Mapping Cover Crops in Southeastern Michigan with Sentinel-2 Remote Sensing data

By

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Abstract

The River Raisin watershed, which spans southeastern Michigan and northwestern Ohio, is a hotspot for negative environmental impacts caused by industrialized and conventional agricultural practices, particularly excess nitrogen leaching and phosphorus runoff polluting the Great Lakes. Planting cover crops is one way for farmers to reduce nutrient losses, and has been adopted by some farmers in this area. To understand the extent of cover crop adoption in the region, in our study we used optical remote sensing data from Sentinel-2 to determine the spatial distribution of cover crops in the River Raisin watershed. The random forest classification algorithm achieved 86.37 % overall accuracy, and for the cover crops in the region, 75.33% (producer's accuracy -PA) and 80.55% (user's accuracy -UA) for cereal rye, and 85.90% (PA) and 83.98% (UA) for red clover. In particular, the red edge wavelengths of Sentinel-2 were the most important bands for classifying cover crops. Our study shows that we can use readily-available satellite data to map cover crops with high accuracies in the US Midwest. This implication will better the assessment process of the adoption and impacts of conservation practices on farms.

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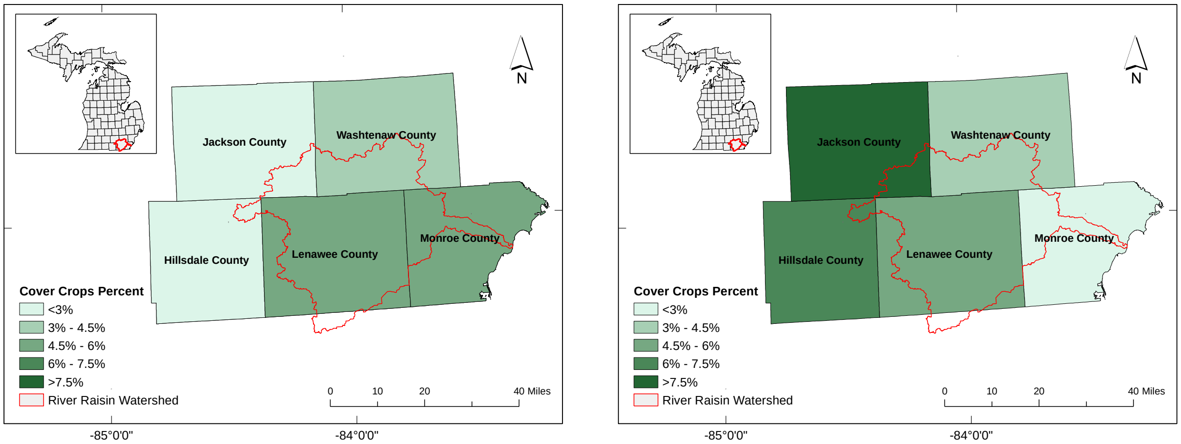
Contents

1. Introduction

Food demand is expected to increase by up to 110% by mid-century (Tilman et al., 2011) to feed the global population. Yet current agricultural practices have large negative environmental impacts in many regions across the globe, making it challenging to increase yields sustainably over the coming decades (Godfray et al., 2010). One of the largest environmental impacts of current agricultural systems is excess nitrogen leaching, phosphorus runoff, and the consequential degradation of downstream water quality (Cassman et al., 2002). The Midwestern United States, in particular, is a hotspot for N and P losses, which contributes to harmful algal blooms and causes eutrophication in the Great Lakes, the Mississippi Delta and the Gulf of Mexico (Liu et al., 2010).

Planting cover crops is an increasingly popular agricultural practice that can address multiple environmental sustainability concerns. Generally, cover crops are non-harvested crops grown in rotation with primary crops (Dabney, 1998) for the purpose of improving ecosystem functions such as pest and weed control, soil fertility, nutrient cycling efficiency, and crop yields (Snapp et al., 2005). Cover crops can reduce N leaching to aquatic systems, especially in irrigated agricultural areas (Meisinger et al., 1991) and cycle phosphorus into plant tissue (Soltangheisi et al., 2018), which can reduce the need for phosphorus fertilizer and help address the eutrophication occurring in the Great Lakes (Kane et al., 2014). In the temperate Midwest, a primary niche for cover crops is in the overwintering season. Winter cover crops are planted in the late summer or early fall and survive during the winter. In the following spring, cover crops continue to grow and provide soil cover until they are terminated by tillage or herbicide application ahead of planting the primary crop.

