soil water content, bulk density (BD), soil texture, organic matter content, soil porosity, any initial compactness, the timing of wheel traffic, and the intensity of loading on the soil (Kilic, Özgöz, and Akbas, 2004; Baumgartl and Horn, 1991; Håkansson, Voorhees, and Riley, 1988).

The BD and penetration resistance (PR) are the most commonly used soil physical properties to quantify soil compaction (Landsberg, Miller, and Anderson et al., 2003; Lanpurlane's and Cantero-Martinez, 2003; Soane and van Ouwerkerk, 1994). The PR refers to the measure of a soil's strength, and a soil's BD is a ratio of mass of dry solids to the bulk volume of the soil (Landsberg, Miller, and Anderson et al., 2003). Typically, as BD increases the soil's porosity will decrease (Keller and Håkansson, 2010), increasing soil strength. Factors affecting BD and PR include water content, soil texture, soil compressibility or its susceptibility to decrease in volume when mechanical stress is applied, soil structure, organic matter content, and gravel content or the presence of coarse fragments in the soil (Kilic, Özgöz, and Akbas, 2004; Landsberg, Miller, and Anderson et al., 2003; Lanpurlane's and Cantero-Martinez, 2003; Vaz, Manieri, and de Maria et al., 2011). The BD and PR increase as soil moisture decreases, and PR values also tend to increase with depth (Landsberg, Miller, and Anderson et al., 2003; Lanpurlane's and Cantero-Martinez, 2003).

Subsoil compaction occurs below the depth of normal tillage operations (Kaspar and Taylor, 1959), and is reported to be very persistent (Håkansson and Reeder, 1994; Alakukku, 1996). Subsoil compaction appears to be more persistent the deeper it penetrates (Håkansson and Reeder, 1994), having been observed to have measurable effects (BD) after nine years (Alakukku, 1996). Typically, the higher the water content the deeper compaction penetrates the soil (Håkansson and Reeder, 1994). It is even theorized to have cumulative effects over time (Horn, Domialb, and Slowihka-jurkiewiczb et al., 1995). Concerns regarding subsoil compaction have become a point of interest due to its persistence and difficulty to alleviate (Berli, Kulli, and Attinger et al., 2004).

The most successful method to alleviate subsoil compaction is subsoiling which is a form of deep tillage occurring between 30- and 90-centimeters (Sidhu and Duiker, 2006). This has been found to be more effective than factors known to alleviate surface compaction because the effects decrease with depth (Håkansson and Reeder, 1994). Subsoiling has been reported to alleviate compaction and recover soil productivity by decreasing PR and increasing yield previously lost to compaction (Borghei, Taghinejad, and Minaei et al., 2008; Abu-Hamdeh, 2003). Unfortunately, not all soil responds to deep tillage treatments (Sidhu and Duiker, 2006). In some cases, this management practice aggravated the issues instead of alleviating them (Berli, Kulli, and Attinger et al., 2004; Håkansson, 1994). It is also known that subsoiling will not necessarily ameliorate all the compaction in the subsoil (Håkansson and Reeder, 1994; Sidhu and Duiker, 2006). To ensure that subsoiling is not a wasted expense, it is important to practice controlled traffic, where tracks must remain in the same positions permanently after a deep tillage event and avoid using subsoiling deeper than necessary, or at all, if compaction impacts are not evident (Sidhu and Duiker, 2006). Many believe the best way to manage subsoil compaction is prevention, and strategies include establishing limits on axle loads, using controlled traffic, and avoiding traffic under moist conditions whenever possible (Håkansson and Reeder, 1994; Håkansson, 1994).

1.1.5 Soil Compaction – Machine Factors

Machine traffic has been found to be a major cause for subsoil compaction especially in agricultural management systems (Defossez and Richard, 2002). The incidence of compaction in deep subsoil layers is determined by the axle load (Abu-Hamdeh, 2003; Håkansson, 1994), and impacts from traffic of heavy equipment on soil include compaction below the normal depth of tillage with similar impacts on crops and soil (Lowery and Schuler, 1991; Horn, Domialb, and Slowihka-jurkiewiczb et al., 1995; Håkansson and Reeder, 1994; Abu-Hamdeh, 2003; Frey, Kremer, and Rudt et al., 2009). Calculations have also shown that when total weight and tire size increase, the depth to which compaction penetrates increases to depths between 30- and 50-centimeters, and sometimes deeper (Lowery and Schuler, 1991; Håkansson and Reeder, 1994; Horn, Domialb, and Slowihka-jurkiewiczb et al., 1995; Håkansson and Reeder, 1994). Repeated traffic from heavy equipment, even in a single day, will exhibit an increase in the vertical stress on the soil (Horn, Domialb; Lipiec, Hing;kansson, and Tarkiewicz et al., 1991; Slowihka-jurkiewiczb et al., 1995; Håkansson, Voorhees, and Riley, 1988).

Construction equipment is known to have higher loads than agriculture machinery and has been observed causing compaction to a depth of one meter (Håkansson and Reeder, 1994). Soils at construction sites have been found to be heavily compacted. Two different types of compaction are known to occur during the construction process. The first is deliberate or intended compaction where it is done on purpose to secure physical soil stability for structures to be built. The second is unintended compaction which is due to inadvertent construction traffic (Randrup, 1997). Efforts have been made to prevent or ameliorate compaction, but they have mostly been failures because during construction the topsoil, 10 to 50 centimeters, is removed during the grading phase, and then replaced when done (Randrup, 1997).

Compaction that occurs in forestry planting areas at new construction sites restricts growth of trees and shrubs, the BD of soil at these construction sites increases and is significantly higher than in undisturbed areas, and similar results have been observed for PR although it was not as consistent (Alberty, Pelett, and Taylor, 1984). Randrup (1997) recommended steps to consider when dealing with compaction on construction sites in production areas of trees. "1) *Expect that soil will be compacted.* 2) *It is important to make all possible efforts to reduce the spread of compaction. Containing the compacted area to a known location is best.* 3) *Fence off all possible future planting areas to protect the soils.* 4) *Alleviate compacted soil with the expectation that it will not be successful for many years.*" Now, with the increase in installation of wind turbines, it is necessary to apply studies like these to agriculture systems to better understand the effects of compaction caused by construction equipment. Alterations in soil physical properties have many environmental and agronomic implications and have the potential to cause significant economic damage (Keller, Lamandė, and Peth et al., 2013).

1.1.6 Soil Compaction – Weather Factors: Precipitation

Soil water content is one of the most important soil physical properties affecting the state of compaction. Compaction may restrict drainage of water from the soil which could result in an increase of flooding (Buttery, Tan, and Drury et al., 1998). Excess moisture is a major component of crop losses to extreme precipitation events due to damage above and below ground because of elevated risks of plant disease, insect infestations, and delayed planting/harvesting because of the inability to operate machinery in the fields (Rosenzweig, Tubiello, and Goldberg et al., 2002). Yearly variation in the severity of the effects of soil compaction can be mostly accounted for by seasonal variation in precipitation (Buttery, Tan, and Drury et al., 1998; Sidhu and Duiker, 2006). Weather conditions have been found to enhance or diminish effects of compaction on root growth through the effect of water on soil strength (Kaspar and Taylor, 1959). Problems associated with soil compaction are significantly found where intense mechanization occurs on soils in areas known for high rainfall or irrigation (Soane and van Ouwerkerk, 1994).

1.1.7 Crop Response to Soil Compaction

There is widespread evidence for problems in crop production attributed to soil compaction caused by traffic of vehicles. Soil compaction is considered a yield-limiting factor (Kilic, Özgöz, and Akbas, 2004; Lowery and Schuler, 1991; Keller and Håkansson, 2010; Soane and van Ouwerkerk, 1994; Lipiec, Hing;kansson, and Tarkiewicz et al., 1991), and most crops have a negative response to compaction. The most common reported effects of soil compaction on plants are reduced root growth, reduced plant height, and limited water transport which can cause nutrient stress and slowed seed germination (Arvidsson and Håkansson, 1996; Kilic, Özgöz, and Akbas, 2004; Lowery and Schuler, 1991; Keller and Håkansson, 2010; Defossez and Richard, 2002; Buttery, Tan, and Drury et al., 1998; Abu-Hamdeh, 2003; Kaspar and Taylor, 1959; Håkansson, Voorhees, and Riley, 1988). The most important soil properties impacting root growth include porosity, mechanical impedance (i.e. penetration resistance), water content and soil structure. Mechanical impedance increases as BD increases and water content decreases, and root growth decreases as PR increases (Lanpurlane's and Cantero-Martinez, 2003; Lipiec, Hing;kansson, and Tarkiewicz et al., 1991; Alberty, Pelett, and Taylor, 1984). The PR reflects the energy required for plant roots to penetrate the soil. The more energy needed for roots to grow; the less energy is available for the rest of the plant to developme (Landsberg, Miller, and Anderson et al., 2003). Optimum crop yields are dependent on optimum root growth (Abu-Hamdeh, 2003). The largest expected yield reductions are due to compaction when the crop is under stress (Sidhu and Duiker, 2006), and typically occur in the first year that compaction occurs (Håkansson and Reeder, 1994; Lowery and Schuler, 1991). This shows that soil compaction effects soil fertility and is a serious concern for landowners (Kilic, Özgöz, and Akbas, 2004).

1.1.8 Remote Sensing Technology in Soil Science

The use of remote sensing (RS) is becoming increasingly popular in the environmental sciences mainly because the approach enables an overview of large areas simultaneously using multispectral information. Remote sensing is the collection of data from a far distance, using electromagnetic radiation (EMR), which acts as an agent between the object of interest and the sensor (Ben-Dor, 2002). The EMR is reflected or emitted from objects on the Earth's surface at varying wavelengths and is collected by sensors on satellites or airborne devices (Grunwald, Vasques, and Rivero, 2015). In soil science this technique has shown a potential for determining soil groups, soil texture, the soil genesis process, soil degradation, estimation of soil organic matter content to assist in estimating regional patterns in soil erosion and grain yield, mapping soil phosphorus and carbon, assessing heavy metal concentrations, estimating effective soil hydraulic properties, and reflect soil environment interactions (Ben-Dor, 2002; Bhatti, Mulla, and Frazier, 1991; Karaburun, 2010; Mohanty, 2013; Grunwald, Vasques, and Rivero, 2015). There are several limitations to using RS for assessing soil properties which include the inability for EMR to penetrate the soil more than a few centimeters, sensor type may have an effect on the quality of data collected, and spatial and temporal resolution of currently available RS data may not be optimum for capturing all the hydrologic processes (Mohanty, 2013).

Correlations of RS normalized differential vegetation index (NDVI) data and soil properties have been reported (Sumfleth and Duttmann, 2007). The NDVI is a parameter commonly used to estimate the cover of green vegetation from satellite and airborne data (Sumfleth and Duttmann, 2007; Narasimhan, Srinivasan, and Luzio, 2005; Ben-Dor, 2002). The index is based on the normalized difference between near infrared (NIR) and the visual (VIS) reflectance values (Ben-Dor, 2002), and ranges in values between -1 and +1 where high positive values generally mean the occurrence of dense green vegetation, low values express limited photosynthetic activity and negative ones correspond to sparse vegetative cover (Sumfleth and Duttmann, 2007).

The NDVI provides inference on important space- and time-varying biotic properties that can be combined across different time intervals depending on their relationship to the soil property of interest. "*Soil properties can be captured directly like images of bare soil or inferred indirectly like sensing biotic properties that are then used in functional models to estimate them*" (Grunwald, Vasques, and Rivero, 2015). Soil properties related to NDVI include root zone soil moisture, soil color, soil texture and water holding capacity, soil carbon and nitrogen content, and soil type (Grunwald, Vasques, and Rivero, 2015). It has been found that NDVI and soil moisture are well correlated, and NDVI can be used as a good indicator for drought related water stress for crops (Narasimhan, Srinivasan, and Luzio, 2005). Limitations of NDVI include that it is very sensitive to the soil background, atmosphere, and the sun angle conditions (Ben-Dor, 2002; Sumfleth and Duttmann, 2007). More research is needed to further determine the correlation between NDVI and soil properties such as BD and PR as they relate to soil compaction.

1.2 COVID-19 Pandemic Impacts on the Study

The 2020 COVID-19 pandemic caused a sudden halt for all normal activity across the world. With mandatory health and safety regulations put in place, the normal routines of work and school were altered. All nonessential positions and industries were put on hold or moved to remote opperation. These mandates changed how this research project was completed. As nonessential work (i.e. not part of critical infrastructure e.g. health care emergency services, etc.), we were made to work remotely. Unfortunately, that meant we could not conduct the intended field sampling of bulk density and penetration resistance measurements. Thus, changing the initial plan for the project.

As an alternative, we focused our efforts towards the development of an application to rate soil organic matter across the state of Indiana. While unrelated to wind turbines, this fits the theme of using digital analysis in soil science providing another example of the technological advancements within the industry. This alternative part of the project is represented in Objecctive 3 and Chapter 3 of this thesis document.

1.3 Objectives

1.3.1 Objective 1: Develop a method to quantify differences in crop response between former construction sites of turbines and adjacent, non-disturbed, agricultural land using remote sensing.

Rapid quantification of the impact to soils of construction equipment traffic from wind turbine installation requires methodology that can rapidly detect changes in crop response or soil conditions. One potential method would compare crop health measured with NDVI as a proxy for soil impairment. We believe that by comparing NDVI between areas impacted by construction traffic and areas without construction traffic we can quantify the extent of soil impairment due to construction traffic.

1.3.2 Objective 2: Evaluate the effect of soil and crop conditions on the persistence of impacts present in the turbine footprints caused by construction equipment.

Determining which factors impact the persistence of soil compaction due to construction equipment traffic can inform management strategies to minimize compaction impacts as well as provide landowners with guidance for how long potential damage may impact their fields. By comparing the compaction impacts from sites of different soil types, we can quantify how the areal extent of compacted areas changes over time and determine which site conditions impact the persistence of compaction effects. This information can provide guidance about which sites will have greater or more persistent compaction impacts and provide landowners and turbine installers with better information on how long fields may be impaired after turbine installation.

