Remote Sensing in Suisun Bay Marsh: Vegetation Classification and LAI Prediction

Clifford Wang

ABSTRACT

Over the last two centuries, humans have transformed the San Francisco Estuary system. Marshes have been altered for agricultural, hunting, and development needs. One major concern is the spread of invasive species. Because wetland systems are fragile and difficult to survey, they have not been well studied. This study examines the distribution of two upland marsh plants, the native *Sarcocornia pacifica* (perennial pickleweed) and the invasive *Salsola soda* (oppositeleaf Russian thistle), in a Suisun Bay marsh using a combination of field and remote sensing methods. First, I used the object-based image analysis software eCognition Developer to classify an aerial photograph by vegetation type. I compared four supervised classification methods and found that the Bayes classifier algorithm produced the highest overall accuracy of 83%. Accuracies varied between classes, but the classifier was able to distinguish the invasive *S. soda* with 97% producer's accuracy. In the second part of the study, I created a multiple regression model that would predict measured LAI (leaf area index) values from object-level spectral data derived from the aerial photograph. I used twelve predictor variables and created models using original values, log-transformed values, and squared values. The best model used log-transformed values and yielded an adjusted R-squared value of 0.42, which indicates some correlation exists, but the predictability of the model is limited. Nevertheless, the fair classification accuracy suggests that *S. soda* can be distinguished from other marsh vegetation using spectral signatures. Therefore, future landscape change studies can monitor the spread and influence of *S. soda*.

KEYWORDS

LAI, classification, pickleweed, Russian thistle, *Sarcocornia pacifica*, *Salsola soda*, eCognition, wetlands

INTRODUCTION

The San Francisco Bay Estuary system is one of the most transformed waterscapes in the world, partially due to invasive plant and animal species (Callaway 2011). Since the 1800s, people have been transforming the wetlands for agriculture, hunting, and development (Callaway 2011). In just the past century, two-thirds of California's coastal salt and brackish marshes have been diked or filled (Lewis 2000). As human mobility increased, people introduced invasive species to the estuary system. Invasive species are often able to establish themselves because of a lack of competitors or native predators. When invasive species have similar ecological adaptations or requirements as native species, there is a potential for competition and pressure on the native population. One pair of species that may be of concern are native *Sarcocornia pacifica* (perennial pickleweed) and invasive *Salsola soda* (oppositeleaf Russian thistle).

Perennial pickleweed is a plant endemic to the Americas, where it is found in all coastal US states (ESF). In northern California, it covers more area than any other salt marsh plant (Josselyn 1983), often forming extensive monospecific stands in the upper intertidal zone (Griffith 2010, ESF). A number of studies have examined changes to pickleweed abundance associated with diking tidal marshes. Normally, tidal exchange keeps the tidal inlet open to the ocean, renewing water and allowing particular organisms to reproduce. When tidal marshes are restricted, the environment sometimes becomes hypersaline or hyposaline (Zedler et al 1980, Jossleyn 1983, St Omer 1994). In hyposaline diked wetlands of the San Francisco Bay, pickleweed is one of the few plant species able to establish dominance (Griffith 2010). Other studies in Northern California also support that pickleweed grows less vigorously when tidal exchange is limited (Seliskar 1985, St. Omer 1994). Although pickleweed has been found in sediments with salinities ranging from 3.4 ppt to 1966 ppt, it can be outcompeted by other plants better adapted to hyposaline environments (Griffith 2010). Zedler (1982) found that pickleweed dominates areas with high sediment salinities. Due to human encroachment into wetlands, they are grazed and trampled by human or animals, which also compact soil. The resulting increase in salinity levels can promote lower marsh species like pickleweed to move up to higher elevations, which have lower salinities (Bakker 1985, Kiehl et al. 1996).

Along with altered biophysical factors, invasive species may also affect the distribution of the native pickleweed. *Salsola soda* (oppositeleaf Russian thistle) is one such species starting to encroach on pickleweed-dominated areas (because *S. soda* utilizes tumbleweeds as a mode of dispersal, I will heretofore refer to the plant as tumbleweed.) Tumbleweed was introduced from Syria in 1969 as an experimental range plant (CDFA). The California Invasive Plant Council currently classifies tumbleweed's potential impact on native ecosystems as moderate (Calflora). It has been found along water body edges, levees in dry soil, along sloughs, and in disturbed areas (Tamasi 1998, CIPC). To distribute its seeds, tumbleweed relies on wind and tidal currents. When conditions are windy enough, tumbleweed stems will break and disperse seeds (CDFA). Tumbleweed is heavily favored by disturbance, therefore it can be found in overgrazed areas, habitat boundaries, waste areas, and disturbed natural or semi-natural plant communities (CDFA). It has been speculated to have a strong ability to persist in an area and potentially replace the native pickleweed (Tamasi 1998). To date, not many studies have looked specifically at tumbleweed (*S. soda*) and its interactions with native species in estuarine systems.

