EVALUATING REMOTE SENSING TECHNIQUES TO RAPIDLY ESTIMATE WINTER COVER CROP ADOPTION IN THE BIG PINE WATERSHED, INDIANA

by

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Dedicated to all my family members

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ABSTRACT

Indiana is the leading state of cover crop adoption within the Upper Mississippi River Basin. However, since 2015 the cover crop adoption has slowed to a plateau. In order to regain the previous momentum, there must be an increased understanding of the spatiotemporal dynamics of cover crop adoption on the county and watershed scale. Currently, the cover crop adoption is monitored annually through a driving transect survey method that investigates only 8.5% of the watershed and extrapolates to the entire county. However, the observations made by the driving transect survey can merely cover limited fields and is time-consuming. In addition, the driving transect survey did not provide comparative analysis like farmer's tendencies and cover crop tenure among consecutive years. Therefore, we developed a rapid cover crop survey method by using remote sensing technology. Our rapid cover crop survey used processed NDVI map to estimate cover crop adoption. The fundamental objectives of this research are: (1) evaluating the accuracy of the rapid cover crop survey method relative to the driving transect data and determining the best cut-off value (COV) of Normalized Difference Vegetation Index (NDVI); (2) performing a hindcasting analysis of cover crop adoption within the Big Pine Creek Watersheds within the period of 2014-2018 by employing a rapid cover crop survey remote sensing techniques; (3) accessing cover crop adoption management tendencies of farmers within the Big Pine Watersheds, and (4) determining the cover crop adoption tenure of farmers within the Big Pine Creek watersheds between 2014 and 2018. The cover crop management tendency represents the farmers' preference on cash crop rotation method after harvesting cover crops, and the cover crop adoption tenure means that how often farmers adopt cover crops in a specific field in the research period.

The results of this research demonstrated that relative to the conventional driving transect, remote sensing is a feasible method to successfully detect cover crop adoption on a county and watershed scale. Over a 4-year period (2015-2018), Producer's Accuracy (PA) under the best COV, which represented how much vegetation-covered field recorded in transect data that can be captured in the processed NDVI map, was 89.02%. This PA value was relatively high compared with previous spatial crop classification research. The rapid remote sensing method also provided individual field locations of cover crop adoption over time within the entire watershed, compared to the driving transect that only gives extrapolated average of adoption. The hindcasting analysis

of cover crop adoption revealed a 74% increase in cover crop acreage in the watershed from 2014 to 2018, which equated to a 0.71% increase in land receiving cover crops among all cultivated land annually. The evaluation of farmer cover crop adoption tendencies demonstrated that over a 4-year period, cover crop adoption going into corn was 19.7% greater on average relative to before soybean. Another key finding was that the level of cover crop adoption annually in the watershed was heavily influenced by the cash crop rotation. The cover crop tenure analysis demonstrated that agricultural fields of greater cover crop tenure represented the smallest portion of the cultivated land in the watershed, where 84.2% of the watershed was void of cover crop adoption and field that received cover crops for more than 4 consecutive years represented only 1% of cultivated land.

To conclude, we are confident that the rapid cover crop survey method could replace the traditional driving transect survey. Our findings suggest that rapid assessment methods of cover crop adoption involving processed NDVI map could help advance the effectiveness, speed, and accuracy of cover crop adoption and assessment in the state of Indiana and the entire Mississippi River Basin region.

CHAPTER 1. LITERATURE REVIEW

1.1 Environmental impact of nutrient loss

1.1.1 Gulf of Mexico

The inner- to mid-continental shelf (depth of 5 to 60 m) of the northern Gulf of Mexico is the second largest zone of coastal hypoxia in the world (Rabalais and Turner, 2001a; Bosesch and Rabalais, 1991). Hypoxia occurs when the concentration of dissolved oxygen is less than 2 mg/L and the low oxygen concentration leads to the failure to capture fish, shrimp and crabs in bottom-dragging trawls (Burkart and James, 1999; Renaud, 1986). Moreover, the prolonged period of low oxygen level diminished the benthic biodiversity and altered the way ecosystem functions (Rabalais and Turner, 2001a,b). In 2019, the hypoxia zone in the Gulf of Mexico is 18,006 square kilometers, the 8th largest ever measured since 1985 (NOAA). Hypoxia is one of the symptoms of eutrophication, defined as an increasing rate of production and accumulation of carbon in aquatic systems (Nixon, 1995). Eutrophication frequently occurs as a consequence of an increase in the influx of nutrient into the waterbody, especially in the forms of nitrogen and phosphorus. The enriched water in turn led to N-limited phytoplankton blooms, particularly diatoms (Burkart and James, 1999). As a result, the increased deposition of organic matter results in hypoxic and anoxic conditions in near-bottom environments (Rabalais et al.,1994). There was 80% of the total freshwater input of the Gulf of Mexico discharged from the Mississippi and Atchafalaya River (Dunn, 1996). These two rivers also discharged estimated 90% of total nitrogen flux annually to the Gulf of Mexico (Dunn, 1996).

1.1.2 Agricultural-Nitrogen Contributions to Hypoxia in the Gulf of Mexico

Agricultural sources of nitrogen and phosphorus dominated inputs from the Mississippi river to the Gulf of Mexico (Burkart and James, 1999; Goolsby et al. 2001; Howarth et al. 1995; Nixon, 1995). Burkart and James (1999) suggested the major agricultural sources of nitrogen included inorganic fertilizer, manure, and atmospheric deposition, while the agricultural nitrogen losses are chiefly attributed to crop harvest, losses to the atmosphere through volatilization of manure and inorganic fertilizer, plant senescence, and denitrification of soil NO_3. Residual nitrogen is thus defined by subtracting losses from sources, which has the potential for leaching, run-off, or being stored in organic and inorganic forms. The region with maximum residual nitrogen (58-129kg ha^{-1}) is the Upper Mississippi River Basin (Burkart and James, 1999). Goolsby pointed out, in his research about nitrogen input to the Gulf of Mexico, that the fertilizer application from 1950s to 1980s led to a significant increase in nitrogen input into the Mississippi River drainage basin. This is particularly true for Upper Mississippi River basin, which generates about 19% of the flow but 43% of the nitrate load to the Mississippi River basin. Iowa and Illinois have the most intensive corn-soybean crop and contribute 16% and 19% of the nitrate, respectively (Goolsby et al. 1999, 2001). Additionally, Iowa and Illinois have the most productive soil and the greatest amount of nitrogen fertilizer used (Keeney, 2002).

1.1.3 Nutrient Reduction Strategy

In order to control the nitrogen load in the waterbody, the Mississippi River/Gulf of Mexico Hypoxia Task Force (HTF) implemented the 2008 Action Plan as a national strategy to reduce, mitigate and control hypoxia zone in the Gulf of Mexico and to improve water quality in the Mississippi River basin. The 2008 Action Plan required twelve major states on the Mississippi River basin to develop a Nutrient Reduction Strategy (NRS) in alignment with their own conservation needs. The HTF also provided a framework encompassing eight recommended measures such as prioritizing watersheds by estimating N and P loadings and identifying watersheds and sub-watersheds that proved chief sources of loads, setting nutrient load reduction goal, reporting implementation activities annually and nutrient load reduction biannually for managing nitrogen and phosphorus pollution in the 2011 EPA memo (Stoner, 2011).

Currently, the numeric thresholds for total phosphorus and nitrate + nitrite provided by Indiana State Nutrient Reduction Strategy are 0.3 mg L^{-1} and 10 mg L^{-1} respectively. To meet this water quality requirement, the Indiana Nutrient Reduction Strategy suggested several agricultural practices for farmers such as applying fertilizer at a proper rate and proper time, planting cover crops, increasing perennials in the cropping system, and adopting conservation tillage practices like no-till, strip-till, ridge till, and mulch till (Indiana State Nutrient Reduction Strategy, 2016).

Cover crop as one suggested conservation practice listed on the Nutrient Reduction Strategy is widely accepted by farmers in Indiana. According to a recent survey carried out by Indiana State Department of Agriculture, farmers planted over 400,000 ha of cover crops in 2018 and it was estimated that 1.4 million tons of nitrogen and 0.7 million tons of phosphorus were kept out of Indiana's waterways (ISDA,2019).

1.2 Cover Crops

1.2.1 Cover Crops and Benefit

Cover crops are the types of vegetation planted in cropping systems for a short time to cover the bare soil so as to reduce soil erosion, improve soil health, and reduce weeds and pests (Kessavalou & Walters, 1997; Snapp et al., 2005b; Hartwig & Ammon, 2002). The primary benefit of cover crop is the reduction of soil water erosion, thus preventing soil nutrient loss and improving soil productivity (Hartwig 1988; Reeves, 1994). Cover crops could keep bare soil from detachment when rainfall occur and slow down the surface runoff (Renard, 1997; Hall et al. 1984). Moreover, the roots of cover crops could break compacted soil and provide space for water infiltration, thereby minimizing soil surface runoff and soil water erosion as well. The residue of cover crops could improve soil fertility and reinforce soil structure by adding organic matter and aggregates to the soil (Hartwig & Ammon, 2002). Legume cover crops can help fix nitrogen from the atmosphere into ammonia and therefore reduce both the demand for nitrogen fertilizer and potential nutrient loss to the adjacent waterbody (Hall et al. 1984). Furthermore, cover crops could help keep weeds in the fields in check: the high-density planting of cover crops can compete directly with weed for space and living resources and some cover crop species can produce chemical substance such as phenolic acids, glucosinolates, and coumarins to restrain the germination or growth of weeds (Creamer et. al, 1996; Dabney et al., 2001). Last but not least, cover crop's pollen and nectar could provide food for predatory mites and parasitic wasps, both important for biological control of insect pests. Cover crops also can provide good habitat for beneficial insects like spiders, and these general insect feeders help decrease pest populations (Dabney et al., 2001; Lal et al., 1991).

1.2.2 Winter Cover Crops and Management

In terms of growing season, cover crops can be categorized into either summer cover crop or winter cover crop, the latter being the most widely adopted in the Midwest Corn Belt states. Winter cover crops are planted after harvesting cash crop and before seeding next crop in the following spring for scavenging nutrients (especially nitrogen) left over from a previous crop

(Magdoff and Es, 2010; and Moncada and Sheaffer, 2011). There are two main categories of winter cover crop, depending on their tolerance for low temperature: winter-killed cover crops and winter-hardy cover crops. The winter-killed cover crops are species that cannot survive through winter such as oats, radish, and certain clovers (Moncada and Sheaffer, 2011). In the upper Midwest, due to the short potential growing period for winter-killed cover crops in soybean-corn rotation, researchers suggested overseeding winter-killed cover crops into soybean in mid-August to establish enough biomass (Johnson et al., 1998). The winter-hardy cover crops are species that can survive in the cold winter and continue their growth in next spring. In Indiana, the most common winter-hardy cover crop is cereal rye, a type of vegetation that can be planted later in the fall than most other cover crop species because it can geminate and establish quickly to cope with the cold winter in the upper Midwest (Magdoff and Es, 2010).

There are two common planting methods for winter cover crops. One is drill seeding, a method that is commonly used after cash crop harvest. The drill seeding can provide the most uniform seed distribution and better seed-soil contact for establishment. However, the harvest time of cash crop can influence the drilling time and lead to insufficient amount of time required for establishment. The other is aerial seeding/broadcast seeding, a method that can plant cover crops into standing corn or soybean to help establish biomass earlier. However, this method needs higher seeding rate than drill seeding due to its uneven seed distribution and lower establishment (Licht, 2019; Moncada and Sheaffer, 2011; Clark, 2007).

All winter cover crops will eventually be terminated before or during soil preparation for the next cash crop planting in spring. For winter-hardy cover crops, the termination methods could be herbicides (for cereal rye and hairy vetch), rolling/crimping (for full bloom hairy vetch, barley, triticale, or milk/dough stage cereal rye), and tillage (Anderson et al., 2006).

1.3 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI), as the most commonly used index to estimate the density of green vegetation, is a dimensionless index of that describe the difference between visible and near-infrared reflectance of vegetation cover (Schinasi, Benmarhnia, and De Roos, 2018). The NDVI is calculated as a ratio of red band (610 to 680 nm) and near-infrared band (780 to 890 nm): NDVI = [NIR – RED]/[NIR + RED] (Tucker, 1979). The NDVI ranged from -1 to 1. Areas of barren rock, soil, or snow usually show NDVI values less than zero. Sparse vegetation such as shrubs and grasslands or senescing crops may have NDVI values in the range of 0.2 to 0.5. Dense vegetation such as that found in temperate and tropical forests or crops at their peak growth stage often show NDVI values in the range of 0.6 to 0.9. Researchers can roughly estimate vegetation type, amount, and condition by transforming raw satellite raster image into NDVI values (Brown, USGS).

Researchers also use NDVI to estimate cover crop adoption. Hively et al. (2009) applied NDVI obtained from SPOT 5 satellite images to estimate cover crop biomass for fields with larger than 210 kg ha^{-1} of vegetation. Their research indicated that NDVI successfully reflected both the amount of green vegetative ground cover and cover crop residue on the surveyed fields in a fallow season.

