A Satellite Remote Sensing Analysis of Cover Cropping Practices in Champaign County, Illinois

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Abstract

This study attempted to analyze cover cropping practices in Champaign County, Illinois. I used Landsat 5, Landsat 8, and Sentinel 2a images from mid-March 2011, 2014, 2017, and 2018 to compare cover cropping distribution across the county, cover cropping adoption over time, and cover cropping practices for fields previously planted with corn versus fields previously planted with soy. I then tested a methodology to distinguish cover crop types. Here, I applied a K-means classification to a November 2017 image of cover cropped fields and paired results to a change detection analysis that looked at differences in NDVI on cover-cropped fields between November and March of that season. Together, my analyses produced a distribution map showing fields that are most often cover cropped in Champaign County, and determined that fields previously planted with corn generally have less cover cropping than fields previously planted with soy. However, these results have questionable validity for reasons described below. My analysis of cover cropping adoption over time also lacks validity, also described below. The tested methodology for cover crop differentiation failed.

Introduction

My project arose from correspondence with Dr. Kevin Wolz, of the Savanna Institute, an organization devoted to the widespread adoption of agroforestry practices in the Midwestern United States. As a fierce advocate of tree-based perennial agriculture, I first reached out to the organization in early March to see how I might support their mission through remote sensing analysis. As it happened, Dr. Wolz had just begun to develop the organization's farmer outreach strategy; he was seeking to systematically identify farmers in the Midwest most likely to consider integration of agroforestry techniques on their farms. We discussed a number of variables that might be revealing, and we concluded that farmer cover cropping practices would be worth investigating further.

A 2015 USDA report found that from 2010-2011, four percent of farmers used cover cropping in some capacity, with notable geographic differences (Wade, Claassen, & Wallander 2015). However, adoption of the practice has risen dramatically with the amount of farm acreage in cover crop increasing approximately 15% per year between 2012 and 2017 (CTIC 2017). The practice provides a suite of ecological benefits to agricultural fields, including the enhancement of soil organic matter, the protection of soil aggregate structure, and the prevention of soil loss due to erosion (Dabney et al. 2001; De Baets et al. 2011). Additionally, cover crops absorb excess nitrogen and phosphorus fertilizers that would otherwise leach into aquifers and create large ocean "dead-zones" downstream (Staver and Brinsfield 1998).

Agroforestry offers many of the same ecological benefits- soil protection, erosion control, uptake of excess nutrients- as well as additional ones- carbon sequestration, biological enhancement, resilience to climate change, etc- and might be thought of as one (or two!) step(s) further along in the transitional to a sustainable food system (*About Agroforestry*). Additionally, though ecological benefits are felt immediately, in both cover cropping and agroforestry practices, economic rewards for the practitioner are often not seen until several years after implementation. For these reasons, it seems likely that those farmers most apt to use cover crops would also be most apt to consider agroforestry techniques.

The focus area of my study was Champaign County, Illinois. The county was selected because it was both in the purview of the Savanna Institute, and it is also home of the University of Illinois at Urbana-Champaign- known for its agricultural expertise, which I thought might be a valuable resource. Champaign County is dominated by agricultural fields, with the two main cash crops being corn for grain (as opposed to silage) and soy. Cover cropping practices are generally frail, with the majority of cover planted in cereal rye (winter hardy) and a potential small minority planted in tillage radish (winter killed by hard frosts below 25 degrees F) (Dennis Boune- University of Illinois Extension Educator personal communication; Santangelo et al. 2011).

Objectives

My primary objective was (1) to determine which landowners in Champaign County use cover crops. Secondary objectives arose after initial exposure to my datasets, including (2) to determine change in cover cropping adoption over time, (3) to analyze the difference in cover cropping practices for fields previously planted with corn vs. fields previously planted with soy, and (4) to test a methodology for classification of cover crop species type.

Data Collection

I collected satellite images encompassing Champaign County for four mid-March dates (03/23/2011; 03/15/2014; 03/22/2017; 03/22/2018) and one mid-November date (11/22/2017) from the USGS Earth Explorer portal. The 2011 image was from Landsat 5 TM (path 023, row 032) the 2014 image was from Landsat 8 OLS (path 023, row 032)- both Level 2 atmospherically corrected products, and the 2017 and 2018 images were from Sentinel 2A (tile numbers 4602 and 4513, later mosaicked together)- all Level 1C top of atmosphere reflectance products.

Images were collected strategically at times in the seasonal agricultural cycle where cover crop presence could be best detected. The seasonal cycle in Champaign County generally follows the below pattern (Boune, personal communication):

(i) Corn is harvested between mid-September and the end of October, dependent on season-to-season productivity

(ii) Soy is harvested during the first three weeks of October

(iii) Where cover cropping is practiced, cover crop is sowed immediately following cash crop harvest

(iv) Hard frosts arrive in mid to late November, killing off non cold-hardy covers like tillage radish, and causing leaf yellowing in winter hardy rye (Prabhakara, Hively, & Mccarty 2015)

(v) Spring green-up occurs with the arrival of warm weather in mid-March

(vi) Fields are tilled-in during the first week of April, in preparation for a new round of cash crops

Thus, spring images were selected as close to April 1 as possible to allow for complete green up of cover crops prior to spring tillage. The November image was selected by investigating historic temperature lows during November 2017, and choosing a date as far into the season as possible to allow for cover crop germination and growth, but prior to hard frost (Image 1).

In addition to the satellite imagery, other data obtained include (I) USDA National Statistical Service Crop Data Layers (CDL) for Champaign County for 2010, 2013, 2016, and 2017- which describe the species of cash crop grown on each agricultural field based on remotely sensed crop phenological patterns in a time series of images, (II) growing degree days (GDD)- a measure of accumulated temperature at which a specific crop can grow that is often a better indicator of plant growth than calendar date- for both corn and rye during the 2010-2011, 2013-2014-, 2016-2017, and 2017-2018 seasons downloaded from the Midwestern Regional Climate Center, and (III) a shapefile of Champaign County downloaded from the Illinois Geospatial Data Clearinghouse.