1.3.3 Objective 3: Develop an application to rate soil organic matter in the state of Indiana.

The push towards better soil quality and health has driven a growing interest in soil organic matter and other soil properties. Unfortunately, there is little guidance as to what appropriate levels of soil organic matter for a given soil should be. Subsequently, farmers and land mangers interested in understanding if their soil has sufficient or optimum soil organic matter do not have sufficient resources to understand their measurements of soil organic matter. Therefore, we developed an application that provides land managers with soil-specific soil organic matter ratings. These ratings can be used to determine if a soil is deficient in soil organic matter or if a soil has sufficient soil organic matter. Chapter 3 of this thesis consists of an extension publication intended to explain the use and utility of the soil organic matter rating application. Details of the application development are available in Appendix B.

CHAPTER 2. WIND TURBINE ANALYSIS

2.1 Introduction

Since the 1970s, use of wind as an alternative energy source has boomed into a massive industry. Over 60,000 wind turbines have been installed in the United States (American Wind Energy Association, 2020). Vast amounts of farmland make the Midwestern United States a hotspot for installation with one of the largest concentrations of turbines in the world residing in Northwest Indiana, (Figure 1.2, Mulvaney, Woodson, and Stalker Prokopy, 2013). Installation of wind turbines has led to an increase in construction equipment operating on agriculture land. Construction equipment is known to have higher loads than agriculture equipment (Håkansson and Reeder, 1994). Increased axle loads raise concerns about subsoil compaction occurring in these areas because the extent of the impacts within a turbine's footprint are still unknown.

Several studies have found that subsoil compaction by traffic of heavy equipment increases penetration resistance (PR) and bulk density (BD), deteriorates soil structure, decreases pore size and air and water permeability, impacts soil biota, and induces a negative crop response (Lowery and Schuler; Horn, Domialb, and Slowihka-jurkiewiczb et al., 1995; Håkansson and Reeder, 1994; Abu-Hamdeh, 2003; and Frey, Kremer, and Rudt et al., 2009). Soane and van Ouwerkerk (1994) reported that these impacts have negative effects on crop establishment, growth, yield or quality.

Research in forestry production has reported that compaction occurring in new construction sites resulted in significant increase in BD and PR compared to undisturbed areas, (Alberty, Pelett, and Taylor, 1984). Consequently, these impacts were associated with restricted growth of trees and shrubs. This research highlighted the negative impacts to soil structure and plant growth that occur in areas trafficked by heavy construction equipment.

The ever-growing demand for alternative energy ensures that wind turbines will continue to be installed on agricultural land. This makes quantifying the impact area of the turbine installation footprint imperative for understanding how construction in agricultural areas affects soil properties and crop productivity.

Field work tends to be extremely time consuming, and the use of remote sensing (RS) technology has become increasingly popular in the environmental sciences (Ben-Dor, 2002). The RS data has been used in soil science to determine many soil properties and environmental interactions (Ben-Dor, 2002; Bhatti, Mulla, and Frazier, 1991; Karaburun, 2010; Mohanty, 2013; Grunwald, Vasques, and Rivero, 2015). Normalized differential vegetation index (NDVI) images have also been found to be helpful for indirectly determining soil properties including root zone soil moisture, soil color, soil texture and water holding capacity, soil carbon and nitrogen content, and soil type as related to changes in vegetation greenness and canopy water absorbance (Grunwald, Vasques, and Rivero, 2015). Due to known correlations between NDVI, crop health and soil properties, NDVI may be valuable in monitoring the impact of construction vehicle traffic on soil properties and subsequent crop response.

A tremendous amount of work has been done to understand how compaction occurs, persists, is alleviated, and the impacts it has on soil properties and crop response. Much of the completed research has focused on compaction from agricultural practices, and it has been reported how compaction at construction sites can penetrate deeper into the soil (Håkansson and Reeder, 1994). Therefore, the increase in construction traffic in agriculture systems demands attention. This study will provide a method to analyze wind turbine sites in order to quantify the area of the turbine footprint where compaction has occurred due to construction traffic with the use of RS technology.

The goal of this study was to quantify the area of farm fields impacted by wind turbine installation using RS. To achieve this goal, we developed a methodology to quantify the differences in crop response on land where construction activities have occurred during turbine installation and adjacent, non-disturbed, agriculture land using RS data. We then used this methodology to evaluate the effect of time on the persistence of wind turbine installation footprints caused by construction equipment and determine which site factors may control the extent and persistence of construction-associated compaction effects. This information will provide landowners additional information for negotiating leasing contracts for future turbine installation or renewals, aid in our understanding of how agriculture is affected by installations of wind turbines or similar structures, and add to our knowledge of the use of RS data in soil science today.

2.2 Methods

2.2.1 Site Selection

We used the U.S. Wind Turbine Database (*USWTDB Viewer* 2020) to find the location of wind turbines in Indiana. From the database we selected two windfarms, the Bluff PointBLUFF POINT and Meadow Lake VMEADOW LAKE V windfarms. These were selected because the windfarms were installed in 2017 which allowed us to include RS data from a year before installation and two years after installation in this analysis. The BLUFF POINT and MEADOW LAKE V are located in Jay and Randolph counties, and White county Indiana, respectively (Figure 2.1). The MEADOW LAKE V windfarm contains 52 turbines spread across an estimated 10,744 acres (*Meadow Lake Wind Farm* 2020), and the BLUFF POINT windfarm contains 57 turbines spread across 18,000 acres (Slabaugh, 2017).

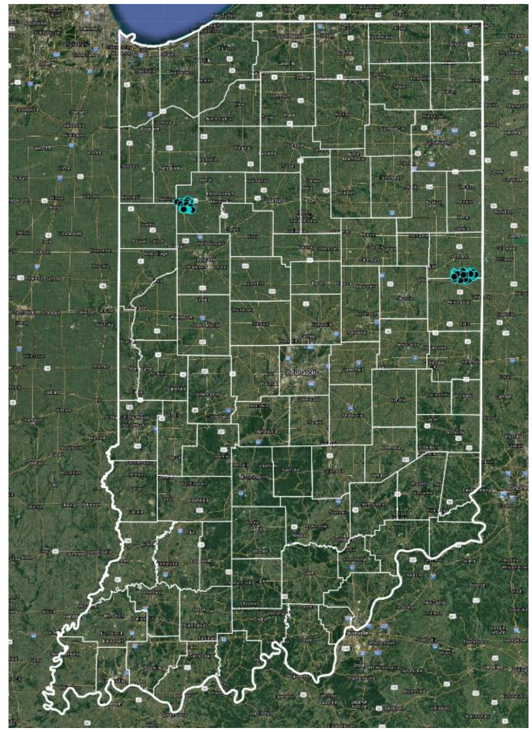

Figure 2.1. Location of Meadow Lake V and Bluff Point windfarms as blue outlined points, respectively.

2.2.2 Satellite Imagery

We used Sentinel-2 satellite imagery of crop reflectance for the analysis in this study. Offered by the Copernicus Program from the European Space Agency, Sentinel-2 was launched as an Earth observation mission operating with two satellites, Sentinel-2A and Sentinel-2B. Sentinel-2 collects data in 13 spectral bands in which bands 2 (blue), 3 (green), 4 (red), and 8 (Near-infrared) have a 10-meter resolution allowing data to be viewed at the field scale. The limitations of using the Sentinel-2 satellite images include extremely limited image selection from 2015, no windfarms were installed during 2016 in Indiana, and cloud cover constrains image selection.

Using the Copernicus Open Access Hub, images were downloaded for the years 2016, 2017, 2018, and 2019 for each windfarm using satellites S2A and S2B, that have a return period of about two weeks, with the product type S2MSI1C. Images with less than ten percent cloud cover were selected during the growing season for corn and soybeans. Image availability dictated the dates selected for each windfarm, table 2.1, and were kept as close to the same time for each year.

Table 2.1. Sentinel-2 image dates for each windfarm used in the analysis.

Windfarm	2016	2017	2018	2019
Bluff Point	July 19	July 9	July 7	August 28
Meadow Lake V	September 3	September 20	August 4	August 4

2.2.3 Image Processing and NDVI Calculation

We imported bands 2(490 nm), 3 (560 nm), 4 (665 nm), and 8 (842 nm) from each Sentinel image into QGIS (QGIS Development Team, 2019). We then stacked the bands from each image into a four-band raster using the Semi-Automatic Classification (SCP) plugin (Figure 2.2-a). The stacked images can be viewed as natural color (i.e. bands 4, 3, and 2 or false color infrared (i.e. bands 8, 4, and 3). We saved the stacked rasters as four-band TIFF files.

For each TIFF image (e.g. 4-band raster), we calculated the normalized differential vegetation index (NDVI) (Figure 2.2-c). NDVI was calculated within the raster calculator using the following equation:

$$\frac{(Band\ 8 - Band\ 4)}{(Band\ 8 + Band\ 4)}$$

Where Band 4 and Band 8 are the visible red and near infrared (NIR) bands from the Sentinel-2 images, respectively. This calculation produces an image in which each pixel is assigned a color based on its value along a specified gradient. High values are assigned green and indicate healthy vegetation and low values are assigned red and indicate bare ground or very poor vegetation.

To constrain the area for our analysis, we needed a shapefile to designate the boundary of each field. For each field containing a wind turbine, we drew a boundary around the field using the shapefile editor in ArcMap (Figure 2.2-b). Boundaries were established using Land Parcel data for Indiana from the Indiana Map (Indiana Geographic Information Office (IGIO), 2018) and aerial imagery of each field. We drew field boundaries to exclude turbine pads and access roads from the field. The field boundaries were then exported from ArcMap as a shapefile for use in later analysis.

Each field boundary is then used to "Extract-by-Mask" the NDVI images for all four years so that the NDVI images entail only the area of a specific field. These NDVI images are then exported as a TIF file for use in later analysis.

2.2.4 Determining the NDVI Threshold

To calculate the area of soil impacted by turbine installation, we needed to determine which values of NDVI constituted impaired or impacted vegetation (Figure 2.2-d). For this study, we assumed that any NDVI value less than the 5% quantile of a reference NDVI population would be considered impaired. For this study, we tested the reference population and subsequent NDVI threshold for single field reference populations. The following section details how the reference population was established.

Before establishing the reference population, we needed to select the NDVI values from areas of fields where soil was unimpacted by turbine installation. To do this, we loaded NDVI images and field boundaries into RStudio (R Core Team, 2013). Using the gBuffer function in the rgeos package (Roger Bivand and Colin Rundel, 2019) we created a 100-m internal buffer 100 meters from all field edges using the field boundary shapefile (Figure 2.2-e). This buffer removed any soil within a reasonable distance from the field borders which could contain unrelated, disturbed values. Next, we selected NDVI values from inside the field boundary buffer using the extract tool in the raster package (Robert J. Hijmans, 2020). This gave us a subset of NDVI values for the locations in the field that were unaffected by field boundary effects and turbine installation.

To calculate the field-level thresholds, extracted NDVI values for each field were used individually to calculate field-specific 5% quantiles. Subsequently, each field had a unique field-level threshold for each year in the study. Field-level thresholds allow for the comparison of individual wind turbines within a windfarm. This enables us to analyze the effect of texture, drainage, and crop type on soil recovery within each windfarm of the study.

In using packages raster, rgeos (Roger Bivand and Colin Rundel, 2019), and rgdal (Roger Bivand, Tim Keitt and Barry Rowlingson, 2019), the corresponding NDVI TIF and field boundary shape files are loaded. Using the hist function, a histogram of NDVI values is generated using this threshold value (Figure 2.2-d). To visualize the size of these areas, a binary raster image is created using this threshold value (Figure 2.2-e). Pixels in green are “impacted” areas and pixels in white are “unimpacted” areas.

2.2.5 Calculating the Impacted Area for Each Turbine

To calculate the area impacted at each turbine, we first converted each NDVI image into a binary raster. To do this, we use NDVI thresholds determined in sec 2.2.4. NDVI values above the threshold were considered unimpacted and assigned a value of 0 and areas below the threshold were assigned a value of 1. Next the number of pixels with a value of 1 were counted within a -150-meter buffer of the turbine (Figure 4-f). This extraction calculates an area of impact in meters squared per turbine, which is later converted into acres per turbine, and the percent of the field impacted for each of the four years. The code for this analysis (sec 2.2.5) can be found under Appendix A.

2.2.6 Crop and Soil Data

To determine if turbine impacts were related to ancillary data (i.e. soil texture, soil drainage, and crop type), we categorized each field based on soil and crop attributes. The soil data used in this study came from the USDA Web Soil Survey (NRCS, *Web Soil Survey* 2019) and the Soil Explorer web app (USGS, Purdue University, & USDA, *Soil Explorer*). Both were used to determine the soil texture and drainage for each windfarm footprint area. In areas where multiple soil textures were found within the turbine footprint, groups were created based on soil texture within 10 to 15 inches from the surface, to allow for larger sample size in statistical analysis. Soil texture groups for the BLUFF POINT windfarm include silt loams containing silt loam and silty clay loam textures and silty clays. Soil texture groups for the MEADOW LAKE V windfarm include loamy containing loam, clay loam, and silt loam textures and sandy containing loamy fine sand and fine sandy loam textures. For soil drainage class, the dominant soil drainage type for the field area around the turbine was selected. For the MEADOW LAKE V windfarm, soils with moderately well or somewhat poor drainage were combined due to small sample size.

2.2.7 Statistical Analysis

To compare differences in the mean area of impact between groups, a Tukey's LSD test was performed. Prior to analysis, all groups were checked for homogeneity of variance using Levene's test. All statistical analysis was performed using RStudio (R Core Team, 2013). The Tukey's LSD test was performed using the Agricole package (Felipe de Mendiburu, 2020). All results displayed in subsequent graphs show the significant differences at 95% confidence level.