Our study area, the River Raisin watershed encompasses part of southeastern Michigan and northern Ohio, including Washtenaw, Jackson, Lenawee, and Monroe counties (Figure 1). As a tributary to Lake Erie, water drains from the north to west, then enters Lake Erie at Monroe Harbor (River Raisin Watershed Council, 2009). It is a highly productive and intensively farmed area of the Midwestern United States (Christopher et al. 2017). Over 75% of the area is composed of agricultural land. Most of the crops cultivated are wheat, soybean, and corn, with a very small percentage of other agricultural cover types, including dairy and horse farms (River Raisin Watershed Council, 2009). Given the high portion of agricultural land use, the water quality and ecological environment of the River Raisin watershed are highly vulnerable to the potential threats caused by modern, industrialized agricultural practices. Currently, most farmers in our study area haven't adopted plant cover crops yet. Based on survey from USDA, less than 8% farms have been planted cover crops (Figure 2); instead, famers follow the conventional agricultural practices: after harvesting the cash crops, they leave the fields as crop residues or bare soil until the next crop season. Although the adoption of cover crops has been increasing (Figure 1 and 2), there still is a need to identify this sustainable intensification strategy that would both increase yields and reduce the environmental footprint of agricultural production in this area.



Figures 1,2 Location of River Raisin Watershed in Michigan and Cover Crop Adoption Percentage in 2012(left) and 2017(right) at County Level.

In this study, we focus on two functional types of winter cover crops that are adopted the most by farmers in our study region: cereal rye and red clover. Cereal rye (*Secale cereale*) is a cool season annual grass, and is one of the most reliable overwintering cover crops across the Midwest (Martinez-Feria et al., 2016). The benefits of using cereal rye as a cover crop include soil stabilization, nutrient scavenging, weed suppression, and biomass production. Because of its hardiness, it can be planted in the late fall, after harvesting corn, and then it survives during the winter (USDA 2019; Pantoja et al., 2016). Therefore, cereal rye is able to fit the seasonal niche of cash crop rotation in the Midwest. An 8-year study in Michigan showed that rye improves N retention and cycling with minimum effects on crop yield in corn-corn-soybean rotations (Snapp et al., 2018). Red clover (*Trifolium pratense*) is a biennial legume cover crop species used in Michigan which provides moderate amount of N through biological N fixation and biomass, and tolerates compaction (USDA, 2019). In the Midwest, the most common management of red clover is intercropping with winter wheat (i.e., frost-seeding in early spring) to improve its establishment and minimize the competition with cash crops (Gibson et al., 2006; Clark, 2007; Gaudin et al., 2013). Research has found that legume cover crops have a positive impact on crop yield and ecosystem functions including nutrient retention and N supply (Coombs et al.; 2017, Blesh, 2018).

Despite their potential benefits for sustainability, there is little understanding of how widespread cover crop adoption is and the factors that are associated with farms that plant cover crops including ecological benefits, government policies, social norms, and etc. One way to assess the land area in cover crops at large spatial-temporal scales is to use remote sensing, which allows one to monitor land cover at large scales at very low cost. Yet to date, there are no cover crop type maps of high-accuracy for the US Midwest produced using satellite data. The Cropland Data Layer, which is provided and updated by the US Department of Agriculture (USDA) National Agricultural Statistics Service (NASS), produces annual maps on crop type at 30m resolution across the United States. Although the CDL contains detailed crop-specific land cover data, the accuracy of the cover crops that are the focus of this study is extremely low. In the CDL accuracy assessment matrix, rye has only a 34.3% producer accuracy and 42.2% user accuracy. Clover was classified together with Wildflowers and reaches a 30.6% producer accuracy and 44.6% user accuracy, respectively (USDA NASS CDL, 2017). In addition, there was one study that mapped cover crops using satellite imagery across the US Midwest with high accuracy (> 80%), however, this study did not identify cover crops to the species level (Seifert et al. 2018).

This study seeks to address this key knowledge gap in understanding the extent of these cover crop functional types by using Sentinel-2 satellite data to map cover crop species across the River Raisin watershed. We use Sentinel-2 imagery for two reasons. First, this satellite has high temporal coverage, with a revisit time of 5 days. Such high revisit times will help obtain useful satellite data even during rainy seasons with cloud cover, such as April. Second, Sentinel-2 data has several bands in the 'red-edge' wavelength of light. This wavelength is critical for mapping vegetation, and previous studies have shown that red-edge bands increase the accuracy of mapping different vegetation types compared to other bands typically found on other satellite sensors, such as red and NIR (Immitzer et al., 2016; Forkuor et al., 2018). This information is critical as it will help identify the extent to which cover crops are planted across southeastern Michigan. This information will help researchers better understand where cover crops are planted, what factors are associated with the use of cover crops, and also what regions do not currently plant cover crops and may be suitable for future interventions to increase cover crop use.

2. Materials and Methods

2.1. Cover Crop and Other Vegetation Phenology

In temperate cropping systems, overwintering cover crops have a different growing season compared to most cash crops. In order to distinguish cover crops from conventional cash crops that are grown during the same time period, it is essential to extract the phenology of cover crops, cash crops, and other land cover types in our study area (Oetter et al., 2001). Therefore, we set our study time from the spring (April 1st) to summer (August 11th) of 2018 to observe the time that cover crops are actively growing while most cash crops are not. Additionally, we created a calendar of cover crops and common cash crops in Southeastern Michigan (Figure 3). The calendar is based on previous studies of cover crops in our study area, information from local newspapers, and information from the MSU Cover Crop Extension.

