# Remote Sensing of Winter Time Cover Crops in California's Central Coast Region

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## ABSTRACT

Winter cover crops are a vital part of sustainable crop systems due to their ability to improve soil quality, increase soil carbon sequestration, and reduce water pollution from agricultural land. Remote sensing offers a cost effective and efficient approach to mapping cover crop adoption on California's Central Coast. Producing spatial and quantitative information on local cover cropping practices is necessary to inform agricultural policies and practices in the region. This study used a Random Forest and CART classifier with Sentinel-2 satellite imagery on Google Earth Engine to remotely sense cover crops in the Central Coast of California. To classify winter crop cover in the region and identify cover crops, normalized difference vegetation index (NDVI) was used. Random Forest was found to be the most accurate at detecting cover crops with an accuracy of 86.7% compared to CART at 74.7%. A total of 72.56 km² of land was found to be cover cropped over the winter season, representing 4.78% of Central Coast farmland. Cover crops were classified with a producer's accuracy of 61.5% and a consumer's accuracy of 80.0% indicating a potential underestimation of cover cropped land. The results of this study provide important baseline data and monitoring methods for scientists and policy makers implementing environmental programs in the region. Results indicate a need for policies that reduce farmers' risks and incentivize cover cropping.

## KEYWORDS

Google Earth Engine, Random Forest, Agriculture, Agroecology, Sentinel-2

## INTRODUCTION

As populations and food demand grow, sustainable alternatives to conventional food production are becoming increasingly important. Current intensive agricultural practices prioritize high yields and profitability at the cost of water quality, soil health, and carbon emissions (Schipanski 2014). Nitrate pollution from traditional fertilizers has polluted waterways, leached into freshwater drinking supplies, and led to anoxic conditions in coastal waters (Harter and Lund 2012). Intensive, monocultural agriculture practices also lower soil's ability to store carbon, resulting in reduced soil quality, and an increase in carbon emissions (Schipanski 2014). Allowing fields to go fallow during the winter season, which often occurs after fall harvest, exacerbates issues of nitrate leaching, lowered carbon sequestration, and soil health as root systems are removed from the soil.

Recent decades have seen a rise in agricultural management practices that take the ecology of agricultural systems into account. Agroecological practices aim to minimize negative environmental impacts while cultivating productive cropping systems (Wezel 2013). Examples of agroecological practices include intercropping, crop rotation, no-till, cover cropping, and agroforestry. Cover cropping in particular has emerged as an agroecological practice with high potential to mitigate unwanted environmental impacts associated with conventional agricultural practices. The use of wintertime cover crops involves planting non-economic crops after fall harvest for the primary goal of preserving field quality (Klonsky 1994). Cover crops provide increased soil carbon storage, weed suppression, reductions in nitrate leaching, beneficial insect conservation, reduced erosion, improved soil structure, and increased organic soil-matter (Brennan 2009, Brennan 2017, Schipanski et al. 2014). The root system and nutrient uptake of cover crops reduce a field's vulnerability to leaching when winter rains fall on fields which might otherwise be fallow (Schipanski et al. 2014). Cover crop's root systems also provide an important carbon source to bacteria, fungi, and earthworms which helps to increase soil carbon levels over time (Schipanski 2014). The use of cover crops support additional agroecological practices such as no-till farming, which is put into place to reduce soil erosion and nutrient loss. Although no-till practices have been shown to decrease weed management and crop yield, cover crops have demonstrated the ability to overcome these issues when no-till farming is paired with cover cropping (Büchia et al. 2018). In addition to their ecological benefits, cover crops have shown to increase yields of subsequent crops, providing potential economic benefits to farmers (Schipanski 2014, Büchia et al. 2018). Despite their innumerable benefits, farmers hesitate to implement cover cropping practices due to economic risk.

Reliable data on cover crop usage is vital to informing agricultural policies that can incentivize adoption. This information is also valuable to scientists looking to study the impact of cover cropping on pollution mitigation. The 2017 USDA Census of Agriculture estimated that around 5.6% of harvested land in the US overall uses cover crops, while the Central Coast in particular is estimated to have less than 5% of harvested land cover cropped each year (Brennan 2017, Myers and LaRose 2017). However there is currently no published quantitative, spatially-explicit data on cover cropping in the region, or anywhere in California. In California, fields often produce multiple different crops in a given year with cash crops planted over the winter season in addition to cover crops (Zhong 2012, Heinrich et al. 2014). This makes it extremely difficult to know how many farmers and exactly how much farmland utilize cover cropping in the Central Coast region year to year. In addition, on the ground agricultural monitoring is difficult for quantifying cover crops due to their short planting season, typically 3-4 months (Brennan 2009). Fortunately, remote sensing offers an efficient way to observe large swaths of land by using satellite imagery to monitor farmland (Campbell and Wynne 2011). Developing a remote sensing method to identify cover crops from satellite imagery provides a quick and affordable way to quantify cover crop extent compared to the high cost and time required of on-the-ground monitoring. This study will not only develop an efficient method of cover crop monitoring, but also provide a quantitative baseline of cover crop adoption levels in the region. This baseline understanding of cover crop extent in the Central Coast, vital to informing agricultural policy and future research, is missing from current literature.

This study uses remote sensing to quantify the extent of wintertime cover crops in the Central Coast region of California. To quantify cover crop extent I explored two sub questions. The first question asks what is the spatial distribution of cover crops in the Central Coast region over the winter 2020-2021 season? The second is how accurate are the classifying techniques I develop at remotely sensing cover crops on California's Central Coast? To answer these questions I used Sentinel-2 satellite imagery and ground truth data to train and test a classification algorithm that can detect cover crops from satellite imagery of the Central Coast.

# BACKGROUND

## California Central Coast cover cropping practices

The intensive production and scale of California's Central Coast agricultural market, makes the region an ideal location to study the extent of cover cropping practices. The region, made up of Monterey, San Benito, Santa Cruz, Santa Barbara, and San Luis Obispo counties, represents an over 5 billion dollar a year agricultural industry (Stuart 2008). Salinas Valley, known as "the salad bowl of America" stretches from Monterey to San Luis Obispo, and is a key region for US leafy green production (Stuart 2008). The unique cropping patterns associated with the region must be accounted for when designing remote sensing methods. The region's fertile land and mild climate make it ideal for highly productive agricultural systems, with fields typically producing 2-3 crops a year (Zhong 2012, Heinrich et al. 2014). Along with leafy green production, the region harvests large amounts of strawberries, broccoli, and winter crops such as artichokes and asparagus (UCCE Monterey County 2020). Typical cover crops used in the region are mixes of cereal rye, mustards, and legumes (Jackson et al. 1993, Brennan 2009, Heinrich et al. 2014). Analysis must be able to distinguish cover crops from fallow fields, as well as other crops planted over the winter months. Cover crops in the region are planted after fall harvest, typically around October/November, and are removed before the start of spring planting in February (Brennan 2009).

The region implements intensive and industrialized practices with crop specialization and high food safety standards. The intensive agricultural practices of the Central Coast region have resulted in detrimental impacts to local water quality from nutrient and sediment pollution. 75% of the land surrounding the three major watersheds of the region—the Pajaro River, Salinas River, and Elkhorn Slough—is used for agriculture (Stuart 2008). Nitrate from agricultural land poses a huge threat to local water quality from fertilizer leaching into local waterways. Nitrate leaching primarily occurs in the wet winter season when rain falls on nitrate rich fallow fields and carries the nutrients and sediment into aquifers and surface waters. When cover crops are planted, their root systems help prevent this leaching from occurring (Jackson et al. 1993). Ninety six percent of the region's groundwater nitrate pollution comes from agricultural land, with 51% of all nitrogen applied in the Salinas Valley region eventually leached to groundwater supplies (Harter and Lund

2012). Ninety five percent of Monterey's water supply is drawn from aquifers, which often fail quality standard tests for nitrate levels (Stuart 2008, Harter and Lund 2012). San Benito and Santa Cruz counties also rely heavily on groundwater supplies. Nitrate contaminated water has major environmental justice implications as well, as high water nitrate levels can lead to infant death, reduced cognitive functioning, and cancer for farm workers in the region (Harter and Lund 2012). Cover crops are a valuable tool for reducing nitrate pollution associated with agricultural land while maintaining crop yields (Jackson et al. 1993). Cereal cover crops in the Chesapeake Bay watershed successfully reduced nitrate leaching by 80%, demonstrating a 60% decrease in groundwater nitrate concentration over a 9 year period (Staver and Brinsfield 1998).

Despite the success of cover crops in mitigating nitrate pollution, the Central Coast region still experiences low adoption of cover cropping practices (Heinrich et al. 2014, Brennan 2017). The high costs of land, food safety standards, and high demand associated with the commercialized farming practices of the region make cover cropping economically risky. One source of economic risk is in cover crop residue, which can be costly to clear at the end of the winter season and can cause delays in spring planting (Heinrich et al. 2014, Brennan 2017). Food safety concerns have also influenced agroecology practices in response to *E.coli* outbreaks in the region. Food safety audits have disincentivized various environmental practices, such as the use of non-food vegetation, which can cause farmers to lose points on safety audits resulting in fines and lost revenue (Stuart 2008). Non-food vegetation is discouraged due to its ability to attract wildlife suspected of carrying *E.coli*. Overall, 15% of surveyed farmers in the region have discontinued environmental practices in direct response to food safety pressure (Stuart 2008). It is important to measure cover cropping levels in order to understand how pressures such as food safety affect cover crop implementation.