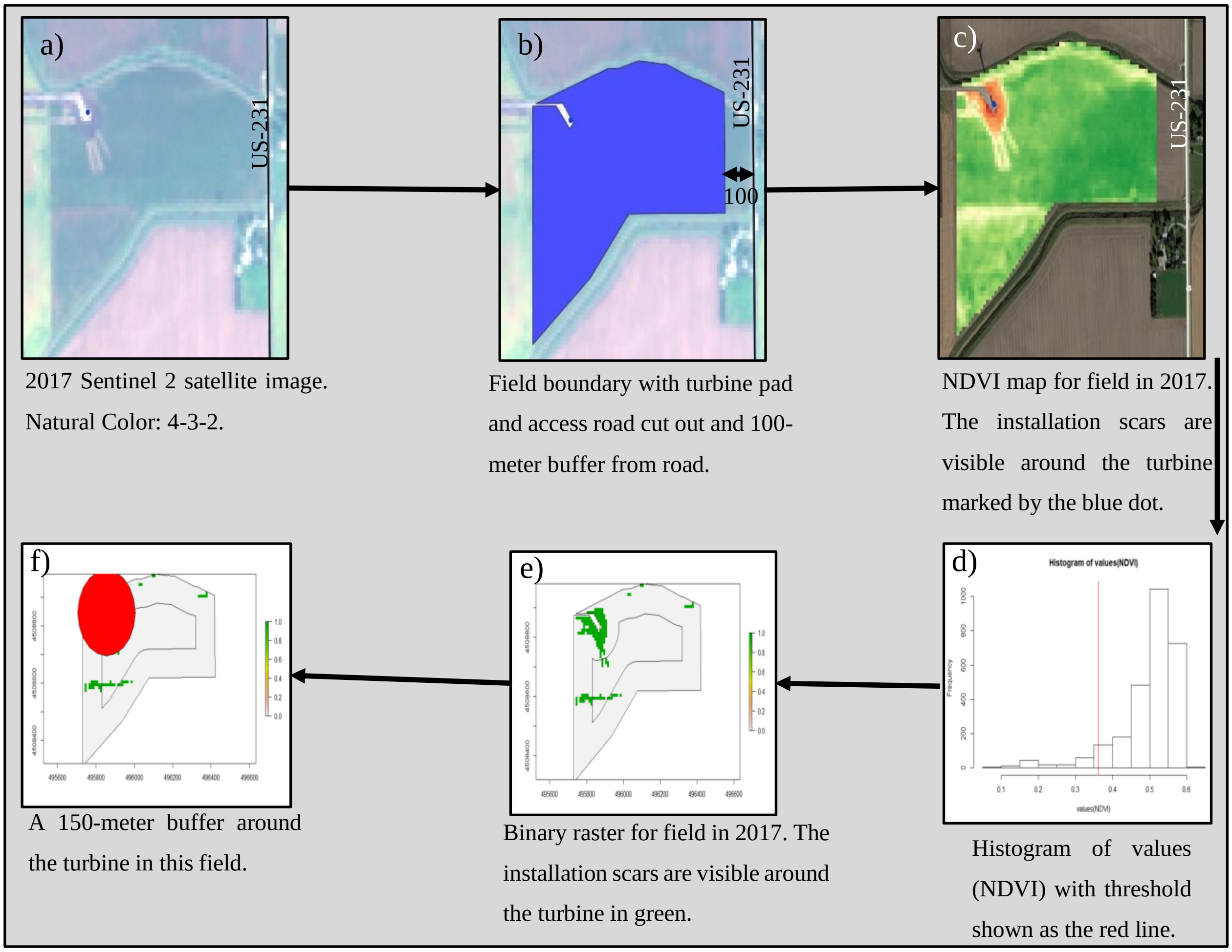

Figure 2.2 Turbine RStudio analysis flowchart.

2.3 Results and Discussion

2.3.1 Windfarm Impacted Area

The average impacted area for each windfarm, Meadow Lake V and Bluff Point, from 2016 to 2019 is shown in figure 2.3. Both windfarms displayed dramatic increases in impacted area between the pre-installation year, 2016, and the year wind turbines were installed, 2017. Each year after 2016, the impacted area was statistically different from 2016 for both windfarms. This result shows that crop greenness, as measured by NDVI, is significantly lower in the wind turbine footprints following turbine installation. NDVI has been shown to correlate to crop growth characteristics including the relationship of crop and vegetation productivity (Sumfleth and Duttmann, 2007), which has been found to relate to soil properties such as soil color, texture, water holding capacity, etc. (Grunwald, Vasques, and Rivero, 2015). Therefore, we believe that it is plausible that NDVI post-turbine installation is correlated to soil compaction.

For both windfarms, the greatest impacted areas occurred during 2017. This result is expected as 2017 would be the point of greatest disturbance in the soil (i.e. year following installation). After 2017, the average impacted area only decreases significantly in the MEADOW LAKE V windfarm, with time. This decrease is to be expected because disturbance via wind turbine installation only happens once in a specific location and subsequently when the area is then returned to its previous use (i.e. row crops) the soil can recover from this disturbance through biological or mechanical processes (Håkansson, Voorhees, and Riley, 1988). The longer the time from wind turbine installation, the more time the soil has had to recover, and subsequently the smaller area of impacted NDVI. The BLUFF POINT windfarm does not see a significant decrease, likely due to a lack of range in the data, as the majority of the turbines were installed on similar soil conditions.

One interesting result is that it appears that soil at each windfarm is recovering at different rates. For MEADOW LAKE V 2018 and 2019 average impact area is significantly different from 2017. However, significant differences with 2017 are not observed at BLUFF POINT. This suggests that windfarm-level factors such as installation procedures and timing, soil type, and weather/climate may impact the recovery of each windfarm.

For both windfarms, the impacted area after three years (i.e. 2019) is still significantly greater than pre-installation areas (i.e. 2016). This suggests that there is still impact on the soil within the turbine footprint for both the MEADOW LAKE V and BLUFF POINT windfarms three years after turbine installation. Because these impacted areas do not return to pre-installation NDVI values in the three years following installation it likely takes more than three years post-installation for crop health and soils to recover from turbine-installation damages.

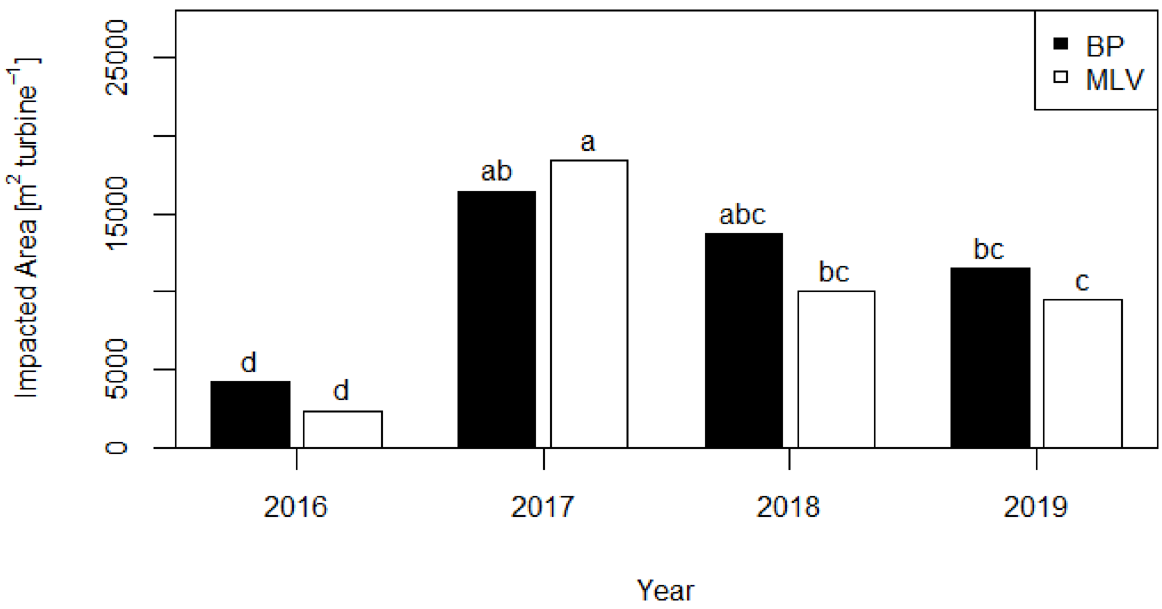

Figure 2.3. Average turbine impact area for each year of the study for Meadow Lake V (MEADOW LAKE V) windfarm and Bluff Point (BLUFF POINT) windfarm, shown in black and white bars respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05.

2.3.2 Potential Factors Affecting Crop Recovery

To determine if ancillary factors affected soil and crop recovery following turbine installation, we categorized fields based on three factors: soil texture, soil drainage, and crop type. We then used these factors as fixed effects in Tukey's analysis to determine if each variable had an effect on the impacted area within each year of the study. For simplicity of interpretations and to avoid windfarm-level interactions, each windfarm was analyzed separately. The following sections detail the results for each ancillary variable analyzed using field thresholds, to observe what effects each factor has on the impacted area of the turbine footprint for both windfarms.

2.3.3 Impacted Area by Texture

The average impacted area for the BLUFF POINT windfarm by soil texture is shown in figure 2.4. Silt loam textures are shown in black and include silt loams and silty clay loams, while silty clay textures are shown in white. Both textures showed a significant increase in the impacted area when the wind turbines were installed. However, no significant decrease was seen for either texture group over time. This is likely due to the lack of range within the data for the BLUFF POINT windfarm being that all textures were high in silts, and that both silty and clayey soils are most susceptible to compaction (Horn, et al., 1995).

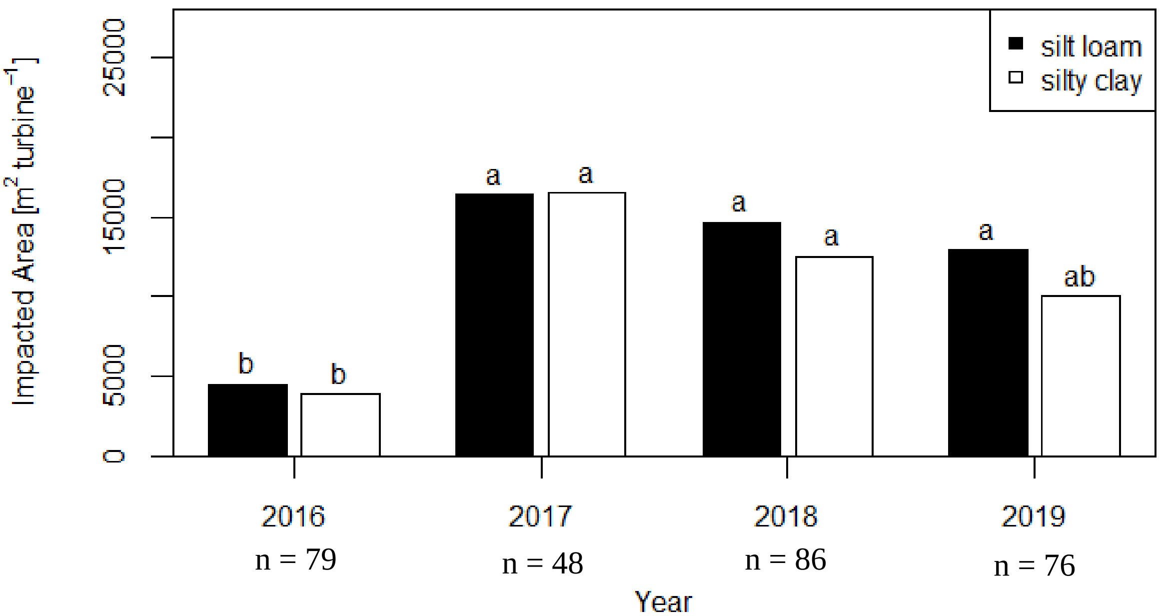

Figure 2.4. Average turbine impact area by texture (m^2/turbine) for each year of the study for Bluff Point (BLUFF POINT) windfarm with silt loam and silty clay soils shown in black and white, respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05.

The average impacted area for the MEADOW LAKE V windfarm by soil texture is shown in figure 2.5. Loamy textures are shown in black and include loams, clay loams and silt loams, while sandy textures are shown in white and include loamy fine sands and fine sandy loams. Only the loamy textures showed a significant increase in the impacted area when the wind turbines were installed and significantly decrease over time. The sandy textures likely did not show a significant increase or decrease because the sample size for this texture group is smaller, sandy soils tend to be well drained, and sands are much less susceptible to compaction as compared to silts or clays (Horn, et al., 1995). After three years with turbines, the loamy soils still show a tendancy for the impacted area to be greater than the pre-installation values. This suggests that loamy textured soils require more than three years to recover from the construction traffic during the installation of wind turbines.

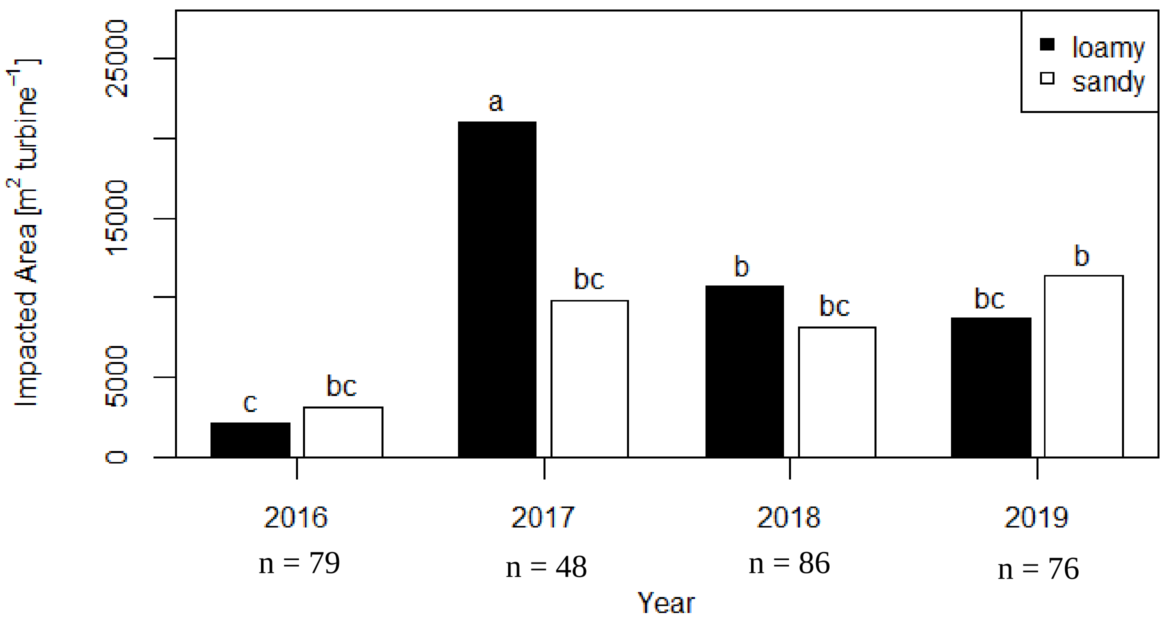

Figure 2.5 Average turbine impact area (m^2/turbine) by texture for each year of the study for Meadow Lake V (MEADOW LAKE V) windfarm with loamy and sandy soils shown in black and white, respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with $\alpha = 0.05$.