CHAPTER 2. EVALUATING REMOTE SENSING TECHNIQUES TO RAPIDLY ESTIMATE WINTER COVER CROP ADOPTION IN THE BIG PINE WATERSHED, INDIANA

2.1 Introduction

Cover cropping, as an in-field conservation practice, has become increasingly relevant to farmers in the Upper Mississippi River Basin. In fact, within the last ten years, cover crop adoption has drastically increased by ~972% within the region (CTIC Cover Crop Survey 2012 and CTIC Cover Crop Survey 2017). The literature has documented many ecosystem services of cover crops that could explain the surge in farmer adoption, such as reduced soil erosion, increased soil health and organic matter (Strock et al., 2004). Additionally, with the contribution of nitrogen (N) from the Upper Mississippi River Basin (UMRB) to the hypoxic zone of the Gulf of Mexico continuing to be an issue of environmental sustainability for row crop agriculture (Mcconnaughey, 2013), N scavenging by cover crops has become highly relevant ecosystem service landscapes with a dense distribution of subsurface drainage. Due to the severity of the nitrogen loading issue, many Corn Belt states were required by the United States Environmental Protection Agency Gulf of Mexico Hypoxia Task Force to develop a Nutrient Loss Reduction Strategy (NLRS) to reduce N and P loading by 45% by 2050. Most of those Nutrient Loss Reduction Strategies (OH, MN, IA, and IL) identify cover cropping as the most effective in-field conservation strategy that can be adopted on a large scale to achieve the non-point nutrient loss reduction goals (Anderson, 2016; Illinois nutrient reduction strategy, 2015; Iowa nutrient reduction strategy, 2012; Ohio nutrient reduction strategy, 2015). Several studies across the UMRB have demonstrated that cereal rye has the capacity to reduce N losses via tile drainage by 30-50% (Dinnes, 2002; Kaspar, 2007; Kladivko, 1999; Roth, 2017).

Cover cropping as a conservation practice among farmers is either voluntarily adopted, or incentivized through several federal, state, and private industry cost-sharing programs in Indiana within agricultural watersheds. These programs provide farmers with financial assistance on a per-acre basis that typically lasts for 2-3 years (Clean Water Act Section 319 Agricultural Guidance for Indiana). Currently, farmers engaged in cover cropping in either case are monitored biannually through a driving survey method. NRCS members drive along the designated route, guided by georeferenced sampling points, where they determine the presence of cover crops. Results from the transect are then analyzed and extrapolated to the entire county. This driving transect occurs in the fall of the year before the first frost and the spring, approximately three weeks before regular cash crop planting. Results released by the driving survey indicate that in the initial years, cover crop adoption was linearly increased. However, within the last seven years, transect results indicate that cover crop adoption has significantly slowed from a rate of approximately 101,120 ha/year (2011-2015) to -20,230 ha/year (2015-2018), resulting in a plateau in adoption at ~404,700 ha/year (at 2018) (ISDA, Cover Crop and Tillage Transect Data 2018). Currently, the state of Indiana has the largest total area of agriculture land that receives cover crops among states in the UMRB. Thus, a cover crop adoption plateau in Indiana is indicative of other states in the UMRB. This plateau is problematic because current cover crop adoption levels are drastically lower than what is needed to significantly decrease N's export from Indiana to the Gulf of Mexico.

The advancement of cover crop adoption beyond the current plateau will require a more robust, spatially and temporally integrated rapid analysis of cover crop adoption rates across the state. Currently, the driving transect provides the state with an annual view of cover crop adoption, which has limited utility to conservation programs that foster cover crop adoption through watershed and county education, engagement, and program facilitation. The driving transect method provides a county estimation of cover crop adoption by examining a small sector of the total agricultural acres. However, it does not provide other critical portions of information that could be vital to understanding the pattern and trends of adoption such as the location of adoption in the county, the tendencies of farmers (the method of adoption preferred by farmers), the tenure (how often farmers adopt in a specific field) and the location of adopting farmers. Rapid spatial and temporal assessments of such critical variables of cover crop adoption could advance and deepen the current understanding of voluntary and incentivized cover crop adoption. Moreover, rapid spatial and temporal assessments can be critical indicators for directing and targeting conservation adoption resources, such as conservation program funds, education and extension, and federal and state conservation program directors' time and effort. The integration of remote sensing could be a sounder solution that is poised to replace the conventional method of assessing cover crop adoption.

A survey of literatures reveals that remote sensing has been used to identify surface vegetation in agricultural land (Ichikawa et al., 2018, Kussul et al., 2017; Reed et al., 1994). In 2009, the National Agricultural Statistics Service (NASS) of the US Department of Agriculture (USDA) built a Crop Data Layer Program (CDL Program), a raster-formatted, georeferenced, crop-specific land cover map that allows researchers to distinguish agricultural vegetative cover types from the satellite. Hively (2015) demonstrated how remote sensing monitors cover crop adoption in southeastern Pennsylvania by combining satellite imagery, CDL, and collected ground truth data. Their research indicated that remote sensing indices successfully detected both the amount of green vegetative ground cover and cover crop residue on the surveyed fields in a fallow season. Moreover, by analyzing the satellite imagery from 2010 to 2013 in four counties in Pennsylvania, their research demonstrated a consistently increasing winter cover crop adoption for all four counties. Wang (2019) also used CDL as a "Crop Mask" in selecting ground truth sample sites when mapping cover crop in southeastern Michigan with satellite imagery. The above studies have demonstrated that satellite imagery can be used to quantify differences in vegetative cover in agricultural ecosystems and to detect cover crop adoption over time. However, there is a need to develop a hindcasting method for a large-scale watershed that investigates field-specific variables such as farmers' cover crop adoption tendency and tenure. The former refers to farmers' decision for the two-year cash crop rotation that includes winter cover crop in the middle, while the latter is defined as the number of year years for each field to adopt cover crops throughout the period of research (2014-2018). Although Hively (2015) mentioned the use of CDL to locate the summer cash crop field, especially corn, before winter cover crop, no published article to date uses a hindcasting analysis of cover crop adoption to quantify farmers' tendencies in their integration of cover crops. Besides, no published articles used the cover crop adoption hindcast result to analyze the tenure of cover crop adoption of an individual farmer. Upon analysis of the tendency and tenure above, it is necessary to give a multi-ear analysis.

This research seeks to quantify field-specific tendencies and tenure of all the adoption in a watershed in an effort to increase the utility of cover crop survey. Therefore, the objectives of this research are (1) evaluating accuracy of the rapid cover crop survey method with driving transect data and determine the best cut-off NDVI value to discern differences between bare soil and vegetation, (2) performing a hindcasting analysis of cover crop adoption within the Big Pine Creek Watersheds within the years of 2014-2018 by employing rapid cover crop survey, (3) accessing cover crop adoption management tendencies of farmers within the Big Pine Watersheds, (4) determining the cover crop adoption tenure of farmers within the Big Pine Creek and Mud Pine Creek watersheds for the years of 2014-2018.

2.2 Materials and Methods

2.2.1 Study Area

The research site is the Big Pine watershed, which is located in west-central Indiana and composed of two ten-digit Hydrologic Unit Codes (HUC): Mud Pine Creek (0512010803) and Bing Pine Creek (0512010804) (Figure 2.1). The watershed is principally located in Benton and Warren County and includes small portions of Tippecanoe and White County, Indiana (Big Pine Creek Watershed Management Plan). The Mud Pine Creek and Big Pine Creek cover 84,866ha and 59,816 ha of area, respectively. On average, the yearly precipitation is 81 cm. The Big Pine watershed has a relatively flat topography: the lowest point is a flat deposit plain at the very southern end of the watershed, while the highest ground is found in Benton County along the watershed boundary (McBeth, 1899). The bedrock of the watershed region - consisting primarily of limestone, siltstone, and shale is covered with unconsolidated drift deposits comprising chiefly dense clay and sand measuring from a few inches to over 400 feet thick (Rosenshein, 1958). Thus, water often runs off the outer soil rapidly, making percolation a prolonged process. There are over 100 different types of soil in the Big Pine watershed area: highly erodible soil accounts for 4% of the watershed while potentially highly erodible soil is found in 29% of total watershed area, covering 60828 acres (The Nature Conservancy, 2015). In the Big Pine watershed, 83.4% of land has been used for cultivation, and the primary crop types are corn and soybean (IDEM: Big Pine Creek WMP). Tile drains are commonly adopted in the area, allowing water to flow down more quickly, but it also inevitably led to more severe flood in downstream areas, loss of nutrients, and soil erosion. The National Agricultural Statistics Survey (NASS) estimates that 7,153 tons of nitrogen and 3,538 tons of phosphorus are applied as fertilizer annually in the Big Pine watershed (NASS, 2007). More staggeringly, over 100 tons of pesticide and herbicide are applied every year in this watershed (NASS 2006). The surface runoff and tile drainage can bring those chemicals into adjacent water bodies, most likely the Mississippi River and thus causing aggravating eutrophication in the Gulf of Mexico.

2.2.2 Transect Data

Transect data for the fall of 2014, 2015, 2016, 2017, and 2018 were provided by Natural Resources Conservation Service (NRCS). The data were generated by cover crop transect surveys of a collaborative state effort led by NRCS, Indiana State Department of Agriculture (ISDA). The transect data were collected in the spring and fall of each year and composed of a point shapefile that contained the georeferenced sampling points, the transect route, and the results of the transect survey. There were 201 transect points of three counties involved in the Big Pine Watershed. For each point, the field information (previous crop, cover crop existence, cover crop quality) on the side of the transect point were added to the attribute table of the field boundary shapefile. This information will help determine best cut-off NDVI value and evaluate the NDVI map's accuracy as reference data later. In this research, we only used fall transect data because the spring satellite images have more weeds, a fact that could affect identification of the winter cover crop.

2.2.3 Satellite Images

We based our research on remote sensing data resources gathered from Landsat-7, RapidEye Ortho, and PlanetScope Ortho Tiles. The Landsat-7 (30-meter resolution) images were acquired from EarthExplorer (https://earthexplorer.usgs.gov/); the RapidEye Ortho (5-meter resolution) and PlanetScope Ortho Tiles (3.125-meter resolution) images were acquired from Planet (https://www.planet.com/). The Big Pine watershed was covered by three Landsat-7 images, seven RapidEye images, and nine PlanetScope images (Table 2.1). In this research, we attempted to choose the satellite images from the closest date to the fall transect survey. Satellite images were limited by the availability of the public resources and the image quality (cloud cover).

2.2.4 Crop Data Layer and Land Parcels Layer

The Crop Data Layer (CDL) is a raster, georeferenced, crop-specific land cover data layer acquired from the United States Department of Agriculture National Agricultural Statistics Service (USDA NASS) (https://nassgeodata.gmu.edu/CropScape/). In this research, we used CDL for Benton, White, and Warren County in 2014, 2015, 2016, 2017, and 2018 to classify the cash crop in agricultural fields of the Big Pine Watershed. Due to the ambiguous boundary of the CDL raster layer, we adopted Land Parcels Layer (LPL) from Indiana Geographic Information Office (IGIO). The LPL is a polygon layer that has a sharp boundary for all land parcels in Indiana.

2.2.5 Boundary Acquisition

The Land Parcels layer (LPL) provided boundaries for each agricultural field (Figure 2.2). However, the area defined as an agricultural field in the Land Parcels shapefile did not match the actual land cover. From the satellite view, the southern end of Big Pine watershed extends to forests along the river, which was defined by Land Parcels as agricultural fields (Figure 2.3). The CDL maps provided better field classification with an ambiguous boundary and lots of undefined pixels (Figure 2.4). By processing the Zonal Statistics Tool in ArcGIS Pro of CDL and Land Parcels, each field was reclassified according to the category that had the majority of pixels within the boundary (Figure 2.5). To facilitate counting of various crop fields, we employed Zonal Statistics as Table tool to combine the information of raster file and polygon file, which was in turn exported to an Excel table. The Spatial Join tool is then used to add the grid information back to the boundary shapefile.

2.2.6 Raster Map of Normalized Difference Vegetation Index

We used the Red and Near-infrared (NIR) bands from surface reflectance of Landsat 7 (band 3 and band 5) and RapidEye Ortho Tile (band 3 and band 5) images to calculate the Normalized Difference Vegetation Index (NDVI; Gelder et al. 2009): NDVI = [NIR – RED]/[NIR + RED]. We covered the field boundary layer and transect point shapefile on the NDVI map to check whether the NDVI map visually matched the ground truth (Figure 2.6). In computing the area of winter vegetation-covered fields, it is necessary to divide the NDVI map into soil and vegetation. Therefore, the cut-off NDVI value was critical for the NDVI map reclassification. The analysis of multiple evaluation methods of binary classification helped determine the best cut-off NDVI value.

2.2.7 Evaluation Methods of Binary Classification

In this research, each polygon on the side of the transect point was extracted and labeled either left or right based on the direction of the transect route. There was a total of 322 polygons in the shapefile used for calculations of accuracy; each polygon has all the information, including previous crop and winter cover crop existence from transect data each year. This research used these 322 polygons as reference data and built an Accuracy Matrix with a processed NDVI map (Table 2.2). In the Accuracy Matrix, (a) represents the number of polygons that meet the following conditions: 1) they were, as observed by transect survey, covered with either cover crop ,winter crop or hay in that field, and 2) over 50% of the area in that polygon was covered by vegetation pixels and defined by processed NDVI map as winter vegetation fields; (b) represents polygons where transect survey did successfully observe vegetation in that field, but NDVI map did not capture enough vegetation pixel in that field, and the same determination method is applied for soil as well, (c) represents polygons where transect survey did not record winter vegetation in that field, were nonetheless defined by NDVI as winter vegetation; (d) represents polygons where both transect survey and NDVI map failed to observe vegetation in that field. The Overall Accuracy (OA) was computed by dividing the total correct polygons (a) + (d) by the total (a) + (b) + (c) + (d) polygons in the matrix (Table 2.3). The Producer's Accuracy (PA) measured omission error by dividing the total number of the correct polygons in a category by the total number of polygons of that category. In this case, PA of vegetation was equal to (a)/(a+b), and PA of soil was equal to (d)/(d+c), indicating how much vegetation-covered field recorded in transect data can be captured in the NDVI map. The User's Accuracy (UA) measured the commission error by dividing the total number of correct polygons in a category by the total number of polygons classified in that category (Story and Congalton, 1986). In this case, UA of vegetation was equal to (a)/(a+c), and UA of soil was equal to (d)/(d+b), yielding results that indicated how much vegetation-covered fields determined by the NDVI map had been recorded in transect data. In this research, we focused on the PA of vegetation because PA is interested in how accurate a vegetation-covered area on the ground can be captured by the map. UA may also be biased when weed on the ground was captured by the satellite but was not recorded as a winter crop in transect data.