**Remote sensing**

Satellite imagery and remote sensing are valuable resources that can be used to quantify regional cover cropping practices. Remote sensing involves the observation of earth's surface from a distance via electromagnetic radiation (Campbell and Wynne 2011). Remote sensing is an extremely useful tool for agricultural monitoring as it can be used to observe large swaths of land over long periods of time with high observational frequency. High frequency satellite monitoring is especially useful in California, where cropping patterns change throughout the year and from one year to the next, making ground monitoring more difficult. Normalized difference vegetation index (NDVI), which uses visible (red) and near infrared spectral properties to analyze vegetation based on chlorophyll content, is the primary indicator used in remote sensing analysis of agricultural fields (Atzberger 2013). NDVI measurements combined with ground truth data from the field can be used to identify crop types, crop biomass, cropping patterns, and ecosystem services such as nutrient uptake and carbon sequestration (Hively et al. 2009, Bégué et al. 2018). Crop classification methods can be used to distinguish between different crop types using satellite imagery of agricultural land (Zhong 2012).

Studies on the remote sensing of cover crops have typically been conducted in regions such as Iowa, Missouri, and Pennsylvania, where economic crops are not grown over the winter season due to winter frost (Hively et al. 2009, Howard et al. 2012, Li et al. 2015, Seifert et al. 2018, and Thieme et al. 2020). Remote sensing in these regions is relatively straightforward: if vegetation is detected on agricultural land during winter months, it is likely to be a cover crop. In the Central Coast region however, a mild climate allows economic crops to be grown year-round. Non-cover crops found over the winter season included crops such as artichokes, kale, strawberries, and brussel sprouts. The presence of various winter crops required more complex remote sensing methods than simply sensing the presence of vegetation. Regional agricultural practices such as field size and short planting times, were taken into consideration within the study design.

### Classification models

Several classification algorithms can be used for crop classification using remotely sensed data such as Random Forest, maximum likelihood, classification and regression trees (CART), support vector machines, or Max Entropy. Maximum likelihood classification uses parametric classification, which assumes normal distribution of class data (Yang et al. 2011). The other algorithms are non-parametric and use AI machine learning to make decisions by learning from the data (Ok et al. 2017). In each classification algorithm, ground truth data is used to train the algorithm to classify satellite imagery's pixels into crop type. Several studies have compared classification algorithms for crop classification. One study looking to classify crop types in

Ukraine found high overall accuracies for various classifiers: CART (75%), Maximum Entropy (72%), and Random Forest (68%) (Shelestov 2017). Other studies show high performance with overall accuracies by Random Forest at 85.86% and maximum likelihood classification at 77.87% (Ok et al 2017). This indicates that high accuracy crop classification can be achieved by several different classification models. It is thus best to choose a classification algorithm that fits the study system and sampling constraints.

CART algorithms use decision trees to classify data. Data is split at a parent node into two child nodes based on a subset of predictors chosen randomly at each node (Ok et al. 2017). Each child node becomes a parent node and subsequent splits are made until a terminal node is reached. The splits are made using the GINI index which measures the homogeneity of data (Ok et al. 2017). Higher GINI values indicate greater heterogeneity and lower GINI indicate greater homogeneity (Ok et al. 2017). Each split is made so that the child nodes have a lower GINI than the parent node. When GINI is 0, the terminal node has been reached and further splitting is not required. The result of the decision tree gives a crop type classification result for each pixel. Multiple CARTs can be combined into a Random Forest algorithm.

Random Forest classifiers use a collection of decision trees to increase classification accuracy. In Random Forest classification, multiple decision trees run through classification and return a classification result. Each decision tree "votes" with their classification result and the class with the most votes "wins" resulting in the pixel being assigned that class (Ok et al. 2017). In Random Forest classification two parameters are set: number of trees (N) and the number of variables used in feature selection to split each node (m) (Pal 2007). If 100 trees are generated, then there are 100 "votes" used to decide each pixel's classification. During each split, a chosen number (m) of random features are examined to determine the split.

This study will compare the accuracy of a Random Forest and CART classifier in classifying cover crops in the Central Coast. Random Forest is an aggregate of CART results which can provide greater accuracy power than using a single decision tree. However the Random Forest model requires large amounts of training data, thus a CART classifier will be compared, given the constraints of ground truth collection. The Maximum Entropy algorithm will not be used as it has only recently been adapted as a classifier and many gaps in knowledge remain. Support vector machines are useful when a class's spectral extremes are already known. Crop classification has not been done in the region, so class extremes are unknown, thus the benefits of support vector machines are not relevant. The maximum likelihood classifier will not be used as it is not integrated with Google Earth Engine. Random Forest and CART were chosen due to their high accuracy in crop classification and availability within Google Earth Engine.

## METHODS

### Study area

My study focused on cover crops within the Central Coast region of California including Monterey, San Benito, and Santa Cruz counties. Cover crops found in the area include cereals (*Avena sativa* L, *Hordeum vulgare* L. and *Secale cereale* L.), legumes (*Pisum sativum* L. and *Vicia*), radishes (*Raphanus raphanistrum*), and mustards (*Brassica juncea*, B. *hirta Moench*) (Brennan 2009). A common method of cover cropping found in the region are mixes of cover crops such as a grain with a legume and/or radish (Figure 1).

**Figure 1. Typical Cover Crop Mix** Most of the cover crops I identified were a grain/vetch mix with either a legume or radish as seen in the image.

I used crop classification methods to distinguish bare fields from the different crops planted over the winter season. In California, crop type can change on an annual or semiannual basis and agricultural fields range in size, with small parcels common in the region (Zhong 2012). A variety of different crops are planted over the winter season, some more common like strawberries, others less common like parsley. Less common crop types such as parsley may only be planted on a few fields in the Central Coast, preventing the collection of enough samples to train a classifier to identify the crop.

I acquired shapefiles for farmland boundaries from county offices and merged them into a single farmland shapefile. I limited my analysis to these farmland boundaries. San Benito shapefiles contained polygons for all county plots including residential and commercial properties. I limited the shapefile to agricultural crop land by creating a Definition Query on ArcGIS to include only polygons of cropland and remove grazing, commercial, and residential land. Grazing land was also removed from the Monterey County shapefile. The Santa Cruz County shapefile was already limited to crop land and did not require any preprocessing.

**Ground truth data collection**

I collected ground truth data points throughout the Central Coast counties of San Benito, Santa Cruz, and Monterey to train and test the classification algorithm. Ground truth data points included GPS coordinates and crop type. I used the mobile app MapPlus to take photographs of each ground truth point while recording GPS coordinates, capture time, and notes on crop type (Duwei Apps). I used GPS coordinates to match crop type from ground truth data to corresponding satellite imagery pixels to create training and testing points for the classification algorithms.

I conducted sampling in San Benito and Santa Cruz Counties on January 11-12th, 2021 and in Monterey County on January 16th-17th, 2021 before crops were removed for spring planting. I created random routes by generating 40 random points within each county's farmland boundaries on Google Earth Engine. I then moved each point to the nearest accessible road and generated a route on Google Maps connecting the points. My sampling procedure involved driving the randomly generated routes in Monterey, Santa Cruz, and San Benito counties and identifying crop type from road/property boundaries and recording the information using MapPlus. I used crop guides from the University of California Cooperative Extension and local agricultural knowledge for crop identification. I gathered additional perennial crop testing points by locating perennial orchards on Google Maps.

The "Brassica" crop class was created for fields that I identified as leafy brassicas such as kale or cabbage, but were unable to be further distinguished. Grape vineyards were identified by vineyard infrastructure and recorded as "Grapes" despite being bare during the winter season. I recorded cover crops mixes whose parts could not be distinguished as cover crops.

When I collected ground truth points, the GPS coordinates recorded were associated with the car's location rather than the center of the crop field. I plotted each point in Google Earth Engine and created new points within the center of the field to create the final training and testing points used in classification.

**Classification on Google Earth Engine**

I performed my remote sensing analysis on Google Earth Engine. Google Earth Engine (GEE) is a free cloud based geospatial processing tool used to perform remote sensing analysis (Gorelick 2017). I used Sentinel-2 satellite imagery and both a Random Forest and CART classifier to perform my classifications of the Central Coast region on Google Earth Engine. Crop fields in the Central Coast can be small in size, with common satellite imagery having too course of a resolution to detect fields smaller than $30m^2$ (Zhong 2012). To capture small fields, I chose Sentinel-2 imagery for its high spatial (10 m) and temporal resolution (5 day), ideal for capturing small fields and multiple dates of imagery (Sentinel-2). The spatial resolution refers to the physical size of each imagery pixel, while the temporal resolution refers to the frequency of imagery capture. The high resolution of Sentinel-2 imagery, ensures that small farming parcels down to $10m^2$ were properly captured by the imagery.