For both windfarms, the impacted areas for loamy and clayey textures after two years (i.e. 2018) are still significantly greater than pre-installation areas (i.e. 2016). Soil texture is a key component to how susceptible a soil will be to compaction. Understanding the impact of soil texture in the turbine footprints will be useful for landowners when choosing a wind turbine location in the future. These impacts will also improve our knowledge of soil compaction in production areas via construction equipment.

2.3.4 Impacted Area by Drainage

The average impacted area for the BLUFF POINT windfarm by soil drainage is shown in figure 2.6. Moderately well drained soils are shown in black, poorly drained soils are shown in grey, and somewhat poorly drained soils are shown in white. There were no well drained soils within the area of the BLUFF POINT windfarm. For all drainage classes, there was no significant increase or decrease in the impacted area during the timeframe of the study. The decreased values are not significantly different from the pre-installation year (i.e. 2016). This result is not expected due to the fact that soil wetness greatly influences compaction, and that wetter the soil when traffic occurs, the greater the impacts from compaction (Håkansson, Voorhees, and Riley, 1988). It should also be noted that the poorly and somewhat poorly drained soils each only accounted for a small sample size. The BLUFF POINT windfarm was also subject to low areal variance as the majority of the windfarm area was moderately well drained and had similar soil textures throughout.

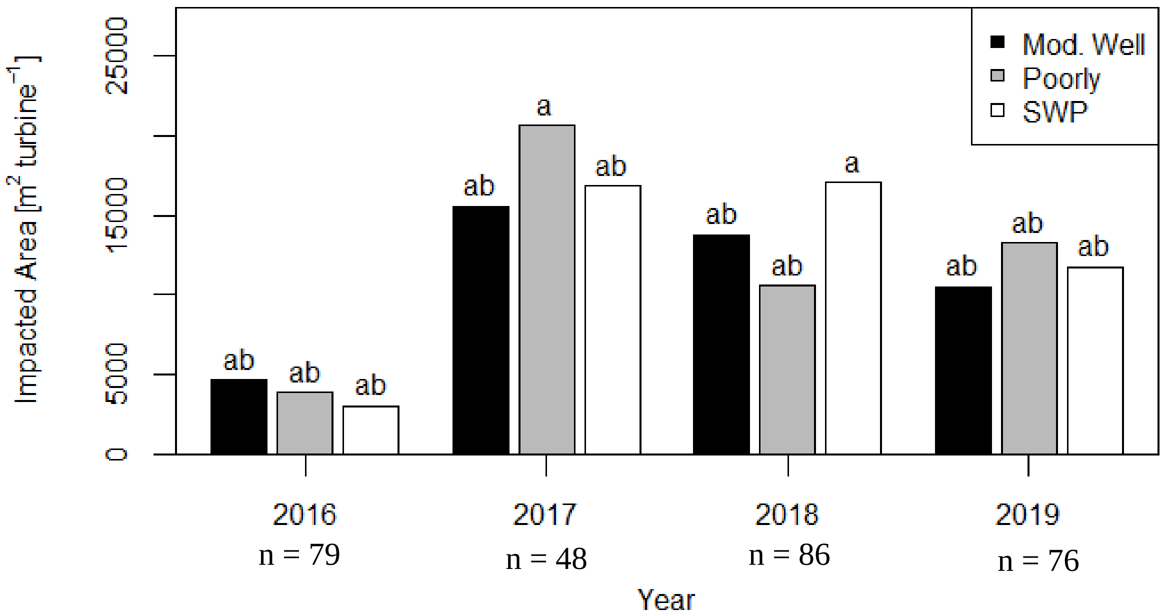

Figure 2.6. Average turbine impact area by drainage (m^2/turbine) for each year of the study for Bluff Point (BLUFF POINT) windfarm with moderately well, poorly, and somewhat poorly drained soils shown in black, gray, and white, respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05.

The average impacted area for the MEADOW LAKE V windfarm by soil drainage is shown in figure 2.7. Moderately well/somewhat poorly drained soils are shown in black and were combined due to small sample size for both drainage classes. Poorly drained soils are shown in grey, and well drained soils are shown in white. The moderately well/somewhat poorly and poorly drained soils showed significant increase in impacted area when wind turbines were installed, but the well-drained soils did not. This is likely because well drained soils tend to be less susceptible to compaction due to the lack of moisture when compared to the others (Håkansson, Voorhees, and Riley, 1988). The moderately well/somewhat poorly and poorly drained soils also showed significant decrease in impacted area over time. The well drained soils showed no significant difference in the impacted area for all years in the study.

For both windfarms, the impacted areas for well and moderately well drained soils, separate from somewhat poorly drained soils, were never significantly greater than pre-installation areas (i.e. 2016). The soils ability to store and move water is a key component to how susceptible a soil will be to compaction. Understanding the impact of soil drainage in the turbine footprints will be useful for landowners when choosing a wind turbine location in the future with regards to being mindful of where water tends to stand in a field. These impacts will also improve our knowledge of soil compaction in production areas via construction equipment.

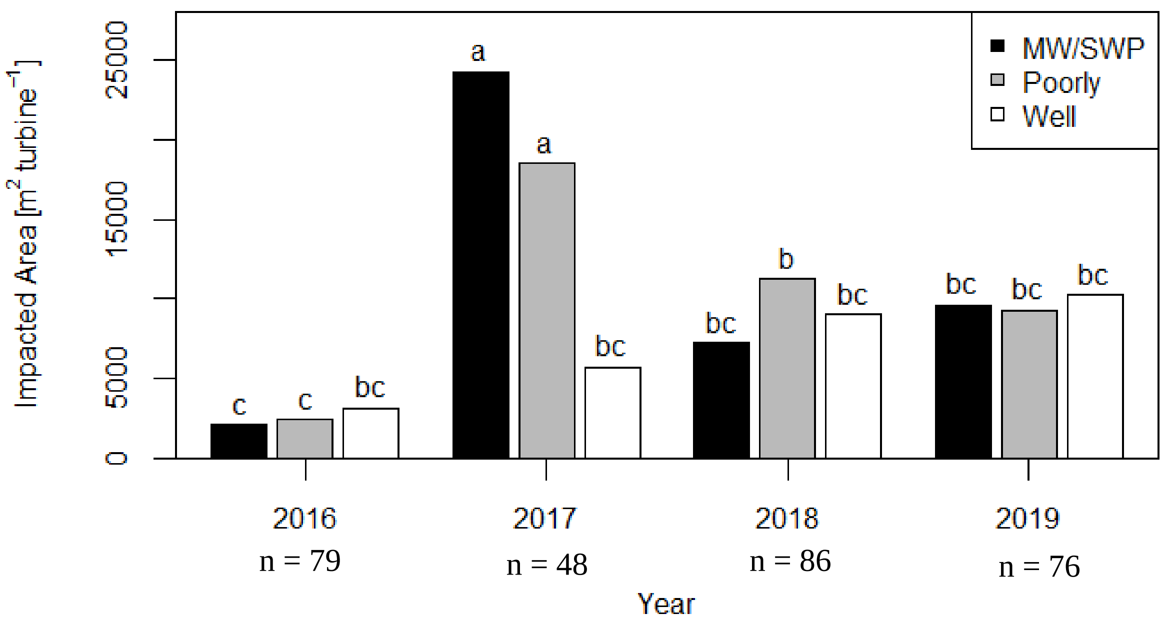

Figure 2.7. Average turbine impact area (m^2/turbine) by drainage for each year of the study for Meadow Lake V (MEADOW LAKE V) windfarm with moderately well and somewhat poorly, poorly, and well drained soils shown in black, gray, and white, respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with α = 0.05.

2.3.5 Impacted Area by Crop

The average impacted area for the BLUFF POINT windfarm by crop type is shown in figure 2.8. Corn is shown in black, and soybeans are shown in white. Both crops show significant increase in impacted area when the turbines were installed (i.e. 2017), and neither show any significant decrease over time. There is also no significant difference between crops for all years of the study. After three years of turbines (i.e. 2019) soybeans still exhibit a significant difference from pre-installation (i.e. 2016), implying that more than three years is required for the soil to recover to avoid impacting a soybean crop.

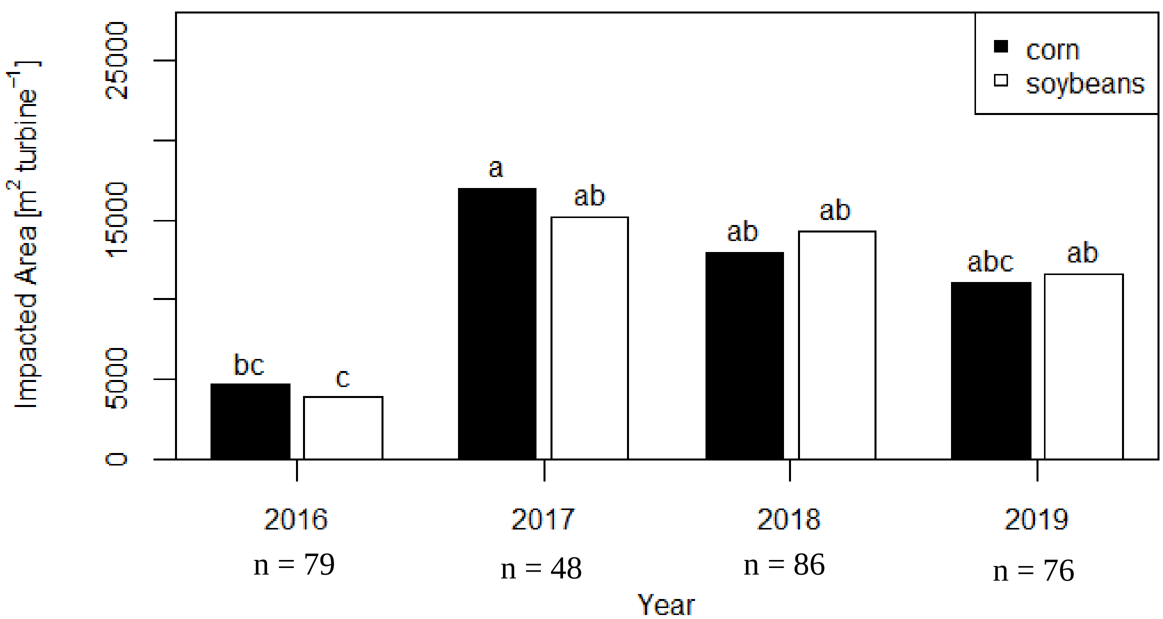

Figure 2.8. Average turbine impact area by crop (m^2/turbine) for each year of the study for Bluff Point (BLUFF POINT) windfarm with corn and soybean shown in black and white, respectively. Bars labeled with the same letter are not significantly different based on a Tukey's HSD test with $\alpha = 0.05$.

The average impacted area for the MEADOW LAKE V windfarm by crop is shown in figure 2.9. Corn is shown in black and includes popcorn, and soybeans are shown in white. Both crops show a significant increase when turbines were installed. However, the crops exhibit different behavior in 2018 and 2019. In those years, the impacted area for fields planted in corn is significantly less than in 2017. However, for soybeans, there is no significant difference between

2017, 2018, and 2019 data. This suggests soybeans appear to be more sensitive to impacts to effects of compaction. Johnson, et. al., 1990 observed that yield response to compaction was “climate dependent”. However, they found that soybeans did respond differently to high axle load traffic than corn. In their study, corn showed a greater initial response to the compaction treatment which dissipated over time. Soybeans demonstrated reduced plant height and leaf area index caused by the compaction treatment that was consistent over time. This could explain our findings of soybeans continuing to be significantly different from the pre-installation (i.e. 2016) values.

Only corn and soybeans were selected for crop type as they are the most common crops planted in the state of Indiana. Crop type was considered because the data used for the analysis is based on crop reflectance values. For both windfarms, the impacted area for soybeans after three years (i.e. 2019) are still significantly greater than pre-installation areas (i.e. 2016). For both

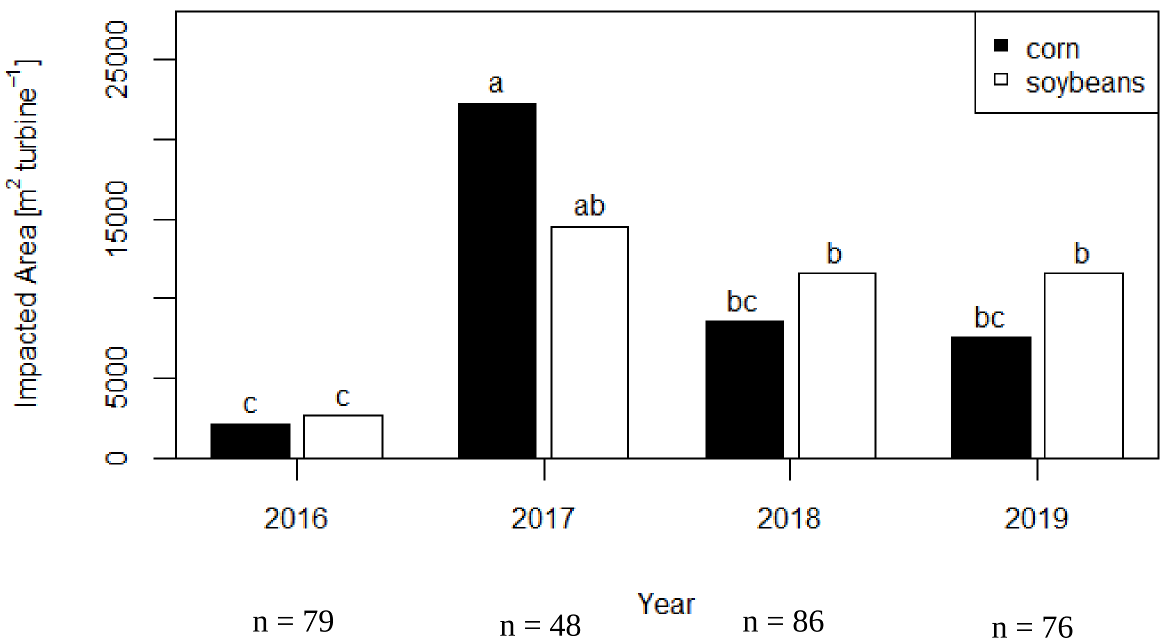

Figure 2.9. Average turbine impact area (m^2/turbine) by crop for each year of the study for Meadow Lake V (MEADOW LAKE V) windfarm, with corn and soybean shown in black and white respectively. Bars labeled with the same letter are not significantly different based on a Tukey’s HSD test with α = 0.05.

windfarms, the impacted area for corn after three years was no longer significantly different than the pre-installation areas. This tells us that compaction impacts affect soybeans more consistently over time than corn, even with corn-soybean rotations. This impact is relevant to NDVI values, and more research is needed to correlate any yield limitations in soybeans for these impacted areas. For now, this data can be used as a reference to landowners when considering where turbines will be installed, and what crops to plant if a turbine is present.