Data Preparation

For each level 2 Landsat image, after downloading the image, (1) I used 7-Zip to extract individual bands, (2) brought each extracted band file into ENVI, and (3) performed a layer stack (making sure bands were in proper order), resulting in a full tile with all bands in a single file. Then, setting my Champaign County shapefile as my region of interest, I (4) subset each tile to clip out only Champaign County, and (5) performed an NDVI operation. Separately, I (6) brought my CDL layer into ENVI for that year, (7) performed an Isodata operation to change the RBG values given in my CDL to classes with discrete numeric values, and then (8) reprojected my classified CDL file into the same projection scheme as my Landsat images (WGS_1984_UTM_Zone_16N). Next, (9) I stacked my NDVI file of Champaign county on top of my reprojected and classified CDL layer and used band math to extract the March NDVI values for only the pixels that had been planted with corn in the prior growing season and only the pixels that had been planted with soy in the prior growing season (i.e. band math equation: ((B2 Eq 7) * B1) + ((B2 NE 7) * (-.99)), where B2 is the CDL layer, 7 is the value assigned to corn fields in the CDL layer after isodata classification, B1 is the NDVI layer for Champaign

County, and (-.99) is a random value that is subsequently set as a "data ignore value" in the file metadata (Image 2).

For each level 1C Sentinel image, a few additional steps were necessary. Here, two images were needed to cover the full span of Champaign County. For each, I subset out Champaign County, and then stitched the subsets together using the seamless mosaic operation to form the full county in one file (Image 3). (Sentinel data appears in ENVI as three separate files for the 10, 20, and 60 meter resolution bands of the satellite. For all images, I used the 10 meter resolution bands. For the November 2017 image, I stacked the 10m and 20m files together, resampling the 10m pixels to the 20m resolution; reasons for this will become clear when I describe my methodology for Objective 3). The subsequent operations for Sentinel data preparation follow steps 5-9 above.

The set of prepared data can be seen in Image 4 in the Appendix.

Methods and Results

Objective 1: Determine which landowners use cover crops. My methodology for objective one followed from a 2015 paper by Hively et al., *Remote Sensing to Monitor Cover Crop Adoption in Southeastern Pennsylvania*. In early December, 2010, cooperative extension agents in Southeastern Pennsylvania conducted a windshield survey on agricultural fields in five counties, rating each field as having "minimal," "low," "medium," or "high" cover based on defined standards. The study authors took advantage of this ground truthing exercise, paring this qualitative assessment with a Landsat 5 image of the same location from November 14 of the same year. The authors calculated NDVI on fields that were grouped into each class, and then using the midpoint of average NDVI values between two classes, they determined a threshold value from which to classify vegetative cover on agricultural fields in winter months during subsequent years (2011, 2012, and 2013). From this, the authors determined a threshold value of NDVI >.29 for “non-minimal cover” (NMC) or “cover cropped” (used synonymously) (Image 5).

Taking my eight mid-March Champaign County NDVI raster images for 2011, 2014, 2017, and 2018, segmented by fields previously planted with corn and fields previously planted with soy, I ran a simple test in ArcMap to see which pixels for each image surpassed the .29 threshold (Image 6). I then aggregated these maps together to count the number of times each pixel was cover-cropped in mid-March over the four images (Image 7). Fields with high cover-crop counts might point to farmers open to the adoption of agroforestry techniques.

Objective 2: to determine change in cover cropping adoption over time. Again using the threshold NDVI value of .29, I calculated the percent of pixels covered for each mid-March image. March 2014 had the highest amount of total cover at 14%, followed by March 2011 at 5.6%, March 2017 at 5.4%, and March 2018 at 1.2%.

Further analyses investigated whether other confounding factors might be responsible for year to year trends in field cover. One variable I thought might be of interest was accumulated cover crop growing degree days at each image date. As mentioned previously, growing degree days (GDD) are a measure of accumulated temperature at which a specific crop can grow that is often a better indicator of plant growth than calendar date. GDD is found by GDD = (Tmax – Tmin) ÷ 2 – Tbase, where Tmax is the daily maximum temperature, Tmin is the daily minimum temperate, and Tbase is a crop-specific baseline temperature at which a crop can grow. Starting from October 15 of each year, I calculated cover crop growing degree days (Tbase = 40 F, a standard base for winter-hardy crops) until the satellite image date of that year. Differences in

GDD across seasons were hypothesized to explain some variation in field cover in the mid-March images (Image 8).

A second relevant variable is days difference to 2700 corn growing degree days. According to the University of Kentucky Cooperative Extension, a standard hybrid corn variety typically requires 2700 GDD (Tbase set at 50 degrees F) from planting until full maturity (Lee 2011). Using this figure, I examined total corn GDD from April 1 of the prior growing season from each mid-March image year, and determined the calendar date at which the 2700 GDD threshold was surpassed (i.e. in Champaign County in 2010, the corn crop would have reached 2700 GDD- full maturity- by August 13 if planted on April 1). For each year, I then determined the difference in calendar days to reach 2700 corn GDD, setting the year with the earliest finish- 2010- as a baseline (i.e. in Champaign County in 2013, the corn crop would have reached 2700 GDD by September 3, 21 days behind the 2010 data of August 13). The rationale behind these steps is that the later the cash crop harvest during a given calendar year, the less likely the farmer would bother planting cover crops. Later harvest would mean later cover crop planting, translating to reduced cover crop growth, and reduced environmental/economic benefits. Data for all image years can be seen in Image 9.

Image 10 plots percent non-minimal cover for each year with cover crop growing degree days, and days difference to 2700 corn GDD on the same chart. Cover crop growing degree days and days difference to 2700 corn GDD seem to be randomly correlated with percent non-minimal cover. Percent non-minimal cover appears to have a slight downward trend over time, though this apparent trend is erroneous for reasons discussed later in the discussion section.

Objective 3: to analyze the difference in cover cropping practices for fields previously planted with corn vs. fields previously planted with soy. Using my NDVI rasters for fields previously planted with corn and fields previously planted with soy, I calculated the percent of total pixels that surpassed the .29 threshold. For all image years, fields that were previously planted with corn averaged a 4.1% cover rate and fields that were previously planted with soy averaged a 9.6% cover rate. Histograms showing the distribution of NDVI values for fields previously planted with corn and fields previously planted with soy show that mid-March NDVI values for fields previously planted with corn in a given year generally lag behind mid-March NDVI values for fields previously planted with soy in a given year (Image 11).

Objective 4: to test a methodology for classification of cover crop species type. My fourth objective sought to determine whether an unsupervised classification using eight sentinel 2a bands could produce a reliable classification scheme to differentiate cover cropped fields planted with winter rye and cover cropped fields planted with tillage radish. The Sentinel 2 series offers excited potential for innovative uses of remote sensing because it has both greater spatial resolution than the Landsat system and greater spectral resolution than the Landsat system. In particular, it has two discrete NIR bands and three discrete "red-edge" bands that have been used in recent literature to sense differences in canopy chlorophyll and nitrogen content, pointing to differences in species composition (Clevers & Gitelson 2013).