The farming practices of the Central Coast made it difficult to perform a simple crop classification to identify cover crops. Certain crops such as parsley and carrots were uncommon and did not provide enough ground truth points to build a classifier that could accurately detect them. I performed multiple classifications to narrow cropland down as much as possible given the limitations of data due to the study region, and measure accuracy at each step.

I limited analysis to the farmland boundary shape files by clipping the Sentinel-2 image collection to the farmland boundaries. I pre-processed satellite imagery to remove cloud cover and create clean images for analysis. I added an NDVI band to the Sentinel 2 image collection to allow for classification based on NDVI. I used temporal aggregation to create composite images by combining multiple days of imagery. For my Random Forest/CART classifiers I took the median pixel values of December 15, 2020 through January 15, 2021. For my threshold classification I took the minimum pixel values from June 15th, 2020 to January 15th, 2021.

I used 80% of ground truth data points per class for classifier training, while the remaining 20% were used for accuracy testing (Zhong 2012 and Shelestov et al. 2017). The number of training points recommended by literature is 10-30x the number discriminatory wavebands used in classification per class (Mather and Koch 2004). NDVI uses two wavebands in analysis, red and near infrared, thus at least 20-60 samples are recommended per class. For classification with NDVI plus blue and green bands, 40-120 samples are required per class. To create training and testing points I added ground truth points for each class on their own Excel sheet and randomized the order to determine training vs testing points.

For my first classification I separated fields with vegetation from bare fields. For the vegetation class I included all crops as training data except for strawberries, as they are primarily covered with plastic over the winter season and have low NDVI values. Grape data points were not used in training, as they are bare over the winter season. I created a feature collection of the points randomly selected for training. I used this feature collection to train a Random Forest and CART classifier. I used 100 trees for the Random Forest algorithm. I ran the classifiers which produced maps of the region showing cropped and bare land. I clipped the classification results to the farmland boundaries. I then exported the classified maps as GEE assets. I used the assets to calculate the area of land for each class and compared the crop area and bare soil area to the total farmland area. I calculated areas of cropped and bare soil for each county, as well as total Central Coast farmland.

I then performed a NDVI threshold classification in order to distinguish perennial crops from non-perennial crops. I created a minimum composite image of June 15th, 2020 to January 15th, 2021, taking the minimum NDVI from that time period. I created an NDVI threshold of 0.2. Any pixels that fell below 0.2 NDVI at some point between June 15th, 2020 and January 15th, 2021 were classified as non-perennial, while those that did not fall below 0.2 were classified as perennial. I used 0.2 NDVI as it is a common cutoff for differentiating between bare soil and vegetation (Sobrino et al 2001). If the NDVI of the pixel never dropped below 0.2, it indicates the soil was never bare and the pixel contained a perennial crop. The use of a threshold for classification did not require any training data, but I used 38 perennial and 38 non-perennial testing points. I calculated the area of perennial and non-perennial land from threshold classification results. I exported the classification to ArcGIS where I used the “Extract by Attribute” tool to extract only the non-perennial pixels. I then used the “Raster to Polygon" tool to convert the classification results raster to a vector. I then used the non-perennial farmland vector as boundaries for subsequent classifications. I ran the same bare vs vegetation classification as before, this time clipping the classification to the non-perennial farmland boundaries. I then exported these classified maps as GEE assets and performed the same area calculations as the previous classification to find the area for non-perennial vegetation and bare land.

I then performed a classification to distinguish non-perennial vegetation, perennial vegetation, strawberries, and bare fields. I used NDVI, along with blue and green bands to perform the classification. I performed the same classification as bare vs vegetation with the new training classes, and the results were clipped to the non-perennial vegetation boundaries. I calculated areas for each class using the same methods as previous classifications.

For my last classification I used cover crops, non-perennial vegetation, perennial vegetation, strawberries, and bare field classes. I used NDVI, along with blue and green bands to perform the classification. I performed the same classification as bare vs vegetation with the new training classes, and clipped my results to the non-perennial vegetation boundaries. I calculated areas for each class using the same methods as previous classifications.

### Accuracy assessment

In order to test the success of the classification algorithm at remotely sensing cover crops, I used testing data points to measure accuracy. I used 20% of ground truth data from each class as testing/validation data. I compared the results of the classification to ground truth testing data points in order to find the percent accuracy of each classification. I used Google Earth Engine to generate a confusion matrix showing overall, producer’s, and consumer’s accuracy.

## RESULTS

### Ground truth survey of Central Coast farmland

I collected a total of 425 points in the ground truth survey, with 171 bare field points, 67 cover crop points, 178 points of various winter crops and 9 points of unidentified seedlings (Figure 1). Cover crops were predominantly grasses or grain/vetch/radish/legume mixes with some vetch, mustard, legume, and radish cover crops also recorded.

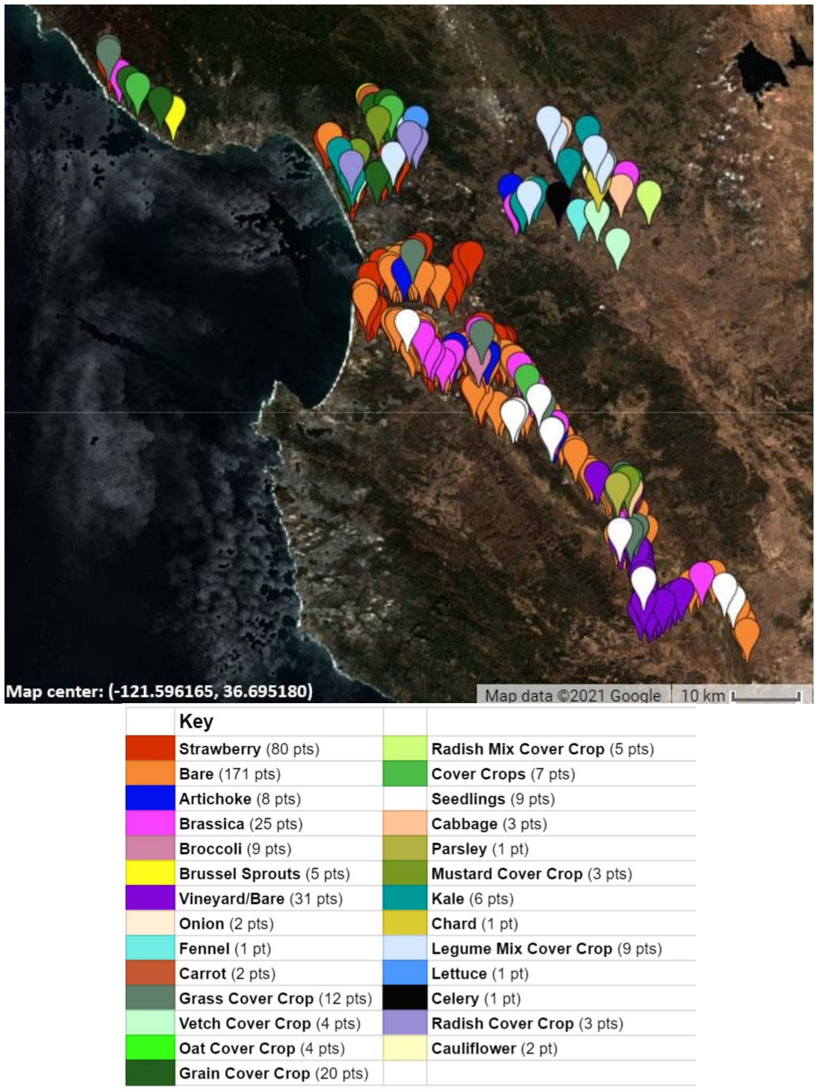


**Figure 2. Map of Ground Truth Data Points** I collected GPS coordinates and identified crop type throughout Monterey, Santa Cruz, and San Benito farmland in the Central Coast of California. Crop types are distinguished by colors.

## Classification results and cropland extent

I found Random Forest to have the highest accuracy for each classification (Table 1). Due to its higher accuracy, I used Random Forest results to calculate areas map results of each classification. Multiple classifications were performed to ensure an understanding of accuracy at each step. Results include a Bare vs Crop classification, followed by a threshold classification separating out perennial land, then a Bare vs Crop vs Strawberry, and then a final Bare vs Crop vs Strawberry vs Cover Crop classification.

*Bare vs Crop classification*

I found a total of 496.77 km² of farmland within Monterey, Santa Cruz, and San Benito counties was planted with crops over the '20-'21 winter season, making up 32.7% of farmland (Table 2). I created maps of classifier results showing the spatial extent of farmland that had crops over the winter season (Figure 4). Farmland in Santa Cruz County had higher levels of crop cover than San Benito and Monterey (Figure 3). Much of the farmland that had crop cover over the winter season was found in Santa Cruz County, and in the northern areas of Watsonville and Salinas. Much of the farmland along the Pajaro and Salinas Rivers was bare over the winter season as seen in the inset maps (Figure 9). San Benito and Monterey Counties had similar crop cover levels as the Central Coast overall (Figure 3).