2.4 Conclusion

Over the last decade, wind turbine installation has increased across the United States, and specifically in the state of Indiana. This has changed the type of equipment used on soils where wind turbines are installed. Typically, agriculture equipment like tractors and combines, etc., are the only large equipment used in fields. However, for wind turbine installation, construction equipment like cranes and bulldozers, etc., are used at these sites, and are heavier than the equipment used in typical farming practices (Engineering, 2011). Subsequently, there is a need to understand and quantify the effect of this increased vehicle traffic on agricultural fields.

To quantify the impacts of turbine installation on agricultural soils, we developed a method for rapidly assessing the area of soil impacted by turbines using remote sensing. This method compares NDIV of crops near the turbine installation site to NDVI of crops in undisturbed sections of fields and then classifies areas into “impacted” and “unimpacted” using a quantile-based metric. This metric then enables us to calculate the impacted area for each turbine.

We tested this methodology on two windfarms in Indiana. The results showed that the impacted area per turbine increased significantly in the year following turbine installation and decreased slightly in subsequent years and suggests that our methodology is a viable method for rapidly assessing cropland disturbance following wind turbine installation. Furthermore, in the three years following turbine installation, most sites did not return to pre-instillation levels of impairment. This suggests that in general, greater than three years are needed for sites to return to pre-installation conditions.

By comparing sites based on soil texture and drainage across the four years in the study we could assess what impact soil properties had on the initial site susceptibility to turbine impacts and subsequent recovery. Sites with soils having coarse, sandier textures and/or well drained soils responded less to wind turbine installation than soils with heavier, clayey textures and/or poor drainage. In general, sandy and well drained soils had lower impacted areas in the year following turbine installation and post-installation showed greater recovery. This result demonstrates that soil characteristics have a large effect on site susceptibility to and recovery from impacts due to wind turbine installation.

We also assessed if crop type had an impact on site susceptibility to and recovery following turbine installation. Our results showed soybeans recovering more slowly than corn, however no significant difference existed between crops for either wind farm during the study.

The information gained from this study will allow for clearer understanding on what kind of timeframe landowners are looking at for their soils to recover after the installation process. Landowners will be able to use this data to assist in negotiations when considering installing wind turbines on their property. Further study should provide the addition of the 2020-21 satellite imagery of these wind farms to strengthen our findings and expand our use and knowledge of remote sensing in soil science. Comparing yield maps to the data could further our understanding of wind turbine installation impacts on crop response, and the collection of in-field data such as bulk density and penetration resistance values could be useful to correlate the remotely sensed data with known soil measurements associated with compaction.

CHAPTER 3. SOIL ORGANIC MATTER RATING APPLICATION

3.1 Soil Organic Matter and its Importance

Soil organic matter (SOM) is a mix of decomposed material, plant litter and roots, and dead and living organisms (Figure 3.1, Gregorich, Carter, et. al., 1994). The SOM stores much of the carbon and nitrogen in soils and is highly biologically active (Sparling, Wheeler, et. al., 2006).

Figure 3.1. Soil organic matter components illustration (Mani, 2014).

Soil organic matter is involved in regulating many soil ecological and agronomic functions. Due to the biologically reactive nature of SOM and the important role of SOM in soil function, SOM is an important indicator of soil quality and health.

Most soils contain anywhere from 2 – 10 percent organic matter (Bot & Benites, 2005). However, soil organic matter is easily lost under intense cropping systems primarily because it is being used faster than it is being replaced (Sparling, Wheeler, et. al., 2006). In this article, we will discuss the important role of SOM in agriculture and ecosystem function, discuss the ways SOM can be lost or added to soil, and show how Purdue's SOM online SOM rating application can help you determine if the SOM levels of your soil need improvement.

3.2 Role of Soil Organic Matter Agronomic and Ecosystem Functions

Soil organic matter plays an intricate part in many soil functions. These include anything from water retention and infiltration to aggregate stability and nutrient availability. The SOM is key to maintaining soil physical, chemical, and biological properties necessary for crop production.

The benefits of soil organic material include increased water retention and availability, greater cation exchange capacity (CEC), improved ability to retain nutrients within the root zone, greater buffering capacity against pH change, better soil structure, increased biological activity and biodiversity, reduced erosion, etc. (Sparling, Wheeler, et. al., 2006; Gregorich, Carter, et. al., 1994; Bot & Benites, 2005).

3.2.1 Cation Exchange Capacity (CEC)

Soil organic matter, along with soil clay content contributes greatly to a soil's CEC. Cation exchange capacity is a soil chemical property that reflects the soil's ability to hold onto positively charged ions. This is especially important for soil fertility because CEC dictates how well a soil can hold and exchange mineral nutrients. Soils with high CEC can typically hold more fertilizer elements for plants to use later and can buffer or resist pH change better (Buechel, 2020).

3.2.2 Aggregation and Soil Structure

The structure of the soil acts as the primary building block for all other soil functions. Strong soil structure leads to proper functioning, whereas, poor structure leads to poor functioning of the soil. The stability of a soil's structure is important for maintaining its integrity while under stress (i.e. cultivation, compaction, and irrigation). Soil organic matter is known to increase soil aggregate stability. Most studies have reported a linear increase between aggregate stability and increasing soil organic matter (Figure 3.2; Krull, et. al., 2004).

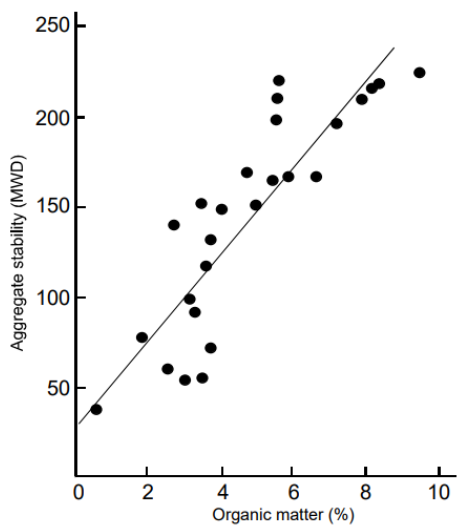

Figure 3.2. Relationship between aggregate stability and organic matter content (Krull, et. al., 2004)

3.2.3 Biological Functions

Because soil organic matter is derived from biological material, it is unsurprising SOM is involved in many biologically important functions. These functions include providing a source of metabolic energy (i.e. metabolism; changing food into energy) for soil organisms, acting as a source of macro-and micro-nutrients for plants, and controlling the sustainable release of both energy and nutrients (Krull, et. al., 2004).

3.2.4 Biogeochemical (i.e. N and C Pools)

Carbon obtained by plants through the atmosphere is eventually added to the soil through litter, root material, and root exudates when the plants die. This addition provides nutrients to soil microbes, fungi, and earthworms, resulting in the formation of organic matter. Soil microorganisms account for a large amount of this transformation and store 1-5% of carbon and nitrogen, and it has been suggested that soil microbiological parameters could act as indicators of soil quality. Apart from fertilizers, soil organic matter is the largest source for macro-nutrients (i.e. carbon, nitrogen, phosphorus, and sulfur). These nutrients are primarily sourced from mineralization of the soil organic matter, and chemically reduced carbon in the fresh organic matter is required as the main energy source for the mineralization of nitrogen (Krull, et. al., 2004).

3.2.5 Soil Water

Soil water holding capacity (i.e. the ability of soil to retain water) is an important factor in determining soil physical fertility. Water holding capacity is mainly controlled by the available pore space or distribution within the soil. Illustrated in figure 3.3, pore space is a function of soil structure or aggregation. Increases in soil organic matter increase soil aggregation, which then increases the total pore space allowing for a greater soil water holding capacity meaning more plant available water (Krull, et. al., 2004).

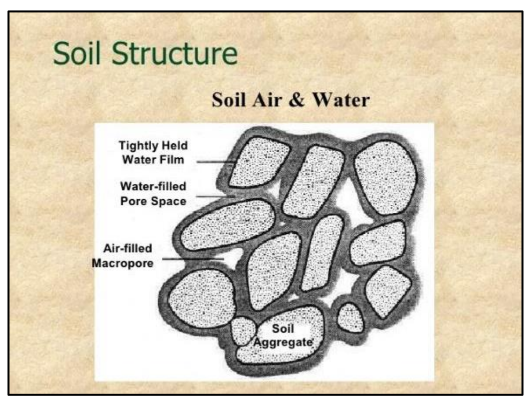

Figure 3.3. Soil pore space components illustration (University of Minnesota-Horticulture Follow, 2012)

3.3 Impacts of Management on Soil Organic Matter

SOM is formed under the decomposition process performed by soil biota (i.e. microbes, fungi, etc.). SOM is difficult to measure, so soil organic carbon (SOC) is measured instead and used to estimate SOM via a conversion factor (Krull, et. al., 2004).

The fate of SOM is determined by the soil carbon budget:

$$SOC = SOCadditions - SOClosses$$

Where the total SOC equals SOC added to the soil minus SOC lost from the soil. If losses exceed additions, then the SOC content of the soil will decrease. Conversely, if additions exceed losses, SOC content will increase.

3.3.1 Addition Mechanisms

Several factors control the rate of soil organic carbon additions to the soil. The primary methods of SOC additions included:

3.3.1.1 Increasing Crop Residue

Crop residue refers to the leaf and stalk litter left on the soil surface and root mass left below ground. Crop residues are primarily composed of carbon and typically, the more residue left on or in the soil, the greater the input of carbon into the soil (Magdoff & Weil, 2004). Crop residues provide the raw material that sustain soil biota like microbes and fungi which assist in the process of making SOM. It has been found that increasing the crop residue left on the soil, will increase the SOC leading to better soil aggregation and water infiltration and retention of soil (Novelli, et. al., 2017).

3.3.1.2 Increasing Organic Amendments

Organic amendments include anything from compost to animal manure to sewage sludge. As with crop residue, these materials act as a source of carbon for soil biota. Additions of these amendments increase SOC. In addition to providing a source of carbon, organic amendments provide crop nutrients to the soils and contribute to improving soil aggregation and benefit soil biota like microbes (Ferreras, et. al., 2006).

3.3.2 Loss Mechanisms

3.3.2.1 Erosion

Soil erosion is the loss of soil via physical mechanisms such as wind and water transportation. Because soil erosion impacts the topsoil where most SOC and SOM are stored there is a strong relationship between soil erosion and SOM/SOC loss. SOM loss due to erosion is also topographically dependent. The slope and position along the slope profile (i.e. summit, back slope, shoulder, etc.) are important factors in determining exactly how much soil and SOC is lost due to erosion at a specific location (Wilson, et. al., 2009). As seen in figure 3.4, the greatest loss from erosion occurs along the shoulder, backslope, and toeslope of the slope profile.

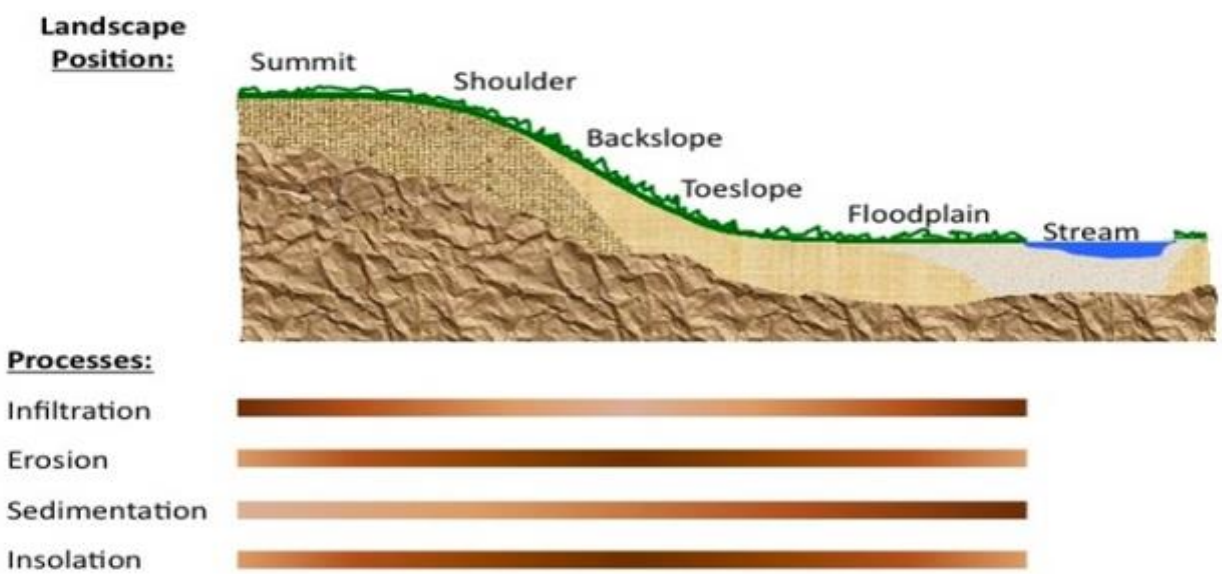

Figure 3.4. Slope profile (i.e. landscape position) relevant to certain processes. The darkest part of the bars indicates high rates of the indicated process, and the lightest part of the bars indicate low rates of the indicated process (Reyes, 2016).

3.3.2.2 Increasing Residue Breakdown (Mechanical and Biological) and Removal

The loss of residue via breakdown and/or removal depends greatly on what field management practices are in use. Certain tillage practices will bury residues, causing them to breakdown and decompose faster. When residue is left on the surface, the breakdown process is much slower because moisture, temperature, and microbial presence is unsuitable for decomposition. If the break down process occurs faster than residues or SOC is replaced, SOM content will decrease. The removal of residues from the field, like in a corn silage harvest, can also cause a decrease SOM because the raw material for SOM creation are removed (Barber, 1979).