Using the November 2017 raster of cover-cropped fields previously planted in corn (extracted from steps described in Objective 1), I (1) first used the focal majority operation in ArcMap to smooth over individual pixels classified as cover-cropped, leaving behind only larger coterminous sets of pixels (i.e. only full fields instead of randomly scattered pixels that had NDVI > .29). I (2) then built a mask in ENVI to isolate only those fields (Image 12) and then ran a K-means classification on my November 2011 Sentinel image of Champaign County (which had been stacked during data preparation with both the 10m RGB and NIR bands as well as the 20m red edge and NIRa bands). I set the number of classes in the K-means classification to 3, hypothesizing that the classification would differentiate cover cropped fields planted with winter rye from cover cropped fields planted with tillage radish from other randomly included pixels (perhaps those on field edges that might not fit neatly into a winter rye or tillage radish class).

Separately, I (3) used band math to subtract the NDVI values from the November 2017 corn fields from the NDVI values of the March 2018 corn fields (the same fields during the same growing season). My thinking was that all of the cover cropped fields planted with winter rye (winter hardy with green-up and continued growth in the spring) would show positive NDVI change from November to March, while all of the cover cropped fields planted with tillage radish (killed by hard frost in winter) would show significant negative NDVI change from November to March. I theorized that if the K-means classification scheme was sensitive to species type, almost all of the pixels with negative NDVI change between November and March should be classified in the same category.

(4) Importing my raster of NDVI change into ArcMap, I assigned all pixels with NDVI values decreasing more than .05 points from November to March a value of 100. (5) Importing my classification raster into ArcMap (where pixels in class 1 received a value of 1, pixels in class 2 received a value of 2, and pixels in class 3 received a value of 3 during the K-means classification), I (5) then added my raster layers together. Pixels with a value of 101 were therefore class 1 pixels that saw negative NDVI change, pixels with a value of 102 were class 2 pixels that saw negative NDVI change, and pixels with a value of 103 were class 3 pixels that saw negative NDVI change (Image 13). I (6) then found the percent of all negative NDVI change pixels that were captured by each class. Class 1 had 12% of negative NDVI pixels, class

2 had 30% of negative NDVI pixels, and class 3 had 59% of NDVI pixels (Image 14). Thus, the K-means classification was more sensitive to other variables (perhaps field moisture levels, or nutrient availability), and was unable to differentiate cover cropped fields based on species type.

Discussion

At the risk of receiving a lower grade, but feeling that full transparency is important, I admit that my conclusions are highly skewed for Objective 1 and completely invalid for Objective 2. Here's why: only now, as I write this paper (with a few hours until the deadline and not enough time to redo all ENVI operations, data analytics, and Excel images!) am I realizing that I compared Landsat atmospherically corrected data from 2011 and 2014 to Sentinel top of atmosphere reflectance data for 2017 and 2018. Without having implemented the QUAC operation on my Sentinel data, NDVI values for 2017 and 2018 are biased to the left (the atmosphere scatters red light at a higher rate than it scatters NIR light. Therefore, relatively more red light would reach the Sentinel sensor than is actually true based on surface reflectance). Thus, my cover crop distribution map (Image 7) highly underrepresents fields in 2017 and 2018 surpassing the .29 surface NDVI threshold. Additionally, this large snafu likely explains the drop-off in mean NDVI values for 2017 and 2018 in Image 10 (cover crop adoption over time), and speaks to the importance of fully understanding data-products and what they represent BEFORE proceeding with analysis!

Assuming that I had atmospherically corrected the Sentinel data, I still would lack confidence in my conclusions. Indeed, the threshold classification technique established by Hively et al. and emulated in this analysis might be lacking rigor. My hypothesis was that we would see a bimodal distribution for NDVI values, whereby one peak would be centered around NDVI = .23 (bare soil) with a small standard deviation, and a second peak would be centered around .30 (cover cropped) with a much larger standard deviation. However, revisiting the histogram displayed in Image 11, we see that the distributions of NDVI values across all field-years are normal. Perhaps this could be explained by other differences in land stewardship that aren't captured by the simple decision to plant cover crops or not after fall harvest. For example, for some fields that aren't cover cropped, some farmers might allow plant residues to remain on the surface of their fields after harvest. For other fields that aren't cover cropped, farmers might perform fall tillage to incorporate plant residues into their soil post-harvest. Likewise, some farmers might apply herbicide to kill off all weed growth in mid-March while some farmers might opt not to use herbicide, allowing weeds to grow before tilling the soil in early April. Thus, for example, a simple threshold approach might classify weeds as cover crops, especially during mild-winter years and above-average early spring temperatures.

But there might be a resolution to this problem that further study should investigate. Looking again at the NDVI distributions in Image 11, there appear to be inflection points for most field-years on the right tail of their distributions. Worth exploring further would be a method that locates this inflection point for every distribution, and then classifies pixels to the right of that point as cover-cropped. This approach has promise to be a much more legitimate way to differentiate intentionally planted cover from other "greened-up" pixels.

Assuming that all requisite data preparation steps are implemented, and assuming a robust methodology for identifying cover cropped fields, further study should also take a few additional steps to assist with the Savanna Institute's farmer outreach strategy. One interesting step might be to acquire the data produced by Lobell et al. in their 2015 paper, *A Scalable Satellite-Based Crop Yield Mapper*. As explained in the abstract, the authors' methodology "uses crop model simulations to train statistical models for different combinations of possible image acquisition dates, and these are then applies to Landsat and gridded weather data," explaining an average of 35% of the variation in field-by-field crop yields in the Midwest (Lobell, Thau, Seifert, Engle, & Little 2015). Field-by-field yield data could be extremely valuable to consider with cover cropping practices; fields that are producing below-average yields might be excellent targets for the implementation of agroforestry practices, because less short-term economic losses would be sacrificed in the transitional phases between annual agriculture to perennial agriculture (granted, 35% yield variation is only a small stepping stone in determination of field-to-field yields). Another helpful step would be to locate cadastral data for Champaign County, in order to pair fields with high rates of cover cropping with land ownership information (and perhaps even contact information).

Lastly, with regards to Objective 4, in this study, K-means classification using Sentinel 2 failed to differentiate between winter rye and tillage radish. A few steps might lead to improved results if this methodology were to be repeated. First, the November 22, 2017 image date followed a series of days where temperature in Champaign County dipped into the mid-twenties (degrees Fahrenheit). According to the Cornell Cooperative Extension tillage radishes are hardy to 20 F. However, it still might be the case that temperature drops into the mid-twenties caused severe leaf yellowing at the time of the November satellite image or even dieback, minimizing any NDVI signals on forage radish fields. Future attempts at this classification scheme should choose a date with all prior seasonal temperatures above frost. Another technique that might improve this classification scheme would be to stack 2 images on top of one another taken during different times in the season. For instance, perhaps stacking the November 22 image with a December, January, February, or March image would moderate the effect of external variables (i.e. field moisture) on classification, leaving a more pronounced species-specific signal. (Of course, if images were stacked from later winter months, the tillage radish would have died off by then. Still, maybe the vegetative signal of rye would be amplified enough to exclude any other vegetation types from its classification).