According to the transect data, the ratio of the area of winter vegetation-covered fields to bare soil fields was almost 1:30. When the dataset is unbalanced (the sample size in one category is much larger than that in another category), the accuracy will provide an over-optimistic estimation of the majority class (Chicco,2020). Due to the negative imbalance of the transect dataset, Precision, Recall, F score, and Matthews Correlation Coefficient were introduced to evaluate the test accuracy (Table 2.4).

In the statistical analysis of binary classification, there are four combinations of test outcomes and actual conditions (Table 2.5): True Positive (TP): both test result and the actual condition are positive; True Negative (TN): both test result and the actual condition are negative; False Negative

(FN): test result is negative but actual condition is positive, and False Positive (FP): test result is positive but actual condition is negative. In this research, TP, FN, FP, TN correspond to (a), (b), (c), (d) in Table 2.2, respectively.

Recall (also called hit rate or true positive rate) is the fraction of the correctly classified positives (TP) in the total condition positive count (TP + FN). Precision (also called positive predictive value) is the fraction of the correctly classified positives (TP) in the total test positive count (TP + FP) (Olson and Delen, 2008). In this research, Recall is equivalent to Producer's Accuracy, and Precision is synonymous with User's Accuracy. F-score is the harmonic mean of Precision and Recall (Chinchor,1992), an attribute that helps balance Recall and Precision. The F-score ranges from 0 to 1, where 1 represents the perfect accuracy with no error. Matthews Correlation Coefficient (MCC) is another binary test evaluation method for the unbalanced dataset (Matthews, 1975), which considers true and false positives and negatives and is generally regarded as a balanced measure (Boughorbel, 2017). MCC returns a value between -1 to +1; the higher the MCC value, the more accurate the binary classification is.

2.2.8 Cut-off NDVI Value

Cut-off NDVI value was the threshold that divides all pixels from the NDVI map into two categories: soil and vegetation. Pixels whose value is larger than cut-off NDVI value were classified as winter vegetation pixels, while the rest were classified as soil pixels. We defined a polygon as a winter vegetation-covered polygon if more than 50% of pixels inside that polygon were vegetation pixels. After producing NDVI map for the Big Pine Watershed agricultural fields, we developed a python program to determine the cut-off value under the highest producer accuracy scenario. First, a range of NDVI values of each year were fed into the program. For instance, the NDVI value in 2015 ranged from 0.00 to 0.15, with an interval of 0.01. The NDVI range varies in each year. The program will pick one value as a cut-off value each time determine whether a field inside a polygon has winter vegetation, and then compare the reference (transect) data of that polygon and build up the accuracy matrix. In the end, the program will compute the highest producer accuracy of both vegetation and soil and produce their corresponding cut-off NDVI values.

2.2.9 Reclassification and Spatial Join

This step applied cut-off value determined by the python program on the whole watershed NDVI map. First, we used the Reclassification tool in ArcGIS Pro, and the cut-off value divided all the pixels of the watershed map into either soil or vegetation category. Raster to Point Tool was then used to transfer vegetation pixels into point shapefile. Each point represents one vegetation pixel. For each field polygon, Spatial Join Tool can help count total vegetation pixels in an individual polygon. Polygons which has over 50% vegetation points will be treated as vegetation field in winter. In this way, it helped eliminate waterway grass or other noises. In the end, we exported polygon attribute table (including previous and post cash crop information from the CDL, winter vegetation information from the reclassified NDVI map and its area) as an Excel file to calculate the adoption of winter cover crop, cover crop adoption management tendencies and cover crop adoption tenures.

2.3 2.3 Results and Discussion

2.3.1 Determination of the Best Cut-off Value

The immediate and primary objective was to evaluate the rapid cover crop survey method as a better alternative to the driving transect to estimate cover crop adoption on a watershed scale. The very first step was to determine the NDVI cut-off value to confidently discern the difference between vegetative cover and soil within the cropping system for each year of the study. In determining the best cut-off value (COV), we computed all the indices (PA, UA, F-score, MCC) of each COV in a specific NDVI range for each year. Through a developed program script, we divided all pixels of the polygons along the transect route into vegetation or soil category to determine whether a field is covered with winter vegetation or bare soil. The next step was to determine whether the field category (vegetation or soil) classified by the processed NDVI map was the same as that recorded in the transect data. The program's final output included a matrix shown in Table 2.4 and the result of those indices. Additionally, we found that the PA (how much vegetation-covered field recorded in Transect data can be captured by the NDVI map) and UA (how much vegetation-covered field determined by the NDVI map had been recorded in Transect data) were critical variables to be taken into consideration when optimizing COV along with the F and MCC values (indices to evaluate binary test). In the year of 2015, although the F-score and

MCC were the same under the NDVI value 0.00, 0.01, 0.02, 0.03, we determined that 0.00 was the best COV due to its higher PA. The COV for the duration of the research ranged from -0.01 to 0.24 over the years from 2014 to 2018 (Table 2.6). The COV varied across different years due to the difference in the satellite product, and the date of satellite image was acquired.

The transect validation dataset was negatively unbalanced. The total number of validation fields for 2014 to 2018 was 319, 324, 324, 322, 316 respectively. In the transect dataset, the cover crop fields were less than 10% of the entire validation fields, and 90% of those fields were recorded as bare soil. The rapid cover crop survey method accurately distinguished bare soil from vegetation 95-97% of the time, compared to the transect ground-truthing data (Table 2.7).

The F-score and Matthews Correlation Coefficient were also used to evaluate the accuracy of the rapid cover crop survey method due to the negatively unbalanced dataset. The F-score and MCC quantified the ability of the COV to discern the difference between soil and vegetation. Among selected COV values, the F and MCC values ranged from 0.48 to 0.81, and from 2015 to 2018, the average F-score and MCC values were 0.72. The lowest F and MCC scores were observed in 2014 and could be attributed to a low-resolution satellite image and a substantial time lag between available satellite images and the date of transect survey.

In the previous literature, researchers also used accuracy and F-score to evaluate their processed satellite images for larger-area cropland (Elodie, 2013). Elodie selected Central and Southern Mali (a land-locked country located in West Africa) covered by three 3,600 ha, 2.5-m resolution SPOT images as the focus of research. In these three areas, a total of 980 GPS waypoints were registered as the validation site of the ground data, and each waypoint was transformed into a 1 km × 1 km polygon with a center labeled by a land-use class ("crop" or "non-crop"). The result of cropland detection with ground data were: PA = 0.742, UA = 0.796, and F-score = 0.724. Moreover, the author pointed out that the method had proven satisfactory.

2.3.2 Quantification of Rapid Cover Crop Assessment Accuracy

PA values ranged from 35.71% to 93.75%, and the range of UA was from 42.86% to 72.22%. The average PA and UA from 2015 to 2018 were 89.02% and 60.52% respectively. For the Producer's Accuracy, the growing conditions of cover crop could contribute to the loss of accuracy. For instance, some fields were recorded as cover crops in the transect data, but the cover crop in those fields was not mature enough to be captured by the processed NDVI map. For User's

Accuracy, the weed area could contribute to the loss of accuracy since the fields identified as vegetation in the processed NDVI map represented all winter vegetation including weed. However, the transect data only recorded cover crops, alfalfa, and winter wheat.

The results in Table 2.6 showed that the processed NDVI map of the year 2015 and 2016 made the most accurate predictions of winter vegetation. For the years 2017 and 2018, the low UA may be caused by two factors. The first factor might be that the weed area increased in 2017 and 2018. The increased weed area gave rise to the fields that the NDVI map identified as vegetation but that failed to be recorded by the transect survey as winter crops increased. In table 2.3 of, UA equals a/(a+c); when c increased, the UA decreased. The second factor could lie in the underestimation of the best COV, which means the real COV for 2017 and 2018 should be on the right side of the dash line in Figure 2.7. In this scenario, the final estimation of the entire watershed winter vegetation area might be overestimated.

The previous study on inventorying cover crop adoptions in Carolina's Graduate Dissertation focused on East-Central Iowa that occupied 245, 463 hectares (Carolina, 2016). The research of cover crop adoption in Iowa also used satellite image and CDL as sources; however, the ground truth was provided by seed dealers. The major difference was that they set a fixed cut-off NDVI value to differentiate cover crop from non-cover crop fields. Our research had more flexible NDVI cut-off values depending on different satellite images. The PA and UA for the cover crop identified in Iowa was 76.92% and 71.43% respectively. Comparing the PA and UA with our results, we had a higher PA (89.02%) and a lower UA (60.52%), meaning that our processed NDVI map could be more accurate for capturing the winter vegetation on the ground, but the transect survey data as ground truth reference limited us for a higher UA.

In the early stage of this research, we only calculated the PA, UA, and OA; the evaluation dataset was based on 201 transect points. The preliminary accuracy test result showed that the Overall Accuracy was heavily influenced by a large amount of soil transect points. After adopting the Python program to help compute the indices for each COV and changing the evaluation dataset from 201 transect points to 322 polygons on the side of the transect points, the new average PA of 2015-2018 was drastically improved, from 75.44% to 89.02%. The implication of this observation means that our new practice was more specific for evaluating cover crop adoption.

2.3.3 Historical Cover Crop Adoption

Using a rapid cover crop survey method to perform a hindcasting analysis of cover crop adoption within the Big Pine Watershed for 2014-2018 was the second objective of this study. The result for objective one provided the best cut-off value for the processed NDVI map. In objective two, we applied the best cut-off value from the transect route to the entire watershed. The green area showed the winter vegetation processed by the satellite images for each year (Figure 2.8).

By comparing the processed NDVI maps to the original Transect Survey data saved in the Excel file, we found that these maps, with a better visual effect, provided the detailed location of each winter vegetated fields for NRCS. Further, compared to limited fields of transect survey observed as shown in Figure 2.9 (322 fields of transect survey out of 2,483 total fields within the Big Pine Watershed), processed NDVI maps could offer a macroscopic view of all 2,483 fields of the entire watershed. In the transect survey, the ratio of winter vegetation fields (including cover crop, winter wheat, and hay) to total transect fields lay within the range of 4.1%~5.5%. However, in our research, the ratio of winter vegetation fields to total watershed fields ranged from 5% to 9%. Thus, the transect survey, merely based on 12,278 ha, might have underestimated the cover crop acreage in the watershed due to its inability to capture the cover crop fields outside the transect route (Figure 2.9).

To quantify the cover crop adoption, we exported the contribute table of the entire watershed field boundary to Excel files. The Excel files included the percentage of vegetation pixel in a polygon, previous and post cash crop and polygon area. The result of the field area based on its winter vegetation condition and previous cash crop was displayed in Table 2.8. The cover crop area ranged from 3,053 to 5,444 ha, while the range of total winter vegetation was from 3,607 to 6,478 ha, and the ratio of the total winter vegetation area to the cultivated crop area of the entire watershed was from 5.1% to 9.18%. The average area of cover crop adoption was 4,295 ha for each year. Among all types of winter vegetation, cover crop adoption increased by around 2,230 ha (~73% increased), and alfalfa area increased by 639 ha (~666% increased). By contrast, winter wheat decreased by 198 ha (~45% decreased). The ratio of overall winter vegetation to total cultivated crops land area within the Big Pine Watershed increased from 5.1% to 8.9% (around 0.76% increased each year).

According to Table 2.8, it was found that although the cover crop increased from 2014 to 2018, it was far from a linear incline, in fact cover crop adoption plateaued since 2017. Moreover, the discussion for objective one pointed out that the adoption of 2017 and 2018 might be overestimated, a fact that warrants careful consideration. We compared our research to the transect data, and the result was shown in Figure 2.8. The transect survey was county-based, so we only had an estimated cover crop area for Benton and Warren County as reference, in which the area of the Big Pine Watershed accounted for around 45% of the total area of Benton and Warren County. As is illustrated by Figure 2.8, the transect survey predicted a downward trend of cover crop adoption from 2015 to 2018. Particularly in 2016, the cover crop adoption for Warren County unexpectedly dropped by over 50% from 2015. The transect data also revealed that the ratio of cover crop fields to total observed fields decreased drastically: in 2015 the ratio was 23 out of 502 fields, but by 2016, the ratio declined to 5 out of 448 fields. Such decrease suggested that the estimated cover crop adoption provided by the NRCS relied heavily on the transect driving survey, which only investigates 8.5% of the actual cultivated land. In contrast, our study showed an increasing trend in the southern watershed (in Warren County) from 2014 to 2018, registering the maximum value of adoption in the Big Pine Watershed in 2017. Alfalfa increased by about 666%, whereas winter wheat decreased by 45% from 2014 to 2018, a result that corroborated the fact provided by NRCS that the livestock industry rose in the Big Pine Watershed, and some winter wheat farmers moved out of the watershed.

According to the Big Pine Creek Watershed Implementation (Contract# 19223) of Indiana Department of Environmental Management, the Big Pine Creek Watershed promoted a cost-sharing program to implement best management practices such as cover crops and conservation tillage since 2016. At the beginning of the implementation phase in 2015 fall, the NRCS had directly funded approximately 25,800 acres (10,440 ha) of cover crops. The funding project mentioned that "the partnership's goal is to deliver an additional 8,000 acre (3,237 ha) of cover crops, 10,100 acres (4,087 ha) of nutrient management and 4,850 acres (1,963 ha) of Conservation Stewardship Program enhancements." Yet, the recent cover crop adoption did not meet the funding goal. Comparing to the traditional driving transect survey, our rapid cover crop survey method can avoid driving around the county and thus reduced the cost on labors and transportations.