In general, it is difficult to monitor estuarine systems like wetlands because of their inherent heterogeneity (Kelly et al. 2011, Martinez-Lopez et al. 2014). What is observed in one part of a wetland may be hardly be representative of the rest of the wetland. On-the-ground monitoring is time-consuming, labor-intensive and often involves trampling fragile habitats and ecosystems (Lee and Yeh 2009, Martinez-Lopez et al. 2014). Repeated data collection may disturb habitats significantly, and may even facilitate the colonization by invasive species. Some areas may not be accessible by wading or boating. Indirect approaches, like remote sensing, can therefore play a major role in capturing a comprehensive picture of wetlands whilst minimizing disturbance. In the past, remotely sensed images had coarser spatial resolution and were analyzed by a pixel-based approach. However, as high resolution imagery have proliferated in recent decades, an object-based approach has become more applicable. Because high resolution imagery contain many more pixels, any one pixel does not contain very informative data. As a result, grouping pixels into objects, which share similar spectral properties, size, shape, or texture, can be a more useful way to analyze the landscape. Studies have shown that object-based image analysis (OBIA) can be more useful when analyzing high resolution imagery (Blaschke et al. 2014, Jawak et al. 2015). OBIA, when applied to UAV (unmanned aerial vehicle) imagery, for example, is more reproducible and more effective for land management purposes than when using satellite images (Laliberte and Rango 2009).

Along with determining where vegetation of interest occurs across a landscape, it is equally, if not more, important to describe key ecosystem parameters of plant cover. Leaf area index (LAI), defined as the ratio of leaf area in a canopy per unit ground area, is one such ecosystem parameter. Since canopy leaf area serves as the dominant control over primary production, transpiration, energy exchange, and other physiological attributes, LAI has become a basic descriptor of vegetation condition (Asner et al. 2003). Comparing average LAI values of pickleweed and tumbleweed may give a general idea of the level of similarity and productivity of the two species.

The objectives of this study were (1) to determine the distribution of pickleweed and tumbleweed through the use of remote sensing and (2) to examine how leaf area index varied between the two species as well as across the site. To determine distributions of the two species using remote sensing, I produced a vegetation classification map from a high resolution aerial image using OBIA software eCognition (Trimble Inc.). Subsequently, I looked for any patterns of tumbleweed and pickleweed occurrence and tested the accuracy of my classification. At the site, I also collected leaf area index (LAI) measurements at a plot level along transects. I conducted a means comparison test for LAI values of the two species and then created a regression model that predicted LAI from spectral variables derived from the classification map. I applied this model to the rest of the image, and created a map of LAI across the site. Through the classification and LAI maps, I analyzed distribution patterns and the ability to distinguish tumbleweed from pickleweed.

METHODS

Study system

I selected *Salsola soda* and *Sarcocornia pacifica* for this study because they are morphologically similar broadleaf plants. Because *S. soda* is an invasive plant and *S. pacifica* is an important native plant, I speculated that they would face competition for resources. To study the distribution of the two plants, I selected a diked salt marsh site where both species were found. Since the marsh is diked, the lack of natural tidal hydrology may facilitate establishment of the upland invasives (Herrick and Wolf 2005). Located in Hill Slough, Suisun City, Solano County, California, the study site covers 120 acres with center of the site at coordinates: 38.239796 N, 122.024596 W (Figure 1).