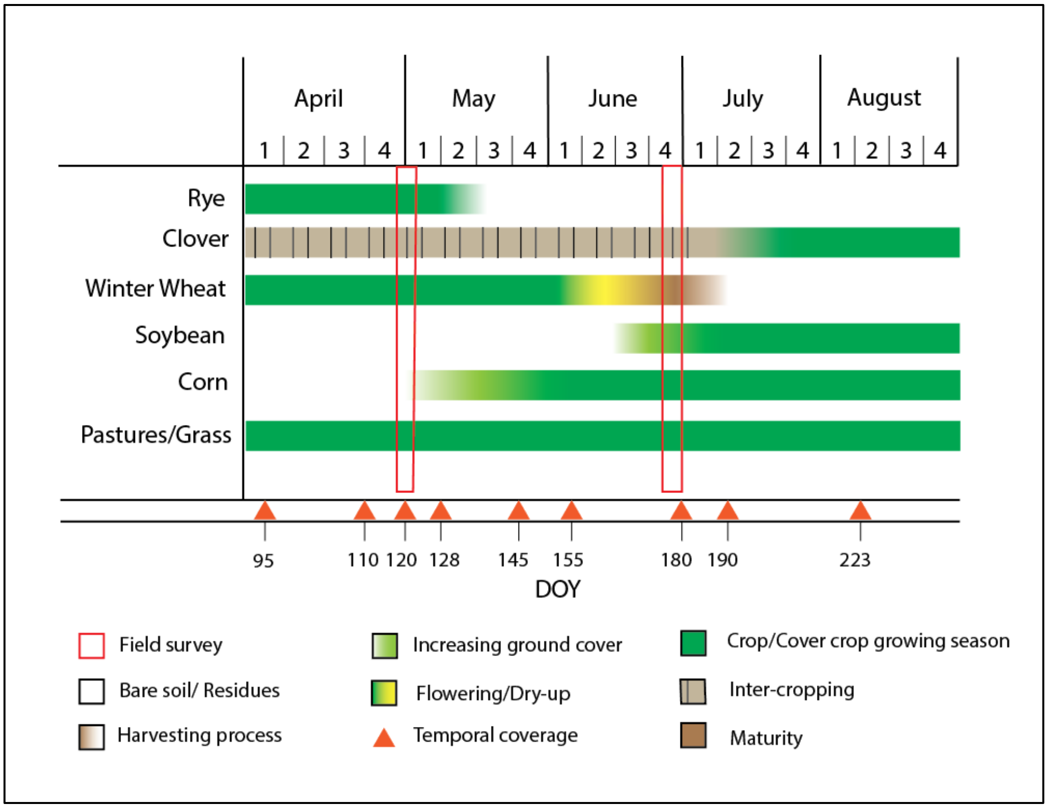


Figure 2 Cover Crops and Cash Crops Calendar along with Remote Sensing Imagery Temporal Coverage. The color of each crop type indicates crop growth stages. The opacity indicates ground cover percentage. Usually, the increase in opacity indicates the early stage of plant growth. On the contrary, the decrease of opacity shows the harvest season or elimination of cover crops. The phenology of three common cash crops: winter wheat, soybean, and corn are also included in the calendar to better understand the critical phenology difference between cash crops and cover crops.

As one of the cash crops, winter wheat begins to grow in early spring and will start to flower and senesce in the middle of June (Figure 3). By the first week of July, winter wheat will reach complete maturity and will be ready to be harvested. Soybean is expected to be planted by the middle of June and grows throughout our study period (Staton, 2018). Corn is planted in early to middle of May and also continues to grow throughout our study season (Silva, 2018). Because of different cover crop management strategies, the two kinds of cover crops considered in our study, cereal rye and red clover, have different termination times (Figure 3). Based on previous literature, cereal rye will be eliminated in the middle of May while red clover intercropped with wheat will stay in the field and will keep growing and stay in the farm after wheat harvested. The red clover will stay in the farm until the next following spring. The other common vegetation class in our study area is Pasture/Grass which represent grazing grasslands.

From the crop calendar above and previous literature, we identified the end of April and the end of June as two critical time periods to observe cover crops. This is because at the end of April, only cover crops and wheat are likely to be growing. However, cereal rye (cover crop) and winter wheat (cash crop) look very similar at initial growth stages. Therefore, we also conducted the second field survey at the end of June because it is much easier to distinguish rye and wheat at this time. We specifically carried out field surveys during two periods of time: from April 25th to May 5th and from June 23th to June 25th.