Conclusion

Classification of cover crops from satellite imagery is not as straightforward as one might expect from a superficial consideration of the topic (i.e. "green on fields in the winter. It must be cover crop!"). Seasonal planting and harvest regimes, weather patterns, and image quality/availability all complicate the process; deep local knowledge of agricultural cycles, including cash crop types and growth patterns, cover crop types and growth patterns, and additional agricultural stewardship practices (fall tillage, herbicide usage, etc) are critical to be successful, especially without ground-truthed data to verify results. With regards to Objectives 1, and 2, conclusions are likely invalid due to comparison of atmospherically corrected data with top of atmosphere reflectance data, and due to a threshold methodology that oversimplifies true ground-based processes. With regards to Objective 4, my methodology to distinguish cover crop types failed. I would not feel confident making any recommendations to the Savanna Institute.

Nonetheless, I do believe that remote sensing holds much promise in this arena. I believe that future studies, which analyze the distribution of NDVI values for natural inflection points, could be robust (especially if backed by ground-truthed data and/or deeper investigation into local agricultural practice). Classification of cover crop type based on remotely sensed data is not without hope either; suggestions described above are worth implementing in future analyses.

Appendix- Images

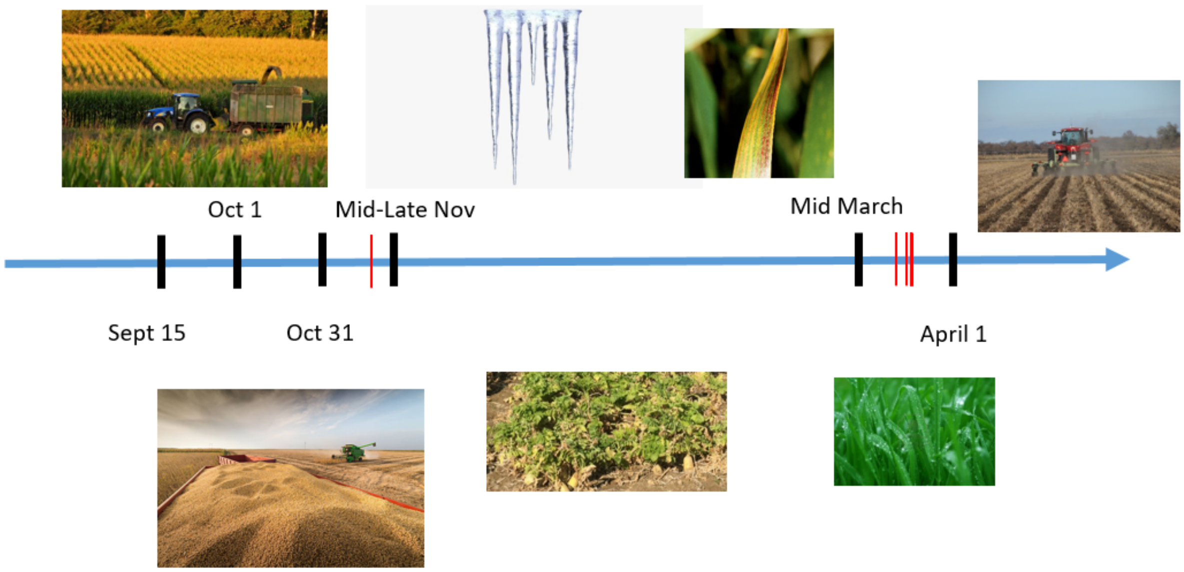


Image 1: The seasonal cycle in Champaign County generally follows as such: (i) Corn harvest between mid-Sept and the end of Oct; (ii) Soy harvest in first three weeks of October; (iii) Cover crop planted; (iv) hard frosts arrive mid-late Nov, killing off non-cold hardy covers and causing leaf yellowing in cold hardy covers; (v) Spring green-up by mid-March; Fields tilled-in first week of April. Red lines show image acquisition times.

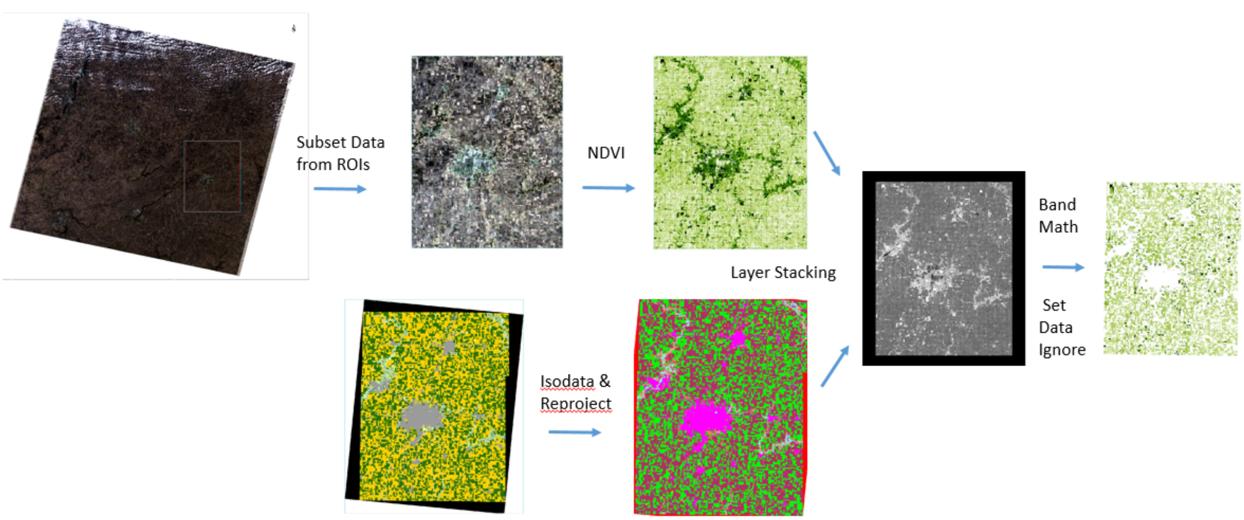


Image 2: Data preparation process for each Landsat image.