3.3.2.3 Increasing OM Oxidation

Oxidation in the soil results from aeration creating bright orange colors in soil profile. This process, along with the addition of residue under the soil surface, encourage microbial growth and activity. This increased activity breaks down existing SOM releasing plant available nutrients to the soil. This process is significant especially when uncultivated land is tilled for the first time (Morris, et. al., 2004)

3.4 Managing Soil Organic Matter

Even though soil organic matter can be lost under intensive agricultural land use, careful soil management can increase soil organic matter content. In order to increase soil organic matter, the soil carbon budget needs to be positive. Soil management practices that improve soil organic matter and health include using more complex crop rotations, reducing tillage, using cover crops, and using organic amendments. Using these practices in combination have shown to be the most effective in having more available water, less compaction, better timing of nutrient availability to crops, and promoting plant growth (Magdoff & Weil, 2004; Bot & Benites, 2005).

Maintaining soil organic matter is done by removing minimal plant material at harvest, decreasing erosion by wind and water, and decreasing C outputs from the soil. (Magdoff & Weil, 2004). Soil restoration depends on maximizing SOM, whether by recycling crop residue or retaining existing SOM, and minimizing the loss of SOM (i.e. leaching, runoff, and erosion). It is important to keep in mind that rebuilding soil quality takes time (Bot & Benites, 2005). The following Table 3.1, explains this in more detail.

Table 3.1. Categorizes soil and crop management practices and lists the corresponding influence on soil organic matter (Magdoff & Weil, 2004).

Influence of Soil Crop Management Practices on Soil Organic Matter			
Practice	Influence on Soil Organic Matter		
Crop Rotations	Increased gains	Decreased losses	Increased beneficial organisms or decrease pathogens, parasites, and weeds
High-residue crops included	Higher average annual residue	Higher amount of residue leads to higher water infiltration and less runoff and erosion (especially if maintained on surface)	Regardless of effect on soil organic matter levels, soil biology is usually more favorable to crops in rotation. Same as above.
Perennial forages	Higher average annual residue	Soil continuously covered leads to reduced raindrop impact and physical holding of soil by roots	Same as above, especially because these are usually longer rotations.
Cover crops	Increase production of biomass when otherwise no primary production Organic matter increased or maintained	Same as above.	Weeds smothered or suppressed (allelopathy) Higher AM inoculation of following crop
Use of organic amendments	Significant amounts of organic material usually applied along with nutrients (as with compost and dairy or beef manure)	If causes higher infiltration and drainage less water runs off, less erosion occurs	Diseases sometimes suppressed. Plants might acquire systemic resistance to disease. Insects might find plants less attractive.
Reduced tillage	Increased water infiltration can increase yields and residues, especially on medium to coarse soils	More residue on surface (because of reduced tillage) reduces runoff and erosion	Reduced weed seed survival and emergence.

3.5 SOM Rating Application

The SOM (soil organic matter) Viewer allows you to compare measured values of soil organic matter content from your soil to known range of organic matter for each soil type in the state of Indiana. To start the comparison, you will need a measurement of the SOM from the field you are comparing. Most of the standard soil fertility tests provide this. The measurement needs to be made on soil from zero to eight inches in depth. If you do not have a measurement of your soil or your measurements are not in the 0-8-inch range, you will need to collect a soil sample from the field of interest and have it analyzed. For help in collecting soil sample please refer to Purdue’s Soil Sampling Guidelines (AY-368-W).

Once you have your soil organic matter measurement, you will open the SOM Viewer app. The app can be found at Purdue’s ArcGIS online portal. Entering the title, “Soil Organic Matter Viewer,” in a search engine should access the application once it’s made public.

The methodology behind the data analysis can be found in Appendix B. The data used within the app are derived from the USDA NRCS SSURGO database (NRCS, 2019), and display the SOM content as a range rated as either “poor”, “medium”, or “good”. Each of these categories are explained below:

- Poor: Soils with SOM percentages in the poor range are depleted in SOM compared to other soils of that same soil type. If you soil has a SOM measurement in the poor category, it may benefit from practices to increase the SOM content.
- Medium: Soils with SOM percentages in the medium range have a near average SOM content compared to other soils of that same soil type. While these soils may benefit form SOM promoting practices, these practices may only show small improvement in SOM content for these soils.
- Good: Soils with SOM in the good category have above average SOM content as compared to other soils of the same soil type. Soils in the good category will not benefit as much from SOM promoting practices and may show only very small additional gains in SOM content.

When you open the app, the app displays a soil map illustrating the SOM content as the Medium percentage range. A color gradient is used to display the data with darkest color signifying higher SOM values and the lightest color signifies the lower SOM values.

Using the search bar in the top right corner of the map, you can search an address or place. Select your desired location from the dropdown menu and the map will zoom to that location (figure 3.5).

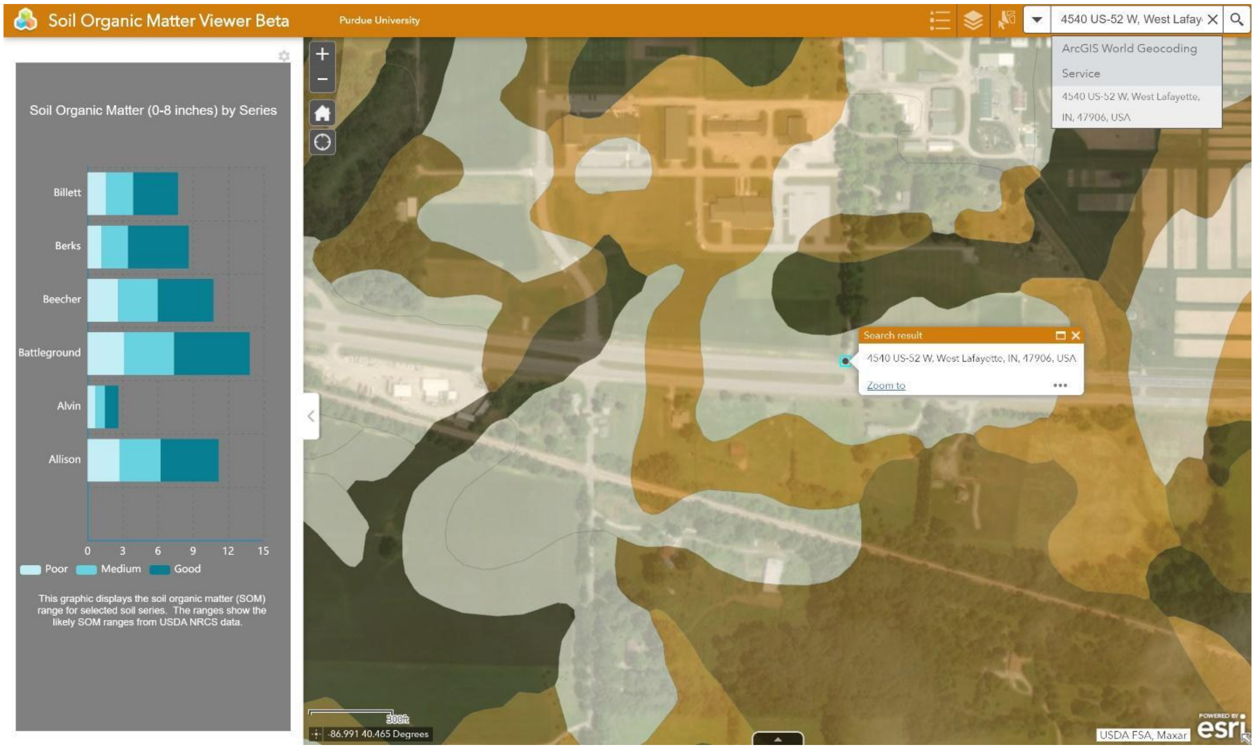

Figure 3.5 Using the search bar to zoom to a specific address or place on the map.

Figure 3.7 Clicking a specific area on the map to view that points data from the selected layer.

Once you've found your field, you can click on a soil polygon to display the layer data. After clicking on a soil, the polygon outlining the soil will be highlighted in blue and a window will pop up on the app. This window displays the data for the selected soil (figure 3.6).

If you want to view the SOM ranges for multiple soils, you can select soils using an "area of interest". To view a specific area of interest (AOI), click the 'Select' icon, right-most icon in the top right corner of the map (figure 3.7). Click and drag the mouse across the map to outline your AOI within a blue box (figure 3.8). The soils within the AOI

Figure 3.6 The Select icon.

will be highlighted in white and the information pane to the left of the map will specify the soil types and their SOM contents, poor, medium, and good, respectively (figure 3.9).

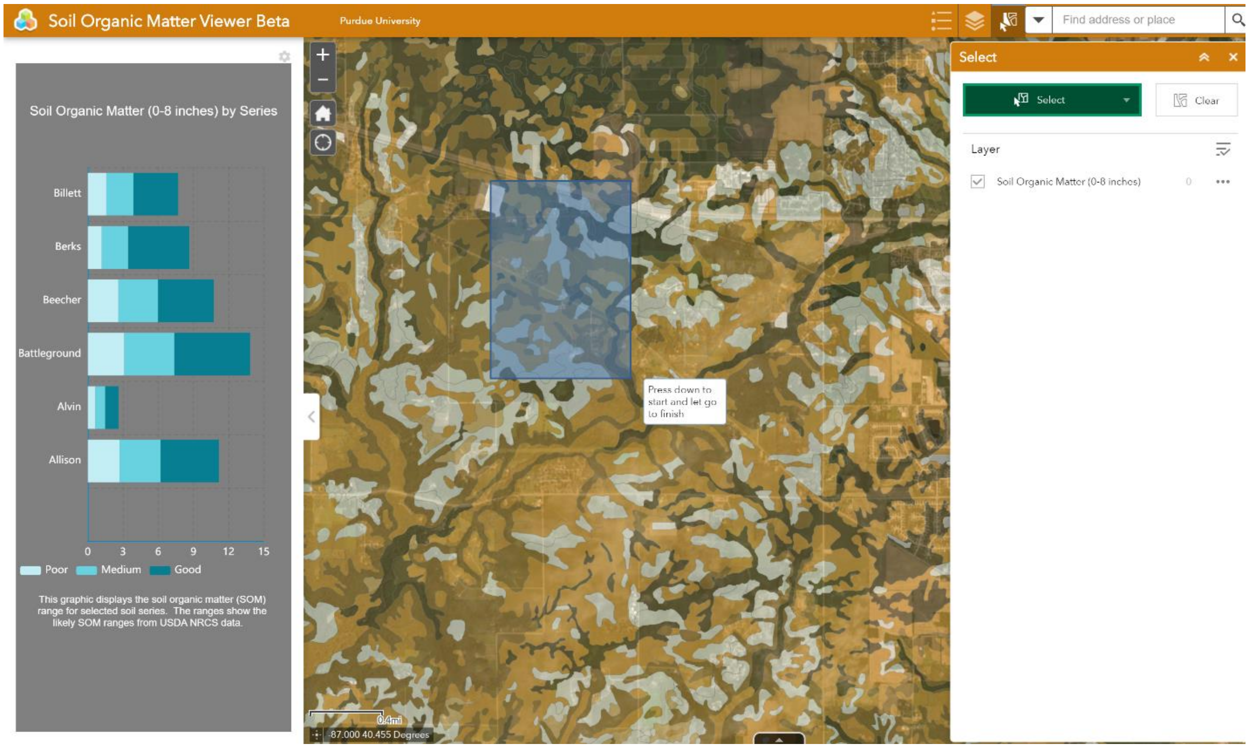

Figure 3.9 Using the 'Select' icon to draw the AOI.

Figure 3.8 Viewing the AOI selection and SOM data by soil type in the left-most information pane.

By scrolling the mouse over the blue bars of the figure in the left information pane, other areas of the map outside of the AOI with the same soil type will be highlighted in blue and the areas within the AOI will be highlighted in red (figure 3.10). This allows for comparison between your AOI soils and other surrounding areas with the same soil types.

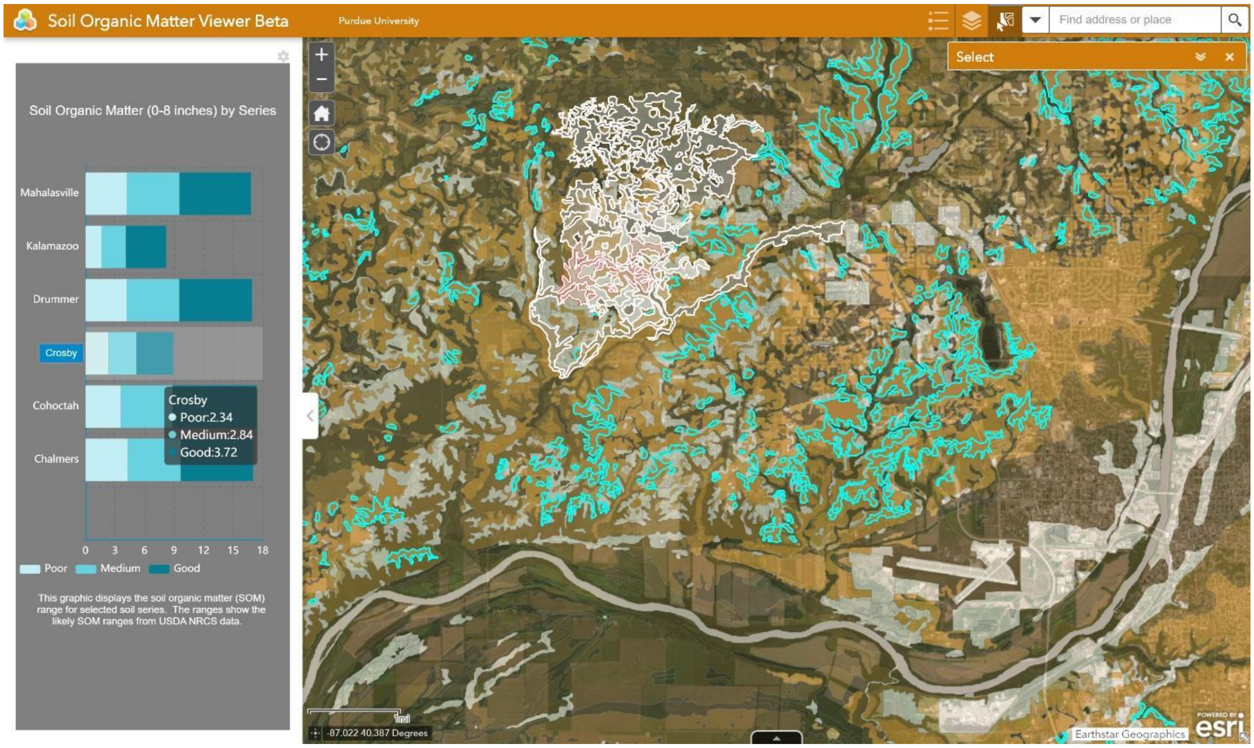

Figure 3.10 Scrolling over the SOM data by soil type in the left-most information pane to see all selected area of the same soil type.

