2016

Development of a remote sensing protocol for inventorying cover crop adoptions

Carolina Bermudez
Iowa State University

Development of a remote sensing protocol
for inventorying cover crop adoptions

by

Carolina Bermudez

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Agricultural and Biosystems Engineering

Program of Study Committee:
Amy Kaleita, Major Professor
Brian Gelder
Peter Wolter

Iowa State University

Ames, Iowa

2016

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER I. GENERAL INTRODUCTION

1.1 Introduction

Agricultural systems are managed ecosystems in which, particularly in the Midwestern United States, generally the soil is covered only for about five months of the year and left bare for the remainder months. The lack of ground cover combined with management practices like tillage, weather conditions, and terrain characteristics – soil slope, soil type, the percentage of organic matter, nutrient concentration, among others – lead to soil erosion and nutrient leaching (Blanco-Canqui et al., 2013; Van der Werf & Petit, 2002). Eroded particles and nutrients are often transported, sometimes reaching roadways ditches and water bodies, and making it necessary to spend money and resources on restoration and cleanup (Knowler & Bradshaw, 2007; Nowak & Cabot, 2004). As a consequence, public concern regarding preservation of soil and water resources in the past decades has put farmland practices in the spotlight, and interest in adoptions of practices that could mitigate these effects have increased (Malone et al., 2014; Sarrantonio & Gallandt, 2003; K. W. Staver & Brinsfield, 1998).

To address this issue, the state of Iowa has undertaken a major effort to provide effective solutions, which might make Iowa an emerging leader in environmental and conservation practices associated with nutrient loss from farmlands and from urban and industrial areas. For this purpose, the Iowa Department of Agriculture and Land Stewardship, the Iowa Department of Natural Resources and Iowa State University released the Iowa Nutrient Reduction Strategy (INRS) in November 2012. The INRS is a scientific and technology-based program for the development and analysis of alternatives to reduce the movement of nutrients from point and nonpoint sources to water sources (Iowa Nutrient Strategy, 2013).

Incorporating cover crops into agricultural production has long been recognized as a management practice that could reduce not only soil erosion but also the leaching of nutrients, and as a consequence, governmental agencies and research groups are promoting its adoption. The Leopold Center for Sustainable Agriculture, Practical Farmers of Iowa, the Midwest Cover Crop Council, and the USDA Natural Resources Conservation Service (NRSC) are some of the groups working with farmers to spread information on the benefits of cover crops, and also giving advice on its management. Cover crops have a direct impact on soil erosion due to their ability to reduce wind and water erosion, enhance water infiltration, minimize runoff rates, and as a result, maintain large aggregate size. Regarding water quality, by including an extra crop in a rotation a more efficient use of nutrients takes place, as a result, there is a reduction in the pool of mobile nutrients that could contaminate nearby water bodies (Dabney et al., 2001; Kaspar, Jaynes et al., 2007; Kessavalou & Walters, 1997; Lal et al., 1991; Langdale et al., 1991; Meisinger et al., 1991; Ryan et al., 2003; Snapp et al., 2005; Weil & Kremen, 2007). Thus, state and federal agencies have an interest in tracking cover crops adoption, to evaluate both the effectiveness of awareness-raising and incentive campaigns and the actual acreage under this conservation practice. In addition, the identification and mapping of cover crops will serve as an essential basis for assessing the impact of this conservation practice on soil and water quality.

Currently, nationwide surveys on cover crop use are being reported yearly by the Sustainable Agriculture Research and Education (SARE) program – supported by the USDA's National Institute of Food and Agriculture – and by the Conservation Technology

Information Center (CTIC). One of the biggest challenges for field surveys methods relies on the high spatial variability in the implementation of conservation practices, making it necessary to sample large areas to obtain results that are representative of the area. In addition, most of the field surveys are based on farmer's responses, which makes them dependent on the data source. To deal with these constraints, the use of remote sensing is proposed in this study to detect cover crop fields. The main advantages of remote sensing data interpretation over field surveys are its independence of the data source, and possibility to cover larger areas.

Since different soil coverages have specific spectral signatures, remotely sensed images are a useful tool for performing land cover classification (Bailey & Boryan, 2010; Ustuner et al., 2014). Several vegetation ratio indexes derived from remotely sensed images have been developed to detect differences between vegetative covers, with the normalized differenced vegetation index (NDVI) being the most commonly used. The NDVI is an indicator that describes the greenness of vegetative covers, and it is sensitive to the percentage of biomass, leaf size, and healthiness of vegetation. Therefore, monthly NDVI of fields can be used to detect changes in land surface related to crops (Bannari et al., 1995; Glenn et al., 2008; Huete et.al, 1985; Rouse et al., 1974; Tucker, 1979).

The current study developed a remote sensing protocol based on monthly NDVI of agricultural fields for identifying vegetative ground covers that could correspond to cover crops.

1.2 Thesis organization

This thesis is organized into four Chapters. Chapter 1 provides a general introduction to the study, its motivations, and objective. A literature review is presented in Chapter 2; it gives an overview on cover crops and the NDVI, the vegetation index selected for the model. Chapter 3 is a paper outlining the remote sensing protocol for cover crop detection. General conclusions and recommendations for future work are presented in Chapter 4.

1.3 References

Bailey, J. T., & Boryan, C. G. (2010). Remote sensing applications in agriculture at the USDA national agricultural statistics service. *Research and Development Division, USDA, NASS, Fairfax, VA*.

Bannari, A., Morin, D., Bonn, F., & Huete, A. R. (1995). A review of vegetation indices. *Remote Sensing Reviews*, *13*(1–2), 95–120. http://doi.org/10.1080/02757259509532298

Blanco-Canqui, H., Holman, J. D., Schlegel, A. J., Tatarko, J., & Shaver, T. M. (2013). Replacing Fallow with Cover Crops in a Semiarid Soil: Effects on Soil Properties. *Soil Science Society of America Journal*, *77*(3), 1026. http://doi.org/10.2136/sssaj2013.01.0006

Dabney, S. M., Delgado, J. A., & Reeves, D. W. (2001). Using cover crops to improve soil and water quality. *Communications in Soil Science and Plant Analysis*, *32*(7–8), 1221–1250. http://doi.org/10.1081/CSS-100104110

Glenn, E. P., Huete, A. R., Nagler, P. L., & Nelson, S. G. (2008). Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape. *Sensors*, *8*(4), 2136–2160.

Huete, A. R., Jackson, R. D., & Post, D. F. (1985). Spectral response of a plant canopy with different soil backgrounds. *Remote Sensing of Environment*, *17*(1), 37–53.

Iowa Nutrient Reduction Strategy (2012). A science and technology-based framework to assess and reduce nutrients to Iowa waters and the Gulf of Mexico, Iowa Dept. of Agriculture and Land Stewardship, Iowa Dept. of Natural Resources, and Iowa State University College of Agriculture and Life Sciences.

Kaspar, T. C., Jaynes, D. B., Parkin, T. B., & Moorman, T. B. (2007). Rye Cover Crop and Gamagrass Strip Effects on NO Concentration and Load in Tile Drainage. *Journal of Environment Quality*, *36*(5), 1503. http://doi.org/10.2134/jeq2006.0468

Kessavalou, A., & Walters, D. T. (1997). Winter rye as a cover crop following soybean under conservation tillage. *Agronomy Journal*, *89*(1), 68–74.

Knowler, D., & Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy*, *32*(1), 25–48. http://doi.org/10.1016/j.foodpol.2006.01.003

Lal, R., Regnier, E., Eckert, D. J., Edwards, W. M., & Hammond, R. (1991). Expectations of cover crops for sustainable agriculture. *Cover Crops for Clean Water. Soil and Water Conserv. Soc., Ankeny, IA*, *1*(11), 1–11.

Langdale, G. W., Blevins, R. L., Karlen, D. L., McCool, D. K., Nearing, M. A., Skidmore, E. L., … Williams, J. R. (1991). Cover crop effects on soil erosion by wind and water. *Cover Crops for Clean Water. Soil and Water Conserv. Soc., Ankeny, IA*, 15–22.

Malone, R. W., Jaynes, D. B., Kaspar, T. C., Thorp, K. R., Kladivko, E., Ma, L., … Searchinger, T. (2014). Cover crops in the upper midwestern United States: Simulated effect on nitrate leaching with artificial drainage. *Journal of Soil and Water Conservation*, *69*(4), 292–305.

Meisinger, J. J., Hargrove, W. L., Mikkelsen, R. L., Williams, J. R., & Benson, V. W. (1991). Effects of cover crops on groundwater quality. *Cover Crops for Clean Water. Soil and Water Conservation Society. Ankeny, Iowa*, *266*, 793–799.

Nowak, P. J., & Cabot, P. E. (2004). The human dimension of resource management programs. *Journal of Soil and Water Conservation*, *59*(6), 128A–135A.

Rouse, J. W. J., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *Third Earth Resources Technology Satellite Symposium : The Proceedings of a Symposium Held by Goddard Space Flight Center in Washington, D.C.*, 309–317.

Ryan, R. L., Erickson, D. L., & De Young, R. (2003). Farmers' motivations for adopting conservation practices along riparian zones in a mid-western agricultural watershed. *Journal of Environmental Planning and Management, 46*(1), 19–37.

Sarrantonio, M., & Gallandt, E. (2003). The Role of Cover Crops in North American Cropping Systems. *Journal of Crop Production*, *8*(1–2), 53–74.

Snapp, S. S., Swinton, S. M., Labarta, R., Mutch, D., Black, J. R., Leep, R., … O'Neil, K. (2005). Evaluating cover crops for benefits, costs and performance within cropping system niches. *Agronomy Journal*, *97*(1), 322–332.

Staver, K. W., & Brinsfield, R. B. (1998). Using cereal grain winter cover crops to reduce groundwater nitrate contamination in the mid-Atlantic coastal plain. *Journal of Soil and Water Conservation*, *55*(3), 230–240.

Tucker, C. J. (1979). Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. *Remote Sensing of Environment*, *8*(2), 127–150.

Ustuner, M., Sanli, F. B., Abdikan, S., Esetlili, M. T., & Kurucu, Y. (2014). Crop Type Classification Using Vegetation Indices of RapidEye Imagery. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XL-7*, 195–198.

Van der Werf, H. M. G., & Petit, J. (2002). Evaluation of the environmental impact of agriculture at the farm level: a comparison and analysis of 12 indicator-based methods. *Agriculture, Ecosystems & Environment*, *93*(1), 131–145.

Weil, R., & Kremen, A. (2007). Thinking across and beyond disciplines to make cover crops pay. *Journal of the Science of Food and Agriculture*, *87*(4), 551–557.

CHAPTER II. LITERATURE REVIEW

2.1 Cover crops

2.1.1. Definition

Cover crops are short-term vegetation planted or managed to cover bare soils for mitigating or preventing soil erosion and degradation, which could be grown either during a time between cash crops or onto bare fields during fallow periods (Kessavalou & Walters, 1997; Pieters & McKee, 1938; Snapp et al., 2005b; Weil & Kremen, 2007). This agricultural practice is not novel, it was first adopted over 2,000 years ago, and according to Pieters (1927), the concept of cover crops was first introduced by Richard Parkinson in 1799. In recent years, the incorporation of cover crops into agricultural rotations has reemerged, in response to the many benefits related to cover crops as a conservation practice (Sarrantonio & Gallandt, 2003).

2.1.2. Management

According to the season in which they grow, cover crops can be classified as winter or summer, with winter cover crops being the most often adopted in the United States Corn Belt. Because there are a broad variety of species which if managed appropriately could serve as cover crops, it is possible to choose the one that would fit best for each agricultural system (Hartwig & Ammon, 2002; Moncada & Sheaffer, 2011; D. W. Reeves, 1994). Figure 1.1 shows the phenological cycle of winter wheat when used as a winter cover crop.

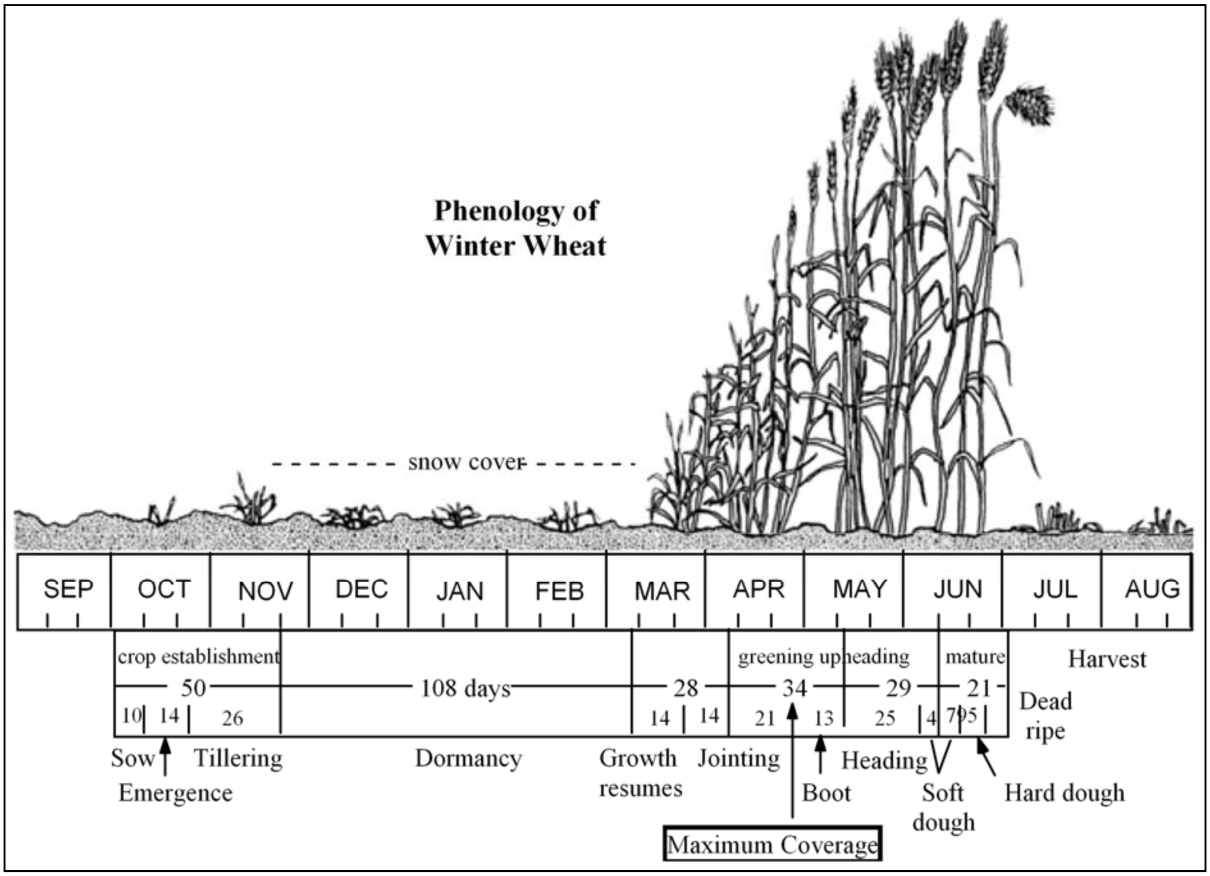

Figure 2.1 Phenology of Winter Wheat in the Midwest United States.
Source: Jensen, 2009.

Similar to when planning which commercial crop to grow, it is also necessary to consider weather and soil aspects when selecting a cover crop. Regarding soil conditions, availability of nutrients and water should be taken into account; while rainfall and temperature are the most important weather variables to consider (Clark, 2007). Cover crop species that survive winter conditions and resume their growth as soon as conditions are favorable again are classified as winter-hardy; on the contrary, species that don't survive winter conditions are known as winter-kill. Because a species could perform as winter-hardy or killed depending on where it is planted, the USDA has produced maps of hardiness regions that can be used by farmers to determine if a crop would survive the winter conditions of the area or not (Figure 1.2).

For the state of Iowa winter cereal rye (Secale cereale), hairy vetch (Vicia villosa), common vetch (Vicia sativa), winter wheat (Triticum aestivum), and winter triticale (Triticale hexaploide Lart.) can be used as winter-hardy crops, while Oats (Avena sativa), spring wheat (Triticum aestivum), and crimson clover (Trifolium incarnatum) would be killed by winter conditions.

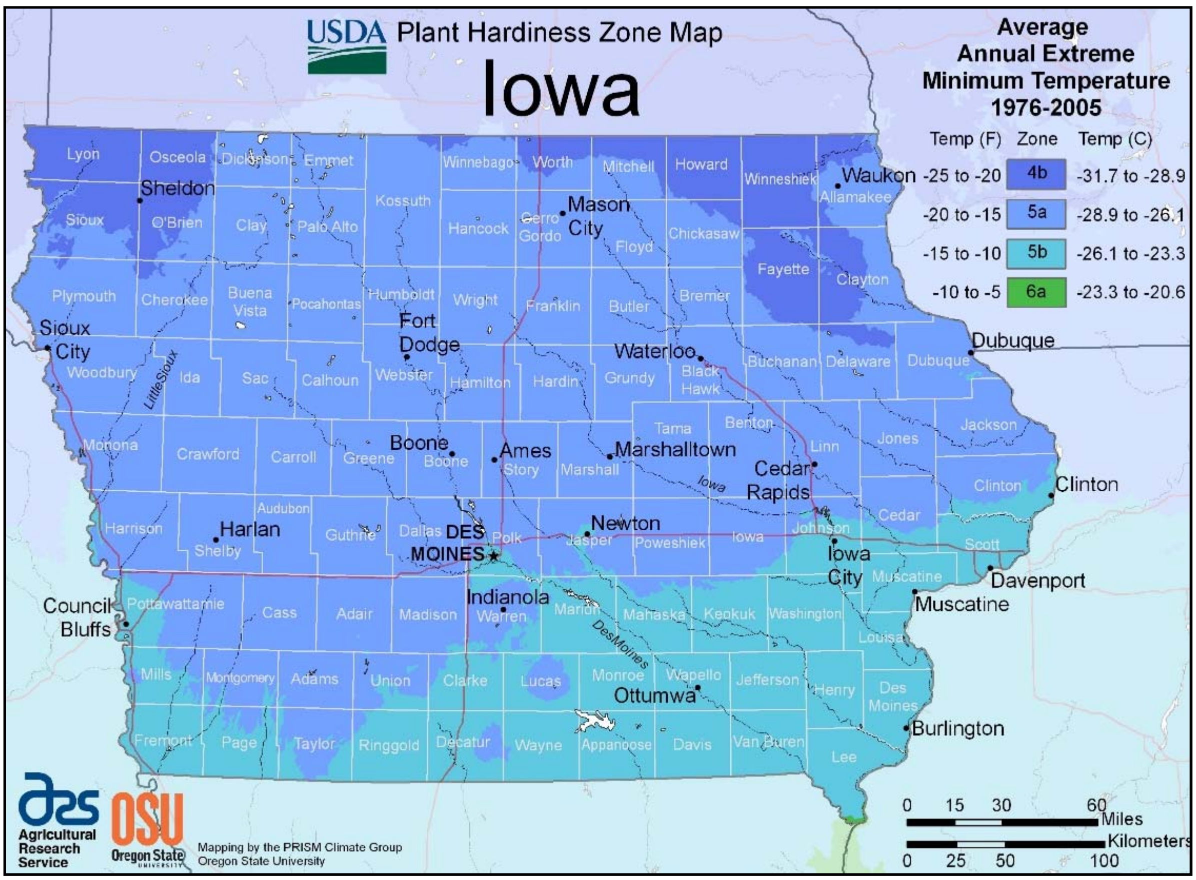

Figure 2.2. Iowa plant hardiness zone map.
Source: USDA, 2012.

There are different possibilities for the establishment of cover crops, being drilling, broadcasting, and aerial seeding the most used. Drill seeding is typically done after the cash crop is harvested, while broadcast and aerial can be used to seed cover crops on fields with standing cash crops (Moncada & Sheaffer, 2011).

In general winter cover crops are terminated during spring, and the termination date would vary depending on season's weather conditions. In addition, the cash crop that is going to be planted after the cover crop needs to be considered. It is recommendable that cover crops are terminated close to or after soybean planting, and a week to ten days before planting if followed by corn.

2.1.3. Benefits of cover crop adoption

Even when the primary purpose of growing cover crops is to create a physical barrier against the erosional forces of wind and water, the integration of cover crops into agricultural systems could lead to other multiple benefits. For instance, cover crops can act as weed suppressors, alleviate effects of compaction, help to regulate pests, and promote the recycling of nutrients among others (Lal et al., 1991; Langdale et al., 1991; Mallory et al., 1998).

2.1.3.1. Soil quality enhancement

Cover crops can modify many aspects of soil properties, and also when the soil is not left bare after a cash crop a more complex and efficient use of nutrients and water takes place. For example, cover crop's canopy can affect soil temperature by narrowing the day-night variation. The canopy intercepts net radiation increasing the solar energy harvested, reduces wind speed at the surface level, and also diminishes the impact of raindrops, as a consequence, some properties of the first portion of soil are modified when cover crops are incorporated in rotations (Blanco-Canqui, et al., 2013; Lal et al., 1991). Cover crops also influence the soil atmosphere at a deeper level, physically by modifying the macropore matrix of the soil with their roots, which contributes to decrease soil bulk density, and chemically by recycling nutrients. Also, the fine roots of cover crops affect the porosity of the soil not only during the growing season but also when roots die and decompose (Dabney, 1998; Kaspar et al., 2007; Reeves, 1994). Cover crops also have an impact on the C : N relationship of soils; this change would vary depending on the species selected. For example, grasses would increase the amount of carbon, while legumes would contribute to increase N by fixation (Malone et al., 2014; Meisinger et al., 1991).

2.1.3.2. Soil erosion reduction

Even in flat terrains or with low slopes, water and wind erosion still takes place, carrying soil sediments, organic matter, agricultural chemicals and even bacteria from manure to water bodies. Due to cover crop's ability to enhance water infiltration, minimize runoff rates and maintain large aggregate sizes the adoption of this practice in cropping systems has a significant impact on soil and water quality (Dabney et al., 2001; Frye et al., 1985; Holderbaum et al., 1990; Kaspar et al., 2007). The reduction in runoff volumes is related to the increased hydraulic roughness of soils where cover crops are being grown, and the green canopy mitigates the kinetic energy of raindrops, reducing soil sealing (Blanco-Canqui et al., 2013; Bonner et al., 2014; Clark, 2007; Dabney, 1998). When topsoil is lost, nutrients and organic matter – containing carbon and nitrogen – are also carried away with sediments, decreasing soil productivity and also contaminating nearby water bodies (Dabney, 1998; Kessavalou & Walters, 1997; Malone et al., 2014; Staver & Brinsfield, 1998).

2.1.3.3. Weed and pest management

Direct competition for space and resources – water, sunlight, nutrients – is the principal factor that makes cover crops great controllers of weeds, in particular when using high-density planting. Moreover, some species used for cover cropping can produce allelopathic compounds – phenolic acids, glucosinolates, and coumarins – that inhibit the germination or growth of other plants. It has been proved that this is a species-specific effect, hence using appropriate mixes could maximize the benefits of allelochemicals (Creamer et. al, 1996; Dabney et al., 2001; Kelton et al., 2012; Reeves, 1994; Teasdale, 1996).

The effect of cover crops on pests would vary depending on the species or mixture selected, management practices adopted and weather conditions. Cover crops could work as refuges for beneficial insects, which would leave or die if cover crops were not planted. Although, organic farmers can take more advantage of the previously mentioned attributes of cover crops as there are not many agrochemicals permitted for products going into this markets (Clark, 2007; S. M. Dabney et al., 2001; Lal et al., 1991).

2.2 Normalized Difference Vegetation Index (NDVI)

The radiometric reflectance values obtained from individual spectral bands does not always provide enough information to quantify and qualify some phenomenon. To deal with this limitation, indices have been developed using two or more spectral domains, resulting in a more sensitive measurement of the parameter under evaluation (Asrar et al., 1984; Bannari et al., 1995). The normalized differenced vegetation index was first reported by Rouse et al. (1974), and it has been one of the most used indexes for evaluating vegetative covers with remote sensing techniques.

The NDVI is a normalized ratio, computed by combining the reflectance values in the Near Infrared and Red spectral bands (1).

$$NDVI = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{1}$$

The usefulness of NDVI relies on the principle that red radiation (630-690 nm) is strongly correlated to the concentration of chlorophyll, while near infrared (760-900 nm) is influenced by cell structures present on leafs and also the leaf area. Visible radiation in the red portion of the spectra is absorbed by chlorophyll, as a consequence, healthy photosynthetic active vegetation would absorb more red radiation than senescent vegetation. Regarding the near infrared, it is scattered because of the intercellular structure of the leaves, thus growing vegetation presents a high area of air-cell walls, which causes the reflection of the NIR radiation (Bannari et al., 1995; Baret & Guyot, 1991; de Paul Obade & Lal, 2013; Glenn, Huete, Nagler, & Nelson, 2008; Heilman & Kress, 1987; Jackson & Huete, 1991; Kumar et al., 2002; Major et al., 1990; Tucker, 1979) (Figure 1.3).