2.3.4 Crop Rotation Tendencies

The third objective of this study was to assess cover crop adoption and crop rotation management preferences of farmers within the Big Pine Watersheds. In the previous step, we defined cover crop fields in alignment with the previous cash crop classified by the CDL. For each winter cover crop field defined in Table 2.8, the previous cash crop was either corn or soybean; and post cash crop was corn or soybean or winter wheat. We combined both previous and post cash crops for each cover crop field and divided all cover crop fields into six categories (Table 2.9 and Figure 2.11). We decided to focus on the two dominant crop rotations: Corn-Soybean and Soybean-Corn, because the average area of Corn-Soybean rotation occupied 46.20% and the average area of Soybean-Corn rotation area occupied 44.30% of the total area of all crop rotations. The cover crop adoption area in Corn-Soybean rotation for 2014, 2015, 2016, and 2017 was 638, 1,797, 1,008, and 1,915 ha, respectively. The cover crop adoption area in the Soybean-Corn rotation for 2014, 2015, 2016, and 2017 was 1,561, 1038, 1,793, and 2,019, respectively. To establish an association between crop rotation preference and cover crops observed, we calculated the percentage of cover crop adoption in each crop rotation category. This would reveal whether there is a preference for a given rotation. The area of cover crop adoption in Corn-Soybean rotation as a percentage of the total area of Corn-Soybean rotation in the Big Pine Watershed for 2014, 2015, 2016, and 2017 were 2.14, 5.59, 3.30, and 5.70%, respectively, while the figure for Soybean-Corn rotation in 2014, 2015, 2016, and 2017 were 5.11, 3.48, 5.83, and 6.75%, respectively.

We found that both the area and percentage of cover crop adoption was higher in the Soybean-Corn rotation in the year of 2014, 2016, and 2017. In the literature, cover crop experts suggested planting cereal rye into corn stalks and planting soybean into the dying or dead cereal rye after terminating the cereal rye in spring (Kladivko, 2015). However, in this research, the Corn-CC-Soybean rotation only exceeded the Soybean-CC-Corn rotation in 2015. We tracked the transect data and found that the percentages of cereal rye fields to total cover crop fields within the Big Pine Watershed for 2014, 2015, 2016, and 2017 were 9.09, 72.73, 37.50, and 77.78%, respectively. The percentage of cereal rye fields to total cover crop fields matched that of the Corn-CC-Soybean rotation to Corn-Soybean rotation, a fact that suggested that the cash crop rotation could drive cover crop species selection. Moreover, although the cover crop adoption was higher in the Soybean-Corn rotation, the cover crop might not be cereal rye.

When comparing our research with the transect survey data (ISDA Cover Crop and Tillage Transect Data), we found that the ISDA estimated cover crop adoption distribution in various cash crops based on the entire county's transect road survey. In the ISDA final report of Living Covers, they developed maps of the estimated living overs planted in all crops, in Corn, in Small Grains, in Soybean, and in Specialty Crops of each year. Each living covers map only included the boundary of each county and a number representing area of living covers under the name of that county in each year. Table 2.11 showed the estimated cover crop adoption after corn and soybean for Benton and Warren County from 2014-2017 was acquired from ISDA Living Cover maps. There was no clear pattern of the preference of cover crop adoption in crop rotation management. As discussed before, the estimated area of cover crop adoption was based on the limited observation of the transect road survey. Moreover, the ISDA did not provide any continuous data about the cover crop field's post cash crop. In contrast, our methodology allowed us to focused on each field in the Big Pine Watershed, specifically relative to only the field in the transect area. Therefore for each field, we can identify winter cover crop existence, previous and post cash crop and could more detailed information of farmer cover crop tendencies on a whole watershed scale with greater accuracy

2.3.5 Cover Crop Adoption Tenure

Determining the cover crop adoption tenure of fields within the Big Pine Watershed was the last objective of this research. After compositing all processed NDVI maps from 2014 to 2018, we developed a raster map that demonstrates the tenure of the winter vegetation (Figure 2.12). On the winter vegetation tenure map, different colors represented different tenure lengths for each field. The first category was the field with no winter vegetation cover from 2014 to 2018, and the following categories were fields with one-year, two-year, three-year, four-year, and five-year winter vegetation adoption. We summarized each category's total area and its percentage to the total cultivated crop area of the Big Pine Watershed (Table 2.12) and found that as cover crop tenure increased the total area of cover crop adoption decreased in the watershed.

The largest transparent area on the tenure map was the fields with no winter vegetation cover in the 5-year range, which occupied 84.18% (59,612 ha) of the total cultivated area of the Big Pine Watershed. Among all other five categories on the tenure map, the green area, representing fields covered with winter vegetation for only one year, occupied over 52.7% (5,906 ha); the blue area, representing fields covered with winter vegetation for two years, occupied around 30% (3,304 ha); the purple area, representing fields covered with winter vegetation for three years, occupied 11.3% (1,263 ha); the orange and dark red area, representing fields that continuously adopted winter vegetation more than four years, only occupied 6.5% (732 ha) area. Although over half of the winter vegetation-covered fields adopted winter vegetation for only one year, this did not imply that half of the farmers who adopted cover crops only had one-year cover cropping experience, it is possible that each farmer had more than one field and farmers may adjust the cover crop adoption in line with their crop rotation plan and chose to plant cover crops in different fields for different years. The blue area on the tenure map, which represented the field that adopted winter vegetation for any two years in the five-year range, occupied an area of 3,304 ha. The two-year continuous adoption, fields that adopted winter vegetation for two consecutive years (e.g., 2014 and 2015, 2015 and 2016), occupied an area of 1,668 ha. The purple area in the tenure map, which represented the field that adopted winter vegetation for any three years in the five-year range, occupied an area of 1,263 ha. The three-year continuous adoption, fields that adopted winter vegetation for three consecutive years (e.g., 2014, 2015, and 2016; 2015, 2016 and 2017), occupied an area of 600 ha. The percentage of the area of two-year continuous adoption to the two-year adoption and three-year continuous adoption to three-year adoption was 50.5 and 47.5%, respectively. This data showed that farmers indicated no preference for either adoption of winter vegetation continuously or adoption of winter vegetation in alternate years in a field. According to Figure 2.12, all the long-time winter vegetation adoption fields were concentrated in the mid-south of the Big Pine Watershed. We tracked the CDL and found that over 90% of the five-year winter vegetation-covered fields were labeled as Alfalfa or Other Hay/Non-Alfalfa.

The farmers' decision on the cover crop tenure may be affected by the cost-sharing program or their crop rotation plan. In the CTIC Cover Crop Survey Annual Report, among farmers who had cover cropping experience, 37% (588 farmers) had used cover crops for three years or less, while the remaining 63% (1,007 farmers) had used cover crops for four years or more (CTIC, 2017). In our research, until the year of 2018, the dominant cover cropping experience was less than three years, this could be attributed to the NRCS established soil conservation strategy and started the cost-sharing program in the fall of 2015. For future research, we plan to perform a cluster analysis of cover crop adoption along the dimension of space. For instance, we can sample several fields with long adoption tenure on the map. By analyzing cover crop adoption in the following years of sample fields and their neighbors, we may ascertain whether fields with extended cover crop adoption tenure can influence adjacent fields and measure the relationship between influence and cover cropping tenure. Assuming that those fields with extended cover cropping adoption tenure have a positive influence on adjacent fields, the NRCS could develop more appropriate crop promotion strategies and save costs.

2.4 Conclusion

The results of this research demonstrated that remote sensing can be used to successfully detect cover crops in agricultural fields, with an average PA of 89.02% from 2015 to 2018. Overall, the area of cover crop adoption increased within the Big Pine Watershed from 3,607 ha to 6,280 ha from 2014 through 2018. The rapid remote sensing method we used in this research was feasible to estimate the area of cover crop adoption and provided the specific location of each winter cover crop field of the entire watershed. However, we found that the recent cover crop adoption seemed to plateau since 2017 and cannot meet the need for the soil water conservation of the Big Pine Watershed. We researched farmers' crop rotation management preference after the cover crop adoption and the cover crop tenure for each field. Our research showed that more cover crop adoption was observed in the Soybean-Corn rotation, and our result of cover crop adoption in the Corn-Soybean rotation shared the same pattern as the percentage of cereal rye adoption to the total cover crop adoption. The result of cover crop tenure showed that over 50% of fields only adopted cover crops for one year, and over 90% of fields adopted cover crops for less than three years.

Given all results above, we can confidently conclude that our rapid cover crop survey method could replace the traditional transect road survey. Furthermore, the rapid cover crop survey has the potential to provide greater field specific spatiotemporal details on cover crop adoption to watershed conservation managers that could help break the current plateaued trend of cover crop adoption in the region and the state. Our evaluation of the rapid cover crop survey method demonstrates that potential advantages of the method are: identifying the actual location of cover crop adoption in the county or watershed, quantification of the cover crop adoption tendencies and tenure on a field specific basis, and a rapid and accurate quantification of cover crop adoption over time on a county or watershed scale. Rapid spatiotemporal assessments of such critical variables of cover crop adoption could advance and deepen the current understanding of voluntary and incentivized cover crop adoption and could more effectively direct and target conservation adoption resources, such as conservation program funds, education and extension, and federal and state conservation program directors' time and effort. Our findings suggest that rapid assessment methods of cover crop adoption involving processed NDVI map could help advance cover crop adoption and assessment in the state of Indiana and the entire Mississippi River Basin region of the eastern corn belt.

Table 2.1. Acquisition details for satellite images

Satellite	Resolution	Tile Code/Raster ID	Dates
Landsat-7	30 m	path: 21 row: 8 path: 21 row: 9 path: 22 row: 8	December 29, 2014
RapidEye Analytic Ortho Tiles	5 m	UTM Zone 16 row: 576 column: 13 UTM Zone 16 row: 576 column: 14 UTM Zone 16 row: 577 column: 13 UTM Zone 16 row: 577 column: 14 UTM Zone 16 row: 578 column: 13 UTM Zone 16 row: 578 column: 14 UTM Zone 16 row: 578 column: 15	November 15, 2015 November 20, 2016 November 24, 2017
PlanetScope Ortho Tiles	3.125 m	1835006_1657613_2018-11-10_1003 1835006_1657614_2018-11-10_1003 1835006_1657713_2018-11-10_1003 1835006_1657714_2018-11-10_1003 1835006_1657813_2018-11-10_1003 1835006_1657814_2018-11-10_1003 1835006_1657713_2018-11-10_1001 1835006_1657813_2018-11-10_1001 1835006_1657814_2018-11-10_101f	November 10, 2018

Table 2.2 Accuracy matrix of the NDVI map.

		Reference (transect data)	
		Vegetation	Soil
NDVI Map	Vegetation	Accurate (a)	Potential Weeds (c)
	Soil	Error (b)	Accurate (d)

Table 2.3 Accuracy calculation formula.

	Producer's Accuracy	User's Accuracy	Overall Accuracy
Vegetation	a/(a+b)	a/(a+c)	a+d/(a+b+c+d)
Soil	d/(d+c)	d/(d+b)	

Table 2.4 Evaluation methods of binary test.

Recall	$\frac{TP}{TP+FN}$
Precision	$\frac{TP}{TP+FP}$
F-score	$2\times\frac{precision\times recall}{precision+recall}$
Matthews Correlation Coefficient	$\frac{TP\times TN-FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$

Table 2.5 Contingency table of binary classification.

	Condition positive	Condition negative
Test outcome positive	True Positive (TP)	False Positive (FP)
Test outcome negative	False Negative (FN)	True Negative (TN)

Table 2.6 Cut-off NDVI Value (COV), Producer's Accuracy (PA), User's Accuracy (UA), F score, and Matthews Correlation Coefficient (MCC) of the vegetation field verified by processed NDVI map through 2014 to 2018

Year	COV	PA (%)	UA (%)	F	MCC
2014	0.24	35.71	71.43	0.48	0.45
2015	0.00	86.67	**72.22**	**0.81**	**0.78**
2016	0.14	**93.75**	71.43	**0.81**	**0.81**
2017	0.01	83.33	55.56	0.67	0.66
2018	-0.01	92.31	42.86	0.59	0.61
Average		78.35	62.7	0.67	0.68
Standard Error		±10.83	±5.86	±0.06	±0.06

Table 2.7 The filed (polygon) numbers in each category mentioned in Table 2 of Method Chapter of processed NDVI map from 2015 to 2018. MVRV, MSRV, MVRS, MSRS represents (a), (b), (c), (d) in Table 2.2 respectively. TP, FN, FP, TN represents True Positive, False Negative, False Positive, True Negative, respectively. The percentage of fields correctly classified represented the ratio of fields that identified into the same category by both processed NDVI map and reference data to total fields.

Year	MVRV(TP)	MSRV(FN)	MVRS(FP)	MSRS(TN)	Total Fields	% fields correctly classified
2014	5	9	7	298	319	94.98
2015	13	2	5	304	324	97.84
2016	15	1	6	302	324	97.84
2017	15	3	12	292	322	95.34
2018	12	1	16	287	316	94.62

Table 2.8 Winter vegetation distribution of the Big Pine Watershed in each year (unit: ha).

	Cover Crops (corn and sb)	Alfalfa	Winter Wheat	Others (non-grass)	total	Ratio to the area of cultivated crops
2014	3,053	96	443	16	3,607	5.10%
2015	4,027	450	377		4,854	6.88%
2016	3,670	460	114	17	4,261	6.04%
2017	5,444	863	171		6,478	9.18%
2018	5,283	735	245	16	6,280	8.90%
Average	4295	521	270	10	5096	7.22%
Standard Error	±464	±133	±62	±4	±561	±0.80%

Table 2.9 Farmers' Tendencies on cover crop adoption management in the Big Pine Watershed from 2014 to 2017 (unit: Ha), the format of the Farmers' Tendencies column was previous cash crop-cover crop-post cash crop.

Farmers' Tendencies	2014	2015	2016	2017
Corn-CC-Corn	248	161	170	148
Corn-CC-Soybean	638	1797	1,008	1,915
Corn-CC-Winter Wheat	290	262	155	72
Soybean-CC-Corn	1,561	1038	1,793	2,019
Soybean-CC-Soybean	153	136	57	304
Soybean-CC-Winter Wheat	138	492	576	391

Table 2.10 The area of different crop rotation in the Big Pine Watershed from 2014 to 2017 (unit: Ha).