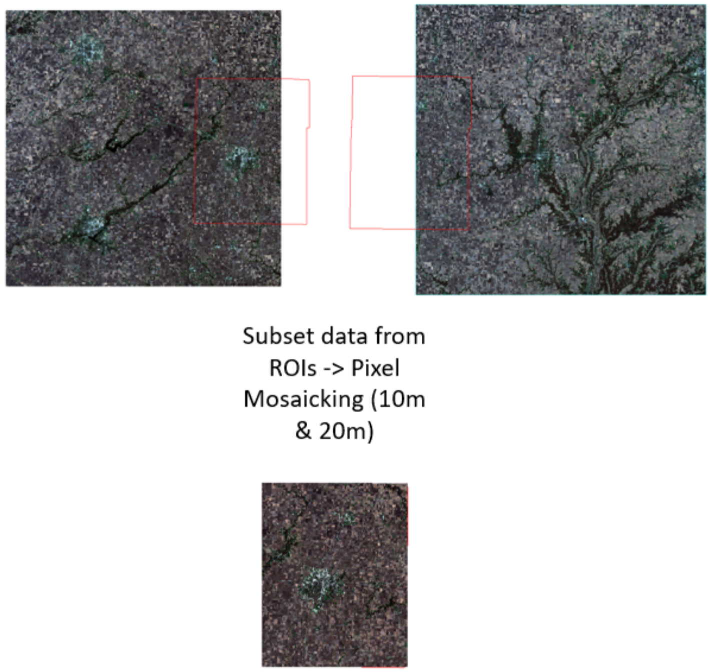


Image 3: Mosaicking operation required for each Sentinel image.

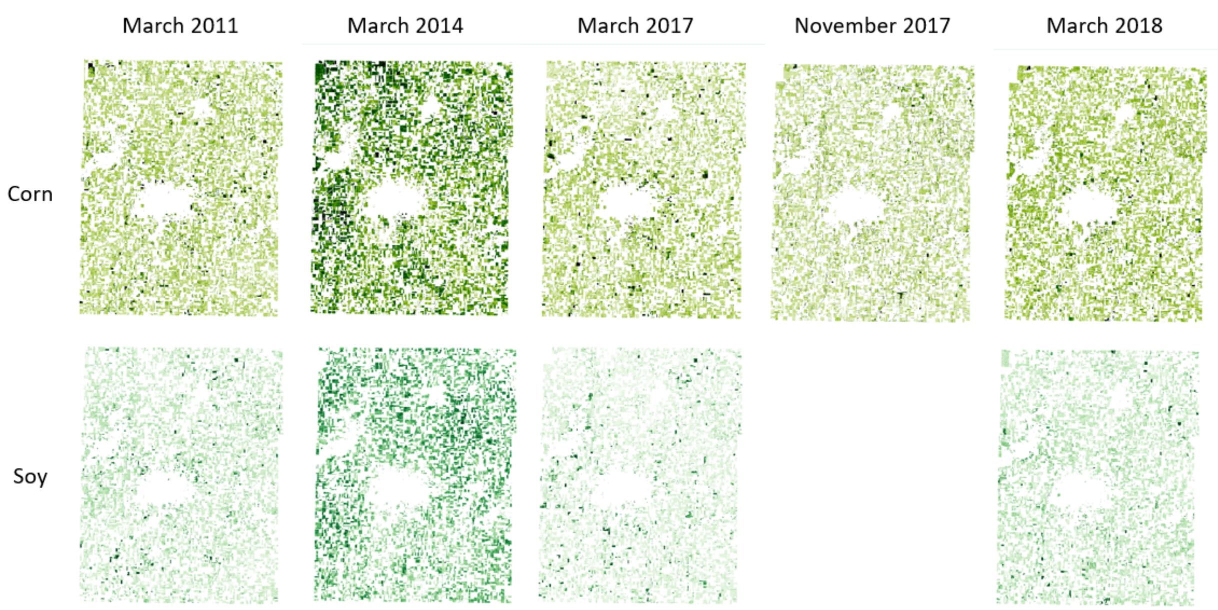


Image 4: Images at the end of the data preparation stage. NDVI values obtained for just pixels previously planted with corn and just pixels previously planted with soy in Champaign County, Il

Nonminimal Cover NDVI threshold = .29

Image 5 (taken from Hively et al.): The authors calculated mean field NDVI values based on a November 14, 2010 Landsat image for each qualitatively assigned category conducted during an early December windshield survey. Taking the midpoint of NDVI values between two classes, they calculated a threshold for which to categorize crops via remote sensing in subsequent years. An NDVI value of .29 is the threshold they established for "non-minimal cover."

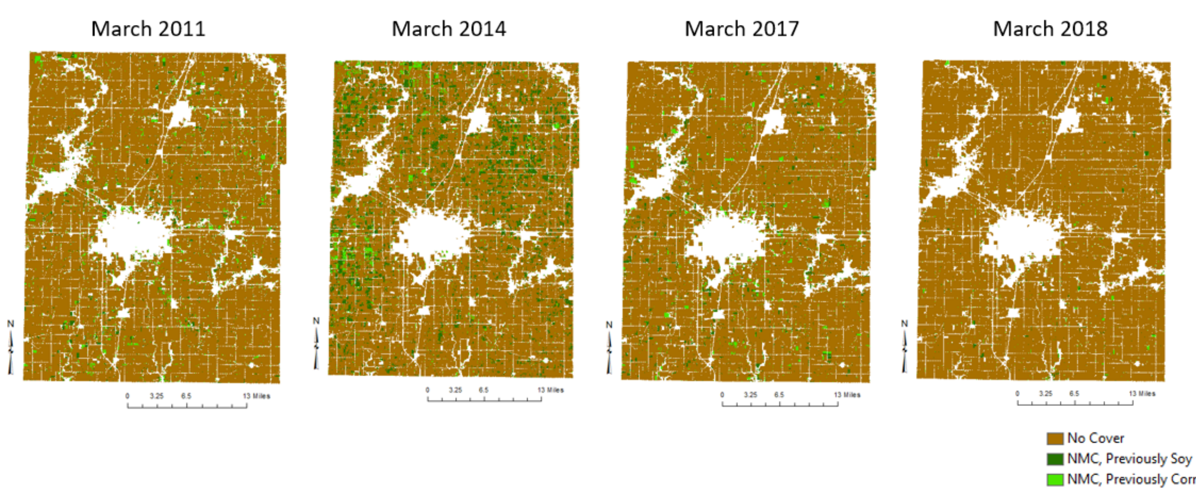


Image 6: March images for each year reclassified into "No Cover," and "Non-Minimal Cover" (NMC). NMC pixels in the darker green have NDVI values above .29 and were previously cropped with soy. Fields in the lighter green have NDVI values above .29 and were previously cropped with corn. Fields in brown had NDVI values below .29. March 2017 and March 2018 images likely under-represent the true pixel count of surface NDVI > .29 due to lack of atmospherically corrected data.