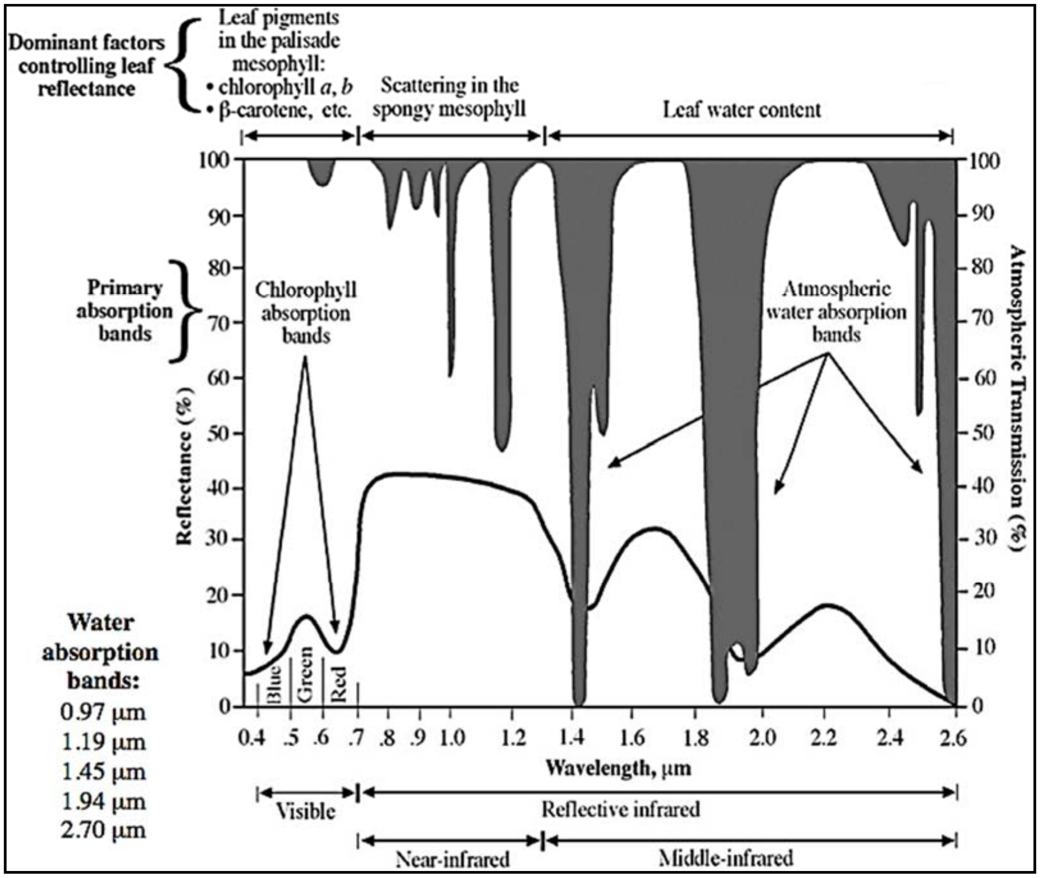

Figure 2.3. Spectral reflectance of healthy vegetation.
Source: Jensen, 2009.

This relationship between the red and NIR bands can be used to differentiate vegetation from others land covers (Tucker, 1979), values lower than 0 correspond to areas without vegetation, values from 0.2 to 0.5 could be associated with vegetation that doesn't have a dense canopy, or is senescent, while values greater than 0.5 would be representative of healthy and vigorous vegetation. Therefore, NDVI can be used to perform a multitemporal evaluation of vegetation and crop classification (Baret & Guyot, 1991; Tucker & Sellers, 1986).

One of the advantages of using the NDVI when evaluating vegetation is its ability of normalizing external effects, like differences in illumination and topography, as both bands are affected in the same manner (Holben and Justice, 1981).

2.3 References

Asrar, G., Fuchs, M., Kanemasu, E. T., & Hatfield, J. L. (1984). Estimating Absorbed Photosynthetic Radiation and Leaf Area Index from Spectral Reflectance in Wheat. *Agronomy Journal*, (2), 300–306.

Bannari, A., Morin, D., Bonn, F., & Huete, A. R. (1995). A review of vegetation indices. *Remote Sensing Reviews*, 13(1–2), 95–120. http://doi.org/10.1080/02757259509532298

Baret, F., & Guyot, G. (1991). Potentials and Limits of Vegetation LAI and APAR Assessment. *Remote Sensing of Environment*, 35(2), 161–173.

Blanco-Canqui, H., Holman, J. D., Schlegel, A. J., Tatarko, J., & Shaver, T. M. (2013). Replacing Fallow with Cover Crops in a Semiarid Soil: Effects on Soil Properties. *Soil Science Society of America Journal*, 77(3), 1026. http://doi.org/10.2136/sssaj2013.01.0006

Bonner, I. J., Muth, D. J., Koch, J. B., & Karlen, D. L. (2014). Modeled Impacts of Cover Crops and Vegetative Barriers on Corn Stover Availability and Soil Quality. *BioEnergy Research*, 7(2), 576–589. http://doi.org/10.1007/s12155-014-9423-y

Clark, A. (Ed.). (2007). Managing Cover Crops Profitably (3rd ed). College Park, MD: Diane Publishing.

Creamer, N. G., Bennett, M. A., Stinner, B. R., Cardina, J., & Regnier, E. E. (1996). Mechanisms of Weed Suppression in Cover Crop-based Production Systems. *HortScience*, 31(3), 410–413.

Dabney, S. M. (1998). Cover Crop Impacts on Watershed Hydrology. *Journal of Soil and Water Conservation*, 53(3), 207–213.

Dabney, S. M., Delgado, J. A., & Reeves, D. W. (2001). Using Cover Crops to Improve Soil and Water Quality. *Communications in Soil Science and Plant Analysis*, 32(7–8), 1221–1250. http://doi.org/10.1081/CSS-100104110

De Paul Obade, V., & Lal, R. (2013). Assessing Land Cover and Soil Quality by Remote Sensing and Geographical Information Systems (GIS). CATENA, 104, 77–92. http://doi.org/10.1016/j.catena.2012.10.014

Frye, W. W., Smith, W. G., & Williams, R. J. (1985). Economics of Winter Cover Crops as a Source of Nitrogen for No-till Corn. *Journal of Soil and Water Conservation*, 40(2), 246–249.

Glenn, E. P., Huete, A. R., Nagler, P. L., & Nelson, S. G. (2008). Relationship between Remotely-sensed Vegetation Indices, Canopy Attributes and Plant Physiological Processes: What Vegetation Indices Can and Cannot Tell Us About the Landscape. *Sensors*, 8(4), 2136–2160.

Hartwig, N. L., & Ammon, H. U. (2002). Cover Crops and Living Mulches. *Weed Science*, 50(6), 688–699.

Heilman, J. L., & Kress, M. R. (1987). Effects of Vegetation on Spectral Irradiance at the soil surface. *Agronomy Journal*, 79(5), 765–768.

Holderbaum, J. F., Decker, A. M., Messinger, J. J., Mulford, F. R., & Vough, L. R. (1990). Fall-seeded legume cover crops for no-tillage corn in the humid East. *Agronomy Journal*, 82(1), 117–124.

Jackson, R. D., & Huete, A. R. (1991). Interpreting vegetation indices. Preventive *Veterinary Medicine*, 11(3), 185–200.

Jensen, J. R. (2009). Remote sensing of the environment: An earth resource perspective 2/e. Pearson Education India.

Kaspar, T. C., Singer, J., Kohler, K. A., Jaynes, D. B., & Moorman, T. B. (2007). Environmental Benefits and Management of Small Grain Cover Crops in Corn-Soybean Rotations.

Kelton, J., Price, A. J., & Mosjidis, J. (2012). Allelopathic weed suppression through the use of cover crops.

Kessavalou, A., & Walters, D. T. (1997). Winter rye as a cover crop following soybean under conservation tillage. *Agronomy Journal*, 89(1), 68–74.

Kumar, L., Schmidt, K., Dury, S., & Skidmore, A. (2002). *Imaging spectrometry and vegetation science*. Springer Netherlands.

Lal, R., Regnier, E., Eckert, D. J., Edwards, W. M., & Hammond, R. (1991). Expectations of cover crops for sustainable agriculture. Cover Crops for Clean Water. *Soil and Water Conserv. Soc.*, Ankeny, IA, 1(11), 1–11.

Langdale, G. W., Blevins, R. L., Karlen, D. L., McCool, D. K., Nearing, M. A., Skidmore, E. L., … Williams, J. R. (1991). Cover crop effects on soil erosion by wind and water. *Cover Crops for Clean Water. Soil and Water Conserv. Soc.*, Ankeny, IA, 15–22.

Major, D. J., Baret, F., & Guyot, G. (1990). A ratio vegetation index adjusted for soil brightness. *International Journal of Remote Sensing*, 11(5), 727–740.

Mallory, E. B., Posner, J. L., & Baldock, J. O. (1998). Performance, economics, and adoption of cover crops in Wisconsin cash grain rotations: on-farm trials. *American Journal of Alternative Agriculture*, 13(1), 2–11.

Malone, R. W., Jaynes, D. B., Kaspar, T. C., Thorp, K. R., Kladivko, E., Ma, L., … Searchinger, T. (2014). Cover crops in the upper midwestern United States: Simulated effect on nitrate leaching with artificial drainage. *Journal of Soil and Water Conservation*, 69(4), 292–305.

Meisinger, J. J., Hargrove, W. L., Mikkelsen, R. L., Williams, J. R., & Benson, V. W. (1991). Effects of cover crops on groundwater quality. *Cover Crops for Clean Water. Soil and Water Conservation Society*. Ankeny, Iowa, 266, 793–799.

Moncada, K. M., & Sheaffer, C. C. (2011). Winter cover crops. Risk Management Guide for Organic Producers. Univ. of Minnesota, St. Paul.

Pieters, A. J. (1927). Green manuring. John Wiley & Sons, NY. Retrieved from http://sustainablefarmer.net/pdflibrary/library-greenmanuring.pdf

Pieters, A. J., & McKee, R. (1938). The Use of Cover and Green-Manure Crops. *Soils and Men*. USDA Yearbook of Agriculture.

Reeves, D. W. (1994). Cover crops and rotations. *Advances in Soil Science: Crops Residue Management*, 125–172.

Rouse, J. W. J., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. Third Earth Resources Technology Satellite Symposium : *The Proceedings of a Symposium Held by Goddard Space Flight Center in Washington*, D.C., 309–317.

Sarrantonio, M., & Gallandt, E. (2003). The Role of Cover Crops in North American Cropping Systems. *Journal of Crop Production*, 8(1–2), 53–74.

Snapp, S. S., Swinton, S. M., Labarta, R., Mutch, D., Black, J. R., Leep, R., … O'Neil, K. (2005). Evaluating cover crops for benefits, costs and performance within cropping system niches. *Agronomy Journal*, 97(1), 322–332.

Staver, K. W., & Brinsfield, R. B. (1998). Using cereal grain winter cover crops to reduce groundwater nitrate contamination in the mid-Atlantic coastal plain. *Journal of Soil and Water Conservation*, 55(3), 230–240.

Teasdale, J. R. (1996). Contribution of cover crops to weed management in sustainable agricultural systems. *Journal of Production Agriculture*, 9(4), 475–479.

Tucker, C. J. (1979). Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. *Remote Sensing of Environment*, 8(2), 127–150.

Tucker, C. J., & Sellers, P. J. (1986). Satellite remote sensing of primary production. *International Journal of Remote Sensing*, 7(11), 1395–1416.

USDA. (2012). Plant Hardiness Zone Map, 2012. Agricultural Research Service, U.S. Department of Agriculture. Accessed from http://planthardiness.ars.usda.gov/

Weil, R., & Kremen, A. (2007). Thinking across and beyond disciplines to make cover crops pay. *Journal of the Science of Food and Agriculture*, 87(4), 551–557.

CHAPTER III. REMOTE SENSING PROTOCOL FOR THE EVALUATION OF COVER CROP ADOPTIONS

3.1 Abstract

The use of cover crops has been recognized as an agricultural management practice that can enhance soil quality, contribute to suppressing weeds, promote the recycling of nutrients, and provide many other benefits when incorporated in farming systems. Because cover crops can mitigate or prevent soil erosion and nutrient leaching, the positive impact of this conservation practice also has an effect beyond farm boundaries, by reducing the contamination of water bodies caused by agriculture. As a consequence, state and federal agencies have been trying to assess farmer's motivations and barriers for cover crop use, and have also intended to track their adoption as a means of assessing conservation practice implementation. Because remote sensing techniques can provide information over large areas, periodically, it can be useful for estimating cover cropped fields.

A decision tree model approach was used in this study to develop sets of criteria for the identification of fields with cover crops, pastures and grasses, and stover, based on monthly NDVI values. The model had an overall accuracy of 82%, while the level of precision for cover crop detection was 76.9%. The results of this study demonstrate that remote sensing can be used successfully to identify the adoption of cover crops in agricultural fields based on monthly average NDVI values.

3.2 Introduction

Over the past decades, the introduction of new technologies has made significant improvements in agricultural production. For instance, yields have been increased, more pests and diseases are under control, and resources are being used more efficiently. However, there is still more that could be done to address one of the biggest challenges of agricultural systems: to produce sustainably, by increasing or maintaining yields at economically acceptable levels while minimizing the environmental impacts (Kirchmann & Thorvaldsson, 2000; Lal et al., 1991; Lowrance et al., 1986; Robertson & Swinton, 2005). Farming practices and management decisions have direct consequences at the farm scale and indirect effects beyond the farm's boundaries too. As a result, integration of appropriate conservation practices and sustainable management decisions in agricultural systems have a significant importance not only for farmers but also for societies (Knowler & Bradshaw, 2007; Nowak & Cabot, 2004; Van der Werf & Petit, 2002).

Among the negative environmental effects of agricultural production, the contamination of water bodies by agricultural nonpoint sources is nowadays one of the major concerns for governments, researchers, and communities (Malone et al., 2014; Mitsch et al., 2001; Pereira & Hostettler, 1993; Staver, 1991). Agricultural pollutants consist mainly of nutrients, pesticides, pathogens, and sediments. However, there are many conservation practices which can be implemented to reduce or minimize the negative impacts of agriculture. For instance, the incorporation of cover crops in crop rotations, buffer strips of perennial vegetation, contour farming, terraces, no-tillage and crop residue management, riparian vegetation buffers, among others, can be implemented separately or combined (Rigby et al., 2001; Tomer et al., 2015). For the purpose of this paper, we will address the importance of incorporating cover crops into farming systems.

Most of the agricultural cropping systems are based on the production of one cash crop per year, which is responsible for most of the farm's income, and only uses the land for about six months. Cover crops are planted after summer cash crops are harvested in the Northern U.S., while summer cover crops complement fall or winter cash crops in Southern regions (Kessavalou & Walters, 1997; Snapp et al., 2005). For the state of Iowa, and other states in the Midwest region, corn (Zea mays L.) and soybeans (Glycine max L.) are the most relevant marketable crops grown, and from the broad variety of species that could be used as cover crops rye (Secale cereale L), oat (Avena sativa L), and wheat (Triticum aestivum L) are some of the most chosen.

Using a cover crop as a physical barrier for reducing wind and water soil erosion has been one of the main reasons for adoption (Lal et al., 1991; Langdale et al., 1991). Even in flat terrains, where the consequences of water erosion are less severe compared to fields with steeper slopes, cover crops protect the upper portions of soils by reducing runoff speed, increasing water infiltration, and protecting soil aggregates from the kinetic energy of raindrops impact. However, cover crops not only prevent soil degradation but also improve its quality. Including a cover cover crop in agricultural rotations can contribute to alleviate soil compaction and reduce bulk density, increase organic matter, infiltration and aeration, and control weeds (Dabney et al., 2001; Langdale et al., 1991; Meisinger et al., 1991; Ryan et al., 2003; Weil & Kremen, 2007). Also, the inclusion of cover crops in rotations increases the biodiversity of the systems, which can contribute to breaking the cycle of weeds and pests – nematodes principally – and increase soil microbial activity during the cooler months (Clark, 2007).

At the landscape scale, cover crops help reduce the contamination of surface water and groundwater that is caused by agricultural activities by limiting nutrient leaching and soil sediment transport. The inclusion of cover crops in rotations generates a more complex, yet efficient, cycling of nutrients. During its growth in the fall, cover crops take up the nutrients that remain in the soil after the cash crop, keeping them from leaving the system. In the next spring, after the cover crops are killed and as a result of the decomposition of residues, part of those nutrients are released back into the soil and are available for the next cash crop. This seasonal reduction in the availability of nutrients reduces the concentration of nutrients leaching farmlands and reaching water bodies (Blanco-Canqui et al., 2013; Bonner et al., 2014; Clark, 2007; Dabney et al., 2001; Kaspar et al., 2007; Langdale et al., 1991; Malone et al., 2014; Meisinger et al., 1991; Reeves, 1994; Staver, 1991).

Cover crops status as an advantageous conservation practice means that state and federal agencies have an interest in tracking their adoption as a means of assessing conservation practice implementation. There are, however, limited means of tracking conservation crops. At the present, cover crop acreage is mainly obtained by reports, generated at different administrative levels (nation, state, county), and most of them are based on field surveys. Because agricultural practices have particular characteristics – high spatial, interannual and seasonal variability – regular survey methods have some limitations for providing accurate information on them. For instance, lack of spatial distribution of the samples could result in inaccurate conclusions on the actual acreage of cover crops.

Therefore, the use of remote sensing techniques for detecting cover crops could be an appropriate alternative method as it gathers information on large continuous areas. Also, it is possible to acquire data periodically, depending on the sensor selected and weather conditions. In addition, satellite imagery is also more accurate for the evaluation and documentation of land cover change over the time, as this information is georeferenced (Carfagna & Gallego, 2005; de Paul Obade & Lal, 2013; Foody, 2002; Leon et al., 2003; Rogan et al., 2003).

Remote sensing technology can be applied to a broad number of fields, with environmental and agricultural research being areas where it has been more developed. Satellite image analysis is useful for monitoring and evaluating environmentally related phenomena like flood, drought and desertification, forestry characterization and fires, volcanic eruptions, and water pollution including oil spill and algae bloom, among others (Chuvieco, 2008; Reeves & Baggett, 2014; Wolter & Townsend, 2011; Wolter et al., 2009). Regarding agriculture, satellite photo interpretation and analysis has been extensively used to predict crop yields; detect spread of diseases; assess vegetation healthiness, phenological stages and plant density; estimate and evaluate crop residues (distribution, volume, and degradation rate); and monitor tillage intensity and crop rotations (Biard & Baret, 1997; Daughtry et al., 2005; Daughtry et al., 2010; Daughtry et al., 2006; Daughtry et al., 2004; French et al., 2000; Gelder et al., 2009; Glenn et al., 2008; Yao et al., 2012). For assessing cover crops, remote sensing has been mainly used combined with on-site sampling data, but not by itself. For instance, Hively et al. (2009) quantified the efficiency of different cover crops species to capture nutrients in the Chesapeake Bay. Prabhakara et al. (2015) evaluated the performance of remote sensing indices for assessing biomass production and soil coverage, which were measured in situ. The fundamentals of remote sensing data for land use and cover characterization relies on the principle that different surfaces have specific responses in the wavelength spectra, making it possible to create spectral signatures for each categorical class or theme (Figure 3.1).

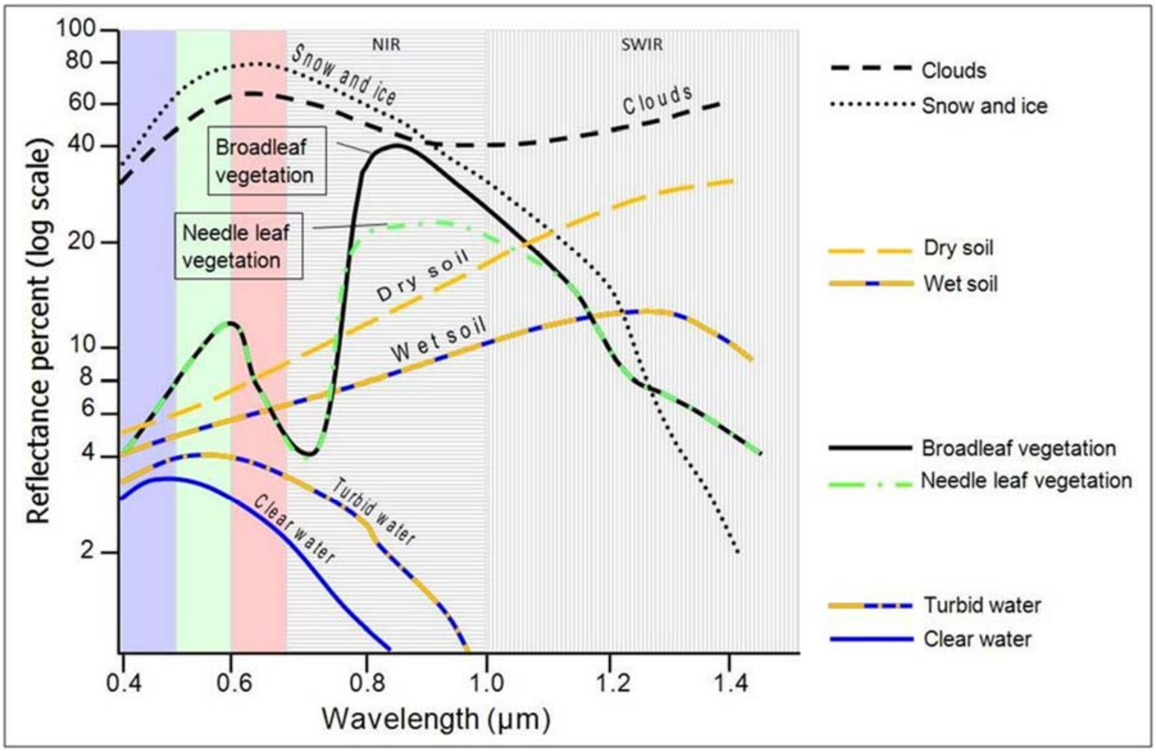

Figure 3.1. Spectral response curves for different land covers and clouds.
Source: Aronoff, 2005.

Since Landsat 1, the first Earth observation satellite launched in 1972, it has been possible to use satellite image information for generating maps of spatial distribution of crops and other surface covers (Bauer & Cipra, 1973; Mulla, 2013). For example, the United States Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS) has developed a geospatial product called Cropland Data Layer (CDL) for estimation of crop acreages. Because CDL products, as well as other land cover maps, typically reflect the crop that occupies an area during the primary growing season, commodity crops mainly, these resources are not suitable for the evaluation of cover crop adoptions.

Indexes derived from remote sensing data are indicators of intensity for a condition or characteristic, constructed by the combining reflectance values. A broad variety of vegetation indexes has been developed for different applications, being the normalized differenced vegetation index (NDVI), reported for the first time in 1973 (Rouse et al., 1974), the most used for vegetative cover analysis. When light strikes vegetation canopies part of it is absorbed, transmitted and reflected, depending on the light's wavelength and the leaf surface. The NDVI is calculated based on the Red (630 - 690 nm) and Near Infrared (760 – 900 nm) reflectance values, according to equation 1 and ranges from -1 to +1.

$$NDVI = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{2}$$

Values from 0.1 or lower usually correspond to areas with no vegetation – barren rock, snow, sand –, moderate NDVI values ranging from 0.2 to 0.5 are representative of sparse vegetation or senescent crops, and higher values are associated with healthy dense vegetation. The NDVI relies on the principle that healthy vegetation absorbs red radiation for photosynthetic processes, while Near Infrared is largely reflected when reaching the intercellular structure (Bannari et al., 1995; Baret & Guyot, 1991; de Paul Obade & Lal, 2013; Glenn et al., 2008; Heilman & Kress, 1987; Jackson & Huete, 1991; Major et al., 1990; Tucker, 1979) (Figure 3.2).

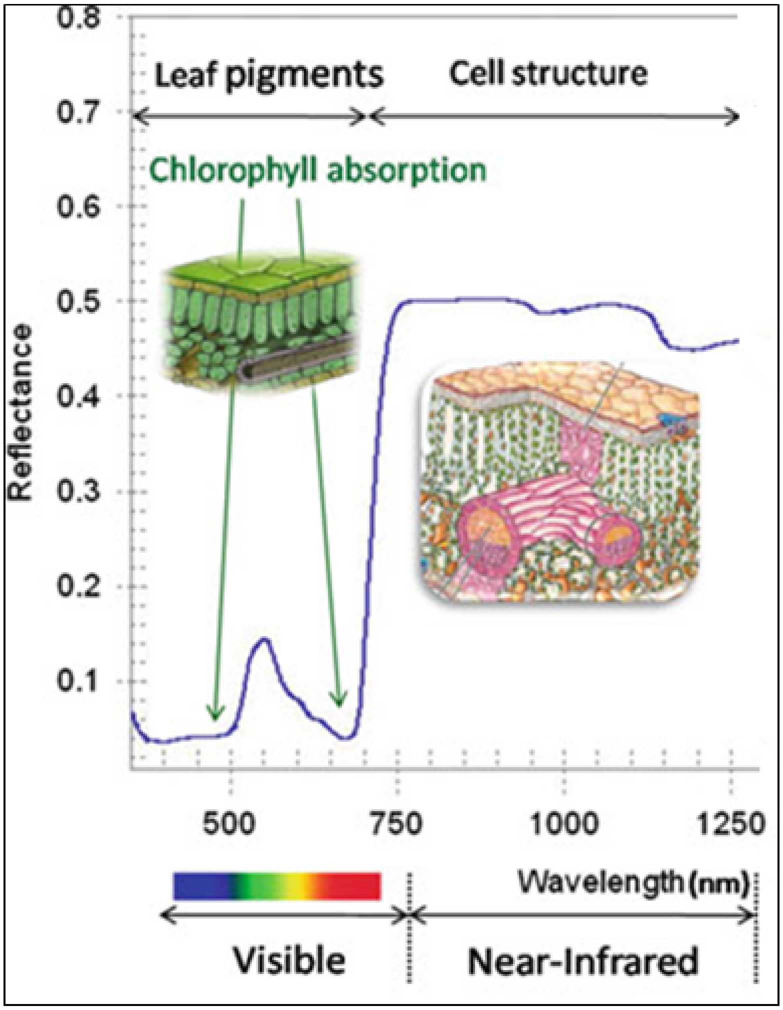

Figure 3.2. NDVI spectral signature for healthy vegetation.
Source: Prabhakar et al.,2012.