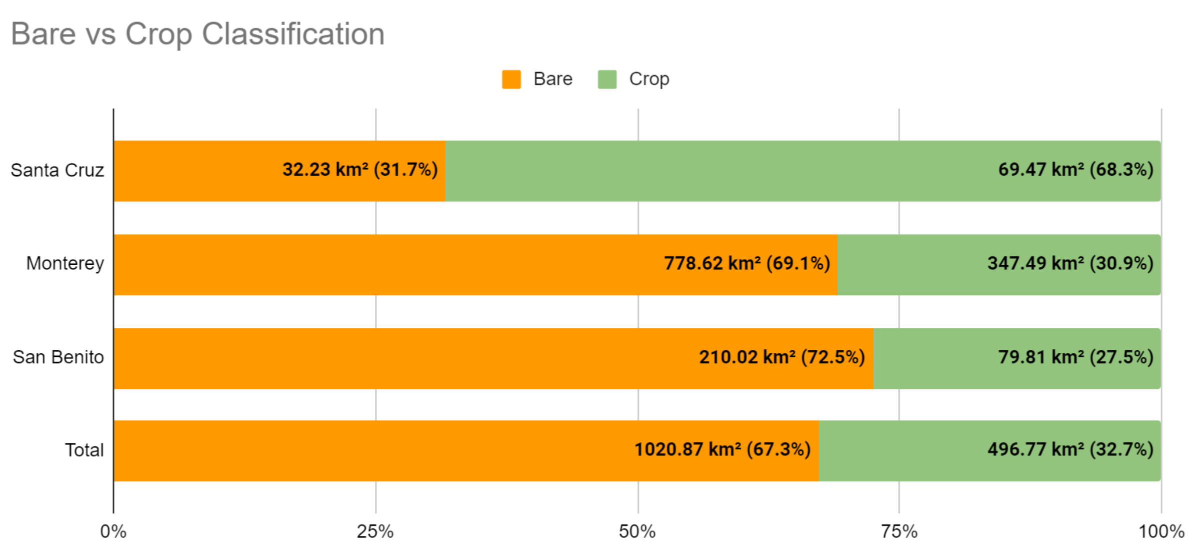


**Figure 3. Chart of Bare vs Crop classification area per county** I calculated areas for each class of Random Forest classification results.

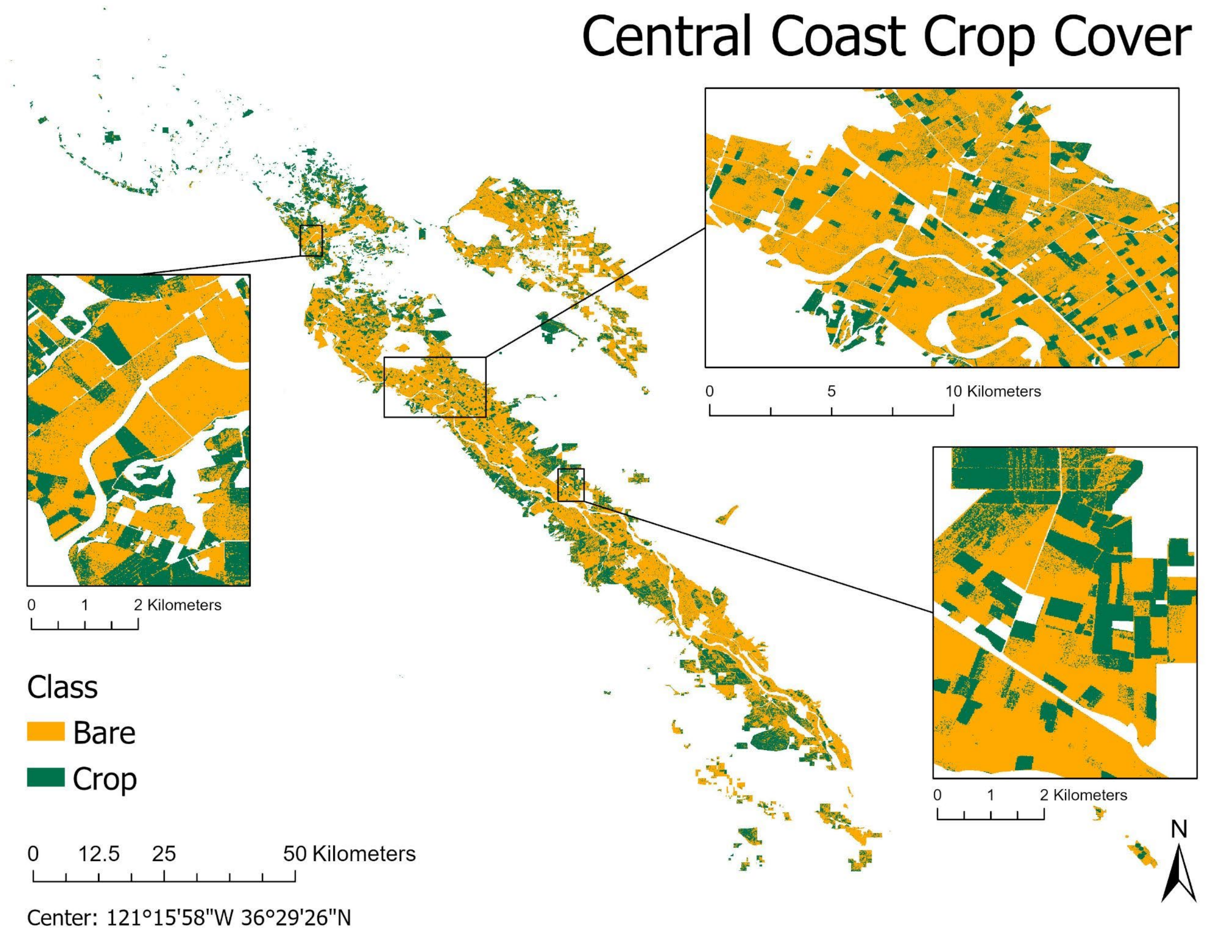


**Figure 4. Map of cropped farmland over the 2020-2021 winter season** I mapped Random Forest classification results for Bare vs Crop.

*Perennial vs Non-Perennial threshold classification*

I found 172.63 km² of farmland in the Central Coast to be perennial farmland, representing 11.4% of farmland. I found 993.48 km² of non-perennial land to be bare, representing 65.4% of farmland. I found 351.53 km² of non-perennial land to have crop cover, representing 23.2% of farmland. I created maps of classifier results showing the spatial extent of perennial crops, non-perennial crops, and bare farmland over the winter 20'-21' season (Figure 10). A large portion of the land classified as perennial, was forested regions in the Santa Cruz and Monterey mountains that were included in county obtained farmland boundaries. I found Santa Cruz County to have the highest percentage of perennial land (23.2%) likely due to the forested mountain regions included in the farmland boundaries (Figure 5). This indicates that some of the perennial land is actually forested regions included in county farmland boundaries. I found large portions of perennial farmland in the mid and southern portions of Monterey County (Figure 6).

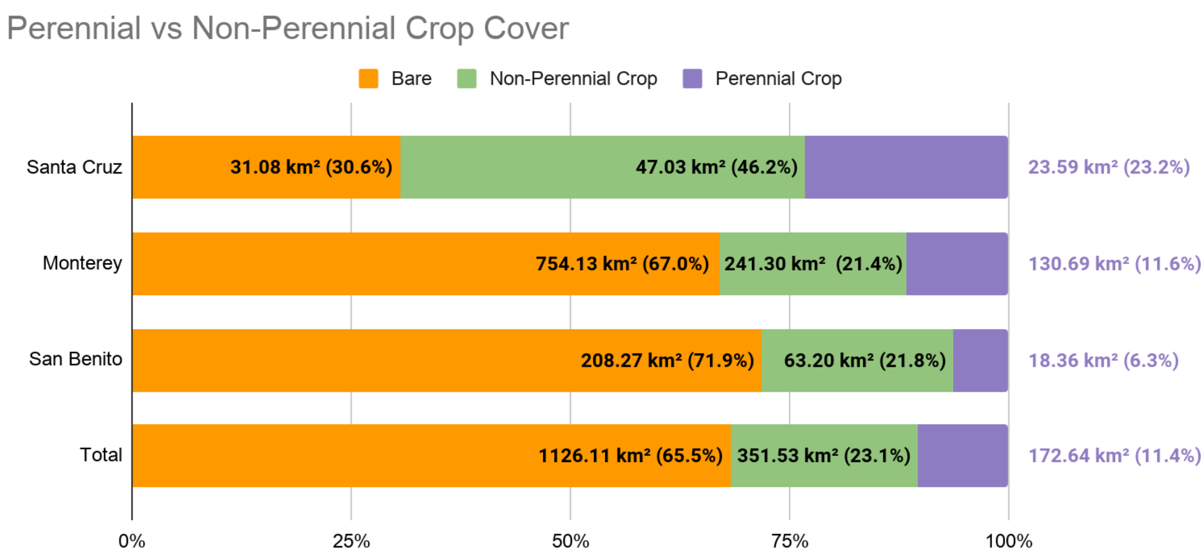


**Figure 5. Chart of Bare vs Non-Perennial Crop vs Perennial Crop classification area per county.** I calculated areas of threshold classification results.