To see more detailed information about the SOM layer, you can open the "attribute table". To open the attribute table, first click on the 'Layer List' icon. It is located as the center icon at the top tight corner of the map. An information pane will open on the right side of the map and list the layers within the map. Click the three dots to the right of the Soil Organic Matter (0-8 inches) layer and select 'View in Attribute Table'. At the bottom of the map the table will appear. You can select any row of data to view in the map. The corresponding soil polygon will be soil highlighted in the map and a color gradient figure will display the SOM data for poor, medium and good percentage values in the information pane to the left of the map (figure 3.11).

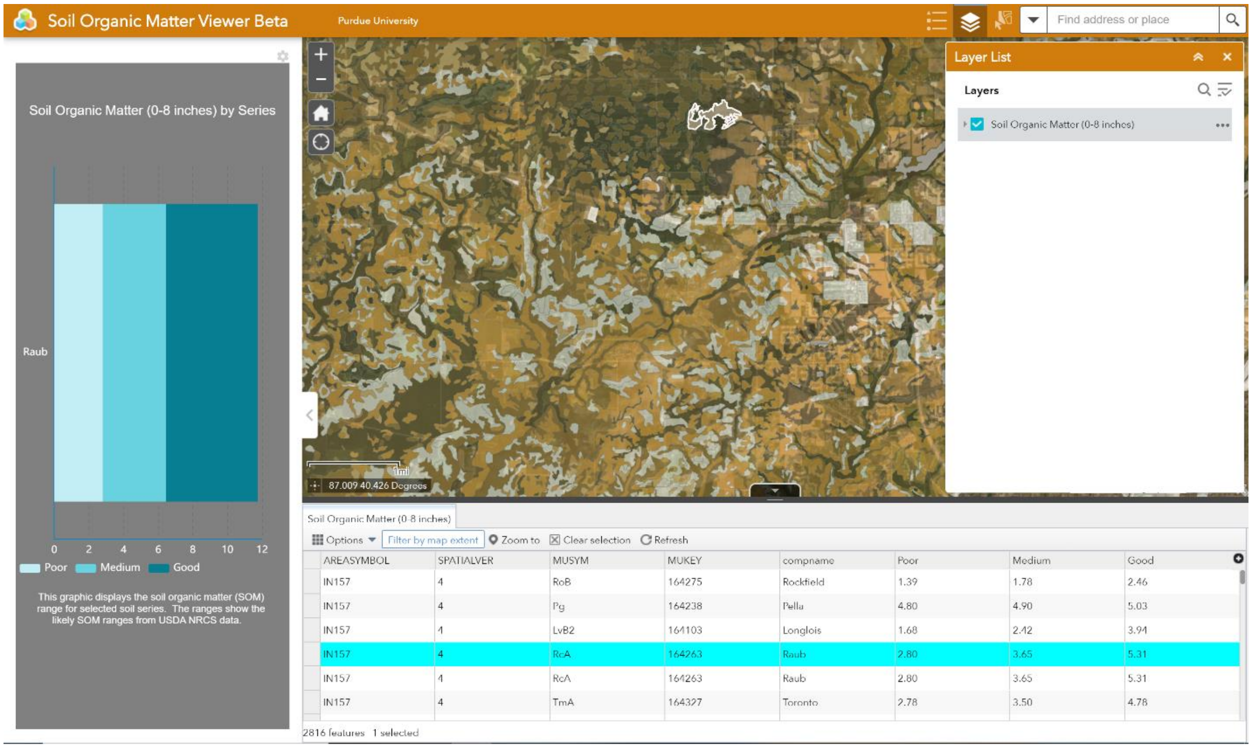

Figure 3.11 Accessing the layer attribute table and selecting a data row to view in the map.

If you would simply like to view the legend, click the 'Legend' icon at the top right of the map (figure 3.12). This will identify which SOM percentage for medium values goes with each color.

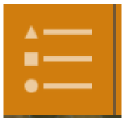

Figure 3.12 Legend icon.

APPENDIX A. ANALYSIS CODE

```
#packages being used
library(raster)
library(rgeos)
library(rgdal)

#loads raster image being processed
NDVI <- raster("NDVI.tif")

#plots the raster
plot(NDVI)

#loads the field boundary of the AOI
bound <- readOGR("field_boundary.shp")
#plots the boundary around the NDVI raster image
bound <- spTransform(bound, crs(NDVI))

plot(bound, add=T)

#creates a 100m buffer within the field boundary and plots it to the NDVI raster image
buff <- gBuffer(bound, width = -100)
plot(buff, add=T)

#extracts values from within the buffer zone and calculates the 95% CI quantile which will be used
as the threshold value
NDVI.buff <- extract(NDVI, buff)
NDVI.95 <- quantile(unlist(NDVI.buff), 0.02)

#plots a histogram of the NDVI values and adds the threshold value as a red line
hist(values(NDVI))
```

```
abline(v = NDVI.95, col = 'red')

#calculates a binary raster image with all boundaries and buffers
NDVI.binary <- NDVI<NDVI.95
plot(NDVI.binary)
plot(bound, add=T)
plot(buff, add=T)

val.bin <- na.omit(values(NDVI.binary))

#sets turbine point coordinates and plots them
turbine.xy <- click(NDVI.binary, xy = T)
coordinates(turbine.xy) <- ~x+y
plot(turbine.xy, add=T)

#sets the number of individual turbines
area.turbine <- array(NA, 3)

#loops the same process for each turbine in a field in the order they were 'clicked' to give individual
outputs
for(i in 1:length(turbine.xy)){

  #creates and plots the 150m buffer around turbines
  turbine.buff <- gBuffer(turbine.xy[i,], width = 150)
  plot(turbine.buff, col = 'red', add=T)
  turbine.buff.ext <- extract(NDVI.binary, turbine.buff)
  val.turbine <- na.omit(unlist(turbine.buff.ext))

  #data from within the 100m buffer around turbines and number of turbines
  sum(val.turbine)
  length(val.bin)
```

```
  res <- xres(NDVI.binary) #raster resolution in m
  res2 <- res^2 #area of raster cell m2

  area.turbine[i] <- sum(val.turbine)*res2 #average area impacted per turbine [m2]

  #area.pct <- sum(val.turbine)/length(val.bin) #area impacted as pct of field

}

area.turbine

area.pct <- area.turbine/(length(val.bin)*res2)
area.pct
```

APPENDIX B. SOM RATING APPLICATION METHODS

Introduction

The primary data for the soil organic matter viewer application is a map of soil organic matter levels for each soil in Indiana denoting the value of soil organic matter as low, medium, and good. These levels correspond to quantiles of empirical SOM probability distributions. This appendix details the methods for deriving these probability distributions.

SOM probability distributions were estimated using data from the USDA NRCS Soil Surveys Geographic Database (SSURGO). SSURGO contains spatial (i.e. polygon of soil unit boundaries) and tabular data (e.g. soil chemical and physical properties) for all soils mapped by the NRCS in Indiana. SSURGO is the digital database of soil survey data. SSURGO does not contain soil property probability distributions, so we needed to develop a method to derive distributions using SSURGO. SSURGO presents three main challenges which our method needed to address:

1. The basic geographic unit in SSURGO is the soil map unit. Mapunits are defined as the smallest geographically discreet soil units that can be displayed at a given map scale. In Indiana this scale is typically 1:12,000 and map units have a nominal minimum size of one acre. Because mapunits are defined by their spatial scale and soil properties, a single map unit can often contain multiple unique soils known as components. For our final map we needed to estimate unique probability distributions for each mapunit. Therefore, our methodology needed to account for multiple component-level data in each mapunit-level probability distribution.
2. Soil characterization data (e.g. soil physical and chemical property data) for each component are stored in SSURGO by genetic horizon. Because unique soils will have a different sets and thicknesses of genetic horizons, the depth intervals of genetic horizons are not the same for all soil components. As a result, aggregating data within given depth ranges across soil components needs to account for the variability in depth intervals of between components. Furthermore, the users of the application (e.g. farmers, CCA) typically do not sample soil by genetic horizon. These users typically sample soil on fixed depth intervals (e.g. 0-8 inches). Consequently, the probability distributions in our final map need to reflect this fixed depth intervals. Our methodology needed to address the inconsistent depth reporting of tabular data in SSURGO and harmonize soil data to a fixed depth interval across all soil components in Indiana.
3. SSURGO tabular data does not contain probability values of confidence intervals for property values. Instead, SSURGO designates a range of likely values for a given property which are denoted as a low, representative, and high value. While these values denote the range of likely values of a property, they are not explicitly linked to a quantile or probability distribution. Therefore, our methodology needed a procedure to convert

low, representative, and high values to quantiles of a known probability distribution function.

We developed a methodology to address each of these challenges. In the following section, we will outline the key steps details of this procedure and in subsequent sections we will provide detail on each step. The procedure consisted of the following steps:

1. For all soil components in Indiana, harmonize low, representative, and high values of SOM to a common depth interval of zero to eight inches using equal area splines.
2. For each component, estimate an empirical probability distribution for SOM values using the splined low, representative, and high values.
3. For each mapunit, perform a Monte Carlo simulation of the SOM probability distribution function using the component-level PDFs and component proportions.

Equal Area Splines

Equal area splines were developed specifically to harmonize soil data onto standardized depth intervals. For our splines, we used the mpsline() function implemented in the GSIF package in R. The function takes two inputs; the depth intervals for the soil property and the value property for each depth interval. The function then estimates a smooth spline function which describes the soil value at any depth interval. By providing the spline function with new depth intervals, you can estimate the soil property over a new set of depth intervals.

In our procedure, the input depth intervals were the depth of the genetic horizon for each component. For the property values, we used the low, representative, and high SOM values. This resulted in three splines representing each of the SOM levels. We then used the spline functions to estimate the SOM for each level on a new depth interval of zero to eight inches.

Estimating empirical probability distribution functions

After harmonizing SOM levels onto the unified depth interval of zero to eight inches, we then needed to convert the SOM levels into a probability distribution function. To do this we first need to assign each property level a percentile. To determine the appropriate percentiles, we compared low, representative, and high values from components in SSURGO with their corresponding series in the NCSS pedon database. For each series with greater than five observations into the database, we estimated an empirical distribution function for OM over the zero to eight-inch depth interval. We then estimated the percentile of low, representative, and high values from SSURGO components with the same series. Next, we averaged the percentiles for low, medium, and high values across all pedons. The resulting percentiles for low, medium, and high values were 9%, 53%, and 85%, respectively.

With percentiles assigned to each OM level, we estimated log-normal distributions for each component using the get.lnrom.par() function in R. This function estimated the mean and standard deviation of a lognormal distribution given a range of percentile and quantile values. In our method, the quantiles came from the splined low, representative, and high SOM levels and the percentiles were the percentiles estimated from the NCSS pedon database. From these estimated functions, we could then describe the probability distribution of SOM for any component as:

$$SOM_i \sim Lognormal(\mu_i, \sigma_i{}^2), \text{ eq. A2.1}$$

Where, SOM_i is the probability distribution function of SOM for component i, over a depth interval of zero to eight inches, and $\mu_i, \sigma_i{}^2$ are the mean and standard deviation of the empirical lognormal distribution function estimated .

Monte Carlo Simulation

The last step in our procedure was to estimate the final probability distribution function at the mapuntit-level using a Monte Carlo simulation. Mapunits have a defined proportion of each component (i.e. 40% component A and 60% component B). Therefor the mapunit-level probability distribution function needs to reflect not only the underlying component-level probability distributions but also the probability of observing each component within a mapunit. To do this we simulated random values of SOM using component-level probability distributions from eq. A2.1. and the component proportions within each map unit.

For each step in the simulation, we first estimated which component to simulate. To do this, we simulated a random number form multinomial distribution:

$$C_i \sim \Pr\,(C_1 = p_1, \ldots, C_n = p_n)\text{ , eq. A2.2}$$

Where C_i is the simulated component (i.e. which component to use for the next step in the simulation), Pr is the multinomial probability distribution with probabilities of each class, C_k, denoted p_k. In our case the probability p_k for each component is the proportion of the component in each map unit.

Next, we simulated a random value of SOM for each component using eq. A2.1. We repeated the procedure of simulating a random component and SOM value based onto that component for 10, 000 simulations resulting in 10,000 simulated values of SOM for the simulated mapunit. Next, we estimated an empirical probability distribution function for the mapunit as:

$$SOM_{mapunit} \sim epdf(SOM_1, \ldots, SOM_n)$$

where *epdf* is the empirical probability distribution based on simulated SOM values.

REFERENCES

Aakre, D., & Haugen, R. (2009). Wind Turbine Lease Considerations for Landowners. *NDSU Extension Service*. Retrieved from https://www.legis.nd.gov/assembly/61-2009/docs/pdf/edt112409appendixf.pdf

Abbasi, S. A., & Abbasi, N. (2000). The likely adverse environmental impacts of renewable energy sources. *Applied energy*, *65*(1-4), 121-144.

Abu-Hamdeh, N. H. (2003). Compaction and subsoiling effects on corn growth and soil bulk density. *Soil Science Society of America Journal*, *67*(4), 1213–1219. https://doi.org/10.2136/sssaj2003.1213

Alakukku, L. (1996). Persistence of soil compaction due to high axle load traffic. I. Short- term effects on the properties of clay and organic soils. *Soil and Tillage Research*, *37*(4), 211–222. https://doi.org/10.1016/0167-1987(96)01016-1

Alakukku, L. (1996). Persistence of soil compaction due to high axle load traffic. II. Long- term effects on the properties of fine-textured and organic soils. *Soil and Tillage Research*, *37*(4), 223–238. https://doi.org/10.1016/0167-1987(96)01017-3

Alberty, C. A., Pellet, H. M., & Taylor, D. H. (1984). Characterization of Soil Compaction at Construction Sites and Woody Plant Response. *Journal of Environmental Horticulture*, *2*(2), 48–53.