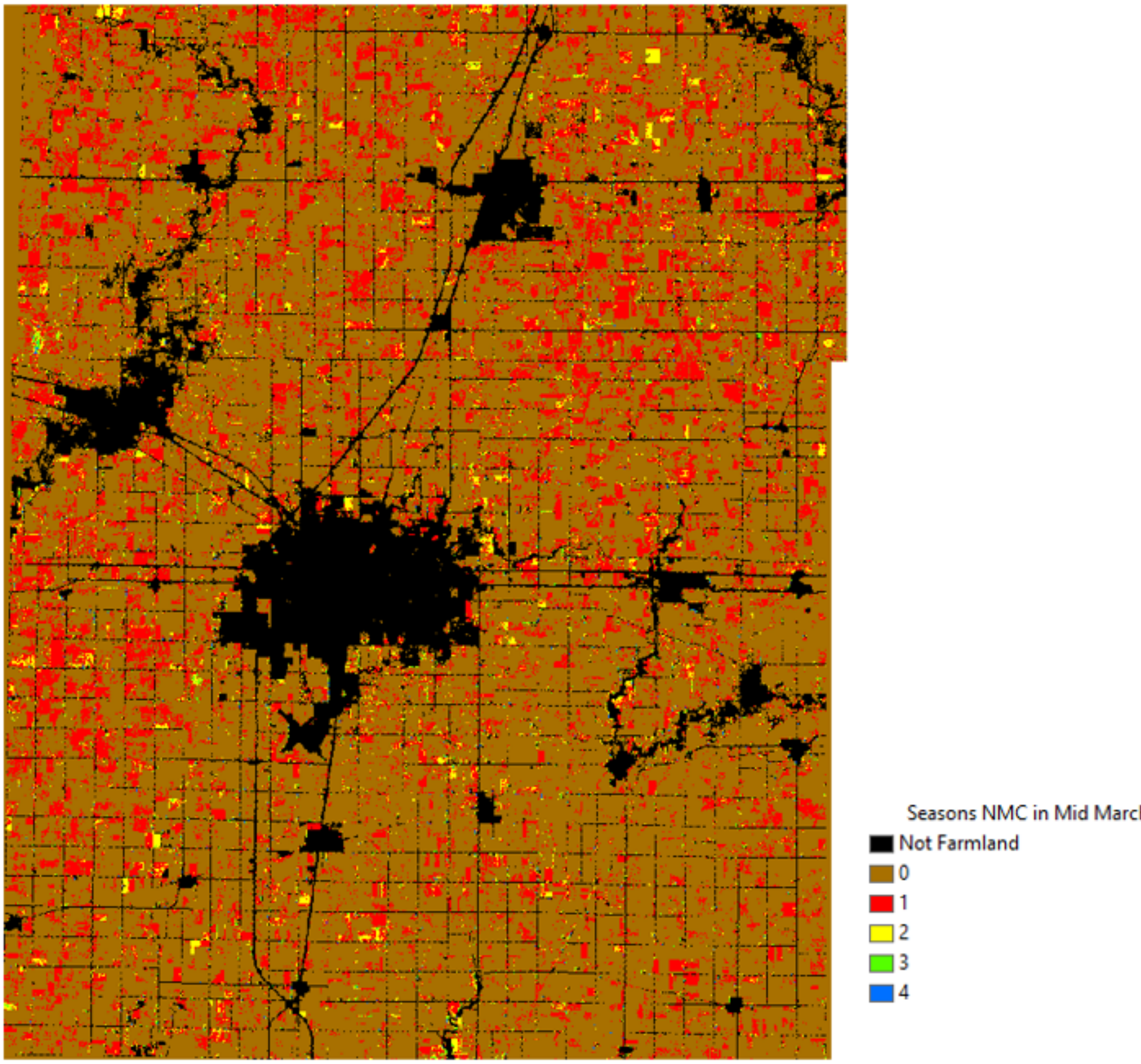
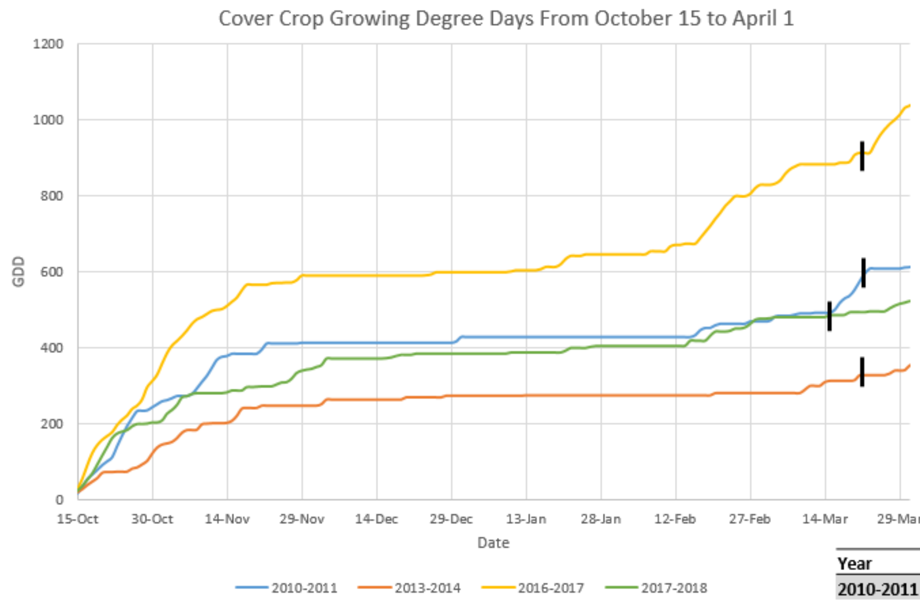
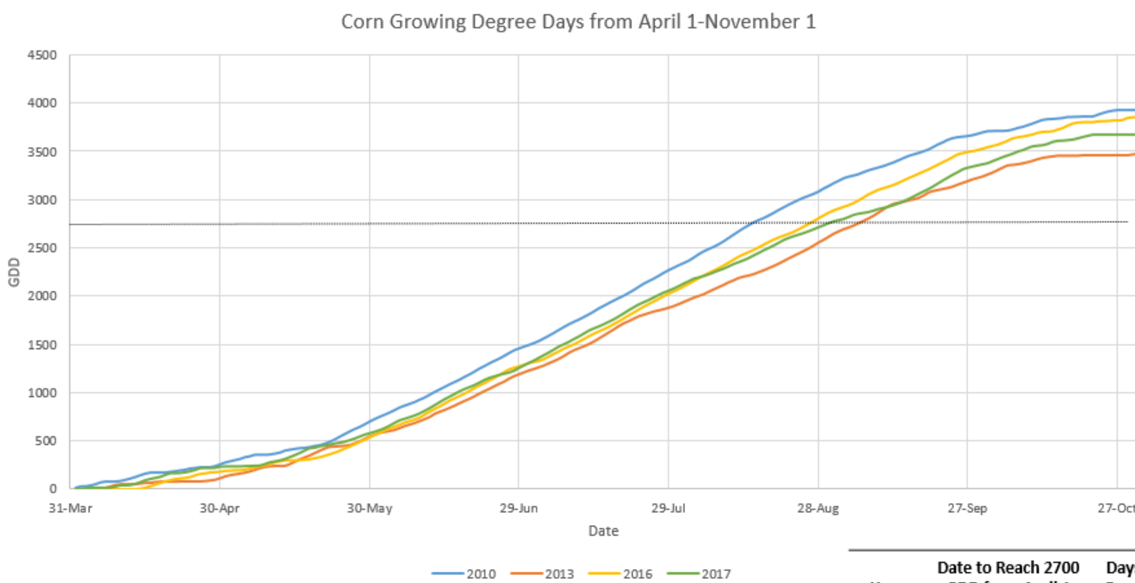