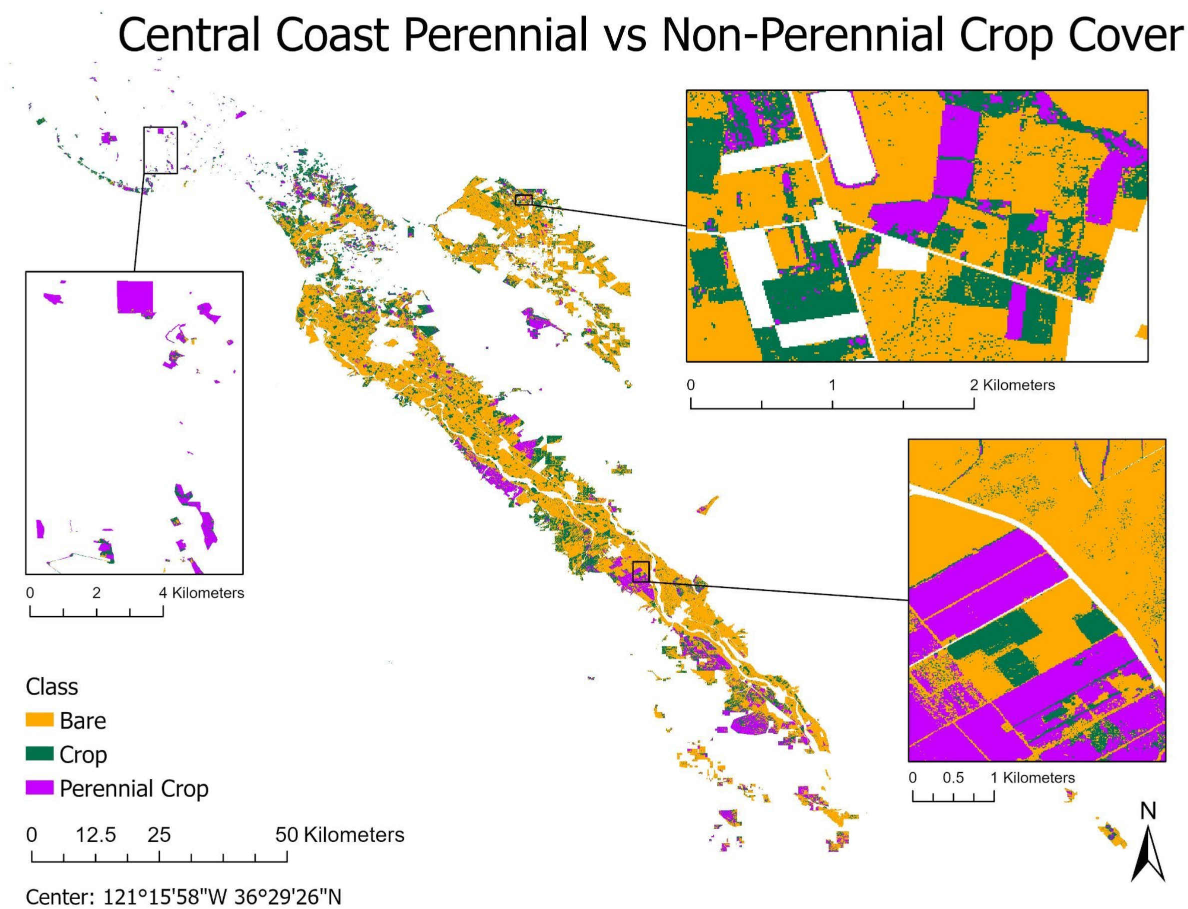


**Figure 6. Map of perennial vs non-perennial farmland over the 2020-2021 winter season** I mapped threshold classification results with my Bare vs Crop classification.

*Strawberry vs Crop vs Bare classification*

I found 144.7 km² of Central Coast farmland had strawberry fields, representing 9.5% of farmland overall. I found 851.22 km² of bare crops, representing 56.1% of farmland. Perennial crops made up 172.64 km² (11.4%) of farmland, while non-perennial, non-strawberry crops made up 349.09 km² (23.0%). I found a majority of strawberry crops to be in northern Monterey and southern Santa Cruz counties (Figure 8). I found a large portion of land in southern Monterey County to be classified as strawberry as well (Figure 8). Monterey County had the highest area of strawberry crops at 115.46 km², with Monterey and Santa Cruz having about equal percent of their farmland devoted to strawberry fields (Figure 7).

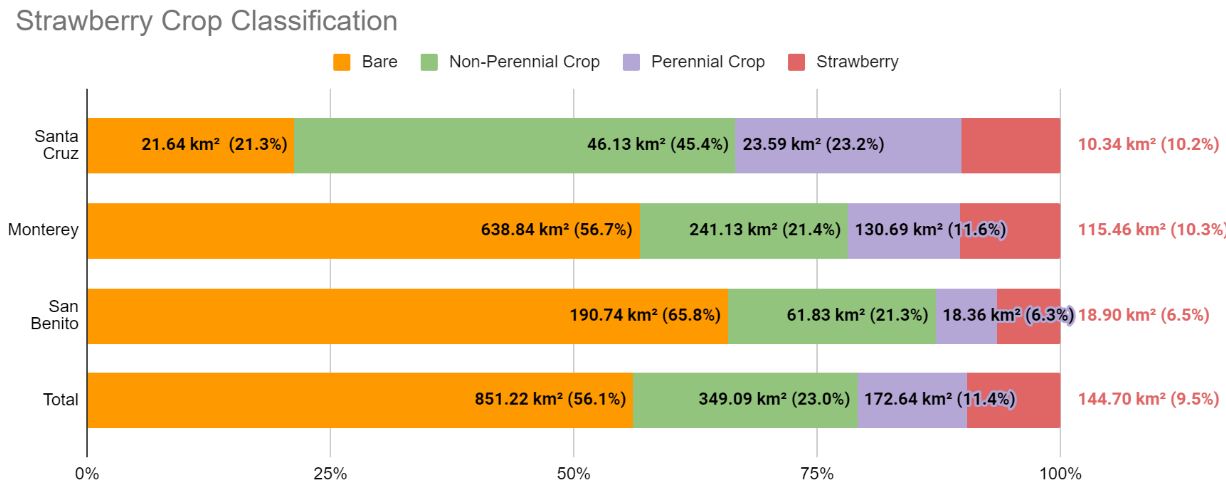


**Figure 7. Chart of Bare vs Crop vs Strawberry classification area per county** I calculated areas of Bare vs Non-Perennial Crop vs Perennial Crop vs Strawberry Random Forest classification.

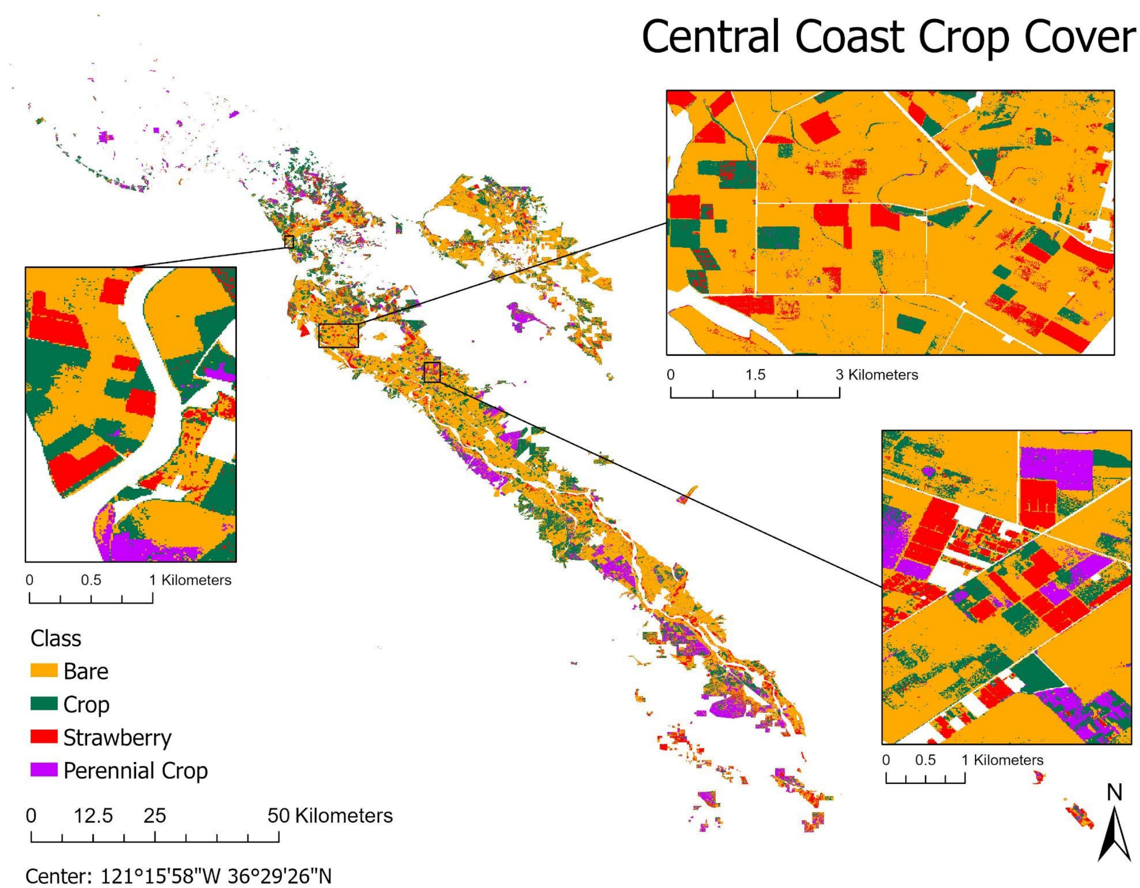


**Figure 8. Map of Strawberry classification over the 2020-2021 winter season** I mapped Bare vs Crop vs Strawberry Random Forest classification with threshold results.