Because NDVI quantifies the spectral response of different vegetative covers, it is an appropriate parameter for performing multi-temporal analysis of land cover change.

The main purpose of this research is to enhance our ability to inventory current, past and future cover crops adoption. To accomplish this goal, the present study developed a remote sensing protocol based on the NDVI to detect cover crops on satellite images from Landsat-7 Enhanced ThematicMapper (ETM+) and Landsat-8 Operational Land Imager (OLI).

3.3 Materials and Methods

3.3.1. Description of the study area

Twenty-seven Hydrological Unit Code (HUC) 12 watersheds where cover crops were planted in 2013 and 2014 were selected for the area of study. The study area is located in East-Central Iowa and occupies a total surface of 245,463 hectares. It is principally situated in Benton County and also includes portions of Tama, Linn, Poweshiek, Iowa, and Johnson Counties (Figure 3.3). According to the landform regions classification, it is located in the Southern Iowa Drift Plain (Tallgrass Prairie) and Iowan Surface (Eastern Tallgrass Prairie), and Peoria Loess is the most representative soil type of the area (Appendix A). The Southern Iowa Drift Plain is the most extensive of Iowa's landforms, composed almost entirely of moderate to thick loess cover, weathered glacial drift, and has integrated drainage. The Iowan Surface landform extends over the northeastern of Iowa and is characterized by long, gently rolling slopes, and most of the terrain is covered in thin, discontinuous loess or loam over drift.

The climate conditions of the area that most affect the development of cover crops are the minimum temperatures, which are in the range of -28.9 to -26.1 C.

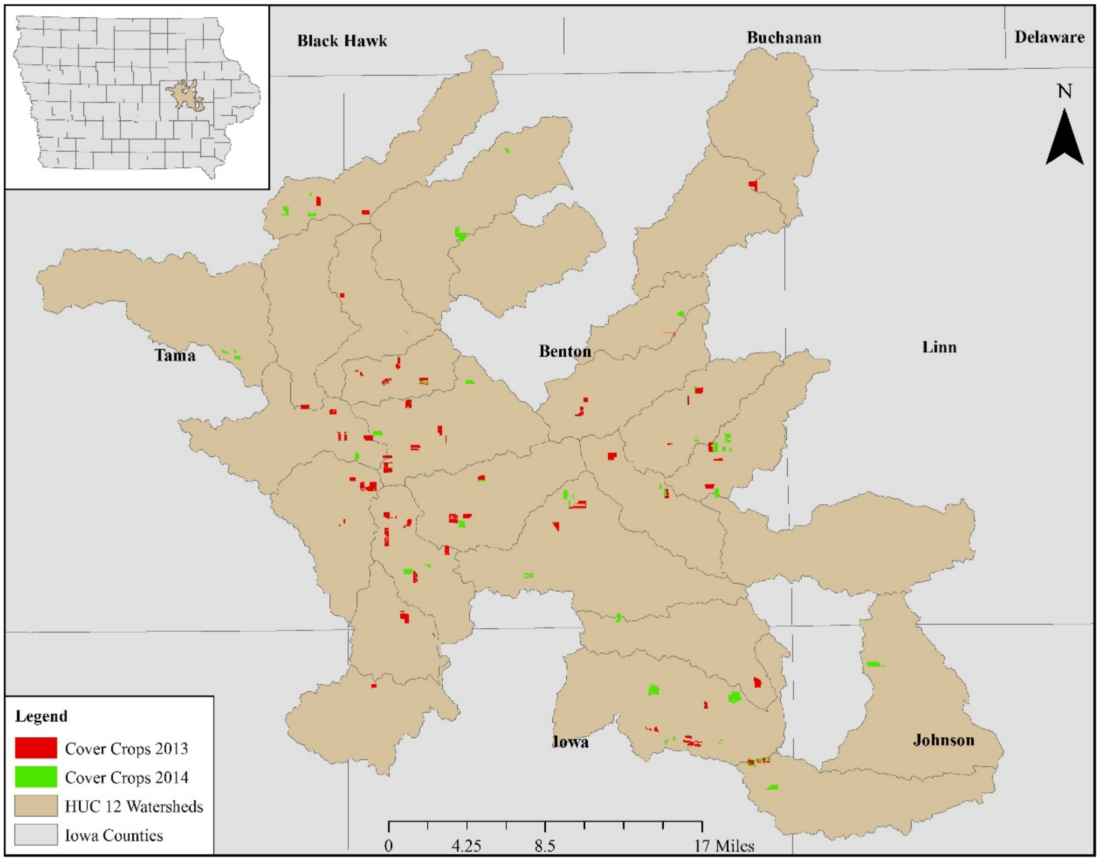

Figure 3.3. Study area

3.3.2. Data acquisition and processing

The first step for detecting cover cropped fields was to create a dataset with three classes: "Cover crops"; "Corn/Soybeans stover", for fields that didn't have growing vegetation while winter cover crops did; and "Pasture/Grass", for fields with vegetative cover that could partially or entirely share the growth season with cover crops. Figure 3.4 shows a flow chart of steps performed to process the acquired data.

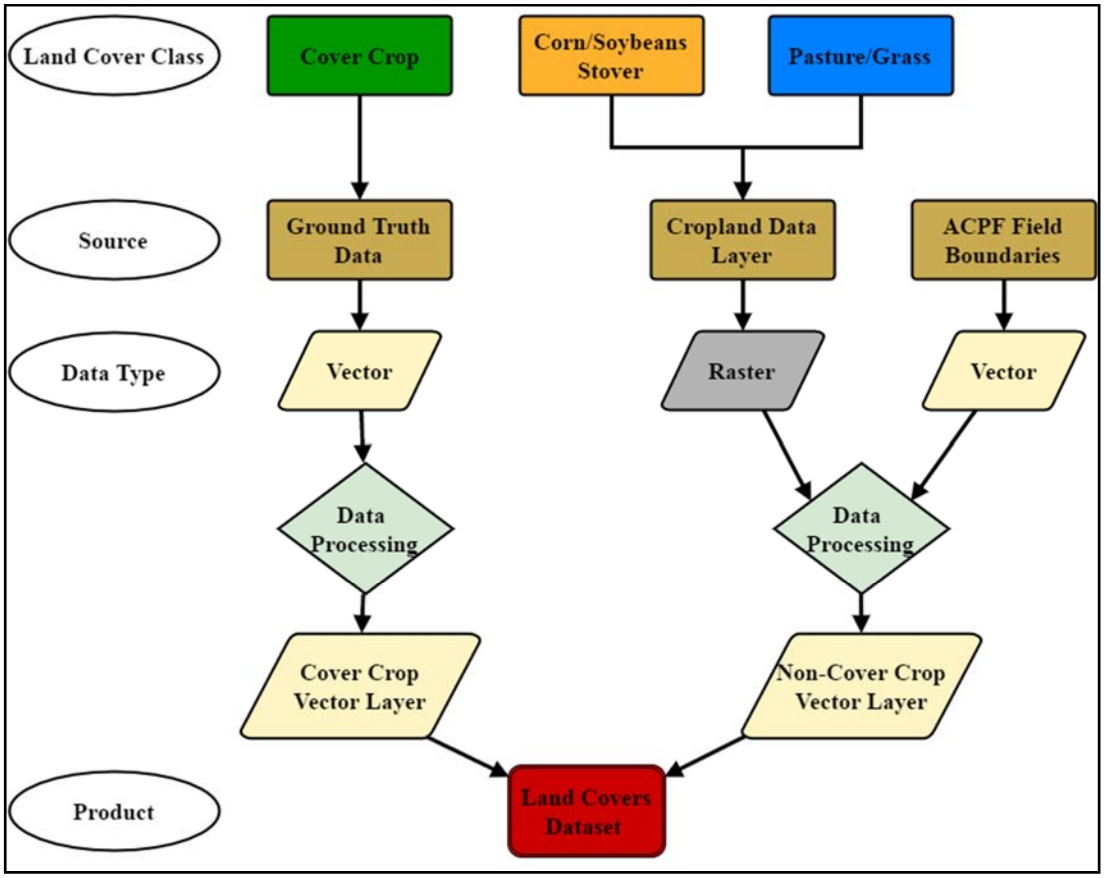

Figure 3.4. Flow chart of the dataset creation process.

For this study, ground truth data for fields in where cover crops were planted in 2013 and 2014 was provided to the research group by a seed dealer. For both planting seasons, Trimble Pathfinder™ GPS (Global Positioning System) and RTK (Real-Time Kinematic) equipment were used to collect and record the georeferenced information of the planter's path. The output data was extracted into shapefiles, one for each year, consisting of the polygon feature classes of the fields planted with cover crops. The attribute tables of the shapefiles included information on the species, date, time, terrain elevation and planting speed, among others, for each polygon.

The Cropland Data Layer (CDL) for 2013 and 2014 was used to select fields with other covers than cover crops (USDA, 2013 and 2014). The CDL is a raster, georeferenced, crop-specific land cover data layer developed by the USDA, National Agricultural Statistics Service, Research and Development Division, Geospatial Information Branch, Spatial Analysis Research Section. It can be downloaded for free from the CropScape website (https://nassgeodata.gmu.edu/CropScape/), has no copyright restrictions, it is considered public domain, and free to redistribute. The 2013 and 2014 layers for the state of Iowa were mostly produced using Landsat 7 ETM+ (only for 2013), Landsat 8 OLI/TIRS, Disaster Monitoring Constellation (DMC) DEIMOS-1 and UK2 sensors

According to the USDA NASS, the CDLs for the state of Iowa presented a relatively high percentage of accuracy classification for the four main land covers found in the study area (Table 3.1). However, when performing a visual inspection of the data, some misclassified pixels were detected and needed to be corrected (Figure 3.5).

Table 3.1.CDL Classification accuracy for 2013 and 2014 state of Iowa layers
Source: USDA, National Agricultural Statistics Service, 2013 and 2014 Iowa Cropland Data Layer.

	2013 – Accuracy (%)	**2014 – Accuracy (%)**
Corn	96.98	97.68
Soybeans	96.28	97.17
Alfalfa	61.87	70.24
Other Hay/Non-Alfalfa	51.78	55.52
Overall accuracy	**95.2**	**96.3**

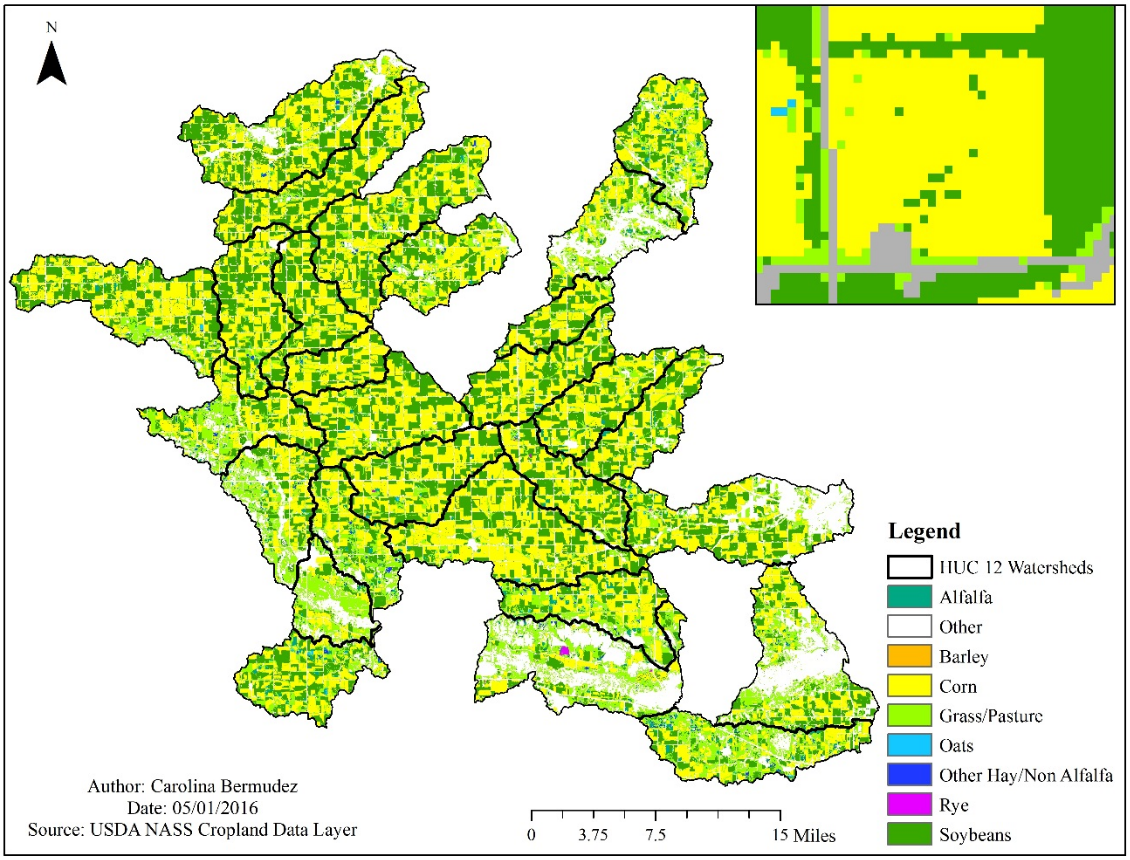

Figure 3.5. CDL for 2013 and corn field with pixels misclassified as soybeans

In order to perform some geoprocessing corrections to reclassify the misclassified pixels, it was necessary to have the fields delimited with borders. For this purpose, the field boundary shapefiles from the USDA Agricultural Conservation Planning Framework Database (ACPF) were used. The ACPF program has combined data from field boundaries, soil surveys, recent land use, and topography among others, for individual HUC12 watersheds in Iowa, Illinois, and southern Minnesota. A geodatabase containing all that information has been created for each HUC 12 watershed, and it is available for free downloading at the USDA ACPF Watershed Database website (http://www.nrrig.mwa.ars.usda.gov/st30_huc/huc.htm).

The land cover classes from the CDL raster files for 2013 and 2014 were matched to the ACPF field boundary polygons, using the Zonal Statistics as Table ArcMap tool. The fields were then reclassified according to the category that had the majority of pixels, within the field's boundaries. For both years, according to the CDL classification, there were five cover types in the study area: corn and soybeans, which were reclassified as Stover, and alfalfa, other hay/non-alfalfa, and grass/pasture, which were re-coded as Pasture/Grass (Figure 3.6).

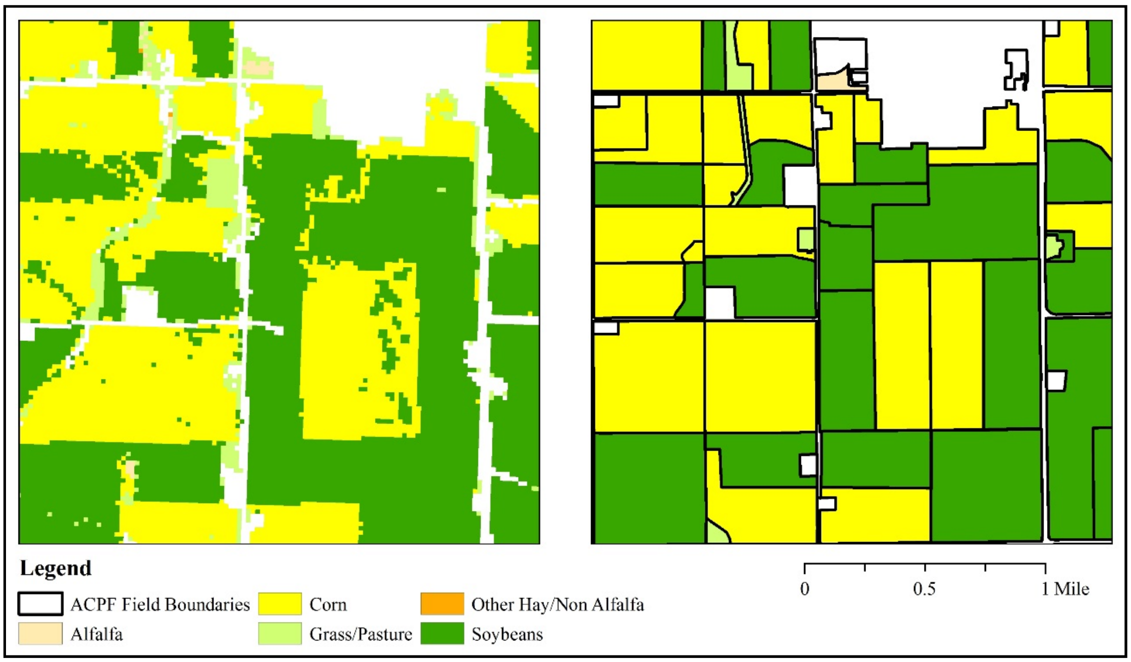

Figure 3.6. Cropland data layer processing.
CDL for 2013 (left). Field classification based on CDL and ACPF datasets (right).

For each year, the cover crop and CDL produced layers were joined, and all the fields were buffered inwards by 30 meters – the size of 1 Landsat pixel –, to make sure all the reflectance data obtained from a field was representative of its cover (Figure 3.7). Fields smaller than 1 hectare and all the CDL fields that overlapped with the ground truth data cover crop fields were deleted. A total of one hundred and thirty-one cover cropped fields were selected, seventy-eight for 2013 and fifty-three for 2014. All these fields were unique; there were not fields with cover crops in both seasons.

Figure 3.7. Field boundary and 30 meters inward buffer.

The objective of this project was to produce a model that could detect cover crops regardless of weather conditions, planting dates, species, and soil types, even though we know weather and planting differences influence the spectral reflectance of the ground surface. Based on usual planting dates reported by the USDA (USDA NASS, 2010) for the most important cover crop species for the region (winter cereal rye, winter wheat, and oats), and seeding recommendations dates from the Midwest Cove Crops Council Cove Crop Decision Tool (MCCC, 2015), planting dates were classified into three categories: Early (August 1st to September 10th), Normal (September 11th to October 31st), and Late

(November 1st to November 15th). Thus, to understand weather conditions affecting cover crop planting dates, establishment and development, rainfall events and growing degree days (GDD) of the study area were analyzed for both of the planting seasons.

Fall rainfall was limited only in 2014, despite two significant events on September 10th (45.21 mm) and October 14th (55.11 mm). Looking at the distribution of fields by planting date (Figure 3.8) it can be noticed that there were not cover crops planted before the first rainfall, it could be inferred that the beginning of the 2014 cover crop planting season was influenced by this event. From the calculation and analysis of growing degree days, it could be expected that cover crops stopped producing biomass after November 7th (3 GDD) for 2013 and November 1st (-2.5 GDD) for 2014.

To include inter-annual variations in conditions, we combined the two years in order to build the model.

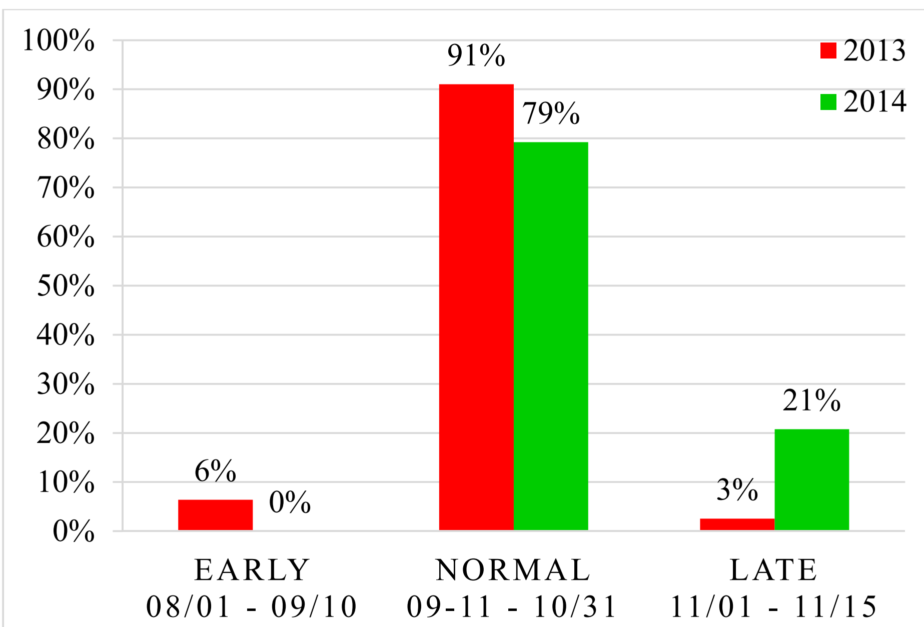

Figure 3.8. Distribution of cover crop fields by planting date

A decision tree classification approach was selected for this study, described in more detail below. As this method is sensitive to the amount of data per category (Rogan et al., 2003), the fields per class were restricted to the total of cover crop fields. Therefore, sixty-five fields for each category were randomly selected from the CDL recoded shapefile; the same sample fields were used for both years (Table 3.2, Figure 3.9).

Table 3.2. Fields per class in the dataset.

Fields	**2013**	**2014**	**Total**
Cover Crops	**78**	**53**	**131**
Oats	17	2	19
Oats - Winter rye	3	1	4
Winter rye	50	40	90
Winter wheat	8	10	18
Corn/Soybeans stover	**65**	**65**	**130**
Corn	38	34	72
Soybeans	27	31	58
Pasture/Grass	**65**	**65**	**130**
Alfalfa	42	42	84
Other hay/non-alfalfa	2	2	4
Grass/Pasture	21	21	42
Total	**208**	**183**	**391**

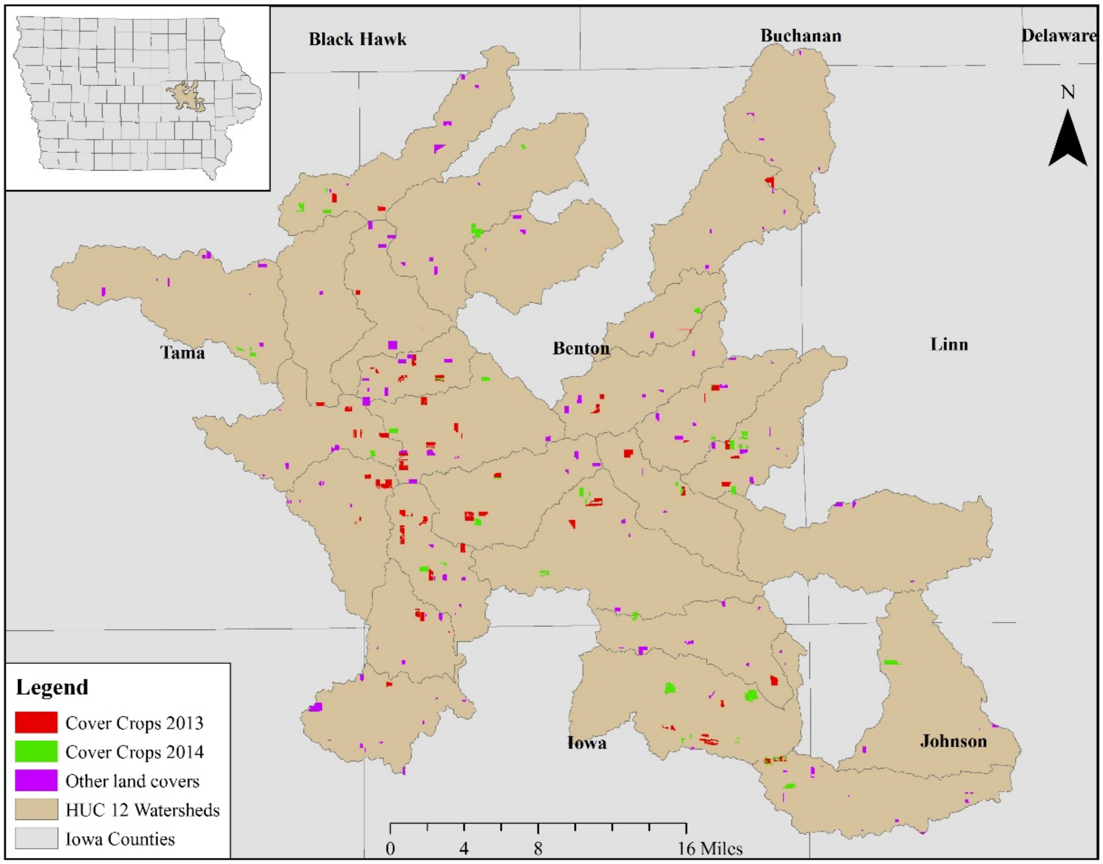

Figure 3.9. Selected fields.