Image 7: Aggregation map show the number of times each pixel had non-minimal cover in mid-March across the four satellite images. Yellow, green, and blue pixels point out locales where farmers might consider the adoption of agroforestry techniques.



Year	GDD
2010-2011	606
2013-2014	310
2016-2017	912
2017-2018	491

Image 8: Accumulated cover crop growing degree days (Tbase = 40 degrees F) from October 15th of each year in Champaign County to image date (shown by black bars). Differences in GDD across seasons were hypothesized to explain some variation in field cover in the mid-March images.



Year	Date to Reach 2700 GDD from April 1	Days Difference From Base 2010
2010	13-Aug	0
2013	3-Sep	21
2016	25-Aug	12
2017	28-Aug	15

Image 9: Accumulated corn GDD (Tbase = 50 degrees F) for all image years beginning on April 1 for each year. The dotted black line marks 2700 GDD, the expected timing of corn maturity. The difference in days to corn maturity between years was hypothesized to explain some variation in March cover. The later the cash crop harvest in a given year, the greater the reduction in benefit from planting cover, and thus the less likely that a given farmer would plant cover during that year.

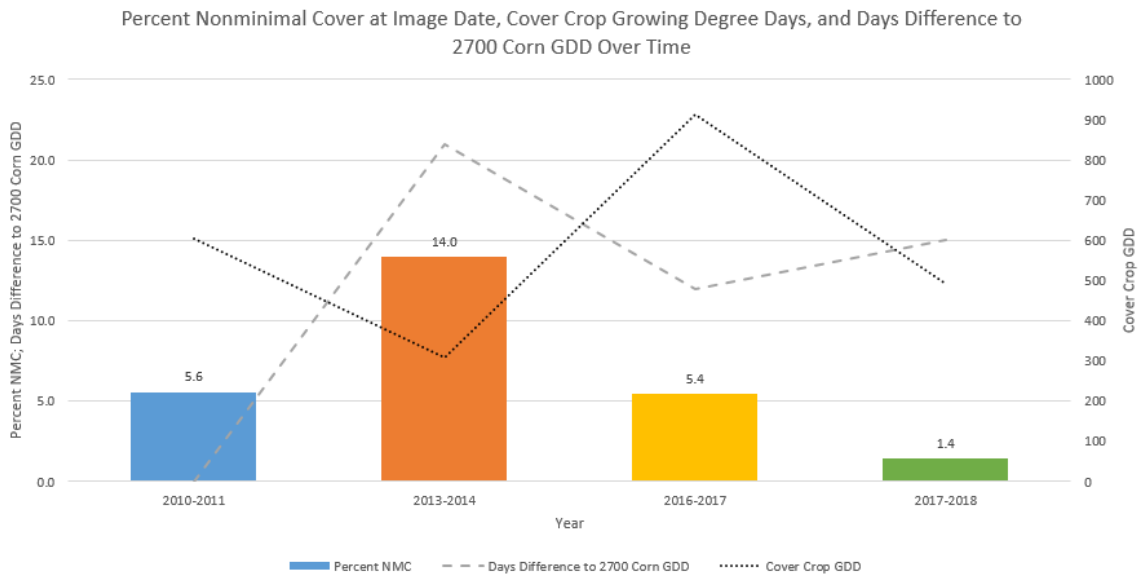


Image 10: Percent Nonminimal Cover at Image Date, Cover Crop Growing Degree Days, and Difference to 2700 Corn GDD Over time. Cover crop growing degree days and difference to 2700 corn growing degree days seem to be randomly correlated with percent non-minimal cover. Non-minimal cover seems to have a slight downward trend over time, though time trends are invalid due to lack of atmospherically corrected data in later years.

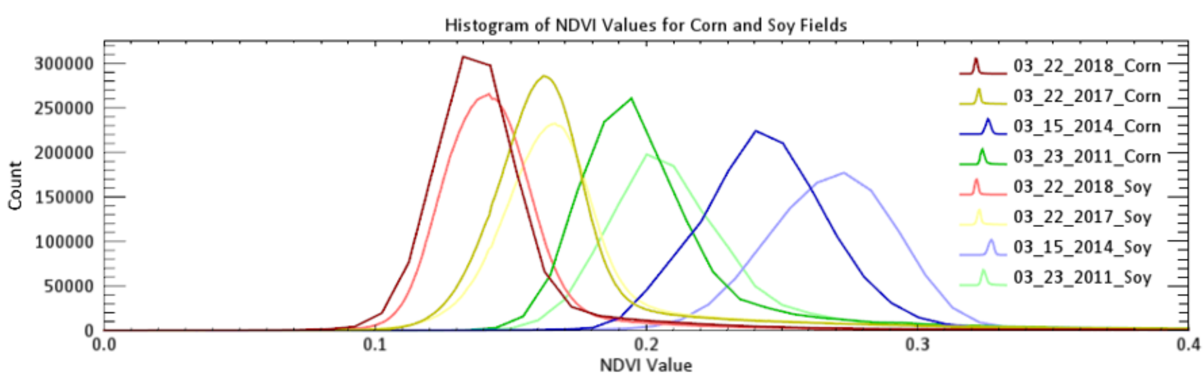
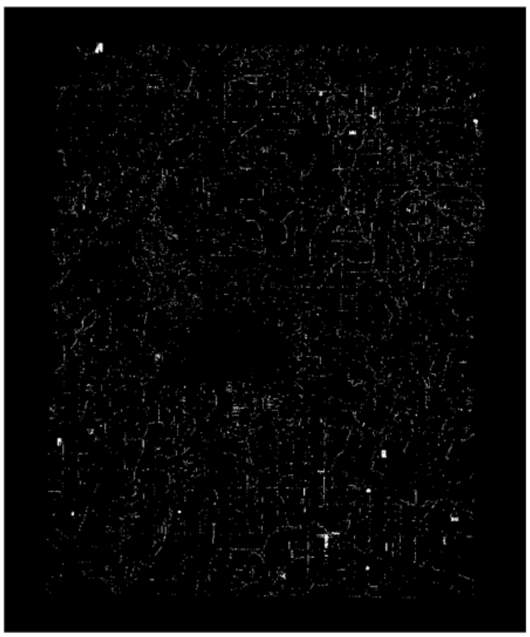


Image 11: Histogram of mid-March NDVI values for fields previously planted with corn and fields previously planted with soy for all image years. Fields previously planted with corn generally have NDVI values that lag behind those of fields previously planted with soy.