2.2.Ancillary Data Collection

To select appropriate fields to visit for our ground survey, we conducted the following steps. First, the USDA NASS Cropland Data Layer (CDL) 2017 was used as a 'Crop Mask" in selecting ground truth data sample sites. The 'Crop Mask' is a layer based on the most recent five years of CDL data. If a pixel is identified as cultivated in at least two out of five years of CDL data, then it is classified as 'Cultivated' (USDA NASS CDL, 2017). Second, we used a road data layer for southeastern Michigan since we wanted to identify fields that could be observed from the road since this allowed us to assess land cover type while driving. Third, we used R Project Software and the package *sp* to generate 5000 random spatial points that were within 10 meters from the road and were classified as 'Cultivated' in the CDL data layer. Finally, to ensure that our randomly selected ground truth points represented the range in vegetation land cover types found in our study region, we created a max NDVI (Normalized Difference Vegetation Index) cropped area map of our study area using data from Sentinel-2 of April 2018 (Figure 4). We then spatially joined the 5000 potential survey points with the NDVI map to extract NDVI values for each point. After that, we stratified 500 of these points across four ranges of maximum NDVI values (Equal intervals): Low (< 0.2), Medium (0.3-0.4), Medium High (0.4-0.6), and High (> 0.6). These 500 farms were then visited in person to collect observational data on the type of land cover.