Crop Rotation Area	2014	2015	2016	2017
Corn-Corn	6580	5584	4709	2672
Corn-Soybean	29866	32170	30584	33602
Corn-Winter Wheat	290	262	155	72
Soybean-Corn	30528	29841	30774	29903
Soybean-Soybean	589	631	1263	1249
Soybean-Winter Wheat	353	544	576	444

Table 2.11 The estimated cover crop area planted after corn and soybean in the ISDA final report of Living Covers for Benton and Warren County from 2014-2017(unit: Ha).

	2014		2015		2016		2017	
	corn	sb	corn	sb	corn	sb	corn	sb
Benton	1548	2082	2580	2499	3464	2681	2002	2645
Warren	2936	1169	2569	2045	1070	1155	678	1236
total	4484	3251	5149	4544	4535	3836	2681	3881

Table 2.12 Winter vegetation tenure area and its percentage to the total cultivated area of the Big Pine Watershed.

Tenure	Area (unit: ha)	Percentage to the area of cultivated crops
No winter vegetation cover	59,612	84.18%
One-year vegetation	5,906	8.34%
Two-year vegetation	3,304	4.67%
Three-year vegetation	1,263	1.78%
Four-year vegetation	439	0.62%
Five-year vegetation	293	0.41%

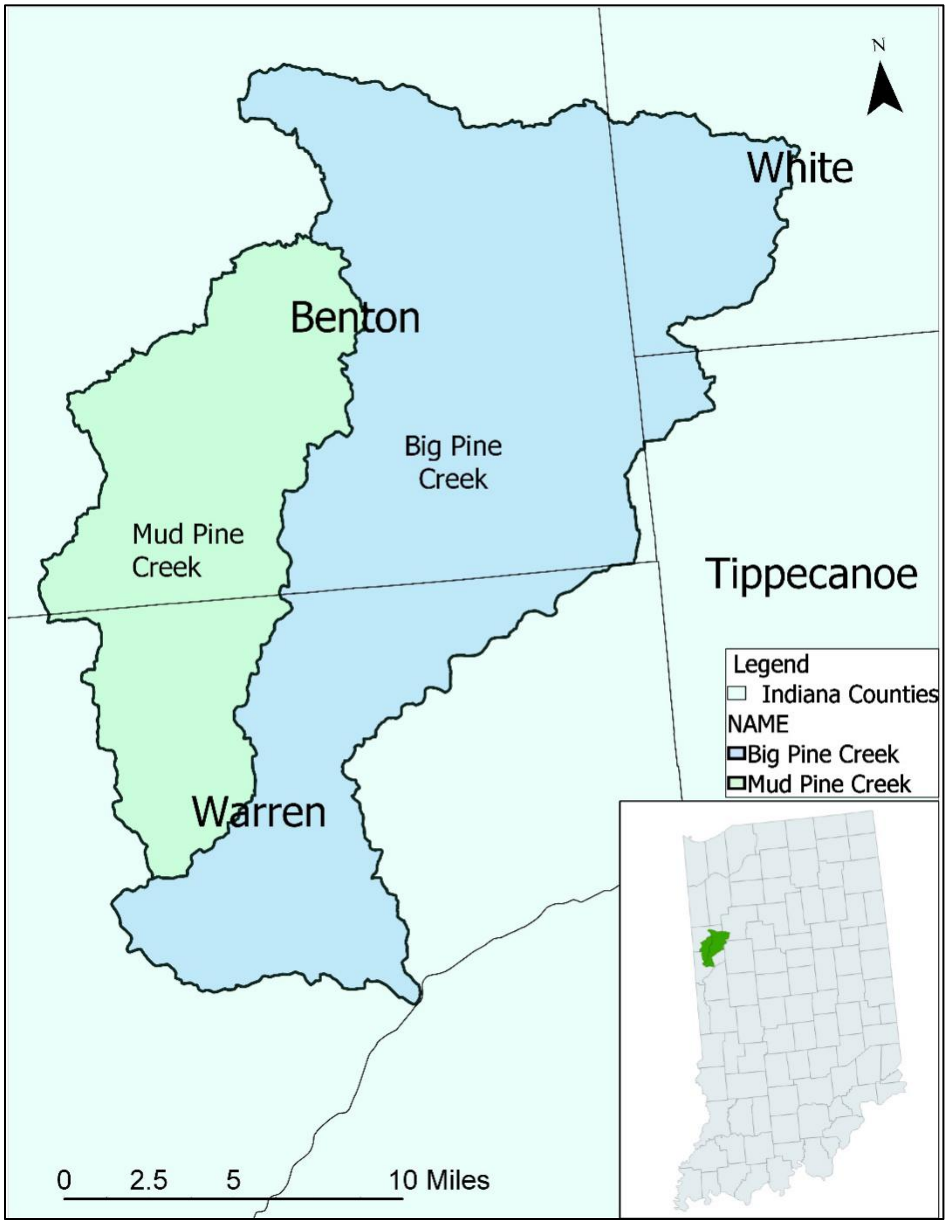


Figure 2.1 The Big Pine Watershed contains the Mud Pine Creek and Big Pine Creek.

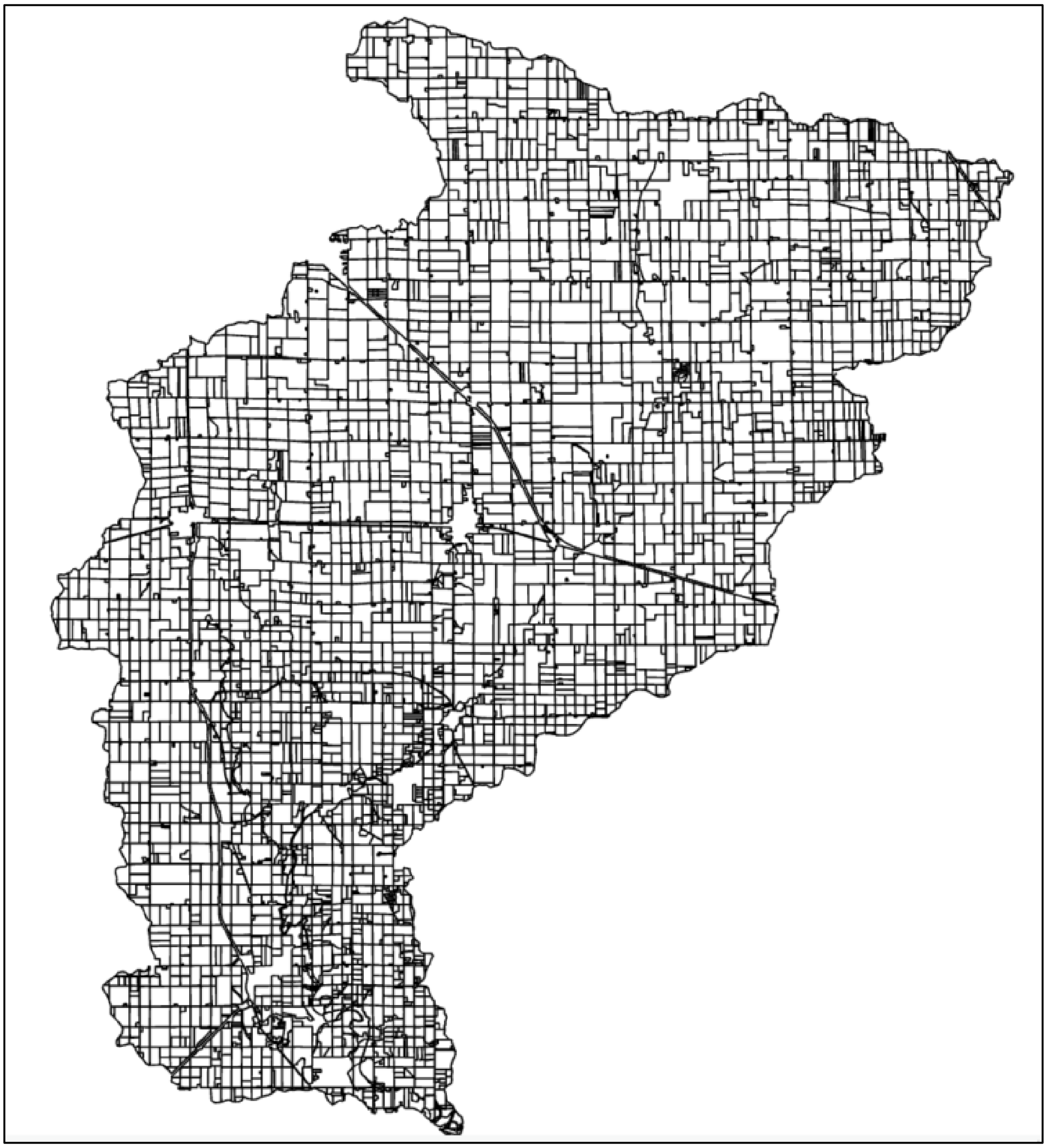


Figure 2.2 Agricultural fields of Big Pine watershed clipped from the Land Parcels Layer.

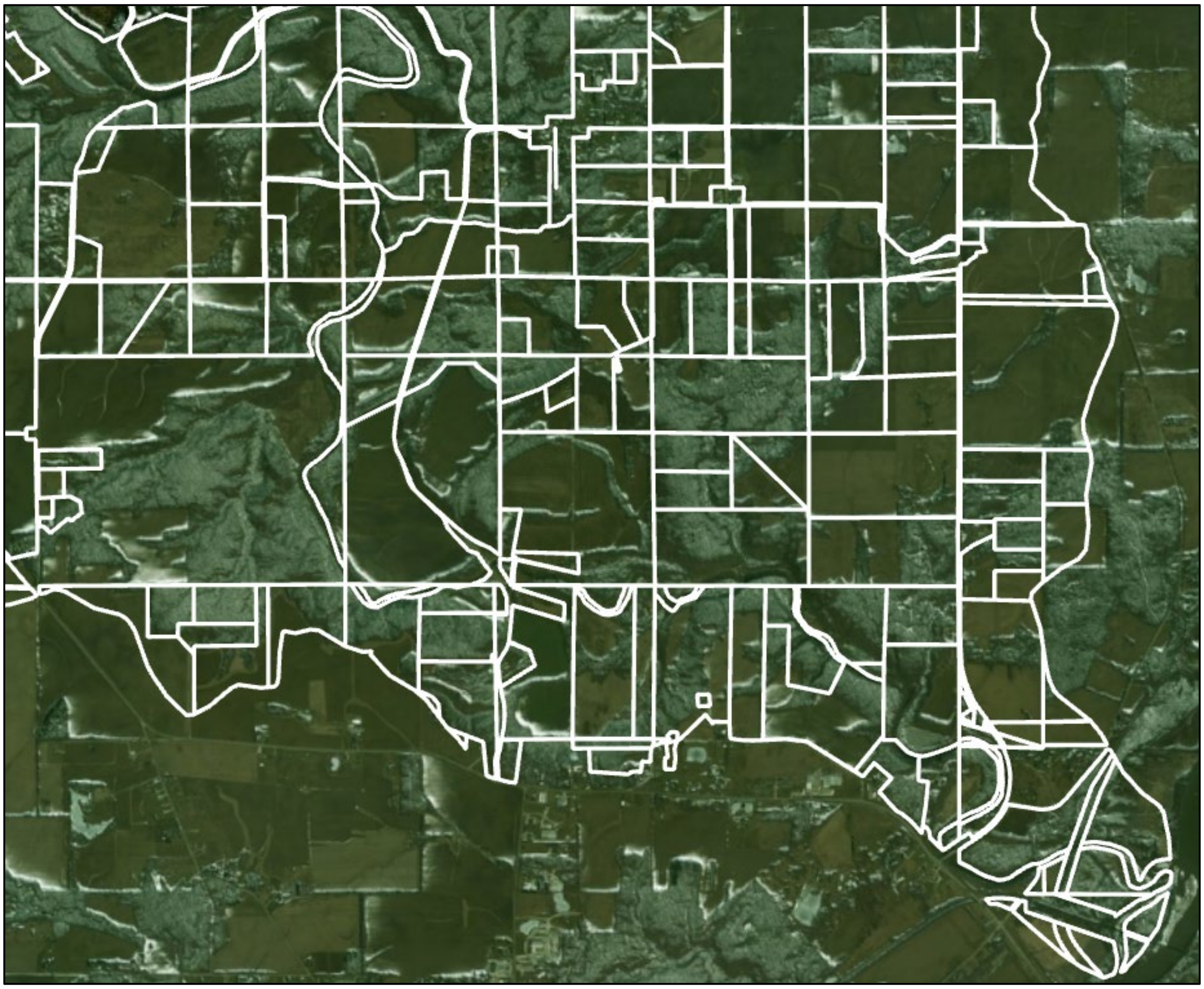


Figure 2.3 Cover the Land Parcels layer on the satellite view Basemap in ArcGIS Pro, all the boundaries defined as agricultural fields in LPL while most of the boundaries in the southern end of the watershed are not actual agricultural fields (forest).