*Cover Crop vs Strawberry vs Crop vs Bare classification*

I found 72.56 km² of Central Coast farmland was planted with cover crops over the winter 2020-2021 season, representing 4.78% of farmland. My findings are consistent with literature estimates of less than 5% of Central Coast farmland cover cropped (Brennan 2017). I found 881.78 km² (58.1%) was bare, 172.64 km² (11.4%) was perennial crops, and 162.67 km² (10.7%) was strawberry fields. I found 227.99 km² (15.0%) of Central Coast farmland was non-perennial/non-cover crop/non-strawberry crops such as carrots, onion, brussel sprouts, etc. Santa Cruz had the largest percentage of cover cropped farmland at 14.4% (Figure 9). Monterey had the largest area of cover cropped farmland at 44.74 km², but they only made up 4.0% of farmland (Figure 9). Bare fields made up a majority of farmland except in Santa Cruz where only a quarter of farmland was bare (Figure 9). This could also be attributed to the large area of forested land included in the Santa Cruz farmland boundaries that was classified as perennial (Figure 9 and 10). Cover crop plots tended to be grouped nearby likely due to owners applying the practice to their various fields (Figure 10). I found cover crop fields to be scattered throughout the Central Coast, making up a small minority of farmland (Figure 10).

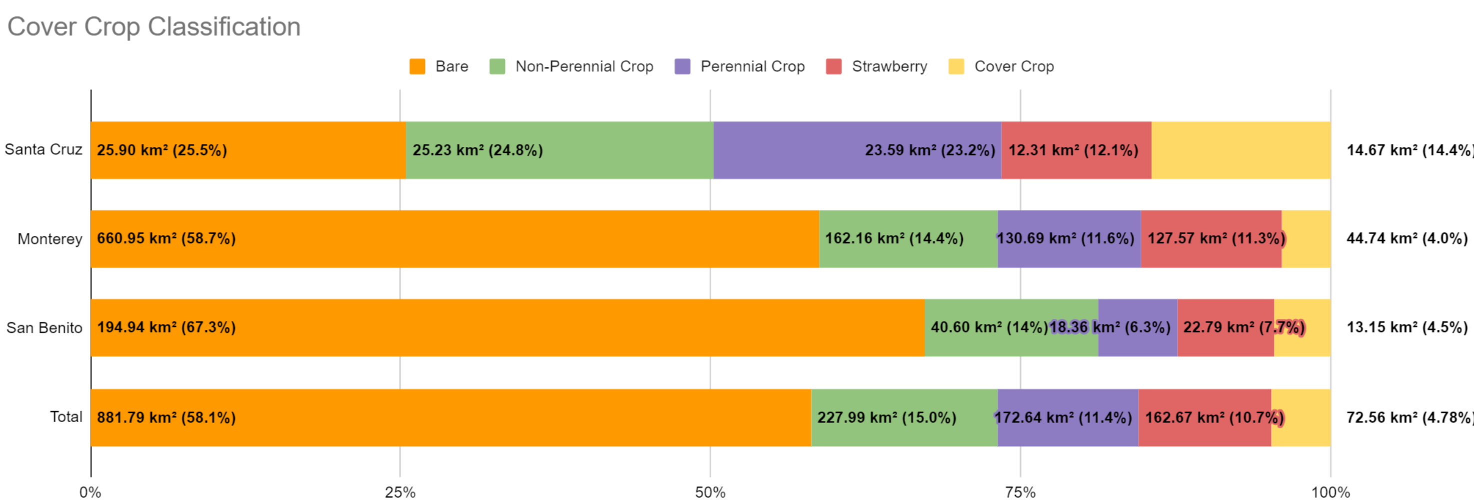


**Figure 9. Chart of cover crop classification area per county** I calculated areas of each crop class from Random Forest classification.

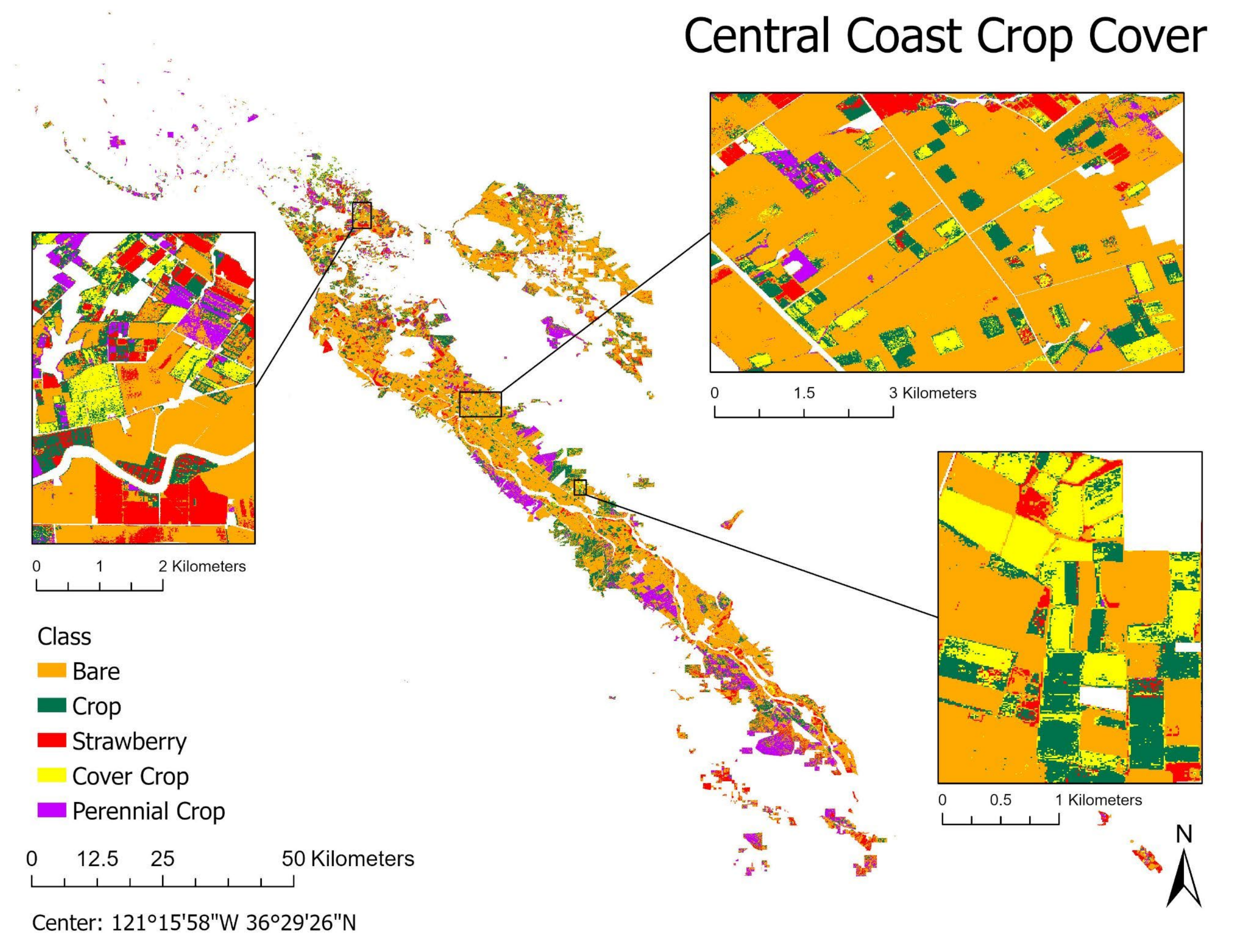


**Figure 10. Map of cover crop classification over the 2020-2021 winter season** I mapped results of Random Forest classification showing Central Coast cover crop distribution.