All non-cover crop fields were visually inspected using eight satellite images for each year to assess the information provided by the CDL. Fields containing mixed pixels and/or fields that seemed to be under different management practices were discarded and replaced with others, also randomly selected (Figure 3.10). In addition, for corn and soybeans fields it was verified that there was no vegetation growth after harvest; and only fields that had the same cover for both years were considered for the items under the Pasture/Grass category.

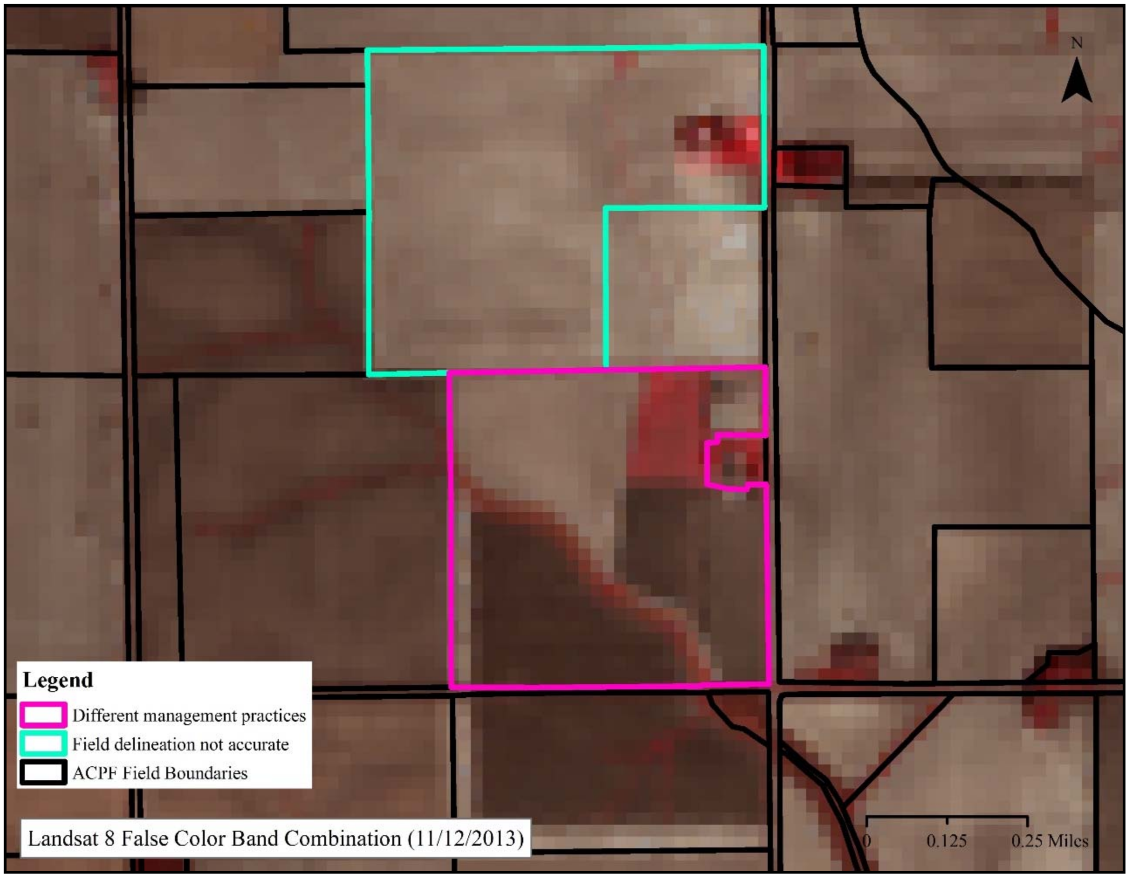

Figure 3.10. Visual assessment of training data

3.3.3. Satellite Image Database

A database consisting of satellite images from Landsat 7 and 8 was created by the research group to evaluate cover crop adoptions and other agricultural conservation practices affecting water quality and landscape change across time series. The images were downloaded from the USGS Earth Explorer website (http://earthexplorer.usgs.gov/) and saved on a shared server. This imagery collection contained all the scenes available for the period 2000-2015 for the state of Iowa, with less than 50% of cloud cover and obtained during the daytime.

3.3.4. Time series selection

To analyze the temporal change using vegetation indexes derived from remote sensing data, it was necessary first to establish a date range that could detect the differences between the land cover categories. For our study, we used the period from June 1 of year 1 to May 31 of year 2 for each crop year (Figure 3.11).

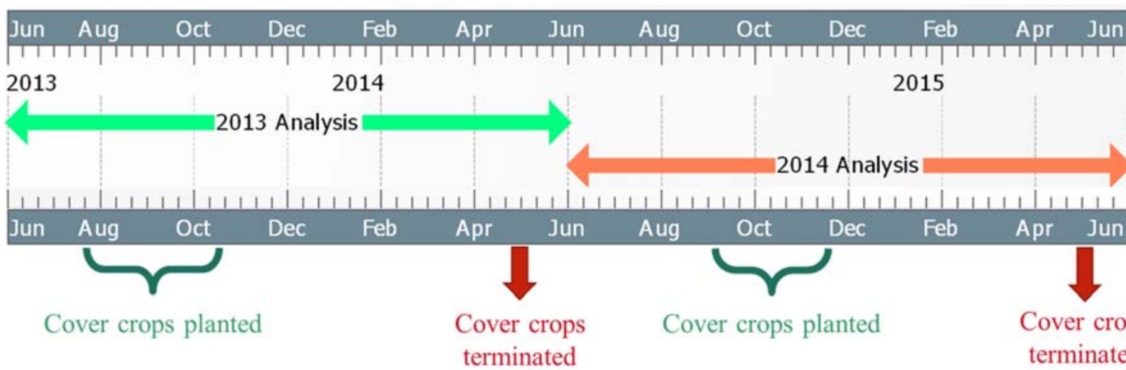

Figure 3.11. Timeline for the selected time series.

This range allowed us to evaluate the change in land use accurately, being able to detect the growing season of corn, soybeans, and pastures, and contrast it to cover crops growth. An example of the phenological cycle of winter wheat, which could serve as a cover crop if killed by April or May, is shown in Figure 3.12.

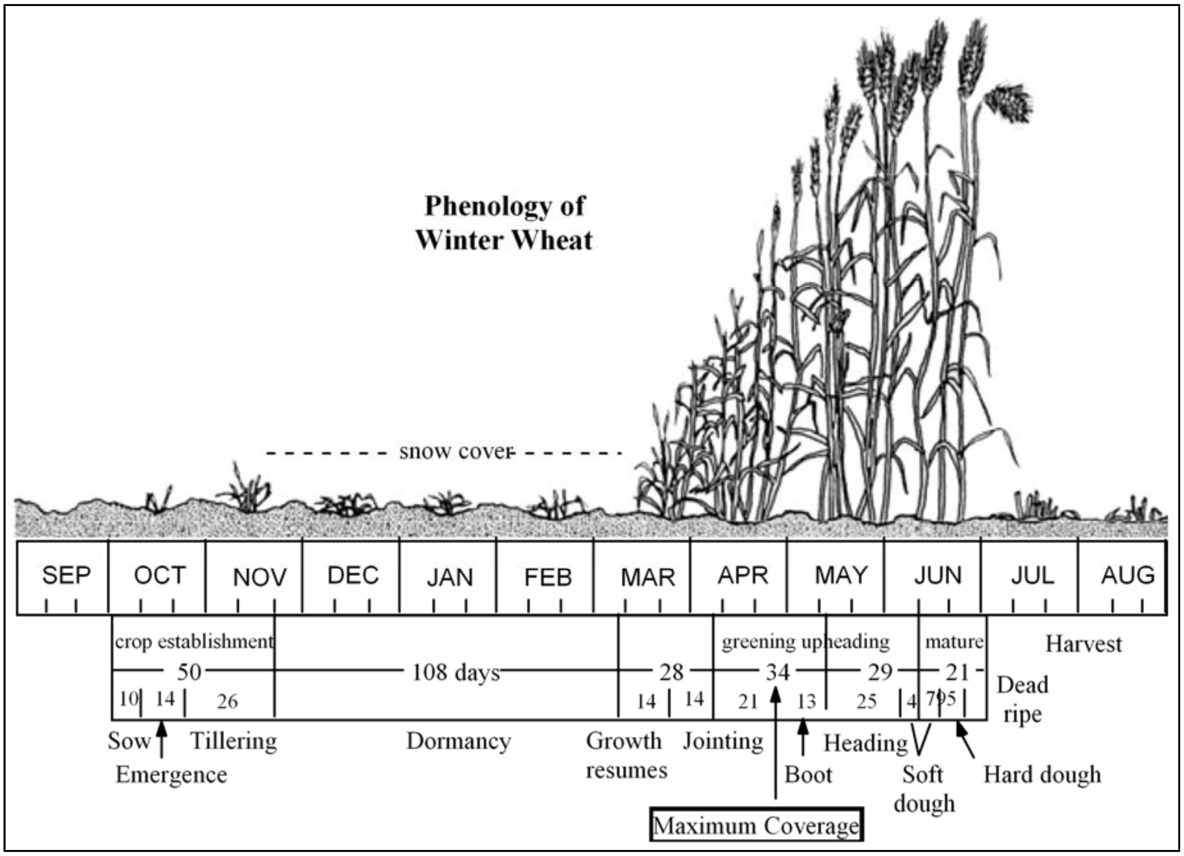

Figure 3.12. Phenology of Winter Wheat in the Midwest United States.
Source: Jensen, 2009.

3.3.5. Landsat data transformation

One of the main goals of Landsat missions is to provide long-term and consistent information that could be combined despite the recording sensor. In order to generate products of higher quality two new bands were incorporated to Landsat 8, signal to noise ratio and radiometric quantization were increased, and all the spectral wavebands were narrowed (Figure 3.13).

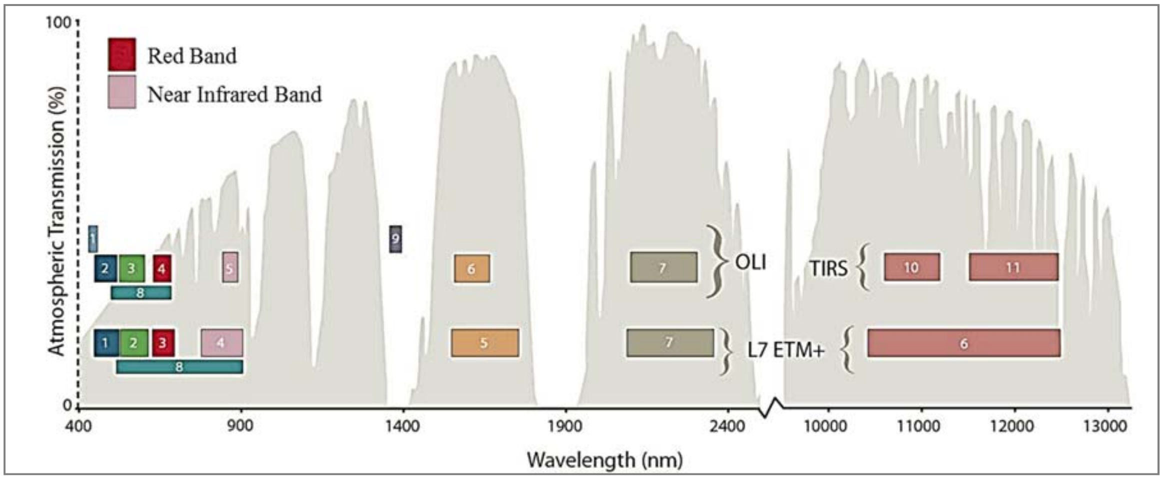

Figure 3.13. Landsat 7 and 8 bandpass wavelengths.
Source: USGS, 2013.

On the one hand, these modifications had improved the ability of Landsat 8 for detecting land changes, on the other hand, the alteration of the bands made it necessary to perform spectral reflectance transformations to compare its data to that from Landsat 7. Previous research has reported that for the calculation of NDVI (1) the narrower bands of Landsat's 8 compared to Landsat 7 (Table 3.3) could generate differences associated with the sensor (Flood 2014; Ke et al., 2015; Li et al., 2013; She et al., 2015; Xu, 2014).

Table 3.3. NDVI bands wavelengths.

Sensor	Band	Near-Infrared (µm)	Band	Red (µm)
Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	5	0.85 – 0.88	4	0.64 – 0.67
Landsat 7 – Enhanced Thematic Mapper Plus (ETM+)	4	0.77 – 0.90	3	0.63 – 0.69

Roy et al. (2015) developed transformation functions using ordinary least squares (OLS) regressions to adjust the top of atmosphere (TOA) and surface reflectances between-sensors differences for each band and also for NDVI. For our dataset, Landsat 7 Red, Near

Infrared, and NDVI values were rescaled to Landsat 8, using (3), (4), and (5). Regarding NDVI, it was reported that, on average, Landsat's 8 surface NDVI was greater than Landsat's 7 by 0.0165, and its mean relative difference was 4.86%. The transformation proposed by the authors (5) is reliable for normalizing the NDVI reflectance values between sensors as its regression coefficient of determination (r^2) was 0.926 and p-value <0.0001.

Red λ (~0.66 µm) $$Landsat\ 8 = 0.0107 + 0.9175\ Landsat\ 7 \quad (3)$$

Near infrared λ (~0.85 µm) $$Landsat\ 8 = 0.0374 + 0.9281\ Landsat\ 7 \quad (4)$$

NDVI $$Landsat\ 8 = 0.0235 + 0.9723\ Landsat\ 7 \quad (5)$$

3.3.6. Model building and accuracy assessment

The vegetation indexes showed on Table 3.4 were used to calculate mean and standard deviation values for each field, using each suitable satellite image during the selected period; images with substantial cloud cover, snow, or ice over the study region were not used.

Table 3.4. Vegetation indexes.

Index	Formula	Author and Year
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{\mathrm{NIR} - \mathrm{RED}}{NIR + RED}$	Rouse et al., 1974
Ratio Vegetation Index (RVI)	$RVI = \frac{RED}{\mathrm{NIR}}$	Pearson and Miller, 1972
Vegetation Index Number (VIN)	$VIN = \frac{\mathrm{NIR}}{RED}$	Pearson and Miller, 1972
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{(NIR - RED)}{(NIR + RED + L)}(1 + L)$	Huete, 1988

The final step of our analysis was to adopt a decision tree classification approach to evaluating NDVI, VIN, SAVI, and RVI time series and detect threshold values that could accurately separate the three land cover categories: cover crop, stover and pasture/grass. Selecting the mean index value for each field and specific image date could overwhelm the decision tree algorithm. Moreover, any resulting model could be used only those years in which the sensor visits the area on the same dates, and records appropriate images. In order to develop a more general model, average monthly indexes per field were calculated and selected as the explanatory variables for the decision tree analysis.

As a decision tree is a non-parametric supervised learning method, it has some characteristics and advantages that make it one of the most suitable classification methods for our dataset. Being non-parametric by nature decision trees do not make any assumptions on the probability distributions of the variables analyzed. Moreover, tree-based methods can combine both numerical data – index values – and categorical data – land cover types –, and are easy for interpretation and visualization. In addition, decision trees can handle datasets with missing or non-continuous data, this feature was particularly important in our study, as the calculation of vegetation index field values depended on the prevailing weather conditions of the day when the image was obtained. For instance, some clouds could partially cover an image, making possible to calculate the indexes values only for a fraction of the total fields, on a specific date.

The dataset was randomly separated into two sub-datasets: one to calibrate the models, consisting of 70% of the data; and the remaining 30% to validate the results. Decision trees are sensitive to the number of samples in each category because the algorithm considers the variations within-class and between-class. Therefore, the number of samples for each category on the sub datasets was kept similar (Table 3.5).

Table 3.5. Subdatasets structure.

	Stover	Cover crop	Pasture/Grass	Total	%
Calibration	91	92	91	274	70
Validation	39	39	39	117	30
Total	130	131	130	391	100

The package Rattle from the R software was used to perform a decision trees for each index, using the calibration dataset. The mean values were selected for the input variables. In order control the size of the tree, and also to generate a model that could be easily adopted, the minimum of fields in any node and leaf were set to nine, and a maximum of three classification levels was chosen.

The performance of the proposed indexes for cover crop detection was evaluated using the validation dataset. An error matrix was constructed, and it was used to calculate the metrics derived from the decision trees, the overall accuracy, the classification accuracy for each class, and the kappa statistic. Although other evaluation measures could have been used for this purpose, the error matrix and analysis provides an overview of the validity of the model that has the advantage of being widely used and straightforward in its interpretation.

3.4 Results and Discussion

The analysis of the decision trees for each vegetative indicated that NDVI performed slightly better than the others indexes to differentiate cover crops fields from other fields. The NDVI showed a higher kappa coefficient, which means that there is a better agreement between the data, higher overall accuracy, and also higher accuracy for classifying cover crops (Table 3.6). As a result, NDVI was the index selected for this study to develop sets of criteria for cover crop detection using a decision tree approach.

Table 3.6. Evaluation of the vegetation indexes.

Index	**Kappa**	**Overall Accuracy**	**Cover Crop Accuracy**
NDVI	0.73	82	76.9
RVI	0.71	81	61.5
VIN	0.70	80	64.1
SAVI	0.71	81	64.1

In order to evaluate whether the mean NDVI is an appropriate measure of central tendency to describe the data the median NDVI was calculated, and both measures were compared by regressing one on the other. Figure 3.14 shows that there seem to be no significant differences between the mean and the median NDVI, which is confirmed by the high R^2 (0.9972). This result supports the mean NDVI as an adequate measure for classifying fields with different vegetative covers. Moreover, a decision tree using the median NDVI values was constructed, and similar results were obtained.

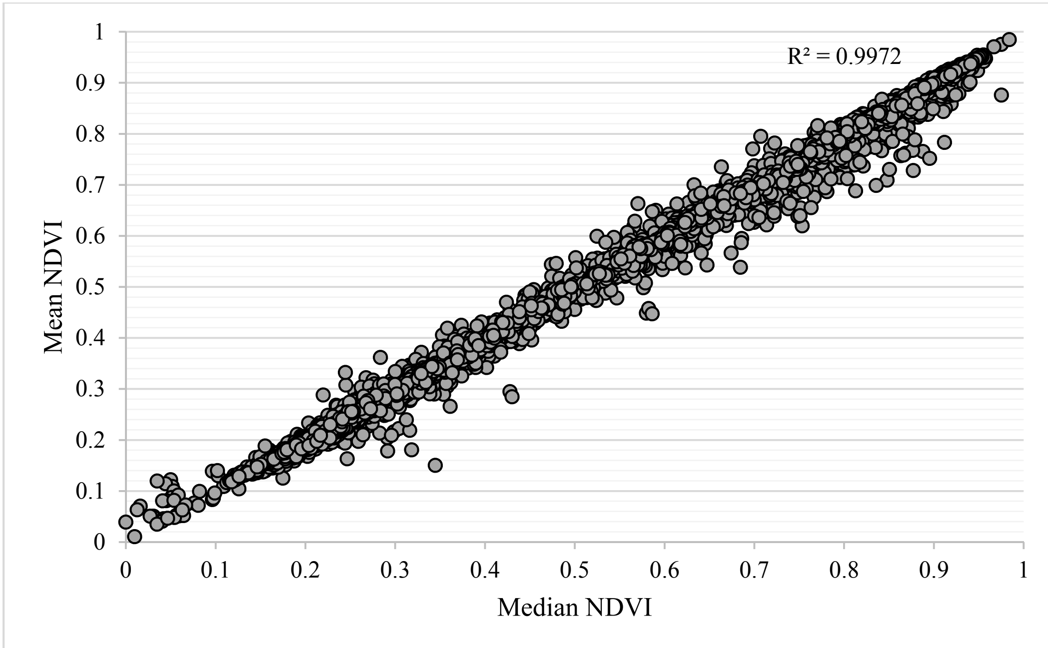

Figure 3.14. Mean and median NDVI comparison.

The spectral signatures for the studied classes were generated based on average monthly NDVI values computed by field and are shown in Figure 3.15. The dotted lines represented the periods when the NDVI was not representative of the category under which the field was assigned. For the case of cover crop fields, reflectance values recorded during June, July, August and September would not be representative of them, but of the cash crop being grown on the same field. The same period would not show values that corresponded to corn or soybeans residues, but to corn or soybeans development.

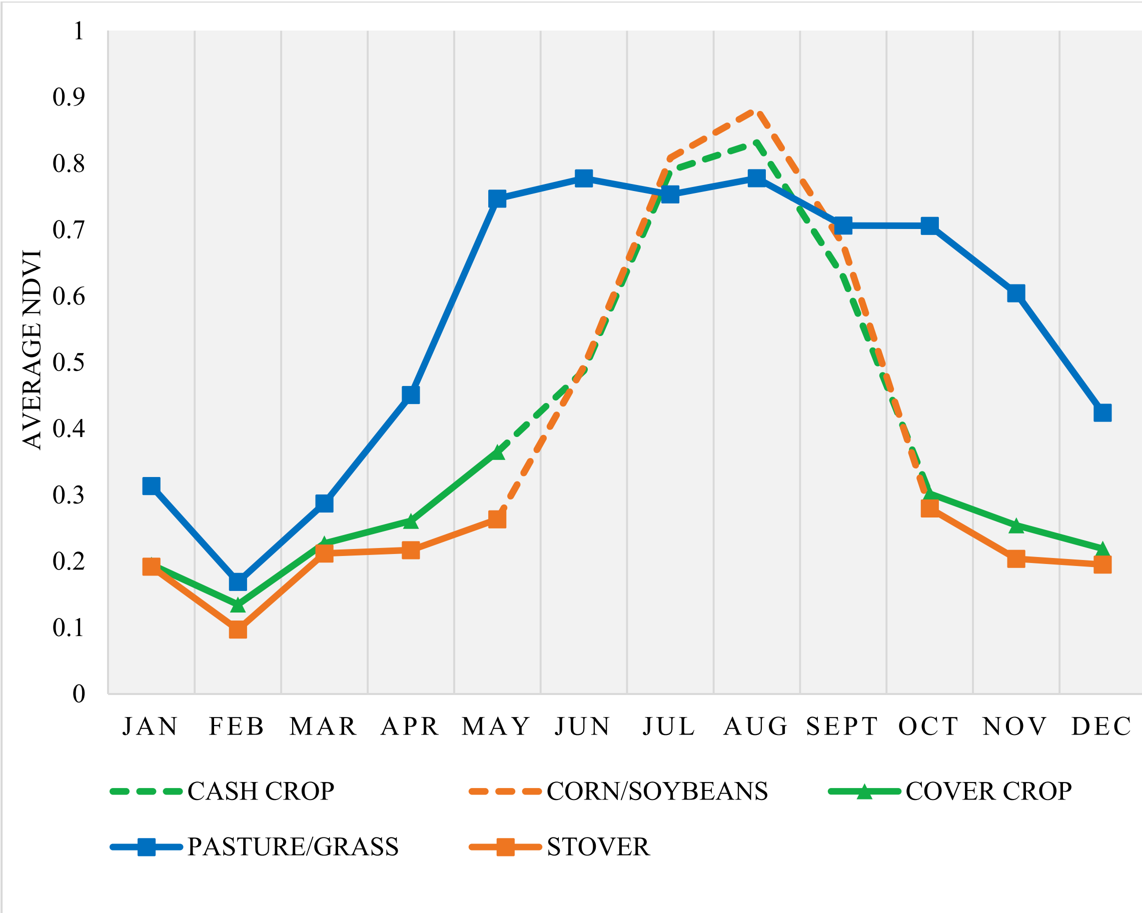

Figure 3.15. Spectral signatures by class using average NDVI.

From this graph, it can be seen that the NDVI spectral signatures for cover crops and stover do not show great differences, and this had an impact on the developed model. However, there are two months: October and December, when the differences between classes were more notorious, and in particular for the Pasture/Grass category.

The NDVI decision tree classification model is shown in Figure 3.16. The 274 fields present in the dataset formed the root of the tree (top of the tree), being Cover Crops the most relevant category, consisting of 92 fields which represented the 34% of the data. The remaining 66% was divided into equal parts under Pasture/Grass and Stover categories, with 91 fields on each one. The boxes (nodes) were labeled with the class that had the highest percentage of observations for that node and were identified with numbers. The probability for predicting the classes is shown in the second line of the box; the first value corresponds to Cover Crops, the second to Pasture/Grass and the third to Stover. The color gradient of the boxes is a visual representation of the node probability for predicting its main class (darker colors indicate higher probability). The third line in the box corresponds to the percentage of observations of the dataset grouped by the node.