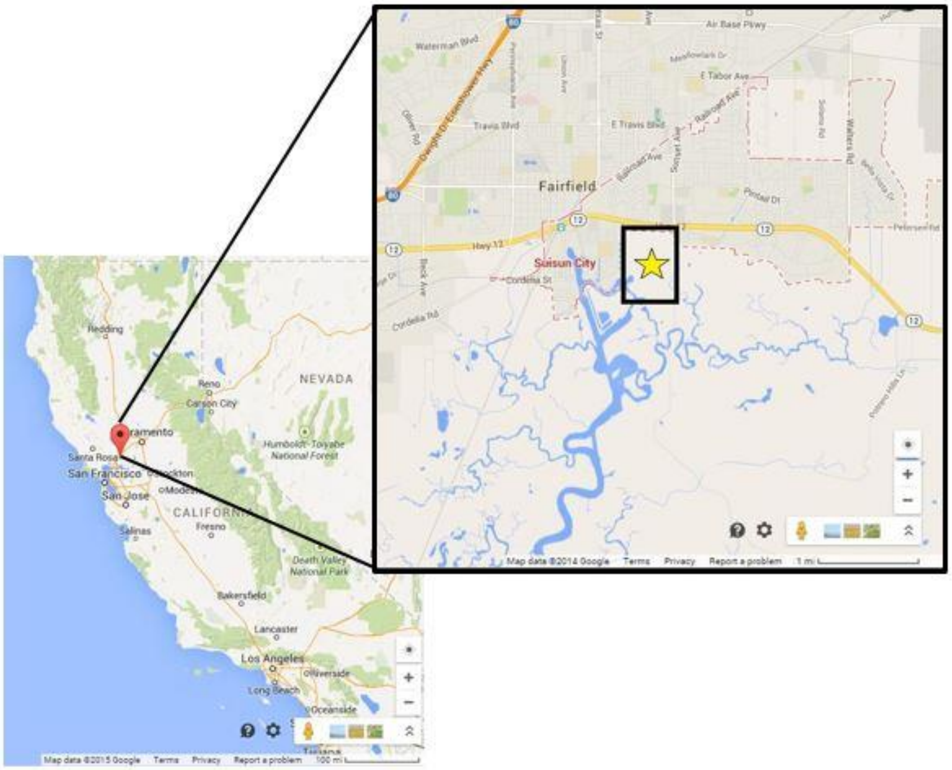


Figure 1. Map of field site. Study site was located just east of Suisun City, CA.

The site is a portion of the 10,000-acre Grizzly Island Wildlife Area managed by the Department of Fish and Game (DFG). The DFG manages this wildlife area in order to enhance habitat for fish and wildlife and provide public recreation. Years ago, the DFG made attempts to manually remove the invasive *S. soda*, but it is still present throughout the site. Not much is known about how *S. soda* (the only plant established in portions of the site) might affect native marsh plant species.

Study period

To map and analyze distributions of *S. soda* and *S. pacifica*, I performed GIS-remote sensing and LAI (leaf area index) analyses. To produce a vegetation classification map, I processed an aerial photo that was acquired on August 15, 2014, by Eagle Digital Imaging Inc. (at 15 cm resolution, covering red, green, blue and near-infrared spectral regions) as part of the larger study of regional wetland vegetation (I. Dronova, *unpublished data*). On October 3, 2014, I visited the site to take GPS points to use in assessing accuracy of the plant classification. In order to create the LAI map, I collected leaf area index (LAI) data from 112 points along 4 north-south transects across the site.

Remote sensing overview

One objective of this study was to generate a classification map of vegetation from an aerial image using object-based image analysis (OBIA). This is accomplished in two general steps, segmentation and classification. First the image is fed into an OBIA software which segments it into objects of similar spectral properties, size, or other attributes. It has been noted that when using high resolution imagery, an object-based approach is more effective than a traditional pixel-based approach (Blaschke et al. 2014). Some objects are then manually selected as representative samples for classes of interest. Once selected, the OBIA software can apply algorithms to the rest of the image so all objects are classified.

Generating a classification map is only useful if it is reliably classifies the landscape. As a result, one conducts an accuracy assessment by ground truthing, which means gathering actual data to serve as a reference for the classification. In this study, GPS measurements and information about the species that occurred at those points were collected at the marsh site. With reference data and classification data, one can set up an error matrix, which enumerates every combination of correctly classified or misclassified vegetation. From the error matrix, one can determine the source of classification errors and make refinements.

Data collection

To determine the distribution of the plant species, I gathered two types of data: plot-level LAI and GPS data and applied those to the analysis of aerial imagery of the site.