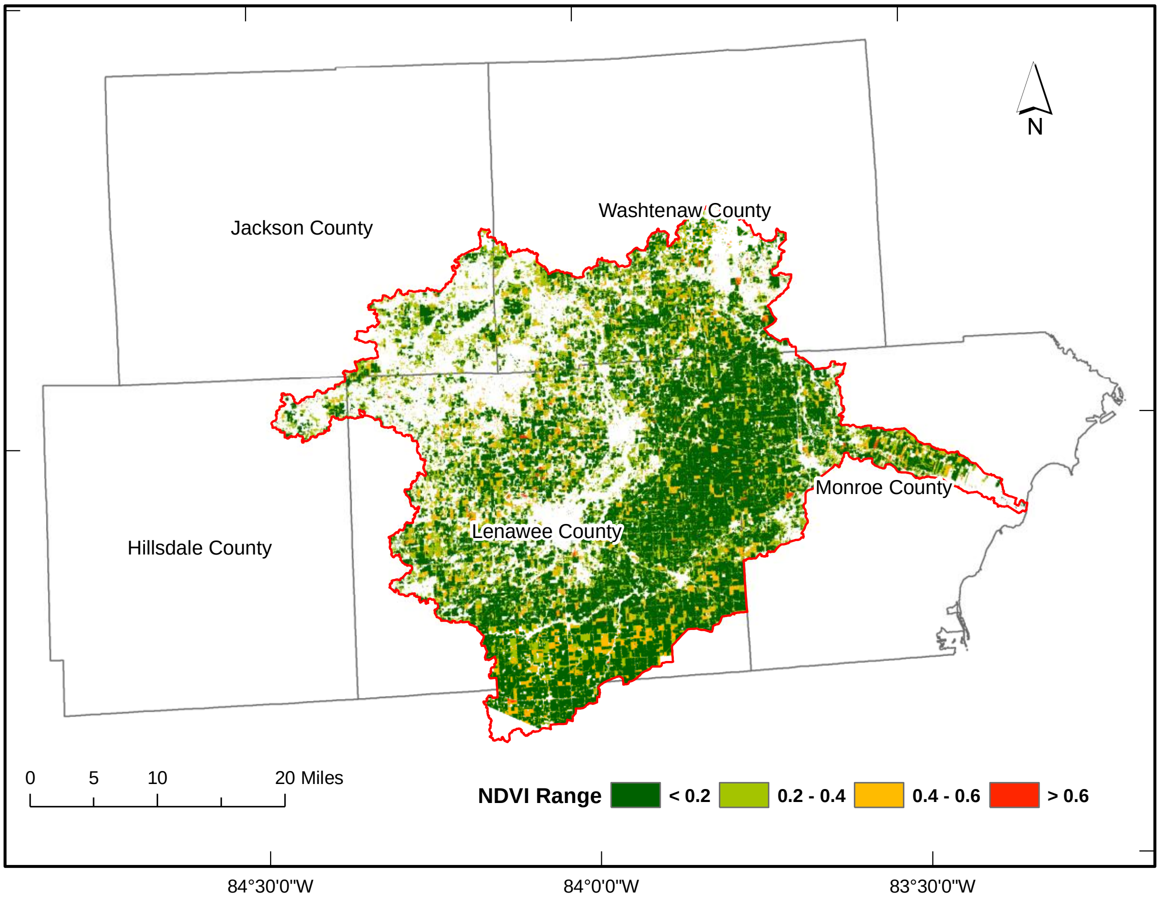


Figure 3 Max NDVI of Cropped Area in April 2018

For each surveyed field, three GPS locations were taken at the start, middle, and end point of the field along the road. We recorded the land cover type based on our observation from the road and also by taking a zoomed in picture of the land cover type from the road. ArcGIS 10.6.1 was used for digitizing field boundaries using 0.3m resolution imagery from Digital Globe as the base map. To minimize edge effects (because farmers often plant grass as a buffer on the edges of farms) and to obtain more uniform spectral reflectance data for each survey site, the boundaries were buffered within 10m from the edge of each site. This method has been used and shown to be effective in removing mixed pixels from remote sensing data (Hively et al., 2015). Based on our field survey and a previous literature review, we developed five land cover classes including four vegetation classes: Red Clover, Winter Wheat, Cereal Rye, Pasture/Grass, and one non-vegetation class: Fallow; which represents the conventional agricultural practices where fields are left as fallow in winter after the cash crops harvest in fall last year. Since winter wheat and cereal rye have very similar characteristics and were hard to distinguish in the early growth stage seen in the first field survey, we did a second field survey where we revisited all winter wheat and cereal rye fields in late June. We were able to distinguish these two vegetation classes in June because, as a cash crop, winter wheat has a much longer growth time in the field compared to cereal rye. By the end of June, winter wheat is at the stages of flower or senescence, while cereal rye has been already removed and the soil tilled to plant a cash crop at this time.

2.3.Remote Sensing Data Acquisition

2.3.1. Image Preprocessing

Satellite data were acquired from Sentinel -2 using Google Earth Engine for the 2018 growing season starting from April 4th to August 11th. The Sentinel-2 Level -1 C cloud mask, which is a developed product from the European Space Agency (ESA) for discriminating clouds and cloud-free pixels, was applied on the satellite images. We also filtered images to those having less than 10 percent cloud cover based on the statistical information from the cloud mask product to reduce the effects of cloud cover on our analyses. In total, we acquired 9 cloud-free satellite images in our study area during the 2018 growing season (Figure 3). An atmospheric correction algorithm was applied to these images to obtain surface reflectance values.

2.3.2. Feature Extraction

For each image, 10 bands (Table 1) were selected from Sentinel-2, which spanned the visible light, infra-red, and short infra-red from the wavelengths 496.6nm to 2202.4nm and at a spatial resolution from 10m to 20m.

Table 1: Selected Sentinel-2 Bands and Spatial and Spectral Resolutions

Band name	Resolution	Wavelength	Description
B2	10m	496.6nm	Blue
B3	10m	560nm	Green
B4	10m	664.5nm	Red
B5	20m	703.9nm	Red Edge 1
B6	20m	740.2nm	Red Edge 2
B7	20m	782.5nm	Red Edge 3
B8	10m	835.1nm	NIR
B8A	20m	864.8nm	Red Edge 4
B11	20m	1613.7nm	SWIR 1
B12	20m	2202.4nm	SWIR 2

Soil background and solar irradiance may have negative effects on classification accuracy. Therefore, vegetation indices have been developed to reduce this noise and enhance the signals for vegetation (Huete et al, 2002). Indices (Table 2) that help classify crops and land cover types were calculated with the 10 bands in Table 1.

Table 2 Vegetation Indices used in this study and the application proposed by the original studies

Index	**Calculation**	**Application**	**References**
NDVI	(NIR-R)/(NIR+R)	LAI	Tucker (1979)
GBNDVI	(NIR-(G+B))/(NIR+(G+B))	LAI	Wang et al. (2010)
GRNDVI	(NIR-(G+R))/(NIR+(G+R))	LAI	Wang et al. (2007)
NDI	(RE1 - R)/(RE1 + R)	LAI	Perez et al. (2000)
PSRI	(R - G)/RE2	Plant senescence	Merzlyak et al. (1999)
NDSVI	(NIR - G)/(NIR + G)	Plant senescence	Qi et al. (2002)
CIre	RE3/RE1 - 1	Leaf chlorophyll	Gitelson et al., 2003)
GCVI	NIR/G - 1	Leaf chlorophyll	Gitelson et al. (2003)
NPCI	(R - B)/(R + B)	Leaf chlorophyll	Peñuelas et al. (1997)
SIWSI1	(NIR-SWIR1)/(NIR+SWIR1)	Vegetation Moisture Status	Fensholt & Sandholt (2003)
SIWSI2	(NIR-SWIR2)/(NIR+SWIR2)	Vegetation Moisture Status	Fensholt & Sandholt (2003)
NDTI	(SWIR1- SWIR2)/(SWIR1 + SWIR2)	Residue Coverage	Van Deventer et al. (1997)

In addition, different crops have different timing and rates of green up, maturity, and harvesting. (Figure 3). Therefore, we developed additional metrics to capture differences in phenologies of the different land cover types (Figure 5). NDVI time series is one of the most widely used methods to extract vegetation phenology features in crop type mapping (Hao et al., 2015; Zhong et al., 2015; Belgiu and Csillik, 2018). From the time series, we extracted two phenology features: Mean NDVI of the first 4 image dates and the Max NDVI of each pixel across all 9 image dates to better distinguish different plant phenologies.