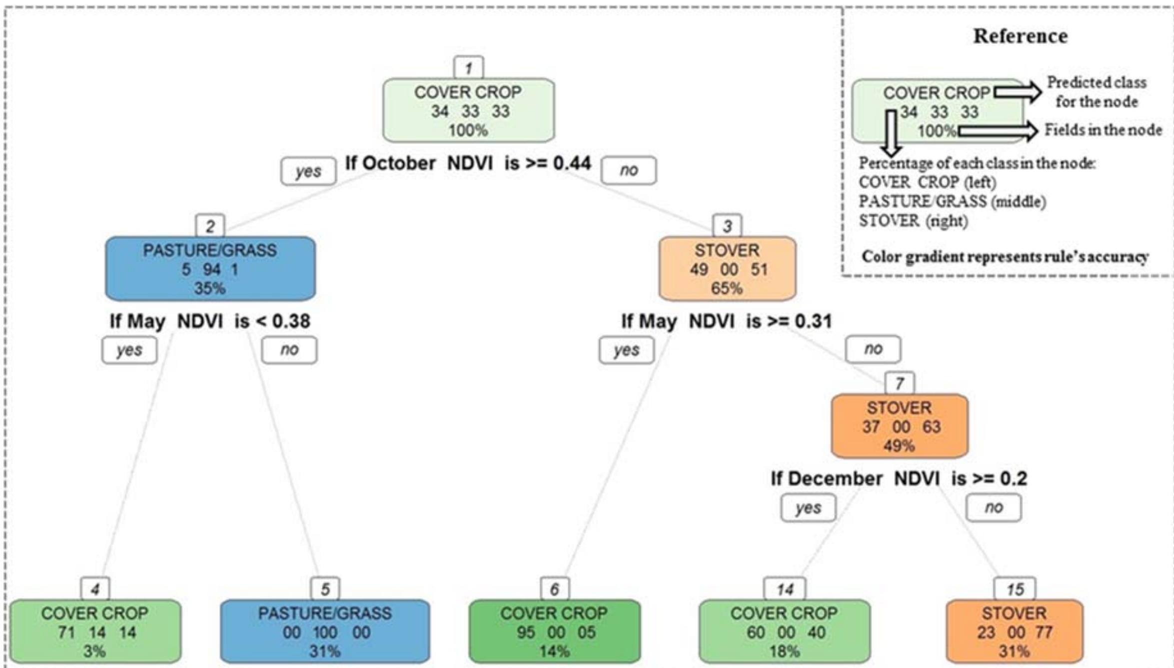

Figure 3.16. Decision tree for land cover classification.

The most relevant variables for the classification model were October, May, and December average NDVI. From Figure 3.15 it can be seen that October and May NDVI presented the greatest differences between classes. Hence it was expected that these variables were selected by the model to separate the categories. Also, to evaluate the sensitivity of the model to the fields in the dataset, different random selections of the 70% calibration datasets were created. Even when some variations on the threshold values were detected among the different models, October and May NDVI were selected for splitting the data in most of them.

Descriptive statistics for the parameters used in the model (October, May, and December NDVI) are shown in (Figure 3.17).

A field's October NDVI value forms the primary split or branching in the model, with a breakpoint value of 0.44. Fields with October NDVI ≥ 0.44 are most likely to be pasture or grass (94%). In order to split the data further from that point, the model uses May NDVI; if May NDVI < 0.38, the field is classified as cover crop, otherwise it is classified as pasture or grass. In effect, this tends to identify fields as grass or pasture if they have relatively high NDVI in both October and May. For fields with cover crops, they may have robust ground cover later in the year after a fall establishment (thus high October NDVI), but are likely to be killed off and/or plowed under early in the spring in preparation for planting the season's regular crop (thus low May NDVI).

The secondary May NDVI threshold is effective at identifying pasture/grass (100% of the fields so categorized are indeed pasture or grass). At the end of the winter or early spring, depending on weather conditions, pastures resume its growth, and as a consequence its levels of greenness increase. Later in the spring, the NDVI reaches the maximum levels, and remains roughly stable during the summer, while the crop produces biomass. A decline in the NDVI is detectable during the fall, when weather conditions turn unfavorable for the crop to keep growing, reaching the minimum in the month of February.

The secondary May NDVI threshold is somewhat less effective at identifying cover crops (only 71% of those fields are in fact cover crops; 14% are corn/soybeans and 14% are pasture/grass). However, this branch of the tree is only 3% of the full dataset, indicating that this set of classification criteria is only useful for a small number of fields. Looking at the fields meeting these criteria, the cover crop fields identified by this rule were planted between August 7th and September 9th, which is somewhat unusual because generally cover crops are planted after corn or soybeans are harvested, mostly in October and early November. As a result, October's NDVI of these fields was higher than typically later-planted cover crops would be, and was similar to pastures, which resume their growth during the spring and show high values of NDVI during summer and early spring. The pasture/grass erroneously classified as cover crop was an alfalfa field, which presented an NDVI of 0.35 for the month of May, and was identified as an outlier when analyzing the distribution for its class (Figure 3.17). For that field, NDVI values for the following months were evaluated to detect if the alfalfa was terminated and replaced with other crop or if the field was left bare. However, the NDVI values for the next months were within the interquartile range, so it could be inferred that the low May NDVI was related to a particular condition, after which the alfalfa continued its growth. For the case of the stover field incorrectly classified as cover crop, it was soybeans grown in 2014 and also identified as an outlier for October's NDVI in its category. The field presented low NDVI values for November and December, so it could be assumed that it was harvested at the end of October or early November, probably before the first November satellite image (11/08/2014).

Fields with October NDVI < 0.44 are roughly equally likely to be stover or cover crop (51% and 49% respectively). May's NDVI was also the variable selected by the model to split the data further for this branching of the tree; if May NDVI ≥ 0.31, the field is classified as cover crop, if not it is classified as stover. Because 40% of the total cover crop fields in the dataset are classified under this rule, and also because it has the highest probability (94.87%) for the category, this set of classification criteria is the most significant for detecting cover crops (darkest green node of the tree). The relatively small predicting error arises from the inclusion of two stover fields with May NDVI of 0.31 and 0.32. From Figure 3.17 it can be observed that these values were close to the maximum of its category, so it might be possible that the fields were planted early in the season, and consequently were able to be detected sooner than others. Inspecting the cover crop fields selected by this rule, all of them were planted during October and the first ten days of November, a range that is considered as normal/late for the state of Iowa. The fall biomass production of the fields in this category would be influenced by the combination of weather conditions, the species selected and planting date, and it could be inferred that plant growth was at least enough to allow its survival. May NDVI would suggest there is at least a normal biomass production during the spring, suggesting that these fields had winter-hardy cover crops.

Because May NDVI is not as powerful to classify stover fields as it is for cover crops, a third breakpoint value is needed. A field is more likely to have a cover crop if December's NDVI $\geq$ 0.20, and stover if NDVI < 0.20. Analyzing the fields classified as cover crops, about 94% of these cover crops were planted during October. December NDVI $\geq$ 0.20 could suggest that the cover crops emerged; however, its survival would depend on the species and weather conditions of the year.

Fields with December's NDVI < 0.20 are most likely to be stover (77%). The relatively high effectiveness of this threshold for detecting stover fields could be explained by inspecting December's medians for cover crops and stover (Figure 3.17). The selected threshold is greater than stover's median (0.19) and smaller than cover crop's median

(0.21), making it more reliable for detecting fields with corn or soybeans residue. The cover crops erroneously included in this category were planted between October 20th and November 10th, and as a consequence they did not produce much biomass by December, showing low NDVI values which are similar to those from fields with stover.

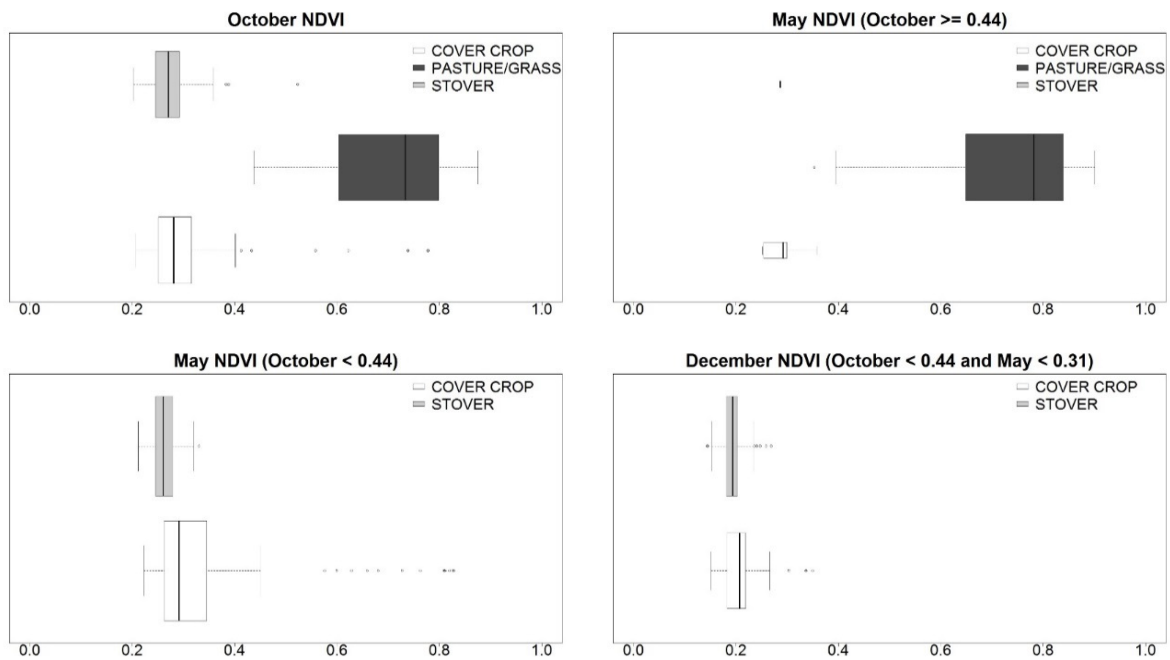

Figure 3.17. Distribution of average monthly NDVI by class.

3.4.1. Model evaluation and performance

The accuracy of the decision tree model for predicting each category was evaluated using a validation dataset, and an error matrix was constructed showing correctly and incorrectly classified fields (Table 3.7).

Table 3.7. Error matrix for land covers classes.

		PREDICTED AS			ROW TOTAL
		COVER CROP	PASTURE/GRASS	STOVER	
CLASS	COVER CROP	30	0	9	39
	PASTURE/GRASS	2	37	0	39
	STOVER	10	0	29	39
	COLUMN TOTAL	42	37	38	117
KAPPA = 0.73					

The validation dataset had a total of 117 fields, 39 for each category, and the overall accuracy of the model for predicting the classes was 82.0%. For the case of cover crops, 76.9% (30 fields) were identified by the model as cover crops, while the remaining ones were classified as stover fields. Overall the model said 35.8% of the data were cover crops when actually 33.3% of the data were cover crops, and pastures and grasses and stover fields were underestimated by the model by 1.6% and 0.9% respectively.

A kappa coefficient of 0.73 indicates a good agreement between the reference data and the results predicted by the model. However, on a dataset level, the model slightly overestimates the number of cover cropped fields.

The proportions of the classes on the dataset evaluated were noted representative of their actual proportions in the area of study, as a real study area will not have equal numbers of the three categories. Thus, a dataset considering the proportion of each category in the area of study (3 % of cover crop fields, 12% of pasture/grass fields, and 85% of stover fields) we created and evaluated. The fields in the dataset were classified using the threshold values identified by the model, and the results were analyzed using an error matrix (Table 3.8).

Table 3.8. Error matrix for a validation dataset representative of the study area.

		PREDICTED AS			ROW TOTAL
		COVER CROP	PASTURE/GRASS	STOVER	
CLASS	COVER CROP	4	0	0	4
	PASTURE/GRASS	0	14	0	14
	STOVER	20	0	79	99
	COLUMN TOTAL	24	14	79	117
KAPPA = 0.58					

For the case of cover crops and pastures, all the fields were correctly identified. However, 20 stover fields were classified as cover crops, which leads to an overestimation of 500% of the cover crop fields. The overestimation occurs because there is a small amount of cover crops in comparison to corn and soybean stover fields.

3.5 Conclusions

The results of this study demonstrate that remote sensing can successfully be used to detect cover crops in agricultural fields, and as a consequence, it is an appropriate tool to evaluate current and future cover crop adoptions. Landsat's 7 and 8 satellite image derived data was used to calculate average monthly vegetation indexes values, and characterize agricultural fields of the study area, being NDVI the most accurate index for the dataset.

A decision tree classification approach was used to develop sets of criteria for identifying cover crops, pastures and grasses, and stover fields based on average monthly NDVI. The model was able to classify fields by category with an overall accuracy of 82%, while its precision for detecting cover crops was 76.9%. Three rules were developed for cover crops detection, being October NDVI < 0.44 and May NDVI ≥ 0.31 the one with the highest probability (95%). In addition, the NDVI threshold can be used to estimate the biomass production by field, as a means of the effectiveness of the cover crop as a conservation practice.

The development of a similar model using more growing seasons could be helpful to account for the effect of plant growth variability, which is strongly associated with weather conditions. Also, further research is required to evaluate the performance of the model in other areas of study, as the breakpoint values might change.

3.6 References

Aronoff, Stanly. (2005). *Remote Sensing for GIS Managers.* ESRI Press. Redlands, California.

Bannari, A., Morin, D., Bonn, F., & Huete, A. R. (1995). A review of vegetation indices. *Remote Sensing Reviews*, 13(1–2), 95–120.

Baret, F., & Guyot, G. (1991). Potentials and Limits of Vegetation LAI and APAR Assessment. *Remote Sensing of Environment*, 35(2), 161–173.

Bauer, M. E., & Cipra, J. E. (1973). Identification of agricultural crops by computer processing of ERTS MSS data.

Biard, F., & Baret, F. (1997). Crop residue estimation using multiband reflectance. *Remote Sensing of Environment*, 59(3), 530–536. http://doi.org/10.1016/S0034-4257(96)00125-3

Blanco-Canqui, H., Holman, J. D., Schlegel, A. J., Tatarko, J., & Shaver, T. M. (2013). Replacing Fallow with Cover Crops in a Semiarid Soil: Effects on Soil Properties. *Soil Science Society of America Journal*, 77(3), 1026.

Bonner, I. J., Muth, D. J., Koch, J. B., & Karlen, D. L. (2014). Modeled Impacts of Cover Crops and Vegetative Barriers on Corn Stover Availability and Soil Quality. *BioEnergy Research*, 7(2), 576–589. http://doi.org/10.1007/s12155-014-9423-y

Carfagna, E., & Gallego, F. J. (2005). Using remote sensing for agricultural statistics. *International Statistical Review*, 73(3), 389–404.

Chuvieco, E. (Ed.). (2008). Earth observation of global change: the role of satellite remote sensing in monitoring global environment. New York: Springer.

Clark, A. (Ed.). (2007). Managing cover crops profitably (3rd ed). College Park, MD: Diane Publishing.

Dabney, S. M., Delgado, J. A., & Reeves, D. W. (2001). Using cover crops to improve soil and water quality. *Communications in Soil Science and Plant Analysis*, 32(7–8), 1221–1250. http://doi.org/10.1081/CSS-100104110

Daughtry, C. S. T., Doraiswamy, P. C., Hunt, E. R., Stern, A. J., McMurtrey, J. E., & Prueger, J. H. (2006). Remote sensing of crop residue cover and soil tillage intensity. *Soil and Tillage Research*, 91(1–2), 101–108.

Daughtry, C. S. T., Hunt, E. R., Doraiswamy, P. C., & McMurtrey, J. E. (2005). Remote Sensing the Spatial Distribution of Crop Residues. *Agronomy Journal*, 97(3), 864.

Daughtry, C. S. T., Hunt, E. R., & McMurtrey, J. E. (2004). Assessing crop residue cover using shortwave infrared reflectance. *Remote Sensing of Environment*, 90(1), 126–134.

Daughtry, C. S. T., Serbin, G., Reeves III, J. B., Doraiswamy, P. C., & Hunt Jr., E. R. (2010). Spectral Reflectance of Wheat Residue during Decomposition and Remotely Sensed Estimates of Residue Cover. *Remote Sensing*, 2(2), 416–431.

de Paul Obade, V., & Lal, R. (2013). Assessing land cover and soil quality by remote sensing and geographical information systems (GIS). CATENA, 104, 77–92. http://doi.org/10.1016/j.catena.2012.10.014

Flood, N. (2014). Continuity of Reflectance Data between Landsat-7 ETM+ and Landsat-8 OLI, for Both Top-of-Atmosphere and Surface Reflectance: A Study in the Australian Landscape. *Remote Sensing*, 6(9), 7952–7970.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80(1), 185–201.

French, A. N., Schmugge, T. J., & Kustas, W. P. (2000). Discrimination of senescent vegetation using thermal emissivity contrast. *Remote Sensing of Environment*, 74(2), 249–254.

Gelder, B. K., Kaleita, A. L., & Cruse, R. M. (2009). Estimating Mean Field Residue Cover on Midwestern Soils Using Satellite Imagery. *Agronomy Journal*, 101(3), 635.

Glenn, E. P., Huete, A. R., Nagler, P. L., & Nelson, S. G. (2008). Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape. *Sensors*, 8(4), 2136–2160.

Heilman, J. L., & Kress, M. R. (1987). Effects of vegetation on spectral irradiance at the soil surface. *Agronomy Journal*, 79(5), 765–768.

Hively, W. D., Lang, M., McCarty, G. W., Keppler, J., Sadeghi, A., & McConnell, L. L. (2009). Using satellite remote sensing to estimate winter cover crop nutrient uptake efficiency. *Journal of Soil and Water Conservation*, 64(5), 303–313.

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote sensing of environment*,25(3), 295-309.

Jackson, R. D., & Huete, A. R. (1991). Interpreting vegetation indices. *Preventive Veterinary Medicine*, 11(3), 185–200.

Jensen, J. R. (2009). Remote sensing of the environment: An earth resource perspective 2/e. Pearson Education India.

Kaspar, T. C., Jaynes, D. B., Parkin, T. B., & Moorman, T. B. (2007). Rye Cover Crop and Gamagrass Strip Effects on NO Concentration and Load in Tile Drainage. *Journal of Environment Quality*, 36(5), 1503. http://doi.org/10.2134/jeq2006.0468

Ke, Y., Im, J., Lee, J., Gong, H., & Ryu, Y. (2015). Characteristics of Landsat 8 OLI-derived NDVI by comparison with multiple satellite sensors and in-situ observations. *Remote Sensing of Environment*, 164, 298–313.

Kessavalou, A., & Walters, D. T. (1997). Winter rye as a cover crop following soybean under conservation tillage. *Agronomy Journal*, 89(1), 68–74.

Kirchmann, H., & Thorvaldsson, G. (2000). Challenging targets for future agriculture. *European Journal of Agronomy*, 12(3), 145–161.

Knowler, D., & Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy*, 32(1), 25–48.

Lal, R., Regnier, E., Eckert, D. J., Edwards, W. M., & Hammond, R. (1991). Expectations of cover crops for sustainable agriculture. *Cover Crops for Clean Water. Soil and Water Conserv. Soc.*, Ankeny, IA, 1(11), 1–11.

Langdale, G. W., Blevins, R. L., Karlen, D. L., McCool, D. K., Nearing, M. A., Skidmore, E. L., … Williams, J. R. (1991). Cover crop effects on soil erosion by wind and water. *Cover Crops for Clean Water. Soil and Water Conserv. Soc.*, Ankeny, IA, 15–22.

Leon, C. T., Shaw, D. R., Cox, M. S., Abshire, M. J., Ward, B., Wardlaw III, M. C., & Watson, C. (2003). Utility of remote sensing in predicting crop and soil characteristics. *Precision Agriculture*, 4(4), 359–384.

Li, P., Jiang, L., & Feng, Z. (2013). Cross-Comparison of Vegetation Indices Derived from Landsat-7 Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operational Land Imager (OLI) Sensors. *Remote Sensing*, 6(1), 310–329.

Lowrance, R., Hendrix, P. L., & Odum, E. P. (1986). A hierarchical approach to sustainable agriculture. *American Journal of Alternative Agriculture*, 1(4), 169–173.

Major, D. J., Baret, F., & Guyot, G. (1990). A ratio vegetation index adjusted for soil brightness. *International Journal of Remote Sensing*, 11(5), 727–740.

Malone, R. W., Jaynes, D. B., Kaspar, T. C., Thorp, K. R., Kladivko, E., Ma, L., … Searchinger, T. (2014). Cover crops in the upper midwestern United States: Simulated effect on nitrate leaching with artificial drainage. *Journal of Soil and Water Conservation*, 69(4), 292–305.

MCCC, 2015. Cover crop decision tool. http://mcccdev.anr.msu.edu/covercroptool.php. Accessed on April 09, 2015.

Meisinger, J. J., Hargrove, W. L., Mikkelsen, R. L., Williams, J. R., & Benson, V. W. (1991). Effects of cover crops on groundwater quality. Cover Crops for Clean Water. *Soil and Water Conservation Society*. Ankeny, Iowa, 266, 793–799.

Mitsch, W. J., Day, J. W., Gilliam, J. W., Groffman, P. M., Hey, D. L., Randall, G. W., & Wang, N. (2001). Reducing Nitrogen Loading to the Gulf of Mexico from the Mississippi River Basin: Strategies to Counter a Persistent Ecological Problem. *BioScience*, 51(5), 373–388.

Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, 114(4), 358–371. http://doi.org/10.1016/j.biosystemseng.2012.08.009

Nowak, P. J., & Cabot, P. E. (2004). The human dimension of resource management programs. *Journal of Soil and Water Conservation*, 59(6), 128A–135A.

Pearson, R. L., & Miller, L. D. (1972, October). Remote mapping of standing crop biomass for estimation of the productivity of the shortgrass prairie. In *Remote Sensing of Environment*, VIII(Vol. 1, p. 1355).

Pereira, W. E., & Hostettler, F. D. (1993). Nonpoint source contamination of the Mississippi River and its tributaries by herbicides. *Environmental Science & Technology*, 27(8), 1542–1552.

Prabhakara, K., Hively, W. D., & McCarty, G. W. (2015). Evaluating the relationship between biomass, percent groundcover and remote sensing indices across six winter cover crop fields in Maryland, United States. *International Journal of Applied Earth Observation and Geoinformation*, 39, 88–102.

Prabhakar, M., Prasad, Y. G., & Rao, M. N. (2012). Remote sensing of biotic stress in crop plants and its applications for pest management. In *Crop stress and its management: Perspectives and strategies* (pp. 517-545). Springer Netherlands.

Reeves, D. W. (1994). Cover crops and rotations. *Advances in Soil Science: Crops Residue Management*, 125–172.

Reeves, M. C., & Baggett, L. S. (2014). A remote sensing protocol for identifying rangelands with degraded productive capacity. *Ecological Indicators*, 43, 172–182. http://doi.org/10.1016/j.ecolind.2014.02.009

Rigby, D., Woodhouse, P., Young, T., & Burton, M. (2001). Constructing a farm level indicator of sustainable agricultural practice. *Ecological Economics*, 39(3), 463–478.

Robertson, G. P., & Swinton, S. M. (2005). Reconciling agricultural productivity and environmental integrity: a grand challenge for agriculture. *Frontiers in Ecology and the Environment*, 3(1), 38–46.

Rogan, J., Miller, J., Stow, D., Franklin, J., Levien, L., & Fischer, C. (2003). Land-Cover Change Monitoring with Classification Trees Using Landsat TM and Ancillary Data. *Photogrammetric Engineering & Remote Sensing*, 69(7), 793–804. http://doi.org/10.14358/PERS.69.7.793

Ryan, R. L., Erickson, D. L., & De Young, R. (2003). Farmers' motivations for adopting conservation practices along riparian zones in a mid-western agricultural watershed. *Journal of Environmental Planning and Management*, 46(1), 19–37.

Shan, J., Hussain, E., Kim, K., & Biehl, L. (2010). Flood mapping with satellite images and its web service. *Photogrammetric Engineering & Remote Sensing*, 76(2), 102–104.

She, X., Zhang, L., Cen, Y., Wu, T., Huang, C., & Baig, M. (2015). Comparison of the Continuity of Vegetation Indices Derived from Landsat 8 OLI and Landsat 7 ETM+ Data among Different Vegetation Types. *Remote Sensing*, 7(10), 13485–13506. http://doi.org/10.3390/rs71013485

Snapp, S. S., Swinton, S. M., Labarta, R., Mutch, D., Black, J. R., Leep, R., … O'Neil, K. (2005). Evaluating cover crops for benefits, costs and performance within cropping system niches. *Agronomy Journal*, 97(1), 322–332.

Staver, et al. (1991). Using cereal grain winter cover crops to reduce groundwater nitrate contamination in the mid-Atlantic coastal plain. (D. R. Kenney, R. M. Cruse, American Society of Agronomy, Soil Science Society of America, Crop Science Society of America, & Crop Science Society of America, Eds.). Madison, Wis: *Soil Science Society of America*.