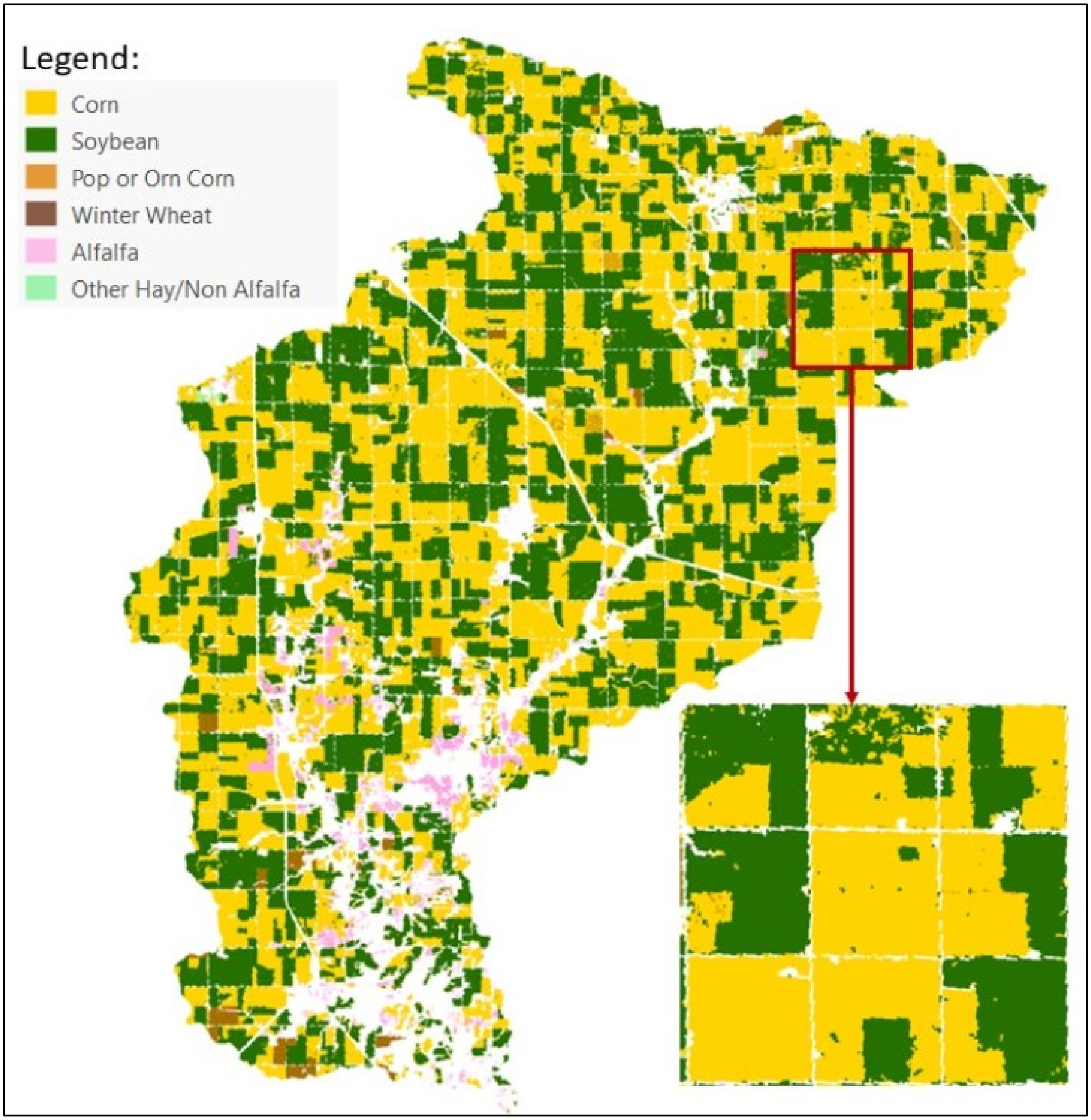


Figure 2.4 Crop Data Layer for Big Pine watershed in 2017, the fuzzy boundary of raster layer made it hard to count the agricultural fields.

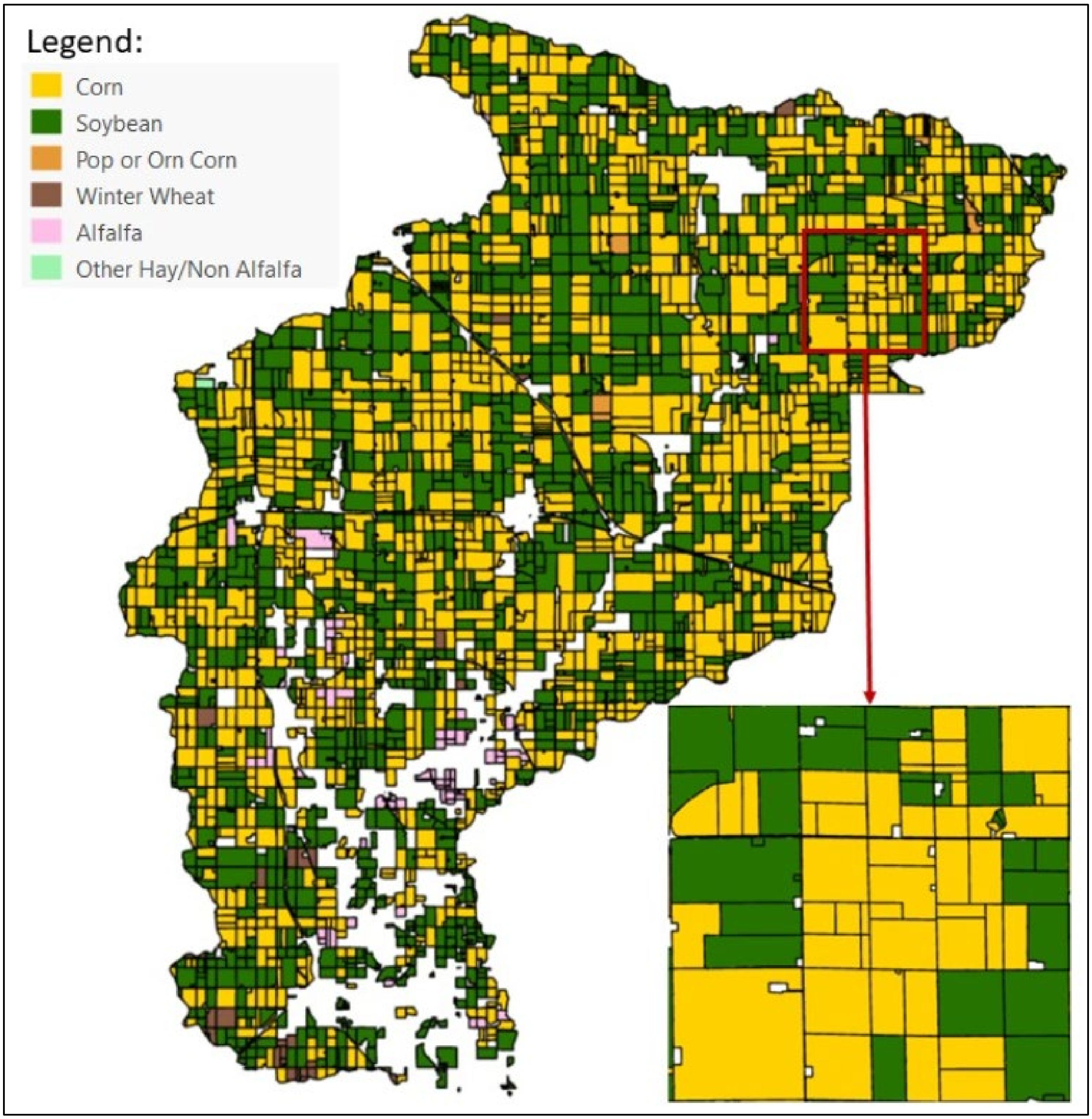


Figure 2.5 Zonal Statistics of 2017 Crop Data Layer and Land Parcel.

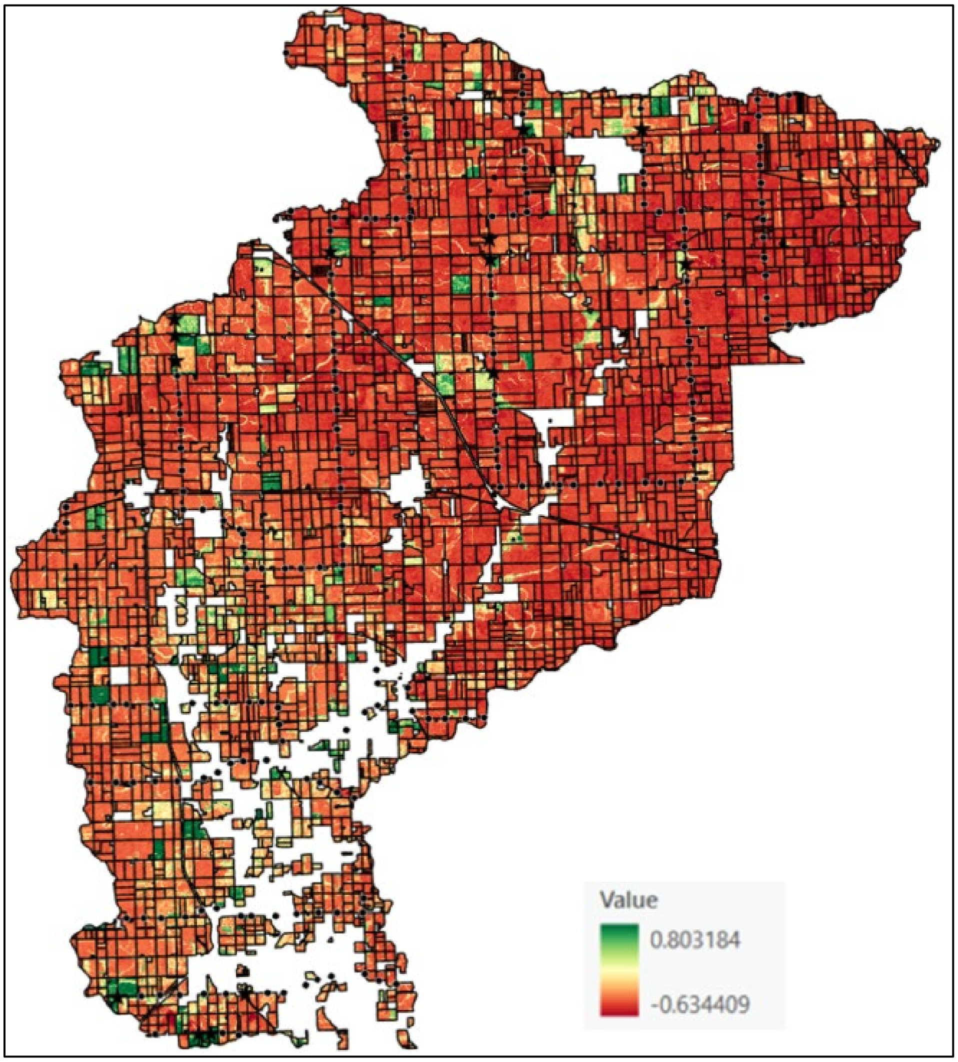


Figure 2.6 NDVI map of Big Pine watershed in 11.20.2016 with transect points and field boundaries. Green area represents winter vegetation, red area represents bare soil.