### Accuracy assessment

I found Random Forest to have a 86.7% accuracy at detecting cover crops in the Central Coast (Table 6). I found the highest degree of accuracy for my Bare vs Crop vs Strawberry classification using Random Forest, at 93.3% (Table 6). My strawberry classification showed the highest degree of accuracy likely due to the inclusion of blue and green bands, and high number of training points for each class. Producer's accuracy gives the probability of a ground truth point being correctly identified, while consumer's accuracy gives the probability of the classified pixels actually representing the class (Congalton 1991). For the Bare vs Crop vs Strawberry vs Cover Crop Random Forest classification I found Bare and Strawberry classes to have high consumer and producer accuracies. Of the Cover Crop points, eight were correctly classified as Cover Crops, three were misclassified as Bare, one misclassified as Crop, and one misclassified as Strawberry for a producer's accuracy of 61.5% (Table 13). Only two points were misclassified as Cover Crop, both were crop points, with no Bare or Strawberry points included as Cover Crops representing an 80.0% consumer's accuracy (Table 13).

**Table 1. Overall accuracy and kappa values of classification results** I calculated the overall accuracy and kappa values for each classification on Google Earth Engine.

| Classification | Overall Accuracy | Kappa |
|---|---|---|
| Bare vs Crop - Random Forest | 89.8% | 0.79 |
| Bare vs Crop - CART | 84.7% | 0.69 |
| Perennial vs Non-Perennial Threshold | 84.2% | N/A |
| Bare vs Strawberry vs Crop - Random Forest | 93.3% | 0.90 |
| Bare vs Strawberry vs Crop - CART | 85.3% | 0.77 |
| Bare vs Strawberry vs Crop vs Cover Crop - Random Forest | 86.7% | 0.78 |
| Bare vs Strawberry vs Crop vs Cover Crop - CART | 74.7% | 0.63 |

**Table 2. Bare vs Crop accuracy error matrix - Random Forest** I used ground truth testing points to perform an accuracy assessment of classification results for the Bare vs Crop classification with Random Forest.

| | | Ground Truth Data | | | |
|---|---|---|---|---|---|
| | | Crop | Bare | Total | Consumer Accuracy |
| Classification Results | Crop | 23 | 3 | 26 | 88.5% |
| | Bare | 3 | 30 | 33 | 90.9% |
| | Total | 26 | 33 | 387 | |
| | Producer Accuracy | 88.5% | 90.9% | | |

**Table 3. Bare vs Crop accuracy error matrix - CART** I used ground truth testing points to perform an accuracy assessment of classification results for the Bare vs Crop classification with CART.

| | | Ground Truth Data | | | |
|---|---|---|---|---|---|
| | | Crop | Bare | Total | Consumer Accuracy |
| Classification | Crop | 23 | 6 | 29 | 88.5% |
| Results | Bare | 3 | 27 | 30 | 90.0% |
| | Total | 26 | 33 | 59 | |
| | Producer Accuracy | 88.5% | 81.8% | | |

**Table 4. Perennial vs Non-Perennial accuracy error matrix - 0.2 threshold** I used ground truth testing points to perform an accuracy assessment of classification results for the Perennial vs Non-Perennial threshold classification.

| | | Ground Truth Data | | | |
|---|---|---|---|---|---|
| | | Perennial | Non-Perennial | Total | Consumer Accuracy |
| Classification | Perennial | 26 | 0 | 26 | 100% |
| Results | Non-Perennial | 12 | 38 | 50 | 76.0% |
| | Total | 38 | 38 | 76 | |
| | Producer Accuracy | 68.4% | 100% | | |

**Table 5. Bare vs Crop vs Strawberry accuracy error matrix - Random Forest** I used ground truth testing points to perform an accuracy assessment of classification results for the Bare vs Crop vs Strawberry classification with Random Forest.

| | | Ground Truth Data | | | | |
|---|---|---|---|---|---|---|
| | | Bare | Crop | Strawberry | Total | Consumer Accuracy |
| Classification Results | Bare | 31 | 2 | 1 | 34 | 91.2% |
| | Crop | 1 | 24 | 0 | 25 | 96.0% |
| | Strawberry | 1 | 0 | 15 | 16 | 93.8% |
| | Total | 33 | 26 | 16 | 75 | |
| | Producer Accuracy | 93.9% | 92.3% | 93.8% | | |

**Table 6. Bare vs Crop vs Strawberry accuracy error matrix - CART** I used ground truth testing points to perform an accuracy assessment of classification results for the Bare vs Crop vs Strawberry classification with CART.

| | | Ground Truth Data | | | | |
|---|---|---|---|---|---|---|
| | | Bare | Crop | Strawberry | Total | Consumer Accuracy |
| Classification Results | Bare | 26 | 1 | 1 | 28 | 92.9% |
| | Crop | 5 | 24 | 1 | 30 | 80.0% |
| | Strawberry | 2 | 1 | 14 | 17 | 82.4% |
| | Total | 33 | 26 | 16 | 75 | |
| | Producer Accuracy | 78.8% | 92.3% | 87.5% | | |

**Table 12. Bare vs Crop vs Strawberry vs Cover Crop accuracy error matrix - Random Forest** I used ground truth testing points to perform an accuracy assessment of classification results for the Bare vs Crop vs Strawberry vs Cover Crop classification with Random Forest.

| | | Ground Truth Data | | | | | |
|---|---|---|---|---|---|---|---|
| | | Bare | Crop | Strawberry | Cover Crop | Total | Consumer Accuracy |
| Classification Results | Bare | 32 | 3 | 0 | 3 | 38 | 84.2% |
| | Crop | 0 | 8 | 0 | 1 | 9 | 88.9% |
| | Strawberry | 1 | 0 | 16 | 1 | 18 | 88.9% |
| | Cover Crop | 0 | 2 | 0 | 8 | 10 | 80.0% |
| | Total | 33 | 13 | 16 | 13 | 75 | |
| | Producer Accuracy | 97.0% | 61.5% | 100.0% | 61.5% | | |

**Table 13. Bare vs Crop vs Strawberry vs Cover Crop accuracy error matrix - CART** I used ground truth testing points to perform an accuracy assessment of classification results for the Bare vs Crop vs Strawberry vs Cover Crop classification with CART.

| | | Ground Truth Data | | | | | |
|---|---|---|---|---|---|---|---|
| | | Bare | Crop | Strawberry | Cover Crop | Total | Consumer Accuracy |
| Classification Results | Bare | 30 | 3 | 2 | 3 | 38 | 78.9% |
| | Crop | 1 | 8 | 1 | 4 | 14 | 57.1% |
| | Strawberry | 2 | 0 | 13 | 1 | 16 | 81.3% |
| | Cover Crop | 0 | 2 | 0 | 5 | 7 | 71.4% |
| | Total | 33 | 13 | 16 | 13 | 75 | |
| | Producer Accuracy | 90.9% | 61.5% | 81.3% | 38.5% | | |

# DISCUSSION

Remote sensing classification was used to quantify Central Coast cover crop use over the 2020-2021 winter season. I found 72.6 km² of cover crops, representing 4.78% of Central Coast farmland. Random Forest had the highest overall accuracy for identifying cover crops at 86.7%. The high accuracy of classification indicates a successful model for quantifying and mapping cover crops in the Central Coast region was developed. Results of this study provide an important baseline of cover crop adoption in the region, previously missing from literature. The study region presented complex challenges to traditional remote sensing methods used for cover crop monitoring and crop classification.

## Central Coast cover crop adoption levels

Cover crop adoption remains low at 4.78% of farmland in the Central Coast region, indicating a need for policies that incentivize adoption. Results are consistent with literature estimates based on expert estimates of less than 5% of farmland in the region being cover cropped (Brennan 2017). While winter cash crops may outcompete cover crops, 58.1% of farmland remains bare over the winter season. These findings indicate a huge opportunity for increasing cover crop adoption in the region that is not being utilized. Remote sensing of cover crops in other regions have found greater rates of cover crop adoption. Cover crops cover 5.1%-9.4% of land in the Midwest, and up to 75% in certain Pennsylvania counties (Hively et al. 2015, Seifert et al. 2018).

Cover crops are being underutilized in the Central Coast due to several direct and opportunity costs for farmers. Barriers to cover crop adoption on the Central Coast involve a combination of economic costs, awareness, perceptions of risk, and policy programs and incentives (Stuart 2009). Residue management is one of the largest obstacles for farmers when implementing cover crops (Brennan 2017). Residue management involves clearing cover crops and/or incorporating them into the soil prior to spring planting (Brennan 2017). Central Coast farms often have multiple crops grown on a field in a given year (Klonsky et al. 1994). Adding a cover crop to this rotation has direct economic costs associated with planting and clearing the land. Aside from the direct costs, cover crops add an additional rotation on top of the 2-3 cash crops that can delay or prevent spring planting. This can have enormous economic implications, especially to small economically constrained farmers, if cover crop management causes a subsequent cash crop to fail. Unpredictable rain patterns such as the 2021 atmospheric river, can also delay the clearing and incorporation of cover crop residue when soils are heavily saturated late in the winter season (Hartz and Johnstone 2006). The high land costs and intensive production of the region make these risks economically impractical for many farmers (Bauer 2020).