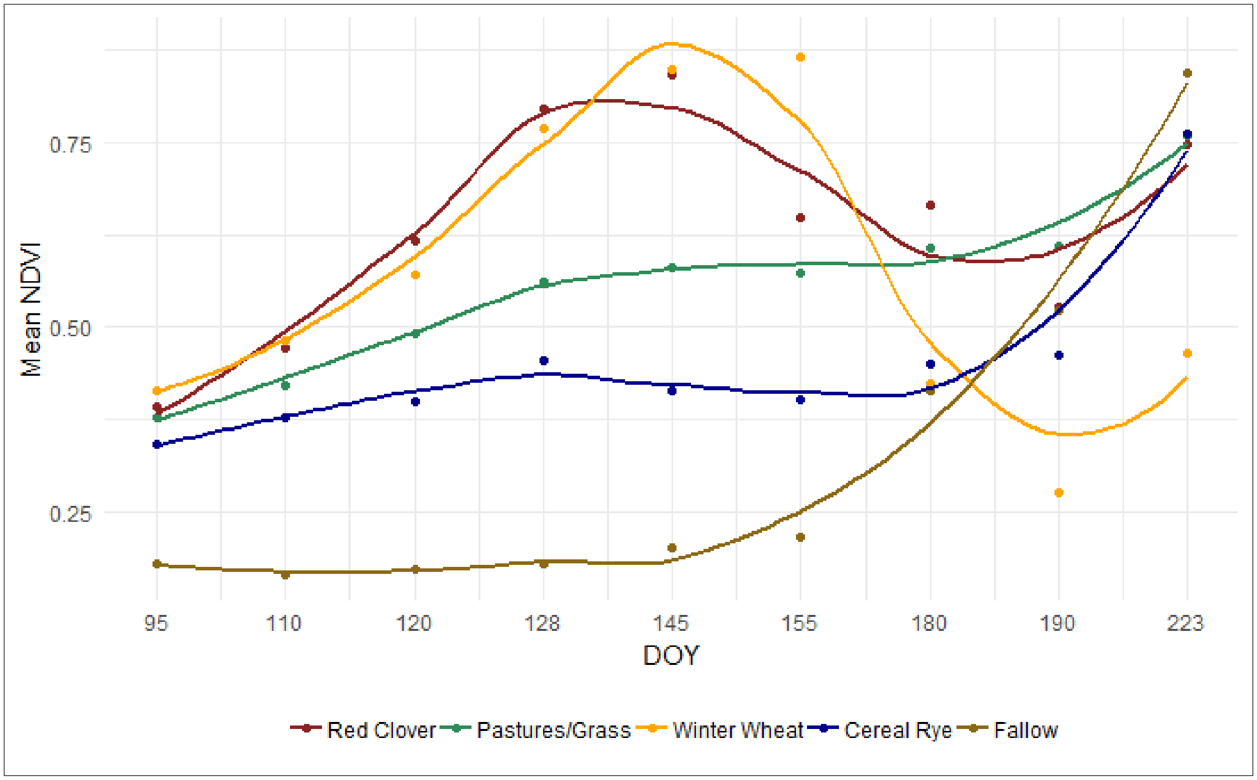


Figure 4 Mean NDVI of sample sites of 5 information classes

2.3.3. Classification Algorithm

As one of the most popular nonparametric classification algorithms, random forest has been used for many studies on land cover mapping across the world and has good performance compared to other classification algorithms (Thanh and Kappas, 2018; Lambert et al., 2018; Inglada et al., 2015; Sonobe et al., 2018). We therefore used random forest as our classification algorithm. We acquired 24 variables including the 10 original bands from Sentinel-2 and 12 vegetation indices that are associated with various plant and land cover characteristics for each image date as well as two phenology features. In total, we assembled 200 variables for each pixel. The R package *randomForest* (v.4.6–12) published by Millard and Richardson (2015) was used in our study. Two parameters need to be tuned for the algorithm: the number of variables used for each tree node (*mtry)* and the number of trees that will be generated in total (*ntree*). Based on previous studies and the reviews of Belgiu and Drăguţ (2016) and Gislason et al. (2006), the *mtry* parameter was set as the root square of the number of variables, which is 14 in this study. The *ntree* parameter was set at 500. To avoid spatial autocorrelation, the sample sites were stratified by class and separated as 30% for test sites and 70% for training sites. We randomly sampled the same number of pixels from each class to ensure the balance of classes. The same sampling method was used for the validation (test) pixels.