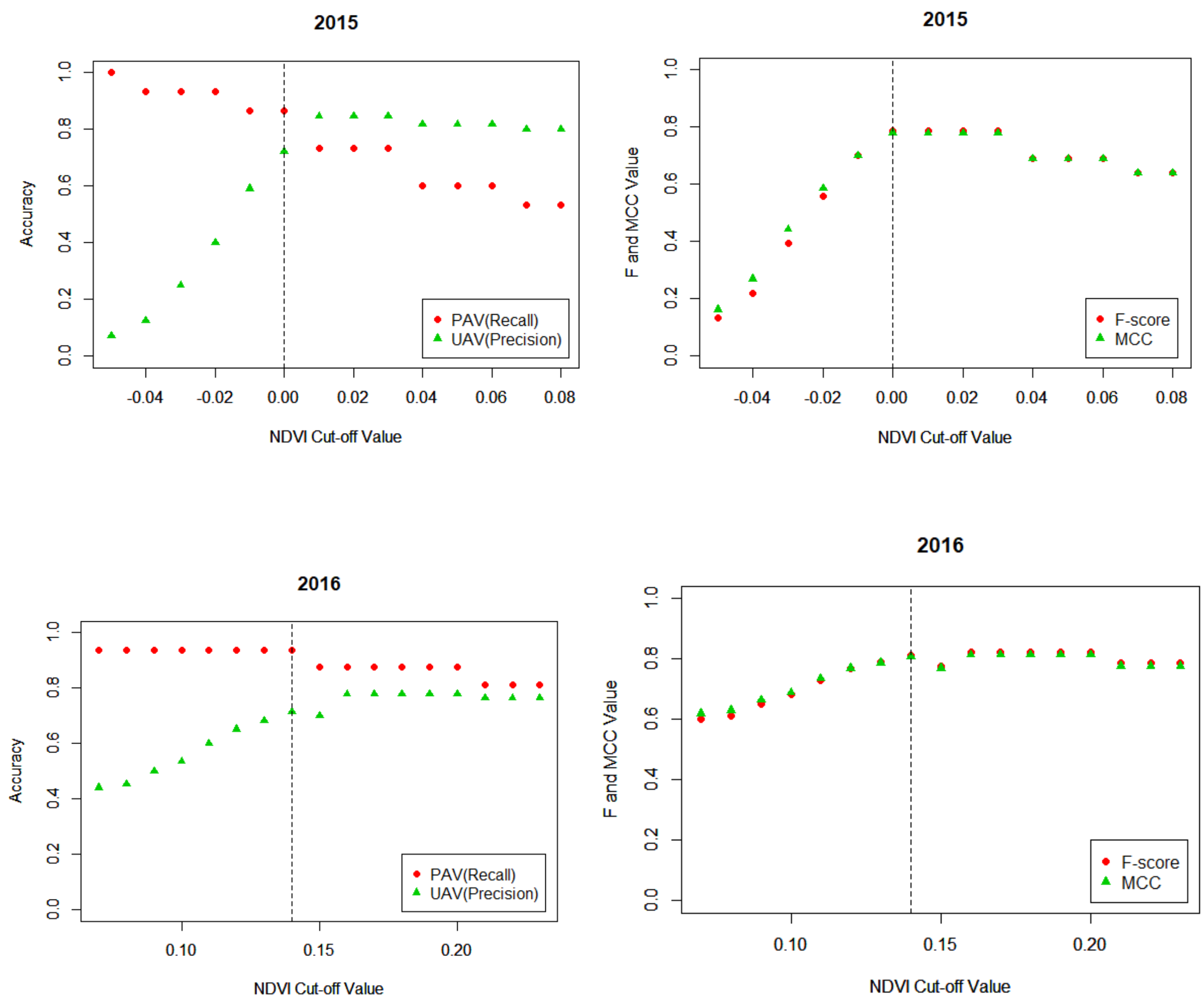
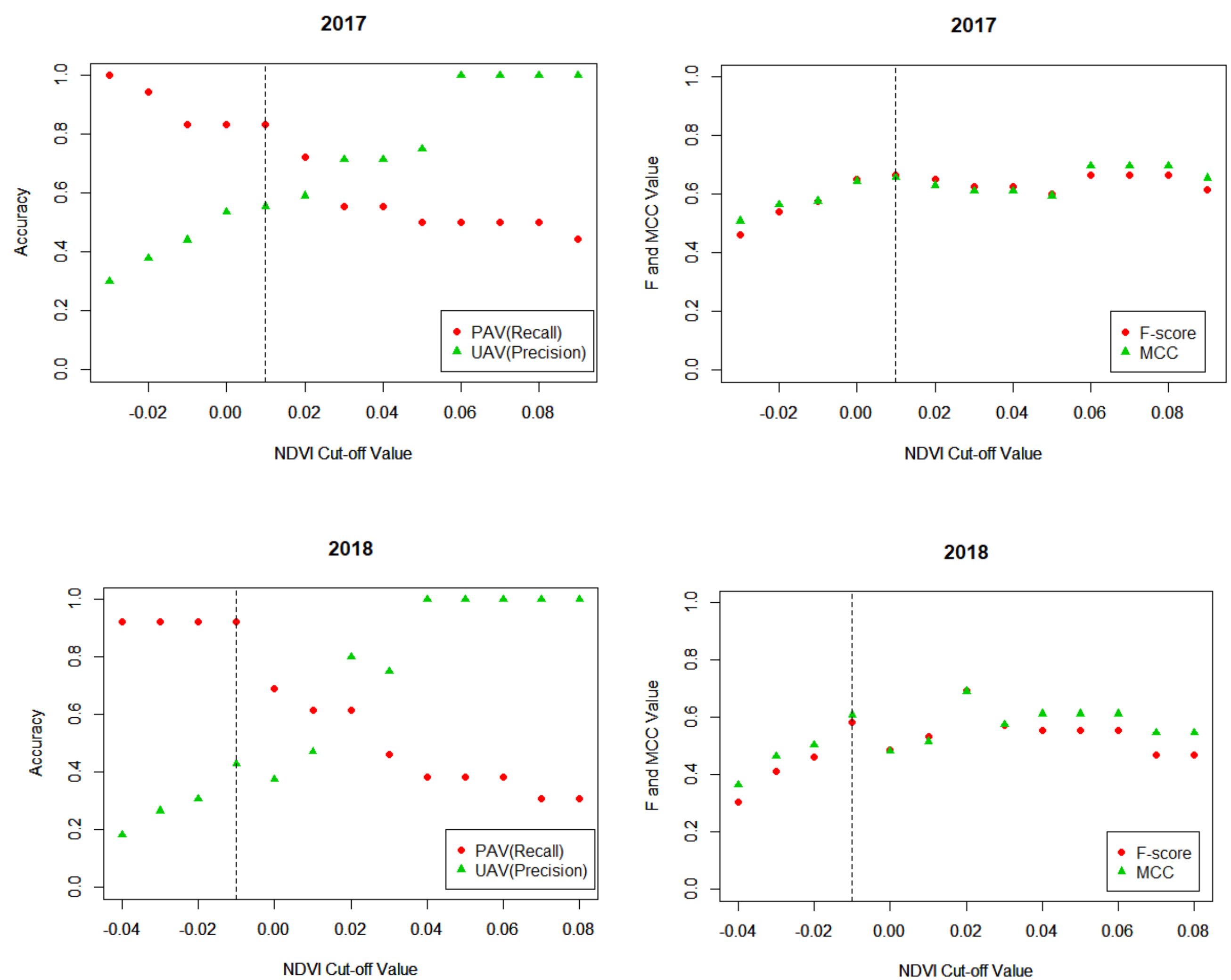


Figure 2.7 Producer's Accuracy, User's Accuracy, F-score, and Matthews Correlation Coefficient (MCC) of various Cut-off NDVI values from 2015 to 2018.

Figure 2.7 continued



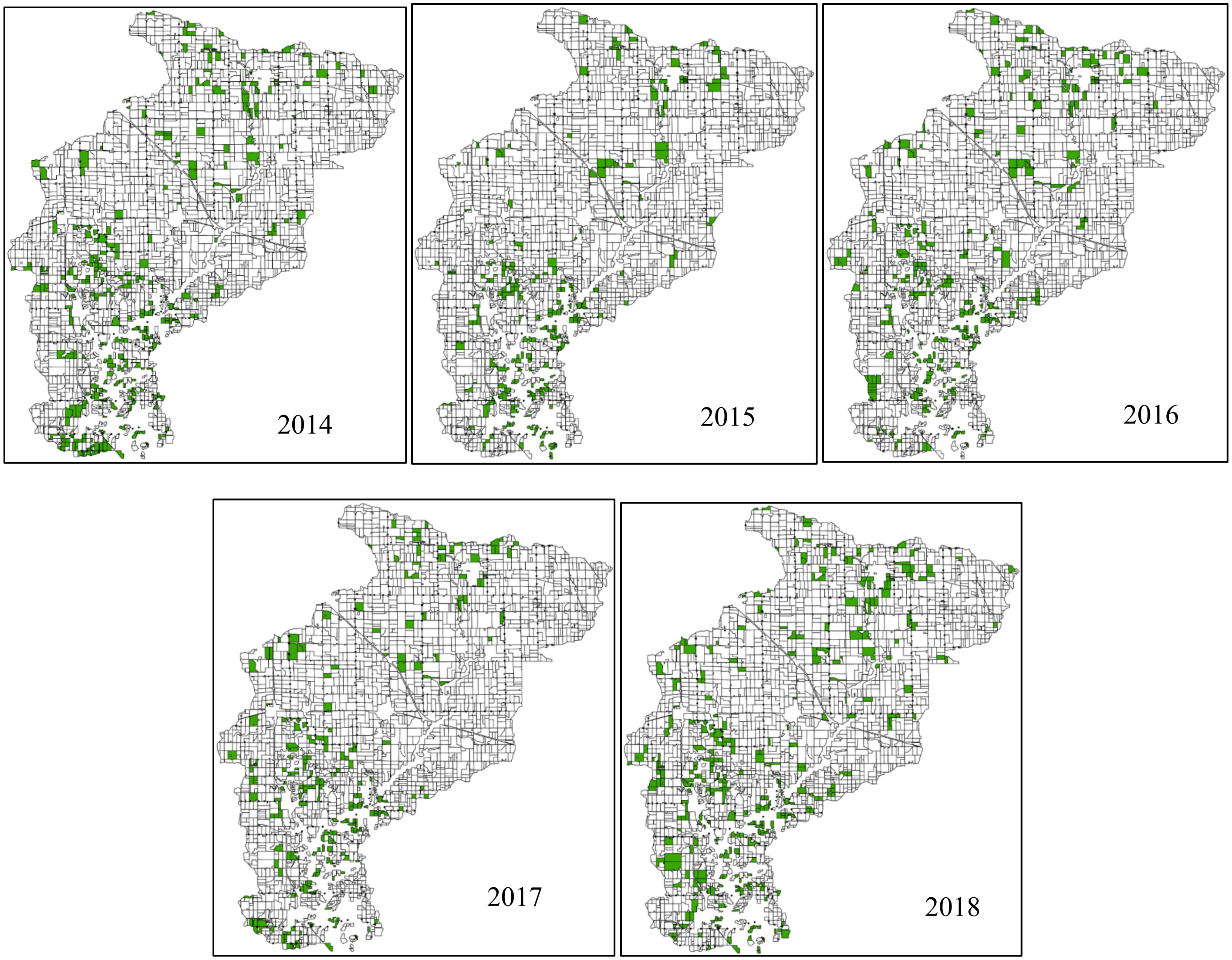


Figure 2.8 Winter vegetation distribution through 2014-2018. The green area was the distribution of winter vegetation processed by the satellite images for each year.

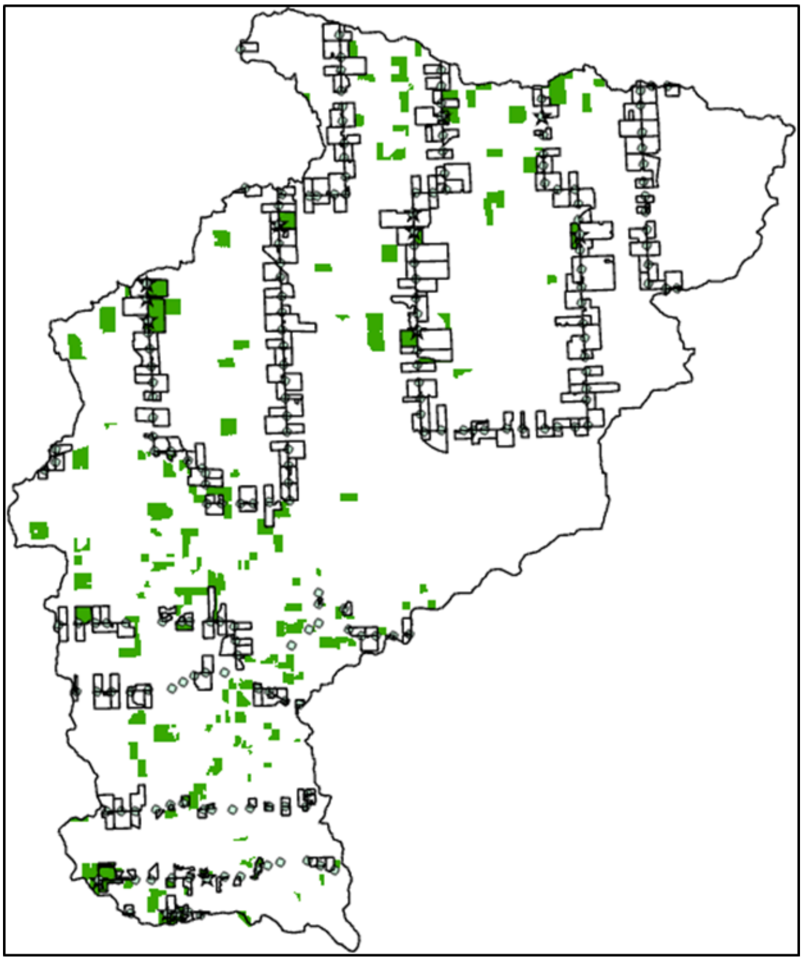


Figure 2.9 Processed NDVI map for 2016, the green area is the winter vegetation detected from the satellite image. Black polygon represents the fields observed in the transect survey.

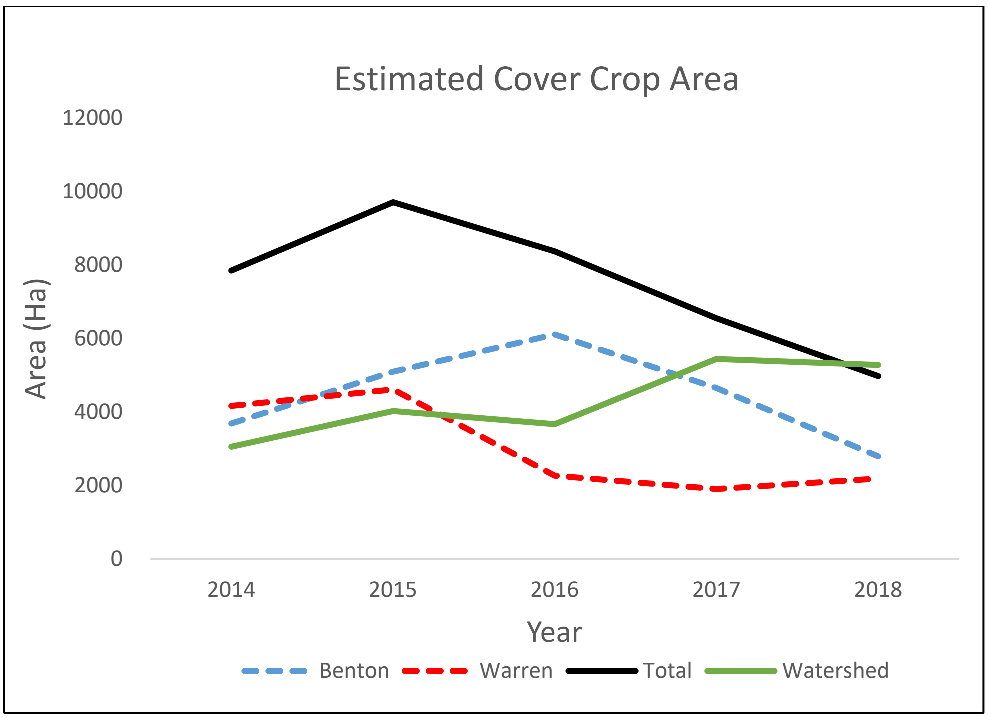


Figure 2.10 The cover crop area for the Benton and Warren County estimated by the transect survey (blue and red dash-line) and the cover crop area for the Big Pine Watershed estimated by the processed NDVI map (green line). The black line is the total estimated cover crop area for Benton and Warren County.