When gathering plot-level field data, I first set up four north-south transects across the site. Each transect ranges from 250 meters to 550 meters long and are 150 meters apart. Across all four transects, there were 112 1-square meter plots each spaced 15 meters apart. I labeled each plot with landscaping flags. I chose to sample using transects because other researchers were conducting a parallel study on the endangered salt marsh harvest mouse in the same site. The transects cover the relatively large study site efficiently and avoid oversampling of very extensive patches of marsh plants. After setting up the transects, I collected three forms of plot level field data, GPS points, dominant and subdominant species information, and LAI data.

To ground truth the plant classification map I created, I used a GeoExplorer 6000 Series GeoXH Handheld GPS receiver (Trimble Navigation Ltd) to collect 1 GPS point at each of the 98 plots. I took an additional 30 GPS points wherever *S. soda* and *S. pacifica* occurred off of the transects in order to improve the groundtruthing capabilities. I also noted the dominant and subdominant plant species in each of the 98 1x1 square meter plots. I took photos of any plots that contained an unknown dominant or subdominant species so I could identify these plants later with the help of the professor. To collect leaf area index (LAI) data for the regression model, I used a LAI-2200C Plant Canopy Analyzer (LICOR Inc.). I took two above-canopy and three below-canopy measurements for each of the plots. The tool computes one LAI value from these five measurements. Consistent with the radiative transfer theory, I covered the optical sensor of the LICOR instrument with the shadow because it could not take reliable measurements in direct sunlight.

To collect remotely sensed field data, I used an aerial photograph from Eagle Digital Imaging Inc. acquired in a related study (I. Dronova, *unpublished data*). One image was adequate for the snapshot analysis because it covered an area greater than the study site. Eagle Digital Imaging Inc. conducted the flight on August 15, 2014, and took one photograph in the four-spectral region (red, green, blue, and infrared). They pre-processed and geo-registered the photograph beforehand. The image had a 0.1524 meter resolution, which is considered very high resolution (VHR).

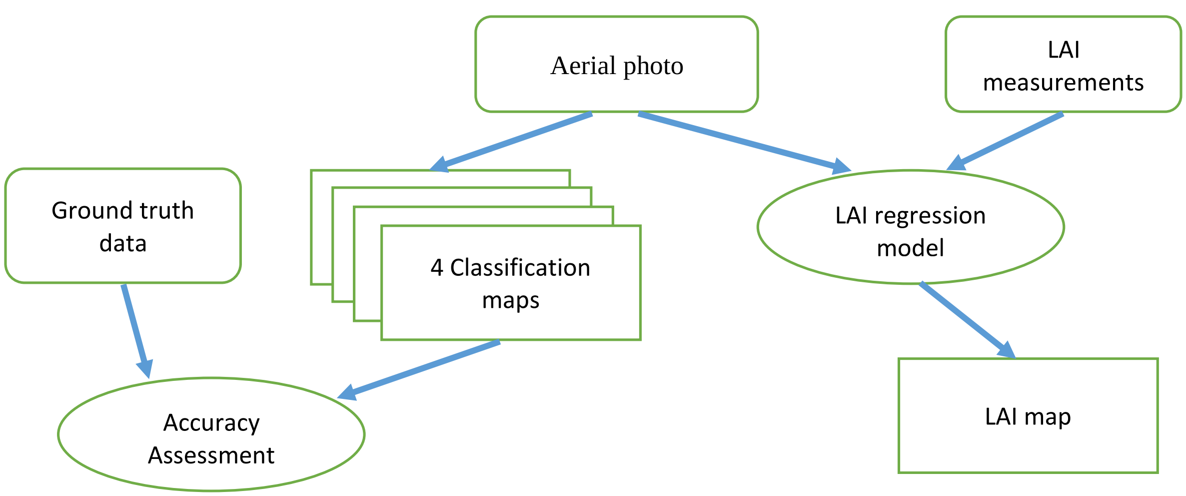


Figure 2. Schematic of methods of the study.