4. Results

4.1. Accuracy Assessment

We generated a Contingency Matrix (Table 3) and calculated the Overall Accuracy (OA), Producer Accuracy (PA), and User Accuracy (UA) for each class. The model had an OA of 86.37%. Overall, winter wheat had the highest PA and UA (90.89%~95.90%). The two cover crop classes, red clover and cereal rye, had moderate PA and UA ranging from 75.33% to 85.90%. Both red clover and cereal rye were most likely to be classed as fallow when misclassified. The class Pasture/Grass had the lowest PA and UA (58.16%~67.67%).

Table 3 Contingency Matrix and Statistical Measures

		Ground Truth (pixels)					
		Red Clover	Pasture/ Grass	Winter Wheat	Cereal Rye	Fallow	UA
Classification results	Red Clover	13357	1816	378	0	355	83.98%
	Pasture/Grass	590	4417	277	394	851	67.67%
	Winter Wheat	560	0	24049	403	64	95.90%
	Cereal Rye	154	335	1323	11263	907	80.55%
	Fallow	890	1028	435	2887	56496	91.51%
	PA	85.90%	58.16%	90.89%	75.33%	96.29%	
						OA	86.37%
						Kappa	83.82%

4.2.Variables of Importance

In Random Forest classification analysis, one of the results that can be examined is variable importance. Figure 6 plots the top 20 variables based on mean decrease of accuracy, which illustrates how much the random forest accuracy will decrease if a given variable is removed from the model (Figure 6). Each variable seen in the left-hand column of Figure 6 is named based on its band number (e.g, B7 represents the 7th band in Sentinel-2) or vegetation index name, followed by the date of the image (e.g., _1 represents the second image date considered in our study). The top 20 variables had a mean decrease of accuracy ranging from 22% to 28%. B5, B6, B7, and B8A represent the red edge bands from Sentinel-2. The two shortwave infra-red bands, 11 and 12 from Sentinel-2, are also found within the top 20 variables of importance. There are also three vegetation indices, PSRI, GRNDVI and NDTI, in the top 20 most important variables. These three indices reflect plant senescence, LAI, and residue coverage, respectively.

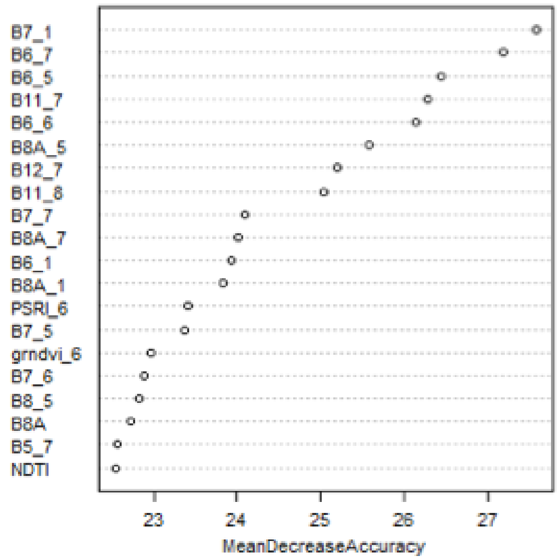


Figure 5 Top 20 Variables of Importance

5. Discussion

5.1.Class-based Performance Analysis and Potential Sources of Error

This study aimed to understand the extent of cover crop adoption across southeastern Michigan, which is a hotspot for nutrient losses that cause eutrophication and algal blooms in the Great Lakes. We used remote sensing satellite data to classify the two main cover crops found in our study region: cereal rye and red cover. Overall, our model was able to distinguish different cover crops, cash crops, and conventional agricultural practices with a fairly high accuracy. While cover crop accuracies were moderate (75.53%-85.9%), they were much higher than existing land cover products that attempt to map rye and clover in this region, such as the CDL. This suggested that our mapped product is significantly more accurate than existing cover crop maps in the region, and can be used to more accurately understand where cover crops have and have not been adopted.

There are some possible factors that may contribute error to our model. First, the numbers of sample sites for each class was different. In total, Fallow had the most sample sites for the reason that most farmers in our study area still followed conventional agricultural practices and this land cover type was easily encountered. Variance within the fallow class is likely well captured by the relatively larger number of sample sites. On the contrary, cereal rye has the smallest number of sample sites compared to the other classes since this land cover type was challenging to find on the ground. In our study, we implemented pixel-based classification. With limited sample sites to select pixels from, the sample pixels may highly spatial auto-correlated. Previous study also found out that spatial autocorrelation of training data contributes to the classification errors of associated class (Millard and Richardson, 2015). This may partially explain the relatively low accuracy of cereal rye.