The high food safety standards of the region also influence cover crop adoption levels. Risk of food safety audits have led farmers to discontinue agroecological practices such as use of non-food crops due to economic risk (Stuart 2008). Farmers can face a huge economic loss if their harvest is rejected by food safety certifiers. This increases the perception of economic risk, leading to lowered rates of cover crop adoption. Methods of monitoring cover crop adoption, as developed by this study, are important for understanding how cover cropping responds to food safety events such as the 2006 *E.coli* outbreak and subsequent tightening of food safety standards.

Santa Cruz showed the highest percentage of cover cropping at 14.4%, more than double that of San Benito (4.5%), or Monterey (4.0%). Santa Cruz has a much higher percentage of land devoted to smaller farms with diversified farming practices, than Monterey or San Benito counties (Klonsky 1994). Smaller, diversified organic farms are much more likely to practice cover cropping, than the larger conventional farms common in Monterey and San Benito counties. Organic farms are also less likely to discontinue conservation practices due to concerns over food safety standards (Stuart 2009). Larger farms, more common in Monterey and San Benito counties, have the highest food safety pressure due to their large retail buyers (Stuart 2009). These factors disincentivize larger farms from adopting cover crops, and can explain the difference in cover cropping levels between Santa Cruz, and San Benito and Monterey counties.

Farmers face several competing pressures when deciding whether to adopt cover cropping or not. Farmers juggle soil health, environmental quality, economic viability, and food safety priorities when making management decisions (Baur 2020). The low levels of cover cropping indicate the status quo does not sufficiently incentivize cover crop adoption. Given the severity of nitrate pollution from the region's agricultural practices, the risks disincentivizing farmers from cover cropping must be addressed for the good of public and environmental health. The low cover crop levels observed demand more robust policy to incentivize cover crop adoption in the region.

**Accuracy of remotely sensing cover crops**

Cover crops were classified with a 86.7% accuracy using Random Forest, indicating a successful methodology for remotely sensing cover crops was developed. Results are comparable to other crop classifications which found accuracies of 68%, 78%, 84.31%, and 86% (Howard et al 2012, Ok et al. 2012, Phan et al. 2020, Shelestov et al. 2017). Regions where remote sensing of cover crops was based solely on vegetation presence found higher accuracies of 91.5% using Random Forest (Seifert et al. 2018). Random Forest outperformed CART in each classification, indicating it is the optimal classifier to use for cover crop classification in the region.

Classification of cover crops had a consumer's accuracy of 80.0% and producer's accuracy of 61.5%. The 61.5% producer's accuracy shows ground truth cover crop points were not identified with a high degree of accuracy (Congalton 1991). Three cover crop points were incorrectly identified as bare, likely due to low growth in the monitoring window. However, the high consumer's accuracy confirms that classification accurately represents actual cover crop levels (Congalton 1991). Only two points were misclassified as cover crops that were not actually cover crops. The points were both cash crop points; no bare or strawberry points were misclassified as cover crops. These results indicate that while cover crop points may sometimes be misclassified as other classes, it is rare that another class is misclassified as a cover crop. This means that cover crop area is likely underestimated rather than overestimated by the classifier.

The Bare vs Crop vs Strawberry classification had the highest accuracy of all classifications at 93.3% with Random Forest. The high accuracy is likely due to the large number of training points and inclusion of green, and blue spectral bands in addition to NDVI. The vegetation of the Crop class, plastic tarp of the Strawberry class, and bare soil of the Bare class gave each class highly distinguishable spectral properties. In contrast, the cover crop classification's greatest misclassifications were between cash crops and cover crops, two spectrally similar vegetation classes.

The threshold classification had a high accuracy of 84.2% at detecting perennial farmland from non-perennial farmland. Perennial land was misclassified as non-perennial for 12 of the 38 testing points, while none of the non-perennial testing points were misclassified as perennial. This indicates that while some perennial crops may have been included in subsequent classifications, it is unlikely that non-perennial crops were misclassified out.

**Limitations and future directions**

The intensive farming practices of the Central Coast, coupled with a diverse array of possible crops including ones that overwinter, make it an exceptionally difficult region to remotely sense cover crops. Typical remote sensing of cover crops is conducted in regions where cash crops are not grown over the winter season. In these studies cover crops are identified by the presence of vegetative ground cover on farmland, without the need to distinguish between different vegetative cover (Hively et al. 2015, Seifert et al. 2018). Crop classification that distinguishes vegetation is typically conducted in regions already well documented by crop maps, with typically large and well defined field boundaries (Howard et al 2012, Li et al. 2015, Ok et al. 2012). Established crop maps allow these studies to gather hundreds of training points without the limitations of ground truth data collection. One crop classification was able to use 50,000 points for training and testing from crop map data of the region (Howard et al 2012). Other studies that rely on ground truth have similar numbers (200-500) to the 425 ground truth points collected for this study (Bargiel 2017). Ground truth data collection showed a variety of winter cash crops, however certain crops like carrots and fennel are unlikely to be planted in enough fields to generate the recommended 40-120 training points needed per class (Mather and Koch 2004). Due to the limited number of ground truth points for many of the crops, winter cash crops were grouped into a single class. In combining multiple crop types, the class contained a high variation of spectral properties. This made distinguishing the crop class from the cover crop class more difficult for the classifier. The limitations of ground truth data collection also resulted in a small number of testing/validation points, ranging from 13-38 points. If a greater number of testing points were available for the accuracy assessment, a higher or lower accuracy may have been revealed. In addition, typical crop classification distinguishes crops based on unique NDVI values, often associated with phenological stages (Zhong 2012). Most cover crops found in the region were a combination of a grain with a legume and/or radish. The combination of crops in cover cropped fields makes distinguishing by phenological NDVI patterns more difficult. Meanwhile certain brassicas may be planted as both a cover crop and a cash crop depending on the field. In this case the crop could be distinguished, but it would not be known if it was planted as a cash crop or as a cover crop.

The Central Coast also lacks accurate field boundaries, making field based classification more difficult. Field based classification is shown to have a higher accuracy than pixel based classification (Ok et al. 2012). In these studies, established field boundaries are used to classify whole fields, based on the average result of classified pixels in the field (Ok et al. 2012). In the Central Coast, even if there were accurate field boundaries already mapped, oftentimes several different crops are planted on one field, or only a portion of the field is used. Object based segmentation is a remote sensing method that can be used to detect field boundaries (Li et al. 2015). Object based segmentation could be combined with field based classification to try and improve the accuracy of remotely sensing cover crops in the Central Coast.

While this study quantified cover crop usage in the Central Coast over the 2020-2021 winter season, additional monitoring years can reveal adoption trends. Additional ground truth data would need to be collected to confirm if initial training data can be used for classification of subsequent years. Understanding how adoption levels change over time, especially in response to different policy measures and food safety incidents, can inform policy makers on how to incentivize cover crop adoption.

## Conclusion

A Random Forest classifier was successfully developed to establish a baseline of cover crop usage in the Central Coast of California. Accuracy results confirm an efficient and accurate methodology for monitoring cover crop adoption was created. The baseline level of cover crop usage that this study established is vital for informing the region's climate management strategies. Regional cover crop adoption levels were previously unknown, with only estimates and no spatially explicit information available. The remote sensing methods developed will allow progress on cover crop adoption to be efficiently tracked.

Understanding cover crop adoption levels is extremely valuable for meeting state climate goals. Cover crops are considered a key management practice for their carbon sequestration potential (Lugato et al 2020). California's 2030 Natural and Working Lands Climate Change Implementation Plan calls for an increase of land management practices that increase carbon sequestration potential in order to meet state carbon neutrality goals (CARB 2019). Farm management practices, including cover crops, are funded through the state's Healthy Soils

Program to implement the plan's soil conservation objectives. The plan includes a goal of increasing the amount of farmland covered by the Healthy Soils program by 5x the amount of acres currently covered (CARB 2019). The baseline 72.56 $km^2$ of cover cropped land established by this study is pertinent to evaluation of the Natural and Working Lands Climate Change Implementation Plan's objectives. The plan includes specific goals of increasing cover cropping in California by 10,400-20,800 acres each year (CARB 2019). The Central Coast's progress will be key to meeting this goal. Without an efficient method of monitoring cover crop adoption, these state goals cannot accurately be tracked. The plan acknowledges the continued need for developing improved monitoring tools. Results of this study provide an accurate cover crop monitoring method to track the objectives of the state's Natural and Working Lands Climate Change Implementation Plan.

In addition to carbon sequestration, the results of this study will be valuable for tracking various environmental goals for the region, such as nitrate pollution and soil erosion. Incorporating cover cropping into yearly crop rotations is vital to the sustainability of a productive system. Despite their numerous benefits, cover crop levels remain low at 4.78% of Central Coast farmland. Without a method of tracking cover crop adoption, previous efforts have had limited data for understanding how to increase and monitor cover cropping. The results of this study provide important data for scientists and policy makers hoping to increase, incentivize, and monitor cover crop adoption.

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