Tomer, M. D., Porter, S. A., Boomer, K. M. B., James, D. E., Kostel, J. A., Helmers, M. J., … McLellan, E. (2015). Agricultural Conservation Planning Framework: 1. Developing Multipractice Watershed Planning Scenarios and Assessing Nutrient Reduction Potential. *Journal of Environment Quality*, 44(3), 754. http://doi.org/10.2134/jeq2014.09.0386

Tucker, C. J. (1979). Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. *Remote Sensing of Environment*, 8(2), 127–150.

USDA NASS (National Agricultural Statistics Service) Cropland Data Layer. (2013). Published crop-specific data layer. Available at https://nassgeodata.gmu.edu/CropScape/. Accessed on April, 09 2015. USDA-NASS, Washington, DC.

USDA NASS (National Agricultural Statistics Service) Cropland Data Layer. (2014). Published crop-specific data layer. Available at https://nassgeodata.gmu.edu/CropScape/. Accessed on April, 09 2015. USDA-NASS, Washington, DC.

USDA NASS (National Agricultural Statistics Service). (2010). Usual Planting and Harvesting Dates for U.S. Field Crops. Available at http://usda.mannlib.cornell.edu/usda/current/planting/planting-10-29-2010.pdf. Accessed on January 06, 2015. USDA-NASS, Washington, DC.

USGS. (2013). How do Landsat 8 band combinations differ from Landsat 7 or Landsat 5 satellite data? Available at http://landsat.usgs.gov/L8_band_combos.php. Accessed on December 22, 2014

Van der Werf, H. M. G., & Petit, J. (2002). Evaluation of the environmental impact of agriculture at the farm level: a comparison and analysis of 12 indicator-based methods. Agriculture, *Ecosystems & Environment*, 93(1), 131–145.

Weil, R., & Kremen, A. (2007). Thinking across and beyond disciplines to make cover crops pay. *Journal of the Science of Food and Agriculture*, 87(4), 551–557. http://doi.org/10.1002/jsfa.2742

Wolter, P. T., & Townsend, P. A. (2011). Multi-sensor data fusion for estimating forest species composition and abundance in northern Minnesota. *Remote Sensing of Environment*, 115(2), 671–691. http://doi.org/10.1016/j.rse.2010.10.010

Wolter, P. T., Townsend, P. A., & Sturtevant, B. R. (2009). Estimation of forest structural parameters using 5 and 10 meter SPOT-5 satellite data. *Remote Sensing of Environment*, 113(9), 2019–2036. http://doi.org/10.1016/j.rse.2009.05.009

Xu, D. (2014). Compare NDVI Extracted from Landsat 8 Imagery with that from Landsat 7 Imagery. *American Journal of Remote Sensing*, 2(2), 10. http://doi.org/10.11648/j.ajrs.20140202.11

Yao, H., Huang, Y., Hruska, Z., Thomson, S. J., & Reddy, K. N. (2012). Using vegetation index and modified derivative for early detection of soybean plant injury from glyphosate. *Computers and Electronics in Agriculture*, 89, 145–157. http://doi.org/10.1016/j.compag.2012.09.001

Zedler, J. B. (2003). Wetlands at Your Service: Reducing Impacts of Agriculture at the Watershed Scale. *Frontiers in Ecology and the Environment*, 1(2), 65. http://doi.org/10.2307/3868032

CHAPTER IV. SUMMARY AND CONCLUSIONS

4.1 Summary and conclusions

Since cover crops have an impact on soil and water quality, knowledge of their implementation plays a main role in the evaluation of current conservation practices and future actions required. Because remote sensing techniques can provide information over large areas, periodically, then can successfully be implemented to gather information from agricultural areas. Satellite image derived data from Landsat's 7 and 8 red and near-infrared bands was used to compute monthly average NDVI values to characterize the different groundcovers of the study area at the field level. A decision tree model approach was used to develop sets of criteria for the identification of fields with cover crops, pastures and grasses, and stover, based on monthly NDVI values. The model was developed based on a calibration dataset and tested using a validation dataset, and showed an overall accuracy of 82%. The level of precision for cover crop detection was 76.9%, and because this category was overestimated by 2.5%, the application of this set of criteria could result in an overestimation of the cover crops acreage. Further research is required to evaluate its performance in other areas of study.

The results of this study indicate that remote sensing techniques have the capability to differentiate cover crop fields from other land covers, although the accuracy of the classification would be strongly influenced by planting date and biomass production.

4.2 Recommendations

The sets of criteria developed to identifying different land covers showed a relatively high accuracy, even so, several factors could hinder its functionality on other datasets. Firstly, the proportions of the classes on the dataset evaluated were not representative of their actual proportions in the area of study. Using a dataset from a surveyed area, with current ratios for the classes, could lead to a more robust model.

The purpose of this study was to develop a remote sensing protocol independent on the species selected as a cover crop, planting date and method, date of emergence, biomass production, termination date, and other management practices related to the cover cropped fields. However, building a model based on a dataset with this information could contribute to elaborate additional conclusions on the application of the detection rules created by the model. Also, if extending the dataset and scaling up of this research to more years of study, variations on crop's NDVI that are related to climate conditions might be accounted better.

The index selected for this study, the NDVI, is one of the most used vegetation indices for the evaluation of vegetative covers. However, factors like vegetation moisture, soil moisture, percentage of vegetative cover, soil type, and management practices can affect the strength of the NDVI for characterizing the vegetation correctly. In addition, high soil's background reflectance during the establishment period of cover crops also influences the NDVI values. Because all the indexes tested in this study are based on the Red and Near Infrared bands, further research on indexes combining these and other bands is needed to evaluate the detection of cover crop fields using remotely sensed data.

APPENDIX A. ANALYSIS OF MEDIAN MONTHLY NDVI

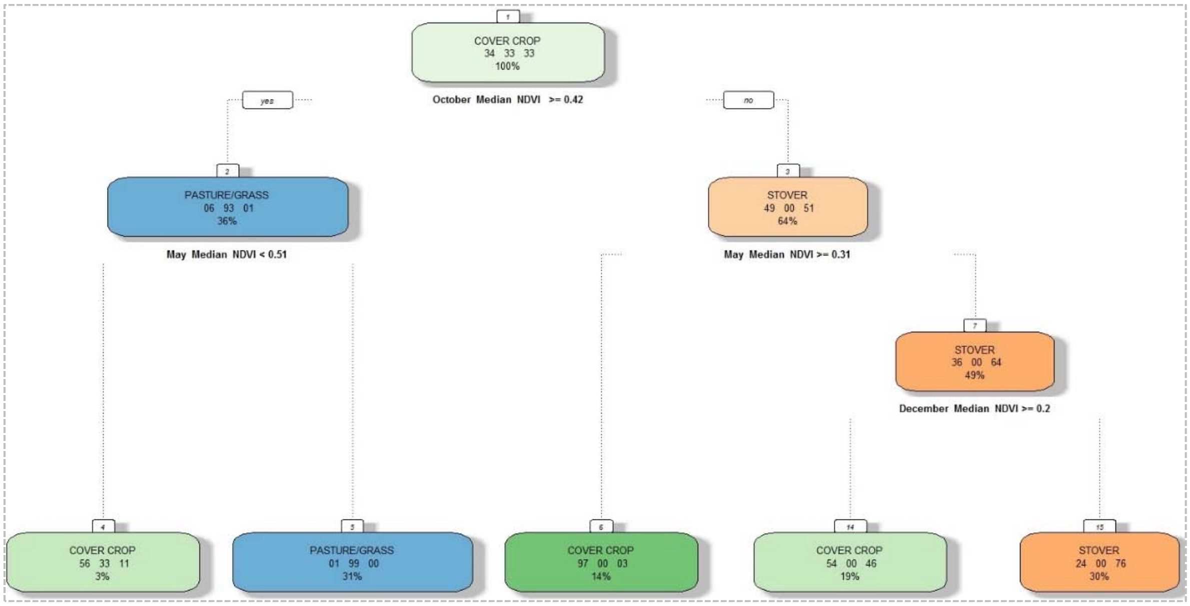

Figure A.1. Decision tree using median monthly NDVI.

Table A.1. Error matrix for median monthly NDVI decision tree.

		PREDICTED AS			ROW TOTAL
		COVER CROP	PASTURE/GRASS	STOVER	
CLASS	COVER CROP	29	0	10	39
	PASTURE/GRASS	2	37	0	39
	STOVER	14	0	25	39
	COLUMN TOTAL	45	37	35	117
OVERALL ACCURACY = 78% KAPPA = 0.66					

APPENDIX B. ANALYSIS OF AVERAGE MONTHLY RVI, VIN AND SAVI

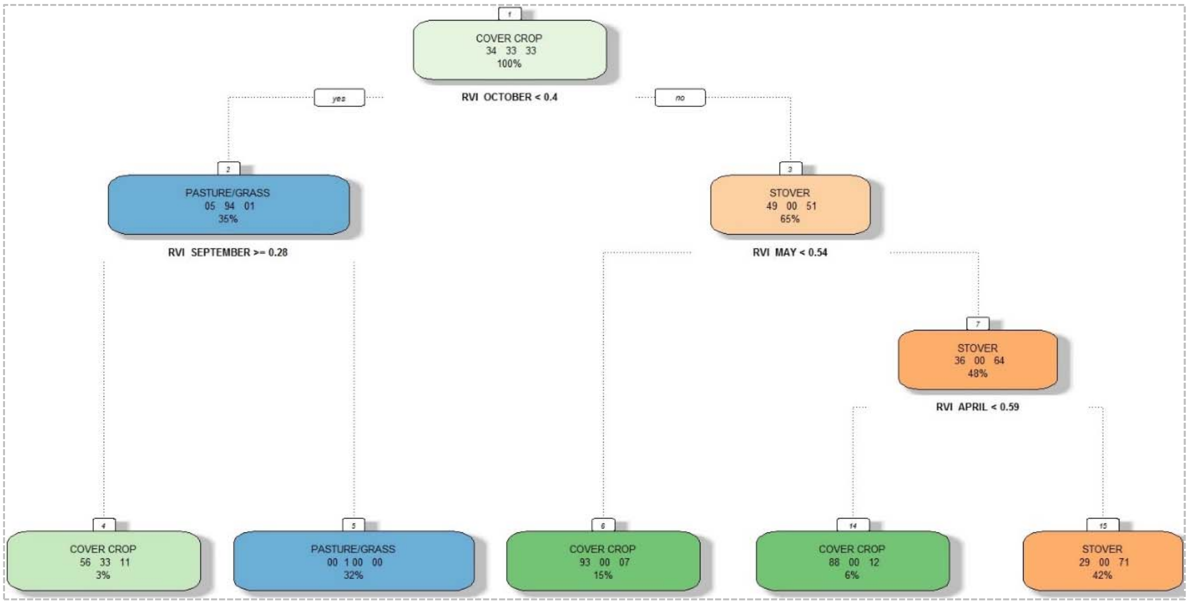

Figure B.1. Decision tree using average monthly RVI.

Table B.1. Error matrix for average monthly RVI decision tree.

		PREDICTED AS			ROW TOTAL
		COVER CROP	PASTURE/GRASS	STOVER	
CLASS	COVER CROP	24	0	15	39
	PASTURE/GRASS	3	36	0	39
	STOVER	3	1	35	39
	COLUMN TOTAL	30	37	50	117
OVERALL ACCURACY = 81% KAPPA = 0.71					

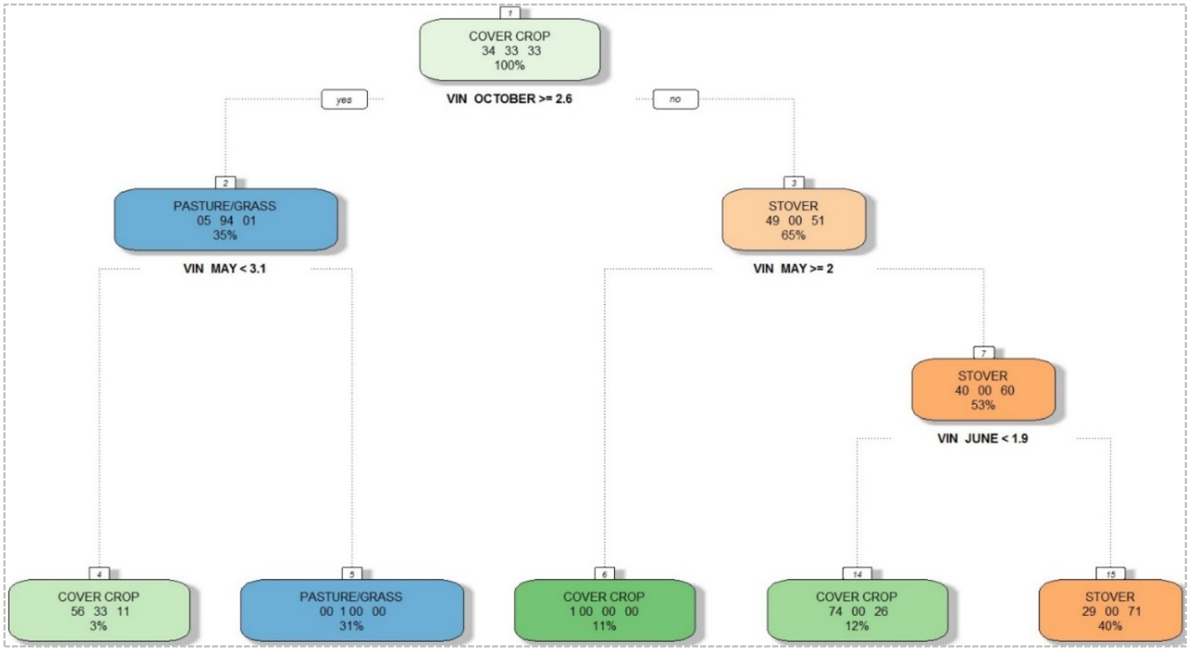

Figure B.2. Decision tree using average monthly VIN.

Table B.2. Error matrix for average monthly VIN decision tree.

		PREDICTED AS			ROW TOTAL
		COVER CROP	PASTURE/GRASS	STOVER	
CLASS	COVER CROP	25	0	14	39
	PASTURE/GRASS	2	37	0	39
	STOVER	7	0	32	39
	COLUMN TOTAL	34	37	46	117
OVERALL ACCURACY= 80% KAPPA = 0.70					

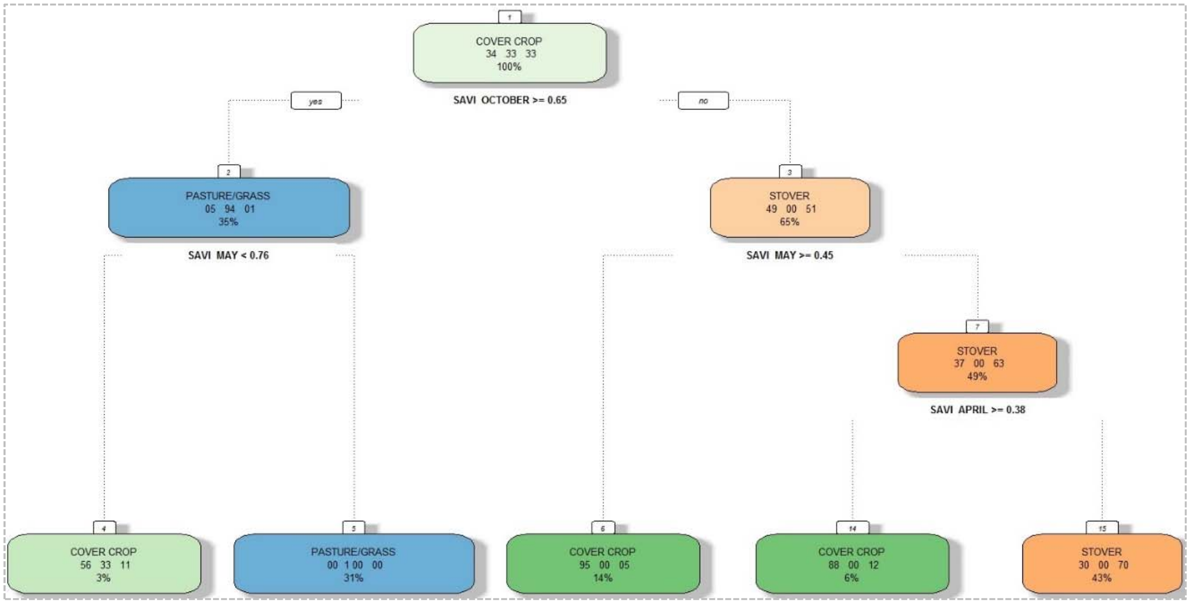

Figure B.3. Decision tree for average monthly SAVI.

Table B.3. Error matrix for average monthly SAVI decision tree.

		PREDICTED AS			ROW TOTAL
		COVER CROP	PASTURE/GRASS	STOVER	
CLASS	COVER CROP	24	0	15	39
	PASTURE/GRASS	3	36	0	39
	STOVER	4	0	35	39
	COLUMN TOTAL	31	36	50	58
OVERALL ACCURACY = 81% KAPPA = 0.71					

APPENDIX C. SATELLITE IMAGES DATASET

Table C.1. Satellite images and dates.

SENSOR	*IMAGE DATE*	*RASTER ID*
Landsat 7	2013-06-13	LE70260302013164EDC00
Landsat 7	2013-06-22	LE70250312013173EDC00
Landsat 8	2013-07-07	LC80260312013188LGN00
Landsat 7	2013-07-08	LE70250312013189EDC00
Landsat 7	2013-07-15	LE70260312013196EDC00
Landsat 8	2013-07-16	LC80250312013197LGN00
Landsat 7	2013-07-24	LE70250312013205EDC00
Landsat 7	2013-07-31	LE70260312013212EDC00
Landsat 8	2013-08-01	LC80250312013213LGN00
Landsat 8	2013-08-08	LC80260312013220LGN00
Landsat 7	2013-08-16	LE70260312013228EDC00
Landsat 8	2013-08-17	LC80250312013229LGN00
Landsat 8	2013-08-24	LC80260312013236LGN00
Landsat 7	2013-08-25	LE70250312013237EDC00
Landsat 7	2013-09-01	LE70260312013244EDC00
Landsat 8	2013-09-02	LC80250312013245LGN00
Landsat 8	2013-09-09	LC80260312013252LGN00
Landsat 7	2013-09-10	LE70250312013253EDC00
Landsat 8	2013-09-18	LC80250312013261LGN00
Landsat 8	2013-09-25	LC80260312013268LGN00
Landsat 7	2013-09-26	LE70250312013269EDC00
Landsat 8	2013-10-11	LC80260312013284LGN00
Landsat 7	2013-10-12	LE70250312013285EDC00
Landsat 8	2013-10-27	LC80260312013300LGN00
Landsat 7	2013-10-28	LE70250312013301EDC00
Landsat 8	2013-11-12	LC80260302013316LGN00
Landsat 7	2013-11-13	LE70250312013317EDC00
Landsat 8	2013-11-28	LC80260302013332LGN00
Landsat 7	2013-12-06	LE70260312013340EDC00
Landsat 8	2013-12-07	LC80250312013341LGN00
Landsat 8	2014-03-04	LC80260312014063LGN00
Landsat 8	2014-03-13	LC80250312014072LGN00
Landsat 8	2014-03-20	LC80260302014079LGN00
Landsat 7	2014-03-21	LE70250312014080EDC00
Landsat 8	2014-03-29	LC80250312014088LGN00

Landsat 8	2014-04-05	LC80260302014095LGN00
Landsat 7	2014-04-22	LE70250312014112EDC00
Landsat 8	2014-05-07	LC80260312014127LGN00
Landsat 8	2014-05-23	LC80260302014143LGN00
Landsat 7	2014-05-31	LE70260302014151EDC00
Landsat 8	2014-06-01	LC80250312014152LGN00
Landsat 7	2014-06-09	LE70250312014160EDC00
Landsat 8	2014-06-17	LC80250312014168LGN00
Landsat 8	2014-06-24	LC80260302014175LGN00
Landsat 7	2014-06-25	LE70250312014176EDC00
Landsat 8	2014-07-03	LC80250312014184LGN00
Landsat 8	2014-07-10	LC80260312014191LGN00
Landsat 7	2014-07-18	LE70260312014199EDC00
Landsat 8	2014-07-19	LC80250312014200LGN00
Landsat 7	2014-07-27	LE70250312014208EDC00
Landsat 7	2014-08-03	LE70260312014215EDC00
Landsat 8	2014-08-04	LC80250312014216LGN00
Landsat 7	2014-08-12	LE70250312014224EDC00
Landsat 7	2014-08-19	LE70260312014231EDC00
Landsat 7	2014-09-04	LE70260312014247EDC03
Landsat 8	2014-09-05	LC80250312014248LGN00
Landsat 7	2014-09-13	LE70250312014256EDC00
Landsat 8	2014-09-28	LC80260312014271LGN00
Landsat 7	2014-10-06	LE70260312014279EDC00
Landsat 8	2014-10-07	LC80250312014280LGN00
Landsat 7	2014-10-22	LE70260312014295EDC00
Landsat 8	2014-10-30	LC80260312014303LGN00
Landsat 7	2014-10-31	LE70250312014304EDC00
Landsat 8	2014-11-08	LC80250312014312LGN00
Landsat 7	2014-12-02	LE70250312014336EDC00
Landsat 8	2014-12-17	LC80260312014351LGN00
Landsat 8	2015-01-18	LC80260302015018LGN00
Landsat 8	2015-02-12	LC80250312015043LGN00
Landsat 8	2015-02-19	LC80260302015050LGN00
Landsat 7	2015-03-31	LE70260312015090EDC00
Landsat 8	2015-04-01	LC80250312015091LGN00
Landsat 7	2015-04-16	LE70260312015106EDC00
Landsat 8	2015-04-17	LC80250312015107LGN00
Landsat 8	2015-04-24	LC80260302015114LGN00
Landsat 8	2015-05-03	LC80250312015123LGN00
Landsat 7	2015-05-18	LE70260312015138EDC00
Landsat 8	2015-05-19	LC80250312015139LGN00
Landsat 7	2015-05-27	LE70250312015147EDC00

APPENDIX D. MEAN MONTHLY NDVI DATASET

Table D.1. Average monthly NDVI

CAL: field used for model calibration

VAL: field used for model validation

DATASET	*YEAR*	*CLASSIFICATION*	*J*	*F*	*M*	*A*	*M*	*J*	*J*	*A*	*S*	*O*	*N*	*D*
CAL	2013	COVER CROP			0.24	0.26	0.30	0.28	0.40	0.39	0.46	0.74	0.74	0.34
CAL	2013	COVER CROP			0.26	0.41	0.29	0.30	0.42	0.39	0.52	0.78	0.76	0.45
CAL	2013	COVER CROP			0.21	0.20	0.25	0.31	0.41	0.38	0.46	0.78	0.76	0.31
CAL	2013	COVER CROP			0.21	0.21	0.25	0.38	0.65	0.51	0.31	0.56	0.69	0.39
CAL	2013	COVER CROP			0.33	0.49	0.36	0.42	0.90	0.85	0.45	0.62	0.64	0.52
CAL	2013	COVER CROP			0.22	0.21	0.25	0.35	0.83	0.72	0.37	0.36	0.47	0.27
CAL	2013	COVER CROP			0.22	0.23	0.26	0.33	0.77	0.72	0.35	0.41	0.48	0.34
CAL	2013	COVER CROP			0.26	0.35	0.37	0.50	0.91	0.86	0.57	0.28	0.36	0.23
CAL	2013	COVER CROP			0.23	0.20	0.24	0.38	0.80	0.89	0.58	0.24	0.29	0.22
CAL	2013	COVER CROP			0.22	0.19	0.24	0.37	0.80	0.90	0.56	0.24	0.28	0.21
CAL	2013	COVER CROP			0.24	0.21	0.27	0.26	0.69	0.69	0.45	0.25	0.26	0.25
CAL	2013	COVER CROP			0.27	0.45	0.25	0.48	0.91	0.88	0.61	0.24	0.28	0.30
CAL	2013	COVER CROP			0.24	0.20	0.25	0.25	0.75	0.69	0.44	0.25	0.22	0.21
CAL	2013	COVER CROP			0.25	0.33	0.27	0.28	0.79	0.90	0.74	0.23	0.22	0.25
CAL	2013	COVER CROP			0.25	0.32	0.26	0.27	0.79	0.89	0.76	0.22	0.22	0.24
CAL	2013	COVER CROP			0.24		0.33	0.31	0.73	0.86	0.72	0.24	0.22	0.26
CAL	2013	COVER CROP			0.26	0.30	0.32	0.27	0.69	0.87	0.76	0.23	0.21	0.25
CAL	2013	COVER CROP			0.23	0.21	0.26	0.30	0.81	0.91	0.64	0.23	0.19	0.18
CAL	2013	COVER CROP			0.24	0.21	0.28	0.32	0.84	0.87	0.60	0.26	0.20	0.18
CAL	2013	COVER CROP			0.23	0.27	0.66	0.54	0.89	0.86	0.46	0.23	0.18	0.21
CAL	2013	COVER CROP			0.26	0.34	0.60	0.34	0.50	0.63	0.45	0.31	0.19	0.22
CAL	2013	COVER CROP			0.30	0.51	0.81	0.40	0.61	0.68	0.58	0.33	0.22	0.25
CAL	2013	COVER CROP			0.22	0.30	0.82	0.47	0.86	0.81	0.44	0.24	0.21	0.21
CAL	2013	COVER CROP			0.23	0.30	0.68	0.42	0.77	0.79	0.51	0.27	0.21	0.24
CAL	2013	COVER CROP			0.31	0.42	0.83	0.51	0.90	0.83	0.42	0.32	0.25	0.26
CAL	2013	COVER CROP			0.29	0.48	0.81	0.43	0.63	0.71	0.50	0.36	0.27	0.28
CAL	2013	COVER CROP			0.21	0.23	0.27	0.31	0.77	0.91	0.65	0.25	0.19	0.21
CAL	2013	COVER CROP			0.22	0.23	0.25	0.29	0.73	0.91	0.75	0.28	0.18	0.21
CAL	2013	COVER CROP			0.24	0.24	0.26	0.26	0.72	0.88	0.64	0.26	0.19	0.22
CAL	2013	COVER CROP			0.23	0.28	0.26	0.29	0.71	0.91	0.71	0.28	0.18	0.21