A second factor that may affect classification accuracy of different classes is the uniformity of each land cover type. For example, winter wheat has the highest classification accuracy among all four vegetation classes likely because wheat fields are homogenous and uniform, and there is little variation in wheat field spectral signatures. Cereal rye, on the other hand, is non-uniform as it is often planted in fields that have harvested corn, and therefore cereal rye is found among corn stalk stubble and may establish unevenly in fields. This is likely why the most common misclassification of cereal rye was fallow, which often had crop residues and some vegetation due to the growth of weeds and wildflowers. Red clover had higher classification accuracy than cereal rye for its higher ground coverage as a broad-leaf plant. Even with the wheat residue in the field in July, once the red clover gets enough sunlight, it will establish a nice ground cover quickly. However, it can often look similar to Pasture/Grass which also has a fairly high ratio of ground cover at the same time, and therefore these two classes are often confused with one another.

The third factor that may lead to error is similar phenologies during our study period of different land cover classes. The crop calendar (Figure 3) and contingency matrix (Table 3), show that winter wheat has the highest accuracy, and it is also the land cover with the most distinct phenology. Cereal rye and fallow have similar phenologies, further complicating the ability to distinguish these land cover classes from one another. This is because fields with cereal rye planted as a cover crop and fallow fields will be tilled for the next crop season at middle of May. Before that the cereal rye may not able to fully establish and show distinct spectral differences with fallow. The Pasture/Grass class contains the most variance in phenology within a given class; this is because this area is mostly used for livestock grazing and the phenology within this class may be less uniform because of different grazing practices across different landowners. It is also possible that this class contains forage or hay fields, which look similar as grazed pastures but are managed differently.

5.2.Most Important Variables and Dates

In this study, we were also interested in identifying the most important bands and image dates to identify cover crops from other classes. We found that the red-edge bands including bands 5,6,7, and 8A from Sentinel-2 are the most frequent variables found in the top 20 important variable analysis, followed by infra-red band 8 and shortwave infra-red bands 11 and 12 (Figure 6). From the model, we also found that PSRI, GRNDVI, and NDTI on certain dates are the most important vegetation indices. According to the crop calendar (Figure 3), these three indices captured several differences across the land cover types considered in our study. Winter wheat has the most regular and uniform plant senescence during the growing season, which is well captured by PSRI on the 6th image date (June 4th). GRNDVI and NDTI captured differences in the amount of vegetation and residue between vegetation dominant classes (Red Clover, Pastures/Grass, and Winter Wheat) and residue dominant classes (Cereal rye and Fallow).

These findings confirmed the importance of using Sentinel-2 data for vegetation classification in our study region, particularly the importance of the red edge bands. With these red-edge bands, Sentinel-2 data are able to detect the rapid changes in vegetation reflectance that contribute most to the classification algorithm. Studies have found that compared with other commonly used remote sensing satellites, such as Landsat 8, using the red-edge and shortwave infra-red bands from Sentinel-2 improve classification results for vegetation (Immitzer et al., 2016; Forkuor et al., 2018).

Given the fact that cover crops have a relatively short growing season and specific management strategies, satellite data with high temporal availability is of vital importance to capture these changes (Jain et al., 2016). Also, using data with high temporal coverage, more accurate and general phenology profiles for different vegetation types can be generated and will improve the classification accuracy when phenology features are extracted (Foerster et al., 2012). We found that the 5th, 6th, and 7th image dates which represent May 25th, June 4th, and July 9th are the main dates that appear in the top 20 variable importance analyses. This finding suggests that late-May, early-June, and late-June are the critical time periods to distinguish different crop types and agricultural practices in this study region. It is important to note that because of the high proportion of missing data caused by cloud cover, not all images during our study period were available. From the crop calendar (Figure 3), we can see that images were missing during multiple periods that may have been important for capturing planting, senescence, or harvest.

5.3.Future Study

To address the challenges that we faced in this study, future work can be conducted. First, more field data on cover crops could be collected, which may improve our ability to classify cereal rye and red clover. This could be done by conducting field survey campaigns at different time periods throughout the plant growing season. In addition, interviews with local farmers may help identify additional farms where cover crops have been planted. Second, other machine learning classification methods can be used for higher classification accuracy, such as deep learning, which is a more complex method to find the patterns in imagery and it can handle missing data caused by cloud cover (Kussul et al., 2017).

6. Conclusion

We used Sentinel-2 imagery to map cover crops across Southeastern Michigan's River Raisin basin with moderately-high accuracies (75.53%-85.9%%). Compared to USDA NASS Cropland Data Layer, the classification accuracies of clover and cereal rye were greatly improved by our model. Our results showed that red-edge bands from Sentinel-2 and vegetation indices including PSRI, GRNDVI, and NDTI are the most important variables in the classification algorithm for our study area. More generally, with the extra red-edge bands and higher spatial and temporal resolutions, Sentinel-2 data has more possibilities and power on pixel-based vegetation classification compared to other commonly used sensors. However, challenges still exist in distinguishing cereal rye cover crops from conventional agricultural practices, likely because we had relatively few samples for cereal rye in our classification algorithm and because it has a similar phenology to fallow.

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