American Wind Energy Association. (2020). Retrieved from https://www.awea.org/

Arvidsson, J., & Håkansson, I. (1996). Do effects of soil compaction persist after ploughing? Results from 21 long-term field experiments in Sweden. *Soil and Tillage Research*, *39*(3–4), 175–197. https://doi.org/10.1016/S0167-1987(96)01060-4

Atwell, B. J. (1993). Response of roots to mechanical impedance. *Environmental and Experimental Botany*, *33*(1), 27-40.

Bach, E. M., Baer, S. G., Meyer, C. K., & Six, J. (2010). Soil texture affects soil microbial and structural recovery during grassland restoration. *Soil Biology and Biochemistry*, *42*(12), 2182-2191.

Barber, S. A. (1979). Corn Residue Management and Soil Organic Matter 1. *Agronomy Journal*, *71*(4), 625-627.

Baumgartl, T., & Horn, R. (1991). Effect of aggregate stability on soil compaction. *Soil and Tillage Research*, *19*(2-3), 203-213.

Bhatti, A. U., Mulla, D. J., & Frazier, B. E. (1991). Estimation of soil properties and wheat yields on complex eroded hills using geostatistics and thematic mapper images. *Remote Sensing of Environment*, *37*(3), 181-191.

Borghei, M. A., Taghinejad, J. G., Minaei, S. undefined, Karimi, M. undefined, & Varnamkhasti, M. undefined. (2008). Effect of subsoiling on soil bulk density, penetration resistance, and cotton yield in northwest of Iran. *International Journal of Agriculture and Biology*, *10*, 120–123.

Bot, A., & Benites, J. (2005). *The importance of soil organic matter: Key to drought-resistant soil and sustained food production* (No. 80). Food & Agriculture Org..

Ben-Dor, E. (2002). Quantitative remote sensing of soil properties. *Advances in Agronomy*, *75*, 173-244.

Berli, M., Kulli, B., Attinger, W., Keller, M., Leuenberger, J., Flühler, H., … Schulin, R. (2004). Compaction of agricultural and forest subsoils by tracked heavy construction machinery. *Soil and Tillage Research*, *75*(1), 37–52. https://doi.org/10.1016/S0167-1987(03)00160-0

Buechel, T. (2020). What is CEC and Why Is It Important? Part.1. Retrieved November 12, 2020, from https://www.pthorticulture.com/en/training-center/what-is-cec-cation-exchange-capacity/

Buttery, B. R., Tan, C. S., Drury, C. F., Park, S. J., Armstrong, R. J., & Park, K. Y. (1998). The effects of soil compaction, soil moisture and soil type on growth and nodulation of soybean and common bean. *Canadian Journal of Plant Science*, *78*(4), 571-576.

Defossez, P., & Richard, G. (2002). Models of soil compaction due to traffic and their evaluation. *Soil and Tillage Research*, *67*(1), 41-64.

Engineering, W. (2011, May 16) What is the equipment used in installing wind turbines? Retrieved from https://www.windpowerengineering.com/construction/what-is-the-equipment-used-in-installing-wind-turbines/

Felipe de Mendiburu (2020). agricolae: Statistical Procedures for Agricultural Research. R package version 1.3-2. https://CRAN.R-project.org/package=agricolae

Ferreras, L., Gómez, E., Toresani, S., Firpo, I., & Rotondo, R. (2006). Effect of organic amendments on some physical, chemical and biological properties in a horticultural soil. *Bioresource technology*, *97*(4), 635-640.

Gregorich, E. G., Carter, M. R., Angers, D. A., Monreal, C., & Ellert, B. (1994). Towards a minimum data set to assess soil organic matter quality in agricultural soils. *Canadian journal of soil science*, *74*(4), 367-385.

Grunwald, S., Vasques, G. M., & Rivero, R. G. (2015). Fusion of soil and remote sensing data to model soil properties. In *Advances in Agronomy* (Vol. 131, pp. 1-109). Academic Press.

Håkansson, I. (1994). Subsoil compaction caused by heavy vehicles-a long-term threat to soil productivity. *Soil and Tillage Research*. https://doi.org/10.1016/0167-1987(94)90046-9

Håkansson, I., & Reeder, R. C. (1994). Subsoil compaction by vehicles with high axle load-extent, persistence and crop response. *Soil and Tillage Research*, *29*(2–3), 277–304. https://doi.org/10.1016/0167-1987(94)90065-5

Håkansson, I., Voorhees, W. B., & Riley, H. (1988). Vehicle and wheel factors influencing soil compaction and crop response in different traffic regimes. *Soil and Tillage Research*, *11*(3–4), 239–282. https://doi.org/10.1016/0167-1987(88)90003-7

Horn, R., Domzzał, H., Słowińska-Jurkiewicz, A., & van Ouwerkerk, C. (1995). Soil compaction processes and their effects on the structure of arable soils and the environment. *Soil and Tillage Research*, *35*(1–2), 23–36. https://doi.org/10.1016/0167-1987(95)00479-C

IndianaMAP. (n.d.). Retrieved from https://maps.indiana.edu/

Indiana Geographic Information Office (IGIO). (2018, April 12). COUNTY_LAND_PARCELS_IGIO_IN.GDB: Land Parcels Maintained by County Agencies in Indiana (Indiana Geographic Information Office, File Geodatabase, Polygon Feature Class). Retrieved September 22, 2020, from file:///D:/Data/Wind%20Turbine%20Analysis/Scaling%20Data/Land_Parcels_County_IGIO/County_Land_Parcels_IGIO_IN.html

Johnson, J. F., Voorhees, W. B., Nelson, W. W., & Randall, G. W. (1990). Soybean growth and yield as affected by surface and suboil compaction. *Agronomy Journal*, *82*(5), 973-979.

Kaldellis, J. K., Kavadias, K. A., & Paliatsos, A. G. (2003). Environmental impacts of wind energy applications:" myth or reality". *Fresenius Environmental Bulletin*, *12*(4), 326-337.

Karaburun, A. (2010). Estimation of C factor for soil erosion modeling using NDVI in Buyukcekmece watershed. *Ozean journal of applied sciences*, *3*(1), 77-85.

Kaspar, C., & Taylor, M. (1959). Soil Compaction and Root Growth : A Review Paul w . Unger * and Thomas EARLY STUDIES BY HOWARD University of California , Davis.

Keller, T., & Håkansson, I. (2010). Estimation of reference bulk density from soil particle size distribution and soil organic matter content. *Geoderma*, *154*(3–4), 398–406. https://doi.org/10.1016/j.geoderma.2009.11.013

Keller, T., Lamandé, M., Peth, S., Berli, M., Delenne, J. Y., Baumgarten, W., … Or, D. (2013, April). An interdisciplinary approach towards improved understanding of soil deformation during compaction. *Soil and Tillage Research*. https://doi.org/10.1016/j.still.2012.10.004

Kiliç, K., Özgöz, E., & Akbaş, F. (2004). Assessment of spatial variability in penetration resistance as related to some soil physical properties of two fluvents in Turkey. *Soil and Tillage Research*, *76*(1), 1-11.

Krull, E. S., Skjemstad, J. O., & Baldock, J. A. (2004). *Functions of soil organic matter and the effect on soil properties* (p. 129). Canberra, Australia: Cooperative Research Centre for Greenhouse Accounting.

Landsberg, J. D., Miller, R. E., Anderson, H. W., & Tepp, J. S. (2003). Bulk density and soil resistance to penetration as affected by commercial thinning in northeastern Washington. *USDA Forest Service - Research Papers RMRS*, (551), 32–35. https://doi.org/10.2737/PNW-RP-551

Lipiec, J., Hing;kansson, I., Tarkiewicz, S., & Kossowski, J. (1991). Soil physical properties and growth of spring barley as related to the degree of compactness of two soils. *Soil and Tillage Research*, *19*(2–3), 307–317. https://doi.org/10.1016/0167-1987(91)90098-I

Lowery, B., & Schuler, R. T. (1991). Temporal effects of subsoil compaction on soil strength and plant growth. *Soil Science Society of America Journal*, *55*(1), 216–223. https://doi.org/10.2136/sssaj1991.03615995005500010037x

Magdoff, F., & Weil, R. R. (2004). Soil organic matter management strategies. *Soil organic matter in sustainable agriculture*, 45-65.

Mani, P. (2014, January 08). Soil organic matter pkm. Retrieved November 17, 2020, from https://www.slideshare.net/pabitramani/soil-organic-matter-pkm

Martino, D. L., & Shaykewich, C. F. (1994). Root penetration profiles of wheat and barley as affected by soil penetration resistance in field conditions. *Canadian Journal of Soil Science*, *74*(2), 193-200.

Meadow Lake Wind Farm. (2020, February 18). Retrieved July 07, 2020, from https://en.wikipedia.org/wiki/Meadow_Lake_Wind_Farm

Mohanty, B. P. (2013). Soil hydraulic property estimation using remote sensing: A review. *Vadose Zone Journal*, *12*(4).

Morris, D. R., Gilbert, R. A., Reicosky, D. C., & Gesch, R. W. (2004). Oxidation potentials of soil organic matter in Histosols under different tillage methods. *Soil Science Society of America Journal*, *68*(3), 817-826.

Mulvaney, K. K., Woodson, P., & Prokopy, L. S. (2013). A tale of three counties: Understanding wind development in the rural Midwestern United States. *Energy Policy*, *56*, 322-330.

Narasimhan, B., Srinivasan, R., Arnold, J. G., & Di Luzio, M. (2005). Estimation of long-term soil moisture using a distributed parameter hydrologic model and verification using remotely sensed data. *Transactions of the ASAE*, *48*(3), 1101-1113.

Novelli, L. E., Caviglia, O. P. and Gervasio Piñeiro, G. (2017). “Increased cropping intensity improves crop residue inputs to the soil and aggregate-associated soil organic carbon stocks. *Soil and Tillage Research, 165,* 128-136.

NRCS. (2019). Web Soil Survey. Retrieved September 22, 2020, from https://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm

QGIS Development Team (2019). QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.osgeo.org

R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
URL http://www.R-project.org/.

Randrup, T. B. (1997). Soil compaction on construction sites. *Journal of Arboriculture*, *23*, 208-210.

Reid, B. (2016, November 9). A Landowner's Legal Introduction to Wind Energy Leases. Retrieved from https://www.huffpost.com/entry/a-landowners-legal-introd_b_8511702

Reyes, S. (2016, January 15). HOW SOIL AND CARBON ARE RELATED. Retrieved November 17, 2020, from https://www.permaculturenews.org/2015/10/13/how-soil-and-carbon-are-related/

Robert J. Hijmans (2020). raster: Geographic Data Analysis and Modeling. R package version 3 0-12. https://CRAN.R-project.org/package=raster

Roger Bivand and Colin Rundel (2019). rgeos: Interface to Geometry Engine - Open Source ('GEOS'). R package version 0.5-2. https://CRAN.R-project.org/package=rgeos

Roger Bivand, Tim Keitt and Barry Rowlingson (2019). rgdal: Bindings for the 'Geospatial' DataAbstraction Library. R package version 1.4-8. https://CRAN.R-project.org/package=rgdal

Rosenzweig, C., Tubiello, F. N., Goldberg, R., Mills, E., & Bloomfield, J. (2002). Increased crop damage in the US from excess precipitation under climate change. *Global Environmental Change*, *12*(3), 197-202.

Sidhu, D., & Duiker, S. W. (2006). Soil compaction in conservation tillage: Crop impacts. *Agronomy Journal*, *98*(5), 1257–1264. https://doi.org/10.2134/agronj2006.0070

Slabaugh, S. (2017, July 14). Wind farm going up in Jay, Randolph counties. Retrieved July 07, 2020, from https://www.thestarpress.com/story/news/local/2017/07/14/wind-farm-going-up-jay-randolph-counties/476342001/

Soane, B. D., & van Ouwerkerk, C. (1994). Soil Compaction Problems in World Agriculture. In *Developments in Agricultural Engineering* (Vol. 11, pp. 1–21). https://doi.org/10.1016/B978-0-444-88286-8.50009-X

Southworth, J., Randolph, J. C., Habeck, M., Doering, O. C., Pfeifer, R. A., Rao, D. G., & Johnston, J. J. (2000). Consequences of future climate change and changing climate variability on maize yields in the midwestern United States. *Agriculture, Ecosystems & Environment*, *82*(1-3), 139-158.

Sparling, G. P., Wheeler, D., Vesely, E. T., & Schipper, L. A. (2006). What is soil organic matter worth?. *Journal of Environmental Quality*, *35*(2), 548-557.

Sumfleth, K., & Duttmann, R. (2008). Prediction of soil property distribution in paddy soil landscapes using terrain data and satellite information as indicators. *Ecological indicators*, *8*(5), 485-501.

Tan, K. H., & Dowling, P. S. (1984). Effect of organic matter on CEC due to permanent and variable charges in selected temperate region soils. *Geoderma*, *32*(2), 89-101.

University of Minnesota-Horticulture Follow. (2012, June 11). Soils 101 for High Tunnels 2012. Retrieved November 17, 2020, from https://www.slideshare.net/UMNfruit/mfvga-12-soils101

USDA. (2020). CropScape - Cropland Data Layer. Retrieved September 22, 2020, from https://nassgeodata.gmu.edu/CropScape/

USGS, Purdue University, & USDA. (n.d.). Soil Explorer. Retrieved September 22, 2020, from https://soilexplorer.net/

USWTDB Viewer. (2020). Retrieved July 07, 2020, from https://eerscmap.usgs.gov/uswtdb/viewer/

van Steen, H., & Zervos, A. (2009, February 13). Wind Summary – The Facts Executive Summary. Retrieved from https://www.wind-energy-the-facts.org/turbine-loads.html

Vaz, C. M. P., Manieri, J. M., de Maria, I. C., & Tuller, M. (2011). Modeling and correction of soil penetration resistance for varying soil water content. *Geoderma*, *166*(1), 92–101. https://doi.org/10.1016/j.geoderma.2011.07.016

Whalley, W. R., Dumitru, E., & Dexter, A. R. (1995). Biological effects of soil compaction. *Soil and Tillage Research*, *35*(1–2), 53–68. https://doi.org/10.1016/0167-1987(95)00473-6

Wilson, C. G., Papanicolaou, A. N. T., & Abaci, O. (2009). SOM dynamics and erosion in an agricultural test field of the Clear Creek, IA watershed. *Hydrology & Earth System Sciences Discussions*, *6*(2).