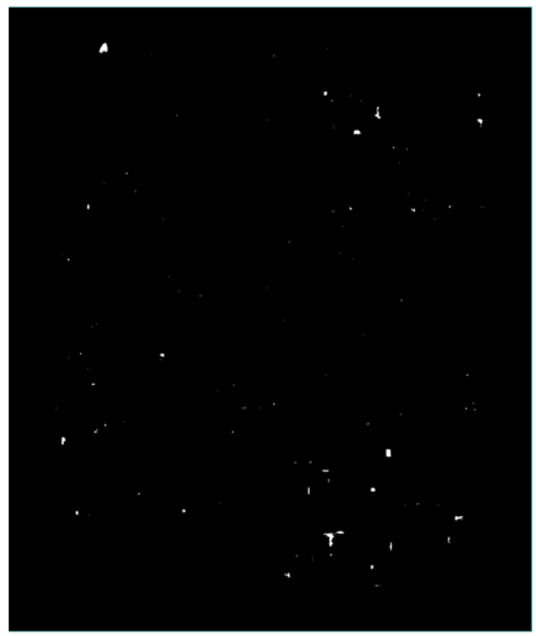


Image 12: On left: mask built of all pixels from November 2017 with NDVI > .29. Includes single scattered pixels throughout the image. On right: mask built after conducting a focal majority operation on all pixels in the November 2017 image where by each pixel looked towards its nearest 20 neighbors and assumes the value of the majority of its surrounding pixels. This smoothing operation allows me to isolate large clumps of coterminous pixels, full fields for later classification.

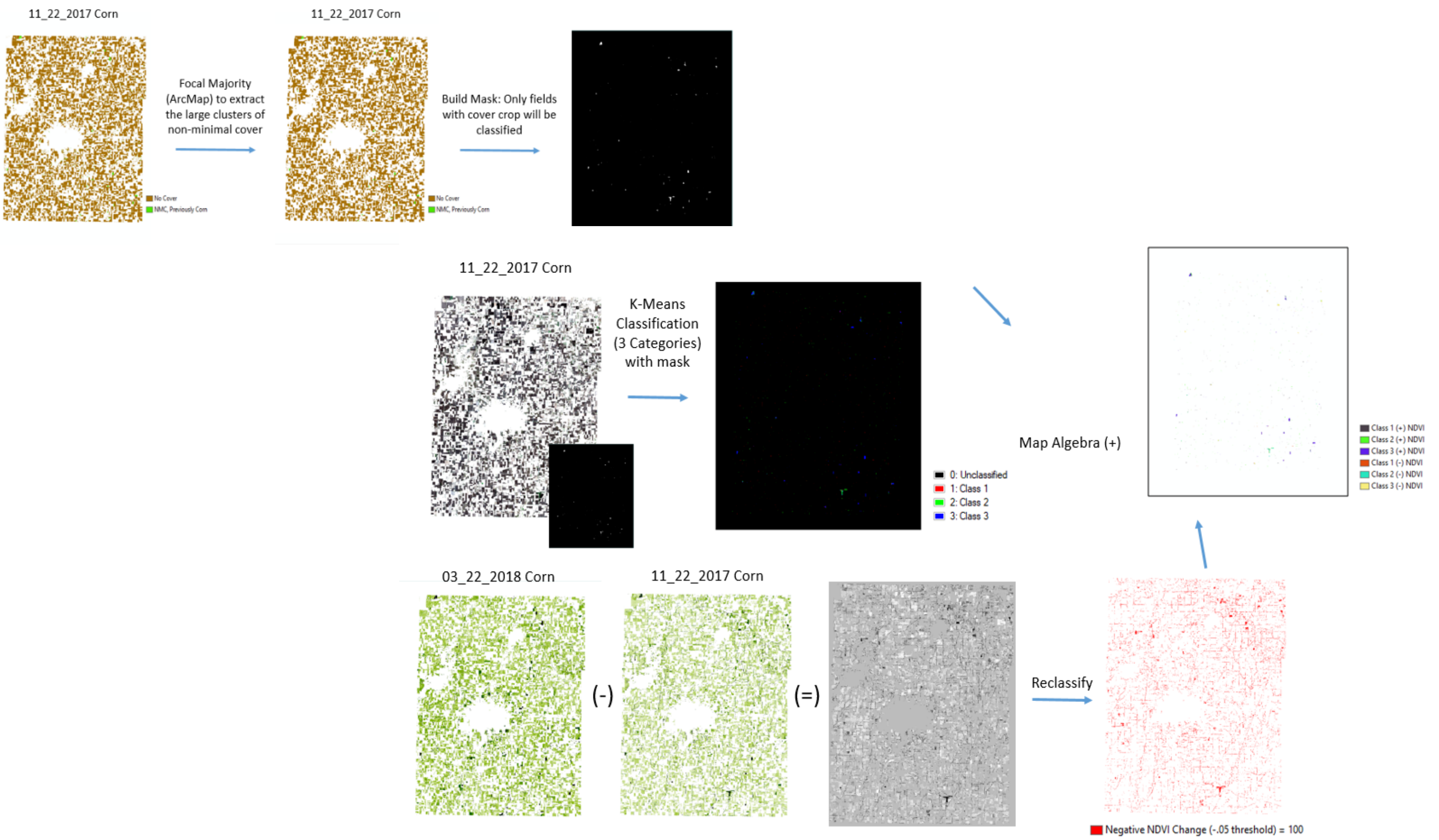


Image 13: method for Objective 3

Class	Percent of Negative NDVI Pixels
Class 1	12
Class 2	30
Class 3	59

Image 14: percentage of negative NDVI pixels captured by each K-means class.

Work Cited

About Agroforestry, www.savannainstitute.org/agroforestry.html.

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