CAL	2013	COVER CROP			0.21	0.28	0.26	0.27	0.74	0.92	0.66	0.24	0.18	0.21
CAL	2013	COVER CROP			0.21	0.30	0.32	0.45	0.62	0.84	0.67	0.28	0.19	0.22
CAL	2013	COVER CROP			0.23	0.27	0.28	0.30	0.86	0.90	0.81	0.31	0.17	0.22
CAL	2013	COVER CROP			0.19	0.20	0.36	0.32	0.88	0.86	0.68	0.37	0.21	0.20
CAL	2013	COVER CROP			0.19	0.23	0.30	0.26	0.89	0.90	0.72	0.26	0.19	
CAL	2013	COVER CROP			0.19	0.20	0.32	0.27	0.89	0.88	0.62	0.29	0.18	0.18
CAL	2013	COVER CROP			0.21	0.21	0.40	0.48		0.86	0.67	0.27	0.16	0.18
CAL	2013	COVER CROP			0.24	0.23	0.35	0.36	0.44	0.81	0.77	0.30	0.14	0.20
CAL	2013	COVER CROP			0.18	0.24	0.37	0.31	0.75	0.86	0.67	0.31	0.19	0.17
CAL	2013	COVER CROP			0.22	0.26	0.31	0.33	0.59	0.82	0.77	0.29	0.20	0.21
CAL	2013	COVER CROP			0.19	0.23	0.33	0.29	0.81	0.87	0.71	0.32	0.19	0.18
CAL	2013	COVER CROP			0.19	0.27	0.33	0.56	0.62	0.86	0.73	0.32	0.20	0.23
CAL	2013	COVER CROP			0.20	0.24	0.27	0.28	0.82	0.88	0.74	0.24	0.18	0.18
CAL	2013	COVER CROP			0.21	0.23	0.28	0.27	0.83	0.89	0.78	0.37	0.18	0.17
CAL	2013	COVER CROP			0.20	0.23	0.34	0.41	0.87	0.88	0.70	0.30	0.18	0.18
CAL	2013	COVER CROP			0.25	0.24	0.26	0.27	0.81	0.89	0.74	0.21	0.19	0.21
CAL	2013	COVER CROP			0.19	0.21	0.28	0.61	0.86	0.89	0.71	0.28	0.16	0.16
CAL	2013	COVER CROP			0.19	0.21	0.23	0.45	0.74	0.88	0.70	0.30	0.17	0.16
CAL	2013	COVER CROP			0.19		0.22	0.46	0.82	0.89	0.71	0.30	0.17	0.15
CAL	2013	COVER CROP			0.23	0.23	0.27	0.28	0.61	0.77	0.84	0.31	0.20	0.21
CAL	2013	COVER CROP			0.19	0.19	0.37	0.35	0.84	0.88	0.67	0.31	0.19	0.17
CAL	2013	COVER CROP			0.26	0.22	0.28	0.31	0.77	0.85	0.61	0.23	0.20	0.21
CAL	2013	COVER CROP			0.19	0.21	0.29	0.51	0.88	0.89	0.63	0.27	0.18	0.17
CAL	2013	COVER CROP			0.25	0.21	0.28	0.30	0.75	0.92	0.81	0.26	0.16	0.19
CAL	2014	COVER CROP	0.33	0.10	0.41	0.26	0.27	0.67	0.88	0.90	0.63	0.29	0.30	0.34
CAL	2014	COVER CROP	0.19	0.06	0.21	0.23	0.28	0.30	0.84	0.92	0.64	0.30	0.25	0.21
CAL	2014	COVER CROP	0.32	0.24	0.43	0.52	0.27	0.46	0.85	0.88	0.63	0.30	0.31	0.35
CAL	2014	COVER CROP	0.19		0.21	0.23	0.26	0.31	0.89	0.88	0.70	0.24		0.20
CAL	2014	COVER CROP	0.20		0.22	0.23	0.26	0.32	0.85	0.88	0.70	0.26		0.20
CAL	2014	COVER CROP	0.18		0.26	0.27	0.24	0.44	0.86	0.80	0.56	0.25	0.22	0.22
CAL	2014	COVER CROP	0.24		0.29	0.30	0.25	0.45	0.86	0.78	0.43	0.25	0.24	0.24
CAL	2014	COVER CROP	0.22	0.22	0.27	0.27	0.27	0.47	0.84	0.94	0.51	0.25	0.24	0.22
CAL	2014	COVER CROP	0.20	0.09	0.24	0.29	0.33	0.69	0.89	0.90	0.69	0.23	0.22	0.19
CAL	2014	COVER CROP	0.20		0.22	0.26	0.31	0.41	0.85	0.89	0.67	0.25	0.25	0.21
CAL	2014	COVER CROP	0.19		0.24	0.36	0.28	0.55	0.80	0.93	0.56	0.27	0.24	0.23
CAL	2014	COVER CROP	0.19	0.21	0.21	0.25	0.30	0.42	0.81	0.87	0.65	0.25	0.24	0.20
CAL	2014	COVER CROP	0.16		0.21	0.20	0.26	0.87	0.88	0.88	0.75	0.22	0.21	0.19
CAL	2014	COVER CROP	0.16		0.20	0.24	0.33	0.70	0.84	0.87	0.59	0.25	0.20	0.18
CAL	2014	COVER CROP	0.16		0.20	0.22	0.27	0.84	0.87	0.88	0.68	0.28	0.22	0.18
CAL	2014	COVER CROP	0.14		0.20	0.23	0.29	0.69	0.86	0.85	0.79	0.31	0.21	0.18
CAL	2014	COVER CROP	0.15		0.21	0.20	0.30	0.68	0.85	0.84	0.66	0.29	0.21	0.20
CAL	2014	COVER CROP	0.21		0.23	0.26	0.27	0.41	0.64	0.89	0.73	0.26	0.23	0.21
CAL	2014	COVER CROP	0.18		0.23	0.32	0.73	0.70	0.87	0.88	0.65	0.25	0.22	0.21

CAL	2014	COVER CROP	0.17	0.05	0.20	0.22	0.34	0.86	0.89	0.88	0.60	0.25	0.20	0.18
CAL	2014	COVER CROP	0.16		0.20	0.23	0.45	0.62	0.89	0.88	0.73	0.26	0.21	0.18
CAL	2014	COVER CROP	0.24		0.30	0.41	0.83	0.67	0.80	0.71	0.58	0.43	0.33	0.27
CAL	2014	COVER CROP	0.22		0.27	0.34	0.76	0.66	0.82	0.69	0.53	0.35	0.29	0.25
CAL	2014	COVER CROP	0.20		0.26	0.33	0.63	0.60	0.85	0.90	0.75	0.34	0.26	0.22
CAL	2014	COVER CROP	0.17		0.22	0.28	0.81	0.59	0.83	0.74	0.87	0.40	0.24	0.20
CAL	2014	COVER CROP		0.08	0.22	0.30	0.44	0.35	0.59	0.89	0.82	0.25	0.25	0.21
CAL	2014	COVER CROP	0.16		0.19	0.21	0.24	0.71	0.91	0.91	0.72	0.31	0.22	0.18
CAL	2014	COVER CROP	0.24		0.24	0.27	0.29	0.61	0.90	0.90	0.75	0.25	0.24	0.21
CAL	2014	COVER CROP	0.17		0.21	0.29	0.58	0.47	0.75	0.91	0.60	0.26	0.22	0.20
CAL	2014	COVER CROP	0.20		0.22	0.23	0.28	0.61	0.89	0.82	0.73	0.33	0.24	0.19
CAL	2014	COVER CROP	0.18		0.19	0.21	0.25	0.58	0.87	0.85	0.74	0.32	0.22	0.18
CAL	2014	COVER CROP	0.17		0.19	0.21	0.33	0.68	0.86	0.88	0.80	0.34	0.23	0.18
CAL	2014	COVER CROP	0.17	0.06	0.20	0.20	0.32	0.61	0.85	0.86	0.81	0.31	0.23	0.18
CAL	2014	COVER CROP	0.16		0.19	0.20	0.31	0.60	0.85		0.84	0.32	0.24	0.18
CAL	2014	COVER CROP	0.21		0.23	0.25	0.31	0.84	0.83	0.87	0.66	0.39	0.24	0.20
CAL	2014	COVER CROP	0.15		0.19	0.21	0.35	0.87	0.90	0.90	0.75	0.30	0.22	0.17
CAL	2014	COVER CROP	0.18		0.20	0.20	0.24	0.66	0.88	0.88	0.72	0.36	0.21	0.18
CAL	2014	COVER CROP	0.17		0.19	0.21	0.25	0.66	0.91	0.91	0.78	0.27	0.23	0.19
CAL	2013	PASTURE/GRASS			0.29		0.77	0.76	0.68	0.70	0.56	0.59	0.44	0.46
CAL	2013	PASTURE/GRASS			0.29	0.61		0.70	0.73	0.68	0.57	0.71	0.45	0.46
CAL	2013	PASTURE/GRASS			0.29	0.43	0.81	0.60	0.78	0.79	0.58	0.76	0.76	0.49
CAL	2013	PASTURE/GRASS			0.25	0.25	0.40	0.80	0.82	0.76	0.65	0.48	0.34	0.31
CAL	2013	PASTURE/GRASS			0.32	0.40	0.60	0.76	0.70	0.66	0.56	0.57	0.44	0.37
CAL	2013	PASTURE/GRASS			0.28	0.35	0.82	0.70	0.76	0.86	0.67	0.85	0.61	0.44
CAL	2013	PASTURE/GRASS			0.28	0.35	0.61	0.74	0.78	0.76	0.73	0.64	0.53	0.45
CAL	2013	PASTURE/GRASS			0.23	0.25	0.67	0.76	0.73	0.74	0.57	0.50	0.41	0.31
CAL	2013	PASTURE/GRASS			0.35	0.36	0.65	0.77	0.80	0.78	0.75	0.65	0.52	0.43
CAL	2013	PASTURE/GRASS			0.24	0.26	0.64	0.78	0.82	0.83	0.75	0.55	0.40	0.33
CAL	2013	PASTURE/GRASS			0.29	0.38	0.68	0.79	0.75	0.70	0.66	0.65	0.44	0.42
CAL	2013	PASTURE/GRASS			0.21	0.30	0.63	0.75	0.71	0.65	0.58	0.54	0.41	0.36
CAL	2013	PASTURE/GRASS			0.27	0.35	0.58	0.74	0.81	0.76	0.59	0.50	0.36	0.32
CAL	2013	PASTURE/GRASS			0.25	0.27	0.53	0.75	0.75	0.72	0.60	0.53	0.38	0.33
CAL	2013	PASTURE/GRASS			0.25	0.27	0.64	0.87	0.84	0.86	0.81	0.59	0.36	0.25
CAL	2013	PASTURE/GRASS			0.21	0.26	0.48	0.78	0.80	0.76	0.61	0.48	0.35	0.30
CAL	2013	PASTURE/GRASS			0.24	0.40	0.73	0.66	0.72	0.73	0.63	0.61	0.47	0.39
CAL	2013	PASTURE/GRASS			0.31	0.54	0.73	0.83	0.76	0.70	0.57	0.59	0.43	0.40
CAL	2013	PASTURE/GRASS			0.20	0.31	0.57	0.75	0.74	0.71	0.57	0.51	0.37	0.30
CAL	2013	PASTURE/GRASS			0.28	0.61	0.68	0.81	0.59	0.70	0.59	0.71	0.52	0.39
CAL	2013	PASTURE/GRASS			0.25	0.35	0.74	0.85	0.81	0.78	0.52	0.57	0.34	0.33
CAL	2013	PASTURE/GRASS			0.30	0.48		0.66	0.76	0.76	0.68	0.75	0.47	0.44
CAL	2013	PASTURE/GRASS			0.31	0.39	0.82	0.78	0.86	0.73	0.76	0.73	0.70	0.50
CAL	2013	PASTURE/GRASS			0.30	0.44	0.84	0.73	0.48	0.75	0.69	0.80	0.73	0.59

CAL	2013	PASTURE/GRASS			0.33	0.26	0.79	0.90	0.67	0.65	0.74	0.83	0.67	0.50
CAL	2013	PASTURE/GRASS			0.30	0.42	0.90	0.90	0.78	0.71	0.79	0.68	0.58	0.55
CAL	2013	PASTURE/GRASS			0.27	0.38	0.85	0.48	0.82	0.79	0.75	0.79	0.74	0.48
CAL	2013	PASTURE/GRASS			0.28	0.37	0.78	0.90	0.83	0.88	0.71	0.88	0.76	0.63
CAL	2013	PASTURE/GRASS			0.28	0.36	0.88	0.75	0.57	0.69	0.73	0.78	0.73	0.63
CAL	2013	PASTURE/GRASS			0.30	0.61	0.87	0.75	0.78	0.78	0.72	0.78	0.76	0.43
CAL	2013	PASTURE/GRASS			0.27	0.69	0.85	0.69	0.76	0.89	0.77	0.81	0.69	0.44
CAL	2013	PASTURE/GRASS			0.26	0.47	0.81	0.87	0.84	0.77	0.70	0.82	0.76	0.56
CAL	2013	PASTURE/GRASS			0.29	0.56	0.77	0.85	0.74	0.74	0.70	0.78	0.65	0.54
CAL	2013	PASTURE/GRASS			0.27	0.54	0.86	0.65	0.72	0.76	0.66	0.68	0.63	0.41
CAL	2013	PASTURE/GRASS			0.26	0.41	0.84	0.48	0.59	0.84	0.83	0.81	0.65	0.34
CAL	2013	PASTURE/GRASS			0.26	0.49	0.62	0.88	0.81	0.80	0.68	0.83	0.80	0.54
CAL	2013	PASTURE/GRASS			0.28		0.81	0.73	0.85	0.84	0.83	0.80	0.64	0.35
CAL	2013	PASTURE/GRASS			0.30	0.40	0.88	0.79	0.77	0.85	0.64	0.69	0.50	0.33
CAL	2013	PASTURE/GRASS			0.29	0.52	0.60	0.74	0.78	0.76	0.68	0.76	0.58	0.45
CAL	2013	PASTURE/GRASS			0.31	0.63		0.54	0.70	0.67	0.60	0.76	0.61	0.55
CAL	2013	PASTURE/GRASS			0.31	0.66		0.52	0.51	0.75	0.77	0.77	0.65	0.47
CAL	2013	PASTURE/GRASS			0.32	0.58	0.81	0.64	0.72	0.77	0.71	0.76	0.67	0.47
CAL	2013	PASTURE/GRASS			0.29	0.69	0.88	0.86	0.79	0.84	0.76	0.87	0.76	0.54
CAL	2013	PASTURE/GRASS			0.27	0.56	0.82	0.66	0.60	0.80	0.74	0.85	0.75	0.49
CAL	2013	PASTURE/GRASS			0.29	0.34	0.83	0.69	0.81	0.83	0.77	0.78	0.71	0.51
CAL	2013	PASTURE/GRASS			0.30	0.38	0.80	0.69	0.77	0.80	0.66	0.72	0.50	0.42
CAL	2014	PASTURE/GRASS	0.31	0.24	0.38	0.53	0.76	0.81	0.68	0.77	0.76	0.62	0.52	0.42
CAL	2014	PASTURE/GRASS		0.17		0.50	0.83	0.74	0.80	0.77	0.80	0.65	0.64	0.43
CAL	2014	PASTURE/GRASS	0.36		0.35	0.54	0.83	0.89	0.67	0.87	0.76	0.75	0.64	0.44
CAL	2014	PASTURE/GRASS	0.28		0.24	0.28	0.59	0.80	0.84	0.81	0.67	0.44	0.37	0.29
CAL	2014	PASTURE/GRASS	0.33	0.20	0.37	0.50	0.70	0.72	0.77	0.76	0.78	0.65	0.52	0.44
CAL	2014	PASTURE/GRASS	0.30		0.28	0.47	0.74	0.75	0.79	0.84	0.89	0.81		0.43
CAL	2014	PASTURE/GRASS	0.27		0.35	0.47	0.69	0.74	0.76	0.79	0.76	0.56	0.56	0.42
CAL	2014	PASTURE/GRASS	0.22		0.23	0.28	0.63	0.79	0.78	0.81	0.68	0.50		0.30
CAL	2014	PASTURE/GRASS	0.38		0.35	0.45	0.64	0.80	0.81	0.77	0.77	0.64		0.49
CAL	2014	PASTURE/GRASS	0.29	0.03	0.26	0.30	0.69	0.87	0.85	0.86	0.71	0.54	0.30	0.34
CAL	2014	PASTURE/GRASS	0.34		0.35	0.45	0.75	0.79	0.69	0.66	0.69	0.65	0.55	0.44
CAL	2014	PASTURE/GRASS	0.25		0.22	0.25	0.62	0.74	0.79	0.76	0.66	0.46		0.27
CAL	2014	PASTURE/GRASS	0.19		0.22	0.28	0.74	0.83	0.86	0.84	0.85	0.60		0.27
CAL	2014	PASTURE/GRASS	0.25	0.18	0.30	0.41	0.75	0.79	0.75	0.77	0.75	0.64	0.52	0.40
CAL	2014	PASTURE/GRASS	0.33	0.15	0.25	0.31	0.61	0.62	0.66	0.73	0.71	0.58	0.53	0.29
CAL	2014	PASTURE/GRASS	0.25		0.35	0.43	0.72	0.84	0.79	0.79	0.73	0.58	0.54	0.40
CAL	2014	PASTURE/GRASS	0.25	0.14	0.32	0.40	0.61	0.73	0.81	0.81	0.76	0.58		0.34
CAL	2014	PASTURE/GRASS	0.27	0.19	0.23	0.30	0.62	0.75	0.73	0.71	0.61	0.47	0.43	0.30
CAL	2014	PASTURE/GRASS	0.26	0.07	0.36	0.52	0.85	0.76	0.67	0.72	0.78	0.65		0.38
CAL	2014	PASTURE/GRASS	0.36		0.36	0.44	0.83	0.84	0.71	0.92	0.92	0.74		0.46
CAL	2014	PASTURE/GRASS	0.24		0.30	0.57	0.66	0.88	0.79	0.77	0.69	0.82	0.74	0.37

CAL	2014	PASTURE/GRASS	0.35		0.39	0.61	0.85	0.77	0.87	0.74	0.68	0.73		0.50
CAL	2014	PASTURE/GRASS	0.36		0.31	0.53	0.84	0.85	0.79	0.83	0.70	0.82		0.50
CAL	2014	PASTURE/GRASS	0.39	0.24	0.36	0.58	0.85	0.80	0.74	0.90	0.87	0.87		0.47
CAL	2014	PASTURE/GRASS	0.33		0.38	0.60	0.79	0.90	0.62	0.87	0.88	0.76		0.48
CAL	2014	PASTURE/GRASS	0.29	0.20	0.30	0.50	0.88	0.78	0.77	0.90	0.71	0.84	0.82	0.33
CAL	2014	PASTURE/GRASS	0.38	0.21	0.33	0.50	0.82	0.78	0.76	0.87	0.74	0.73	0.80	0.36
CAL	2014	PASTURE/GRASS	0.33		0.35	0.53	0.88	0.82	0.76	0.87	0.83	0.84	0.82	0.50
CAL	2014	PASTURE/GRASS	0.32	0.22	0.30	0.45	0.61	0.78	0.78	0.91	0.70	0.61	0.64	0.27
CAL	2014	PASTURE/GRASS	0.28	0.21	0.34	0.48	0.88	0.79	0.77	0.81	0.81	0.78	0.68	0.42
CAL	2014	PASTURE/GRASS	0.26		0.29	0.40	0.68	0.84	0.77		0.76	0.83	0.79	0.30
CAL	2014	PASTURE/GRASS	0.31		0.35	0.54	0.81	0.83	0.73	0.90	0.78	0.66	0.75	0.40
CAL	2014	PASTURE/GRASS	0.36		0.34	0.56	0.35	0.93	0.78	0.88	0.79	0.76	0.74	0.47
CAL	2014	PASTURE/GRASS	0.33		0.32	0.62	0.88	0.86	0.62	0.81	0.85	0.79		0.53
CAL	2014	PASTURE/GRASS	0.32		0.33	0.54	0.85	0.79	0.80	0.77	0.75	0.80	0.76	0.47
CAL	2014	PASTURE/GRASS				0.36	0.87	0.75	0.66	0.90	0.68	0.82	0.86	0.50
CAL	2014	PASTURE/GRASS	0.33		0.33	0.51	0.73	0.70	0.73	0.82	0.76	0.74	0.66	0.45
CAL	2014	PASTURE/GRASS	0.36	0.11	0.30	0.50	0.59	0.79	0.75	0.87	0.85	0.82	0.67	0.44
CAL	2014	PASTURE/GRASS		0.24		0.56	0.83	0.77	0.69	0.79	0.63	0.72	0.72	0.47
CAL	2014	PASTURE/GRASS	0.31		0.41	0.40	0.81	0.67	0.68	0.89	0.59	0.86	0.84	0.50
CAL	2014	PASTURE/GRASS	0.31	0.13	0.32	0.49	0.89	0.81	0.70	0.70	0.92	0.80	0.77	0.41
CAL	2014	PASTURE/GRASS	0.35	0.14	0.29	0.51	0.87	0.76	0.71	0.87	0.85	0.79	0.71	0.48
CAL	2014	PASTURE/GRASS	0.32		0.30	0.50	0.85	0.89	0.75	0.79	0.80	0.74	0.80	0.44
CAL	2014	PASTURE/GRASS	0.37	0.19		0.53	0.83	0.84	0.82	0.87	0.85	0.83		0.44
CAL	2014	PASTURE/GRASS	0.37		0.37	0.40	0.85	0.67	0.83	0.69	0.75	0.66	0.55	0.46
CAL	2013	STOVER			0.19	0.21	0.22	0.23	0.76	0.89	0.76	0.26	0.17	0.14
CAL	2013	STOVER			0.21	0.24	0.24	0.34	0.60	0.80	0.53	0.23	0.18	0.20
CAL	2013	STOVER			0.21	0.26	0.29	0.38	0.65	0.91	0.78	0.31	0.28	0.19
CAL	2013	STOVER			0.18	0.20		0.65	0.90	0.88	0.55	0.27	0.20	0.17
CAL	2013	STOVER			0.19	0.21		0.58	0.92	0.89	0.68	0.32	0.18	0.17
CAL	2013	STOVER			0.22	0.21	0.26	0.27	0.71	0.88	0.74	0.21	0.19	0.17
CAL	2013	STOVER			0.19	0.20	0.23	0.43	0.84	0.89	0.60	0.33	0.19	0.20
CAL	2013	STOVER			0.17	0.17	0.21	0.55	0.85	0.87	0.66	0.26	0.16	0.17
CAL	2013	STOVER			0.18	0.19	0.23	0.40	0.87	0.86	0.79	0.38	0.19	0.17
CAL	2013	STOVER			0.21	0.21	0.28	0.31	0.70	0.91	0.83	0.28	0.18	0.15
CAL	2013	STOVER			0.18	0.19	0.22	0.44	0.88	0.87	0.73	0.36	0.23	0.18
CAL	2013	STOVER			0.22	0.21	0.28	0.33	0.63	0.89	0.68	0.25	0.18	0.17
CAL	2013	STOVER			0.20	0.21	0.25	0.31	0.72	0.93	0.79	0.26	0.20	0.19
CAL	2013	STOVER			0.26	0.25	0.29	0.38	0.77	0.74	0.47	0.25	0.21	0.24
CAL	2013	STOVER			0.24	0.23	0.28	0.33	0.55	0.84	0.64	0.23	0.17	0.22
CAL	2013	STOVER			0.21	0.19	0.24	0.44	0.87	0.88	0.64	0.27	0.20	0.20
CAL	2013	STOVER			0.19	0.18	0.23	0.49	0.88	0.89	0.69	0.28	0.18	0.18
CAL	2013	STOVER			0.26	0.21	0.27	0.54	0.90	0.88	0.52	0.22	0.18	0.22
CAL	2013	STOVER			0.18	0.20	0.26	0.51	0.88	0.86	0.52	0.25	0.20	0.19