Data processing

Classification

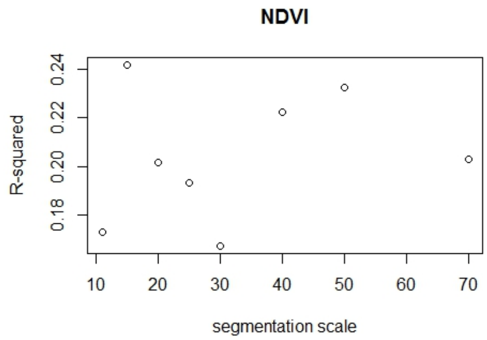
In order to analyze distributions, I first created a map that classified vegetation cover in an aerial photograph. I selected an object-based image analysis (OBIA) as opposed to a pixel-based method because OBIA is very suitable for very high resolution photographs (Blaschke et al. 2014). I used eCognition Developer 9.0 (Trimble Navigation Ltd) to classify the image. I tested 4 different supervised classification methods: nearest neighbor, K nearest neighbor (KNN), support vector machine (SVM), and Bayes classifiers. Supervised classification implies that eCognition is first trained by selecting representative sample objects for each vegetation class. The software subsequently classifies the rest of the objects in the image based on user-selected features of the sample objects. Nearest neighbor is the basic supervised classification method. The KNN, SVM, and Bayes classifiers are three other statistical classification algorithms considered machine learning approaches to classification.

For each classification method, I wrote a rule set that first segmented the image into appropriately-sized objects at a scale of 40. Then, I applied a threshold to split the image into green vegetation and dead vegetation, because the study focus was green vegetation. With the aid of GPS points and a broad vegetation classification map created by the Department of Fish and Game in 2009 (CA DFG 2012), I designated 160 objects as samples for the four classes. These classes were *S. pacifica, S. soda,* other green vegetation, and dry vegetation. After training eCognition with the samples, I used object-level features like spectral band mean values, standard deviation values, and vegetation indices to classify the remaining image objects into four classes using each of the four supervised classification methods. Following the first round classification of the image, I checked for accuracy in ArcGIS v.10.2 (ESRI Inc.) by setting up a testing sample of at least 50 GPS points per class and checked if eCognition classification matched on-site identification. To determine accuracy of the classification, I set up error matrices that tallied how many objects were misclassified or correctly classified in a table. Until the accuracy was about 85%, a universally accepted standard (Congalton and Green 2009), I located the classification errors in the image, revisited the rule set and refined the choices of discrimination features and rules. After I assessed the accuracy of the results of each of the four classification methods, I compared the resulting maps. Ideally, the best classification map has an accuracy of at least 90%.

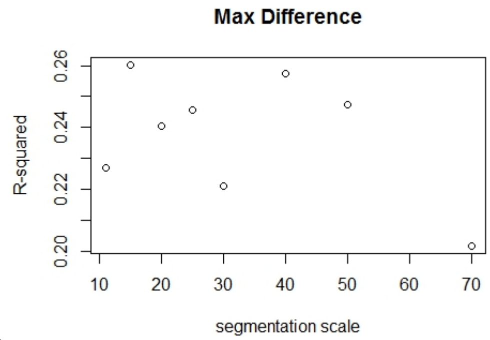
Leaf area index

Along with visualizing the distributions of *S. pacifica* and *S. soda* with a classification map, I wanted to see how leaf area index varied between the two species and across the site. LAI can be used as an indicator of the productivity of an ecosystem (Asner et al. 2003). The higher the LAI, the more productive the system is.

To determine whether mean LAI significantly differed between *S. pacifica* and *S. soda*, I conducted a t-test in R 3.1.1 (R Core Team 2014) using 80 measurements derived from field plots. I wanted to see whether there were any differences in light attenuation. To produce an LAI map for the study area, I generated multiple linear regression models to predict LAI from spectral data in the aerial photograph. I used a combination of twelve raw spectral variables and vegetation indices: GNDVI, green/blue, green divergence, max difference, mean red layer, mean green layer, mean blue layer, NDVI, simple ratio, standard deviation, mean infrared layer, and brightness. I first segmented the image at 8 different scales: 11, 15, 20, 25, 30, 40, 50, and 70. To determine the best scale to work with, I performed univariate regression between PAI and each of the twelve variables for each segmentation scale. For a top few variables like NDVI, max difference, and simple ratio, I graphed adjusted R-squared values over scale (Figure 3). From this analysis, I determined that a scale of 15 was most optimal for generating an LAI model.



(a)



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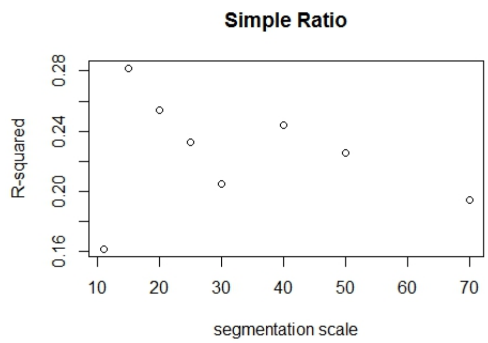

(c)

Figure 3. A graph of univariate R-squared values over different segmentation scales. The three variables shown are most related to LAI. From the three graphs, a segmentation scale of 15 appears to yield the highest R-squared.