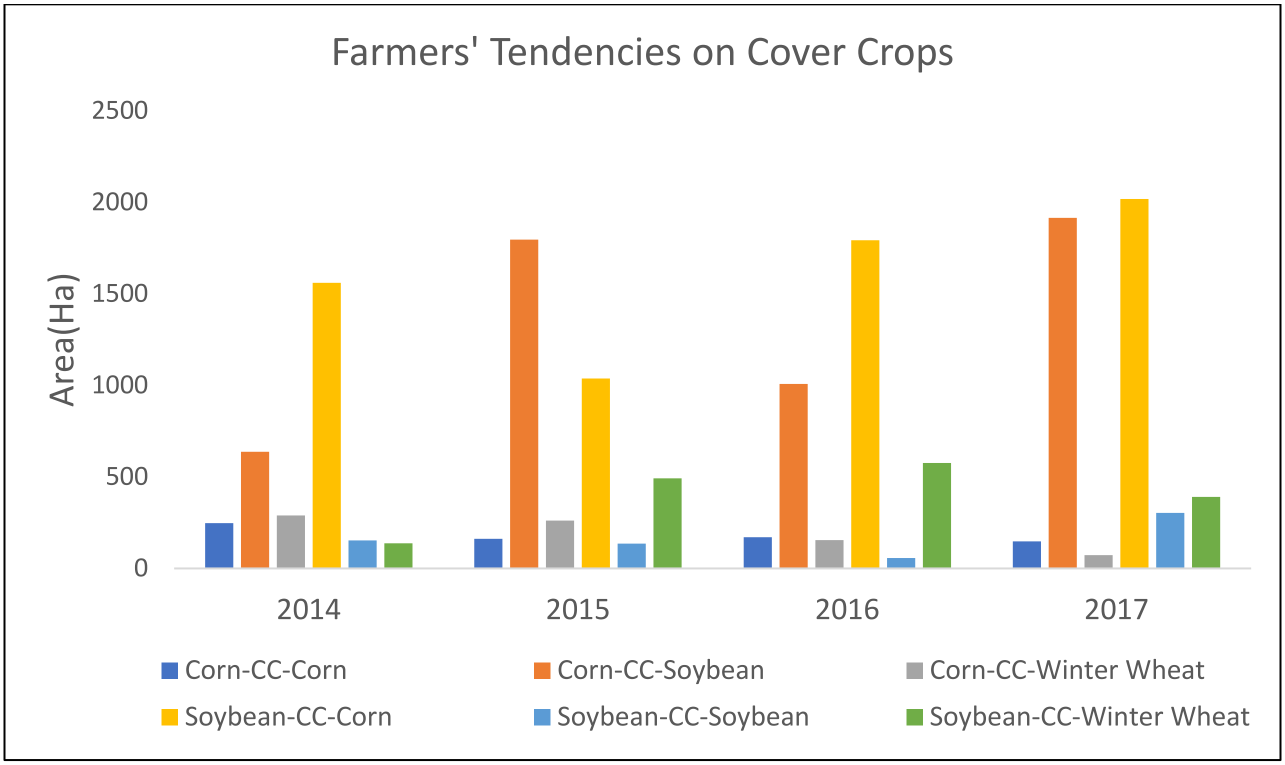


Figure 2.11 Histogram of Farmers' Tendencies on cover crop adoption management in the Big Pine Watershed from 2014 to 2017, the format of six categories of Farmers' Tendencies was previous cash crop-cover crop-post cash crop.

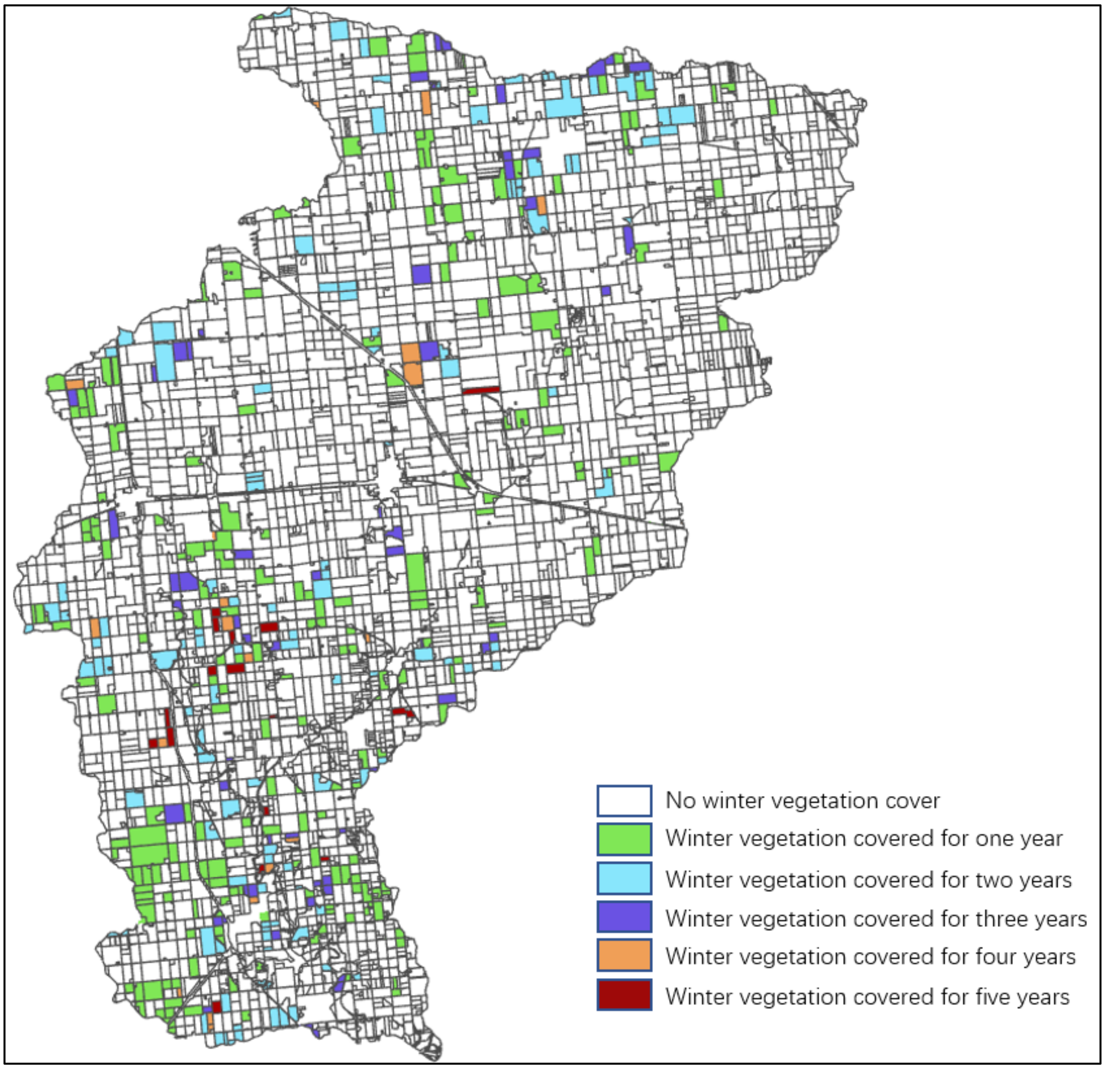


Figure 2.12 Winter vegetation tenure in the Big Pine Watershed from 2014 to 2018. Different colored fields represent different winter vegetation tenure length in that field.

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APPENDIX

Python code for computing best COV and accuracy values for 2015

[2015-1]

```
import geopandas as gpd
import numpy as np


years = ['15']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(-0.01, 0.00, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2015_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2015_type'] == 'V':
                    vs += 1
```

```
                print('vs point:' + str(i))
            else:
                ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] /
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2015-2]

```
import geopandas as gpd
import numpy as np


years = ['15']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.01, 0.02, 0.01)

for year in years:
```

```
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2015_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2015_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] /
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
```

```
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2015-3]

```
import geopandas as gpd
import numpy as np


years = ['15']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.07, 0.09, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
```

```
                sv += 1
                print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] / (fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '    Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '    PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '    PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '    [vv, vs, sv, ss] \n'
    out_line += '    Fuse Matrix: ' + str(final_matrix) + '\n'
```

[2015-4]

```
out_file.write(out_line)
out_file.close()

import geopandas as gpd
import numpy as np
years = ['15']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''
```

```
ndvi_l = np.arange(0.1, 0.12, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] / 
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
```

```
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2015-5]

```
import geopandas as gpd
import numpy as np


years = ['15']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.13, 0.15, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
```

```
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] / (fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

Python code for computing best COV and accuracy values for 2016

[2016-1]

```
import geopandas as gpd
import numpy as np
```

```
years = ['16']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.05, 0.09, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
```

```
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] / (fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '    Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '    PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '    PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '    [vv, vs, sv, ss] \n'
    out_line += '    Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2016-2]

```
import geopandas as gpd
import numpy as np


years = ['16']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''
ndvi_l = np.arange(0.1, 0.14, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
```

```
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] /
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2016-3]

```
import geopandas as gpd
import numpy as np


years = ['16']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.15, 0.19, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
```

```
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] /
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '    Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '    PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '    PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '    [vv, vs, sv, ss] \n'
    out_line += '    Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2016-4]

```
import geopandas as gpd
import numpy as np


years = ['16']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.2, 0.24, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
```

```
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] /
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
```

```
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()


import geopandas as gpd
import numpy as np
```

[2016-5]

```
years = ['16']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.25, 0.28, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
```

```
            if poly.loc[i, '2014_type'] == 'V':
                vs += 1
                print('vs point:' + str(i))
            else:
                ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] /
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

Python code for computing best COV and accuracy values for 2017

[2017-1]

```
import geopandas as gpd
import numpy as np


years = ['17']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''
```

```
ndvi_l = np.arange(-0.02, 0, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] / 
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
```

```
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2017-2]

```
import geopandas as gpd
import numpy as np


years = ['17']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange( 0.01, 0.02, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
```

```
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] /
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2017-3]

```
import geopandas as gpd
import numpy as np
```

```
years = ['17']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.03, 0.05, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
```

```
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] / (fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '    Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '    PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '    PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '    [vv, vs, sv, ss] \n'
    out_line += '    Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2017-4]

```
import geopandas as gpd
import numpy as np


years = ['17']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.06, 0.08, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
```

```
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] /
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2017-5]

```
import geopandas as gpd
import numpy as np


years = ['17']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.09, 0.11, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
```

```
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] /
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

Python code for computing best COV and accuracy values for 2018

[2018-1]

```
import geopandas as gpd
import numpy as np


years = ['18']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.18, 0.19, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
```

```
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] / 
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '    Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '    PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '    PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '    [vv, vs, sv, ss] \n'
    out_line += '    Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2018-2]

```
import geopandas as gpd
import numpy as np


years = ['18']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.2, 0.21, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
```

```
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] /
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '    Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '    PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '    PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '    [vv, vs, sv, ss] \n'
```

```
    out_line += '    Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2018-3]

```
import geopandas as gpd
import numpy as np


years = ['18']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.22, 0.23, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
```

```
                vs += 1
                print('vs point:' + str(i))
            else:
                ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] / (fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '    Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '    PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '    PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '    [vv, vs, sv, ss] \n'
    out_line += '    Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2018-4]

```
import geopandas as gpd
import numpy as np


years = ['18']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.24, 0.25, 0.01)
```

```
for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
                    vv += 1
                else:
                    sv += 1
                    print('sv point:' + str(i))
            else:
                if poly.loc[i, '2014_type'] == 'V':
                    vs += 1
                    print('vs point:' + str(i))
                else:
                    ss += 1
        fuse_matrix.append([vv, vs, sv, ss])
        print('Now processing: {}\r'.format(str(j)))
        j += 1

    fuse_matrix = np.array(fuse_matrix)
    loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] / 
(fuse_matrix[:, 0] + fuse_matrix[:, 1])
    final_matrix = fuse_matrix[loss.argmax()]
    print('Optimal NDVI and fuse matrix of ' + year)
    print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
    print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
    print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
    print('Fuse Matrix: ' + str(final_matrix))
```

```
    out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
    out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
    out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
    out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
    out_line += '   [vv, vs, sv, ss] \n'
    out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```

[2018-5]

```
import geopandas as gpd
import numpy as np


years = ['18']
poly = gpd.GeoDataFrame.from_file('field_poly/transect_area_type.shp')
out_file = open('optimal_NDVI.csv', 'w')
out_line = ''

ndvi_l = np.arange(0.26, 0.27, 0.01)

for year in years:
    ndvi = gpd.read_file('NDVI/NDVI_' + year + 'p.shp')

    fuse_matrix = []
    j = 0
    for ndvi_t in ndvi_l:
        vv = 0
        ss = 0
        vs = 0
        sv = 0
        for i in range(len(poly.geometry)):
            print(i)
            polygon = poly.geometry[i]
            subset = ndvi[ndvi.within(polygon)]
            if sum(subset['grid_code'] > ndvi_t) / (len(subset['grid_code'])+1) > 0.5:
                if poly.loc[i, '2014_type'] == 'V':
```

```
                vv += 1
            else:
                sv += 1
                print('sv point:' + str(i))
        else:
            if poly.loc[i, '2014_type'] == 'V':
                vs += 1
                print('vs point:' + str(i))
            else:
                ss += 1
    fuse_matrix.append([vv, vs, sv, ss])
    print('Now processing: {}\r'.format(str(j)))
    j += 1

  fuse_matrix = np.array(fuse_matrix)
  loss = fuse_matrix[:, 3] / (fuse_matrix[:, 2] + fuse_matrix[:, 3]) + fuse_matrix[:, 0] / (fuse_matrix[:, 0] + fuse_matrix[:, 1])
  final_matrix = fuse_matrix[loss.argmax()]
  print('Optimal NDVI and fuse matrix of ' + year)
  print('Optimal NDVI: ' + str(ndvi_l[loss.argmax()]))
  print('PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])))
  print('PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])))
  print('Fuse Matrix: ' + str(final_matrix))
  out_line += 'Optimal NDVI and fuse matrix of ' + year + '\n'
  out_line += '   Optimal NDVI: ' + str(ndvi_l[loss.argmax()]) + '\n'
  out_line += '   PA_Veg: ' + str(final_matrix[0] / (final_matrix[0] + final_matrix[1])) + '\n'
  out_line += '   PA_Soil: ' + str(final_matrix[3] / (final_matrix[2] + final_matrix[3])) + '\n'
  out_line += '   [vv, vs, sv, ss] \n'
  out_line += '   Fuse Matrix: ' + str(final_matrix) + '\n'

out_file.write(out_line)
out_file.close()
```