CAL	2013	STOVER			0.18	0.18	0.23	0.44	0.82	0.89	0.67	0.28	0.18	0.16
CAL	2013	STOVER			0.22	0.23	0.24	0.33	0.84	0.88	0.78	0.35	0.24	0.20
CAL	2013	STOVER			0.19	0.18	0.22	0.33	0.86	0.89	0.71	0.32	0.19	0.17
CAL	2013	STOVER			0.32	0.26	0.29	0.32	0.72	0.90	0.69	0.23	0.15	0.17
CAL	2013	STOVER			0.24	0.22	0.25	0.37	0.89	0.92	0.62	0.21	0.18	0.20
CAL	2013	STOVER			0.23	0.22	0.25	0.54		0.83	0.43	0.25	0.20	0.21
CAL	2013	STOVER			0.21	0.22	0.24	0.46	0.94	0.90	0.71	0.27	0.18	0.18
CAL	2013	STOVER			0.19	0.22	0.25	0.52	0.82	0.86	0.55	0.25	0.16	0.17
CAL	2013	STOVER			0.26	0.26		0.48	0.75	0.91	0.71	0.24		
CAL	2013	STOVER			0.23	0.24	0.29	0.36	0.70	0.90	0.69	0.24	0.18	0.20
CAL	2013	STOVER			0.24	0.22	0.29	0.34	0.62	0.88	0.67	0.23	0.19	0.22
CAL	2013	STOVER			0.20	0.20	0.26	0.41	0.88	0.88	0.69	0.28	0.19	0.19
CAL	2013	STOVER				0.17	0.27	0.28	0.65	0.88	0.85	0.29	0.13	0.20
CAL	2013	STOVER			0.21	0.20	0.25	0.41	0.87	0.89	0.67	0.29	0.18	0.20
CAL	2013	STOVER			0.25	0.26	0.31	0.34	0.62	0.87	0.68	0.35	0.34	0.27
CAL	2013	STOVER			0.23	0.21	0.24	0.35	0.78	0.73	0.38	0.27	0.39	0.25
CAL	2013	STOVER			0.22	0.21	0.25	0.36	0.89	0.88	0.66	0.28	0.19	0.17
CAL	2013	STOVER			0.23	0.21	0.29	0.30	0.64	0.91	0.81	0.31	0.19	0.19
CAL	2013	STOVER			0.20	0.19	0.26	0.28	0.77	0.89	0.69	0.20	0.16	0.14
CAL	2013	STOVER			0.19	0.19	0.24	0.38	0.92	0.87	0.73	0.34	0.21	0.16
CAL	2013	STOVER			0.19	0.19	0.25	0.34	0.63	0.89	0.86	0.27	0.16	0.19
CAL	2013	STOVER			0.25	0.21	0.24	0.58	0.85	0.85	0.71	0.28	0.19	0.20
CAL	2013	STOVER			0.18	0.19	0.22	0.37	0.85	0.87	0.70	0.32	0.18	0.18
CAL	2013	STOVER			0.24	0.21	0.26	0.34	0.87	0.89	0.56	0.26	0.18	0.22
CAL	2013	STOVER			0.19	0.22	0.25	0.34	0.87	0.90	0.68	0.25	0.19	0.18
CAL	2014	STOVER	0.17	0.09	0.19	0.22	0.31	0.40	0.73	0.91	0.70	0.28	0.23	0.19
CAL	2014	STOVER	0.17		0.20	0.23	0.28	0.87	0.87	0.88	0.60	0.28		0.20
CAL	2014	STOVER	0.17	0.11	0.22	0.21	0.28	0.79	0.83	0.86	0.61	0.33	0.23	0.21
CAL	2014	STOVER				0.23	0.29	0.31	0.83	0.93	0.89	0.21	0.21	0.18
CAL	2014	STOVER	0.17		0.20	0.21	0.27	0.71	0.91	0.89	0.75	0.31	0.23	0.18
CAL	2014	STOVER		0.05		0.23	0.28	0.36	0.87	0.93	0.81	0.29	0.22	0.19
CAL	2014	STOVER	0.18		0.20	0.20	0.22	0.57	0.90	0.90	0.72	0.28	0.23	0.17
CAL	2014	STOVER	0.19	0.05	0.22	0.25	0.27	0.38	0.71	0.89	0.64	0.28	0.23	0.21
CAL	2014	STOVER	0.23	0.06	0.22	0.24	0.25	0.36	0.74	0.92	0.58	0.23	0.22	0.22
CAL	2014	STOVER	0.19	0.05	0.20	0.22	0.23	0.85	0.90	0.80	0.45	0.25	0.24	0.19
CAL	2014	STOVER	0.22	0.11	0.22	0.23	0.27	0.53	0.82	0.93	0.60	0.25	0.26	0.22
CAL	2014	STOVER	0.19	0.14	0.20	0.21	0.24	0.36	0.62	0.86	0.68	0.25	0.21	0.20
CAL	2014	STOVER	0.20		0.21	0.21	0.26	0.85	0.91	0.91	0.78	0.35	0.23	0.19
CAL	2014	STOVER	0.19		0.20	0.24	0.27	0.46	0.75	0.89	0.73	0.25	0.23	0.20
CAL	2014	STOVER	0.21	0.12	0.21	0.22	0.29	0.57	0.87	0.92	0.58	0.52	0.50	0.25
CAL	2014	STOVER	0.19			0.22	0.26	0.65	0.88	0.87	0.78	0.32	0.21	0.19
CAL	2014	STOVER	0.23		0.23	0.27	0.26	0.34	0.79	0.88	0.77	0.25		0.22
CAL	2014	STOVER	0.18		0.21	0.21	0.26	0.77	0.89	0.87	0.62	0.26	0.21	0.19

CAL	2014	STOVER	0.18		0.20	0.22	0.30	0.35	0.69	0.90	0.64	0.25	0.22	0.20
CAL	2014	STOVER	0.21			0.22	0.28	0.44	0.79	0.93	0.62	0.23	0.21	0.20
CAL	2014	STOVER	0.19		0.21	0.21	0.25	0.71	0.84	0.89	0.71	0.30	0.25	0.19
CAL	2014	STOVER	0.15		0.18	0.20	0.25	0.63	0.87	0.89	0.77	0.31	0.22	0.18
CAL	2014	STOVER	0.21	0.04	0.21	0.21	0.27	0.46	0.81	0.92	0.70	0.24	0.20	0.21
CAL	2014	STOVER	0.20	0.14	0.22	0.23	0.27	0.51	0.82	0.88	0.60	0.26		0.20
CAL	2014	STOVER	0.17	0.08	0.20	0.19	0.26	0.89	0.90	0.89	0.68	0.31	0.22	0.18
CAL	2014	STOVER	0.26		0.27	0.25	0.25	0.72	0.87	0.87	0.64	0.29	0.23	0.20
CAL	2014	STOVER	0.19	0.11	0.21	0.21	0.25	0.84	0.86	0.82	0.60	0.24		0.19
CAL	2014	STOVER	0.21		0.21	0.22	0.29	0.57	0.73	0.88	0.72	0.29	0.24	0.20
CAL	2014	STOVER	0.19	0.13	0.20	0.20	0.27	0.42	0.72	0.93	0.88	0.26	0.20	0.19
CAL	2014	STOVER	0.21		0.23	0.22	0.28	0.72	0.85	0.83	0.63	0.28	0.24	0.22
CAL	2014	STOVER	0.19		0.21	0.21	0.28	0.53	0.85	0.83	0.45	0.27	0.22	0.19
CAL	2014	STOVER			0.21	0.25	0.33	0.57	0.81	0.88	0.62	0.23	0.22	0.21
CAL	2014	STOVER	0.14		0.20	0.22	0.27	0.74	0.88	0.88	0.76	0.25		0.18
CAL	2014	STOVER	0.17		0.19	0.20	0.26	0.86	0.88	0.90	0.75	0.33	0.24	0.19
CAL	2014	STOVER	0.18		0.19	0.18	0.23		0.90	0.91	0.79	0.28		0.18
CAL	2014	STOVER	0.17		0.19	0.20	0.24	0.59	0.91	0.90	0.66	0.26	0.22	0.18
CAL	2014	STOVER	0.19		0.20	0.21	0.25	0.85	0.88	0.91	0.68	0.39	0.28	0.21
CAL	2014	STOVER	0.20	0.09	0.20	0.21	0.27	0.49	0.85	0.93	0.70	0.23	0.19	0.19
CAL	2014	STOVER	0.26	0.08	0.29	0.38	0.28	0.46	0.76	0.89	0.65	0.26	0.26	0.26
CAL	2014	STOVER	0.16	0.12	0.19	0.19	0.27	0.87	0.90	0.90	0.68	0.29	0.22	0.17
CAL	2014	STOVER	0.26	0.15	0.24	0.24	0.29	0.56	0.90	0.93	0.49	0.23	0.18	0.24
CAL	2014	STOVER	0.24		0.31	0.41	0.32	0.60	0.84	0.77	0.45	0.28		0.25
CAL	2014	STOVER	0.26		0.24	0.25	0.28	0.48	0.79	0.91	0.62	0.22		0.23
CAL	2014	STOVER	0.18	0.16	0.20	0.23	0.25	0.34	0.60	0.92	0.73	0.23	0.21	0.20
CAL	2014	STOVER	0.22		0.22	0.24	0.27	0.66	0.90	0.91	0.85	0.35		0.21
CAL	2014	STOVER	0.17	0.14	0.19	0.21	0.29	0.70	0.87	0.92	0.67	0.26	0.19	0.18
CAL	2014	STOVER	0.16	0.15	0.22	0.23	0.30	0.58	0.84	0.93	0.71	0.23	0.23	0.19
VAL	2013	COVER CROP			0.24	0.21	0.29	0.28	0.75	0.67	0.37	0.32	0.42	0.25
VAL	2013	COVER CROP			0.21	0.19	0.25	0.42	0.87	0.91	0.58	0.24	0.25	0.21
VAL	2013	COVER CROP			0.24	0.25	0.27	0.28	0.67	0.69	0.40	0.26	0.27	0.26
VAL	2013	COVER CROP			0.24	0.23	0.26	0.25	0.67	0.68	0.41	0.24	0.24	0.24
VAL	2013	COVER CROP			0.26	0.30	0.26	0.33	0.92	0.86	0.50	0.24	0.22	0.24
VAL	2013	COVER CROP			0.21	0.22	0.25	0.30	0.84	0.93	0.70	0.23	0.20	0.20
VAL	2013	COVER CROP			0.28	0.44	0.71	0.40	0.76	0.81	0.43	0.26	0.21	0.23
VAL	2013	COVER CROP			0.23	0.44	0.75	0.39	0.74	0.78	0.66	0.29	0.22	0.22
VAL	2013	COVER CROP			0.22	0.25	0.39	0.40	0.76	0.82	0.51	0.27	0.20	0.23
VAL	2013	COVER CROP			0.22		0.47	0.41	0.77	0.80	0.51	0.29	0.21	0.23
VAL	2013	COVER CROP			0.23	0.29	0.72	0.39	0.76	0.84	0.48	0.25	0.19	0.22
VAL	2013	COVER CROP			0.24	0.23	0.28	0.36	0.76	0.90	0.68	0.26	0.17	0.19
VAL	2013	COVER CROP			0.23	0.24	0.27	0.29	0.80	0.90	0.69	0.28	0.19	0.21
VAL	2013	COVER CROP			0.21	0.29	0.80	0.49	0.91	0.90	0.64	0.24	0.19	0.20

VAL	2013	COVER CROP			0.21	0.26	0.25	0.26	0.70	0.92	0.74	0.28	0.18	0.21
VAL	2013	COVER CROP			0.26	0.23	0.28	0.28	0.68	0.89	0.67	0.24	0.20	0.23
VAL	2013	COVER CROP			0.25	0.30	0.31	0.31	0.63	0.80	0.75	0.28	0.18	0.22
VAL	2013	COVER CROP			0.19	0.20	0.33	0.47	0.86	0.85	0.68	0.32	0.16	0.17
VAL	2013	COVER CROP			0.20	0.21	0.33	0.50	0.92	0.87	0.64	0.27	0.16	0.18
VAL	2013	COVER CROP			0.20	0.23	0.33	0.39	0.86	0.89	0.74	0.34	0.18	0.17
VAL	2013	COVER CROP			0.20	0.20	0.31	0.29	0.85	0.89	0.70	0.31	0.18	0.19
VAL	2013	COVER CROP			0.23	0.26	0.34	0.40	0.54	0.84	0.78	0.30	0.21	0.23
VAL	2013	COVER CROP			0.19	0.20	0.34	0.45	0.88	0.90	0.68	0.28	0.17	0.17
VAL	2013	COVER CROP			0.20	0.19	0.25	0.53	0.90	0.89	0.55	0.26	0.17	0.18
VAL	2014	COVER CROP	0.28	0.35	0.27	0.28	0.31	0.38	0.57	0.81	0.73	0.33	0.36	0.28
VAL	2014	COVER CROP	0.22		0.28	0.30	0.50	0.68	0.87	0.89	0.61	0.24	0.24	0.22
VAL	2014	COVER CROP	0.25		0.26	0.32	0.32	0.39	0.70	0.90	0.86	0.28	0.25	0.26
VAL	2014	COVER CROP	0.20	0.05	0.21	0.24	0.28	0.45	0.87	0.89	0.66	0.26	0.23	0.20
VAL	2014	COVER CROP	0.15		0.20	0.20	0.27	0.66	0.86	0.89	0.83	0.34	0.22	0.18
VAL	2014	COVER CROP	0.17		0.20	0.20	0.28	0.62	0.86	0.84	0.86	0.32	0.22	0.17
VAL	2014	COVER CROP	0.22		0.25	0.27	0.27	0.68	0.88	0.88	0.76	0.27	0.23	0.20
VAL	2014	COVER CROP	0.18		0.21	0.25	0.28	0.48	0.70	0.93	0.70	0.23	0.23	0.18
VAL	2014	COVER CROP	0.23			0.35	0.81	0.55	0.79	0.64	0.60	0.32	0.29	0.25
VAL	2014	COVER CROP	0.22			0.38	0.70	0.53	0.76	0.63	0.52	0.37	0.33	0.27
VAL	2014	COVER CROP	0.24		0.26	0.32	0.83	0.57	0.82		0.54	0.32	0.28	0.24
VAL	2014	COVER CROP	0.19		0.25	0.39	0.84	0.59	0.82	0.66	0.55	0.39	0.36	0.24
VAL	2014	COVER CROP	0.17		0.20	0.23	0.44	0.54	0.88	0.90	0.69	0.28	0.22	0.19
VAL	2014	COVER CROP	0.18	0.12	0.21	0.21	0.25	0.50	0.89	0.85	0.73	0.36	0.24	0.19
VAL	2014	COVER CROP	0.15		0.18	0.20	0.37	0.62	0.89	0.89	0.81	0.33	0.22	0.17
VAL	2013	PASTURE/GRASS			0.31	0.32	0.78	0.75	0.68	0.68	0.58	0.59	0.43	0.46
VAL	2013	PASTURE/GRASS			0.30	0.49	0.86	0.70	0.66	0.71	0.87	0.75	0.58	0.39
VAL	2013	PASTURE/GRASS			0.23	0.31	0.61	0.62	0.75	0.64	0.49	0.43	0.39	0.30
VAL	2013	PASTURE/GRASS			0.30	0.48	0.54	0.65	0.70	0.68	0.53	0.51	0.32	0.36
VAL	2013	PASTURE/GRASS			0.28	0.47	0.69	0.87	0.89	0.79	0.75	0.83	0.69	0.39
VAL	2013	PASTURE/GRASS				0.25	0.78	0.87	0.67	0.83	0.74	0.87	0.82	0.48
VAL	2013	PASTURE/GRASS			0.30	0.41	0.89	0.84	0.75	0.80	0.75	0.86	0.84	0.54
VAL	2013	PASTURE/GRASS			0.24		0.86		0.73	0.84	0.71	0.82	0.69	0.44
VAL	2013	PASTURE/GRASS			0.29	0.52	0.88	0.86	0.89	0.80	0.72	0.82	0.80	0.58
VAL	2013	PASTURE/GRASS			0.26		0.77	0.87	0.78	0.76	0.68	0.82	0.73	0.55
VAL	2013	PASTURE/GRASS			0.30	0.52	0.66	0.86	0.66	0.85	0.66	0.74	0.68	0.48
VAL	2013	PASTURE/GRASS			0.31	0.37	0.82	0.83	0.72	0.77	0.77	0.82	0.69	0.50
VAL	2013	PASTURE/GRASS			0.32	0.41	0.87	0.69	0.80	0.84	0.65	0.84	0.67	0.49
VAL	2013	PASTURE/GRASS			0.31	0.61		0.79	0.80	0.66	0.79	0.74	0.54	0.48
VAL	2013	PASTURE/GRASS			0.29	0.54	0.79	0.69	0.75	0.76	0.73	0.62	0.47	0.43
VAL	2013	PASTURE/GRASS			0.26	0.63		0.60	0.92	0.79	0.70	0.86	0.71	0.53
VAL	2013	PASTURE/GRASS			0.31	0.66	0.87	0.68	0.62	0.78	0.82	0.82	0.67	0.43
VAL	2013	PASTURE/GRASS			0.31	0.70	0.80	0.66	0.57	0.75	0.86	0.83	0.67	0.44

VAL	2013	PASTURE/GRASS			0.30	0.37	0.82	0.69	0.80	0.84	0.76	0.78	0.69	0.55
VAL	2014	PASTURE/GRASS	0.29		0.36	0.46	0.80	0.81	0.78	0.72	0.73	0.66	0.48	0.42
VAL	2014	PASTURE/GRASS	0.25		0.25	0.32	0.64	0.81	0.81	0.82	0.75	0.52		0.30
VAL	2014	PASTURE/GRASS	0.27		0.25	0.31	0.56	0.72	0.78	0.70		0.59		0.35
VAL	2014	PASTURE/GRASS	0.32		0.35	0.58	0.85	0.92	0.70	0.63	0.87	0.80	0.69	0.40
VAL	2014	PASTURE/GRASS	0.27	0.09	0.24	0.28	0.74	0.74	0.74	0.72	0.64	0.51	0.38	0.31
VAL	2014	PASTURE/GRASS	0.22		0.26	0.35	0.79	0.89	0.83	0.83	0.77	0.65	0.53	0.34
VAL	2014	PASTURE/GRASS				0.47	0.82	0.80	0.77	0.80	0.80	0.62	0.61	0.41
VAL	2014	PASTURE/GRASS	0.32		0.40	0.52	0.82	0.80	0.73	0.87	0.54	0.76		0.49
VAL	2014	PASTURE/GRASS	0.31		0.27	0.69	0.74	0.81	0.91	0.90	0.82	0.82		0.48
VAL	2014	PASTURE/GRASS	0.34		0.31	0.62	0.49	0.87	0.71	0.75	0.84	0.82		0.41
VAL	2014	PASTURE/GRASS	0.37	0.21	0.32	0.52	0.59	0.83	0.76	0.91	0.77	0.79	0.76	0.54
VAL	2014	PASTURE/GRASS	0.40		0.34	0.57	0.89	0.78	0.90	0.67	0.83	0.85	0.83	0.54
VAL	2014	PASTURE/GRASS	0.33		0.37	0.60	0.82	0.66	0.87	0.72	0.85	0.83	0.81	0.45
VAL	2014	PASTURE/GRASS	0.31	0.22	0.24	0.41	0.88	0.92	0.76	0.81	0.76	0.70	0.82	0.44
VAL	2014	PASTURE/GRASS	0.31		0.29	0.48	0.86	0.87	0.85	0.79	0.74	0.80	0.72	0.47
VAL	2014	PASTURE/GRASS	0.23	0.11	0.28	0.46	0.34	0.91	0.71	0.85	0.69	0.84	0.84	0.33
VAL	2014	PASTURE/GRASS	0.34		0.36	0.61	0.67	0.75	0.74	0.89	0.74	0.82		0.52
VAL	2014	PASTURE/GRASS				0.54	0.86	0.81	0.80	0.74	0.65	0.75	0.76	0.48
VAL	2014	PASTURE/GRASS	0.35	0.21	0.39	0.59	0.86	0.87	0.72	0.73	0.82	0.80	0.82	0.48
VAL	2014	PASTURE/GRASS	0.32	0.13	0.29	0.44	0.70	0.75	0.87	0.82	0.78	0.74		0.43
VAL	2013	STOVER			0.19	0.22	0.28	0.50	0.91	0.87	0.66	0.33	0.19	0.17
VAL	2013	STOVER			0.20	0.19	0.29	0.33	0.73	0.92	0.79	0.27	0.21	0.18
VAL	2013	STOVER			0.30	0.26	0.34	0.39	0.84	0.92	0.81	0.29	0.15	0.25
VAL	2013	STOVER			0.25	0.21	0.24	0.30	0.68	0.90	0.74	0.27	0.18	0.21
VAL	2013	STOVER			0.20	0.19	0.23	0.45	0.82	0.85	0.63	0.28	0.17	0.19
VAL	2013	STOVER			0.20	0.17	0.24	0.30	0.58	0.92	0.76	0.24	0.15	0.18
VAL	2013	STOVER			0.20	0.19	0.23	0.45	0.88	0.87	0.68	0.29	0.20	0.19
VAL	2013	STOVER			0.19	0.21	0.22	0.45	0.92	0.90	0.77	0.38	0.23	0.18
VAL	2013	STOVER			0.23	0.21	0.26	0.36	0.71	0.87	0.68	0.21	0.20	0.20
VAL	2013	STOVER			0.18	0.19	0.23	0.48	0.92	0.88	0.72	0.30	0.17	0.17
VAL	2013	STOVER			0.22	0.20	0.23	0.33	0.89	0.88	0.76	0.33	0.17	0.20
VAL	2013	STOVER			0.21	0.19	0.27	0.33	0.77	0.93	0.69	0.21	0.18	0.18
VAL	2013	STOVER			0.26	0.27	0.32	0.39	0.82	0.91	0.61	0.24	0.23	0.21
VAL	2013	STOVER			0.19	0.20	0.27	0.44	0.84	0.87	0.75	0.45	0.17	0.17
VAL	2013	STOVER			0.19	0.19	0.22	0.44	0.88	0.87	0.70	0.32	0.21	0.18
VAL	2013	STOVER			0.24	0.22	0.30	0.37	0.79	0.87	0.52	0.23	0.19	0.21
VAL	2013	STOVER			0.18	0.18	0.21	0.34	0.91	0.89	0.68	0.28	0.18	0.17
VAL	2013	STOVER			0.19	0.22	0.24	0.26	0.86	0.87	0.77	0.37	0.21	0.18
VAL	2013	STOVER			0.25	0.23	0.27	0.30	0.89	0.87	0.64	0.29	0.20	0.21
VAL	2013	STOVER			0.25	0.21	0.26	0.33	0.76	0.93	0.61	0.20	0.17	0.18
VAL	2013	STOVER			0.19	0.22	0.25	0.34	0.82	0.84	0.66	0.27	0.20	0.20
VAL	2014	STOVER	0.15		0.19	0.20	0.24	0.79	0.87	0.90	0.60	0.29	0.20	0.18

VAL	2014	STOVER	0.14		0.21	0.23	0.32	0.59	0.79	0.84	0.72	0.32	0.24	0.20
VAL	2014	STOVER	0.17		0.18	0.18	0.22	0.65	0.89	0.90	0.73	0.31	0.22	0.18
VAL	2014	STOVER	0.23	0.05	0.22	0.25	0.30	0.48	0.81	0.88	0.58	0.25	0.20	0.22
VAL	2014	STOVER	0.19		0.21	0.21	0.24	0.66	0.90	0.87	0.75	0.28	0.23	0.19
VAL	2014	STOVER	0.18		0.19	0.21	0.25	0.88	0.90	0.90	0.72	0.32	0.24	0.19
VAL	2014	STOVER	0.21		0.21	0.21	0.26	0.47	0.73	0.89	0.69	0.26	0.21	0.20
VAL	2014	STOVER	0.19		0.21	0.23	0.30	0.33	0.64	0.89	0.70	0.29	0.27	0.21
VAL	2014	STOVER	0.20	0.19	0.21	0.22	0.28	0.34	0.71	0.87	0.60	0.23	0.19	0.19
VAL	2014	STOVER	0.15		0.19	0.21	0.25	0.62	0.88	0.88	0.67	0.33	0.23	0.18
VAL	2014	STOVER	0.18	0.07	0.23	0.22	0.29	0.44	0.81	0.87	0.59	0.26	0.21	0.19
VAL	2014	STOVER	0.14		0.21	0.21	0.25	0.68	0.83	0.86	0.78	0.31	0.23	0.14
VAL	2014	STOVER	0.16	0.10	0.19	0.21	0.30	0.30	0.60	0.83	0.80	0.27		0.20
VAL	2014	STOVER	0.19		0.20	0.23	0.27	0.39	0.69	0.89	0.87	0.23		0.19
VAL	2014	STOVER	0.19	0.06	0.20	0.21	0.24	0.64	0.91	0.90	0.78	0.30	0.20	0.18
VAL	2014	STOVER	0.19		0.21	0.23	0.27	0.72	0.90	0.92	0.85	0.34	0.19	0.18
VAL	2014	STOVER	0.18	0.10	0.21	0.23	0.29	0.35	0.63	0.89	0.69	0.30		0.21
VAL	2014	STOVER	0.21		0.22	0.22	0.25	0.86	0.89	0.90	0.58	0.21		0.20