Using spectral data from the objects produced from a segmentation scale of 15, I ran a backwards elimination stepwise regression R 3.1.1 (R Core Team 2014) to reduce the twelve variables to the most important predictor variables. I used the stepwise regression method on the original variables, squared variables and log-transformed variables. Once the best model was generated, I applied it to the rest of the image using Field Calculator in ArcGIS v.10.2 (ESRI Inc.) and generated a map of LAI. I merged adjacent polygons of the same species and then created a histogram of patch sizes for each species. I looked for any differences in patch size and distribution between the two species.

RESULTS

Classification and accuracy assessment

I created four classification maps of *S. pacifica* and *S. soda* distribution using four classification methods: nearest neighbor, K nearest neighbor (KNN) classifier, support vector machine (SVM) classifier, and Bayes classifier. Using a combination of ground truth GPS points collected in the field as well as informed visual assessment, I measured overall accuracy, producer's accuracy and user's accuracy with error matrices. Figure 4 shows the map produced using the Bayes classifier, which had highest overall accuracy.

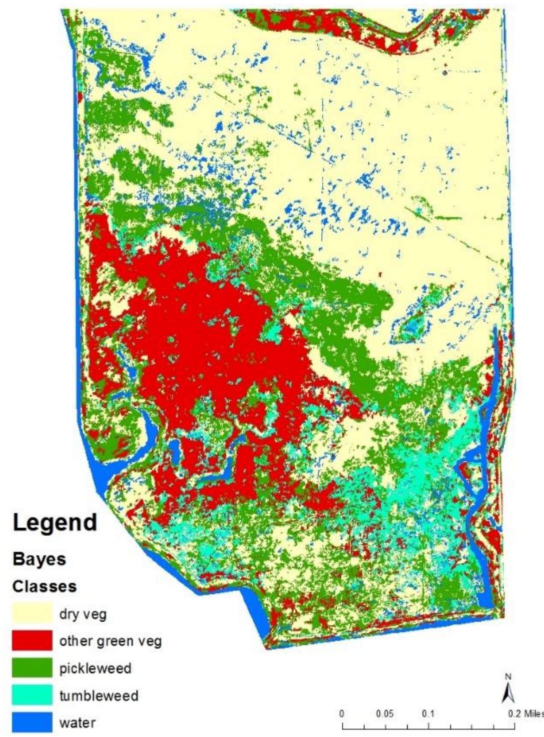

Figure 4. Classification map using Bayes method.

Table 1 is an example of an error matrix I created to assess accuracy for the nearest neighbor method. The four vegetation classes I used were pickleweed, tumbleweed, dry vegetation and other green vegetation. The reference data are the actual classification values for the objects in the image, summed vertically in the column totals. A good classification concentrates the majority of data in the diagonal that goes from top left to bottom right. Wherever classified data match reference data, the classification method has correctly classified the object of interest. The producer's accuracy indicates the percentage of reference data (in each class) were classified correctly. The user's accuracy tests how effective the classification algorithm is in identifying objects in each class.

Table 1. Accuracy assessment for nearest neighbor method.

	Ground truth					
Class	pickleweed	tumbleweed	dry veg	other green veg	**row total**	**user's accuracy**
pickleweed	27	3	2	1	33	82%
tumbleweed	5	44	0	7	56	79%
dry veg	15	13	52	0	80	65%
other green veg	8	1	3	52	64	81%
column total	55	60	57	60	232	
producer's accuracy:	49%	73%	91%	87%		
					overall accuracy:	75%

Table 2. Accuracy assessment for KNN classifier method.

	Ground truth					
Class	pickleweed	tumbleweed	dry veg	other green veg	**row total**	**user's accuracy**
pickleweed	31	2	5	1	39	79%
tumbleweed	8	57	1	7	73	78%
dry veg	13	0	44	0	57	77%
other green veg	8	2	9	52	71	73%
column total	60	61	59	60	240	
producer's accuracy:	52%	93%	75%	87%		
					overall accuracy:	77%

Table 3. Accuracy assessment for SVM classifier method.

	Ground truth					
Class	pickleweed	tumbleweed	dry veg	other green veg	**row total**	**user's accuracy**
pickleweed	36	1	10	1	48	75%
tumbleweed	12	60	0	3	75	80%
dry veg	6	0	45	0	51	88%
other green veg	5	0	4	56	65	86%
column total	59	61	59	60	239	
producer's accuracy:	61%	98%	76%	93%		
					overall accuracy:	82%

Table 4. Accuracy assessment for Bayes classifier method.

	Ground truth					
Class	pickleweed	tumbleweed	dry veg	other green veg	**row total**	**user's accuracy**
pickleweed	32	2	1	0	35	91%
tumbleweed	8	59	2	1	70	84%
dry veg	10	0	43	0	53	81%
other green veg	7	0	9	59	75	79%
column total	57	61	55	60	233	
producer's accuracy:	56%	97%	78%	98%		
					overall accuracy:	83%

Given the overall accuracy results (Table 5), the classified map derived from Bayes classifier yielded the most accurate classification. The mutual confusion column indicates the total percentage error contributed by pickleweed misclassified as tumbleweed and vice versa. The nearest neighbor algorithm had the lowest mutual confusion rate as well as the lowest overall accuracy. The Bayes algorithm had the highest overall accuracy and an average mutual confusion.

Table 5. Compilation of accuracies of all four classification methods. The mutual confusion column denotes the percentage of test objects that were tumbleweed misclassified as pickleweed or picklweed misclassified as tumbleweed.

METHOD	OVERALL ACCURACY (%)	MUTUAL CONFUSION (%)
Nearest Neighbor	75	3.4
KNN classifier	77	4.2
SVM classifier	82	5.4
Bayes classifier	83	4.3

Leaf area index

LAI model

Before creating a LAI prediction model to apply across the whole site, I compared mean LAI values of pickleweed and tumbleweed. There was no significant difference between the two species, given the p-value of 0.3559.

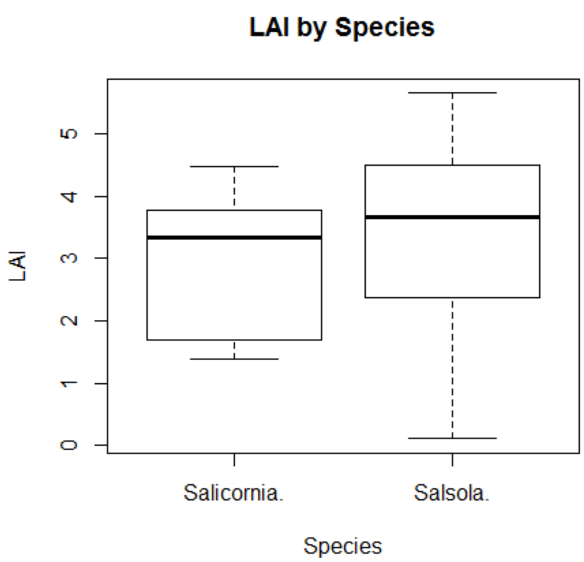

Figure 5. Boxplots comparing mean LAI of pickleweed and tumbleweed. P-value: 0.3559, t(26.432): -0.9397.

To generate a map that predicted LAI across the whole image, I performed multiple linear regression between LAI values of objects containing ground truth points and twelve spectral features of the original image. I had 80 data points across the site. The twelve spectral features were GNDVI, green/blue, green divergence, max difference, mean red layer, mean green layer, mean blue layer, NDVI, simple ratio, standard deviation, mean infrared layer, and brightness. I compared the R-squared values of 3 backward elimination regression models: (1) using the original variable values, (2) using log-transformed variable values, and (3) using squared and original variable values. The second method produced the best model, using 6 variables. The 6 features were log(brightness), green divergence, log(max difference), mean red layer, log(standard deviation), and GNDVI.

MODEL:

LAI = 11.33827*log(brightness) + 0.03060 *green_divergence – 3.63720 *log(max_difference) - 0.09146 *mean_red - 0.86056 *log(standard_deviation) + 28.57778*GNDVI – 50.29069

LAI map

I applied the above model to all polygons in the image. Wherever there was negative predicted LAI, I converted it to a value of 0 because LAI only exists as a positive ratio. Areas where LAI was 0 were designated regions of dry vegetation. The upper bound of LAI range was 3.7.

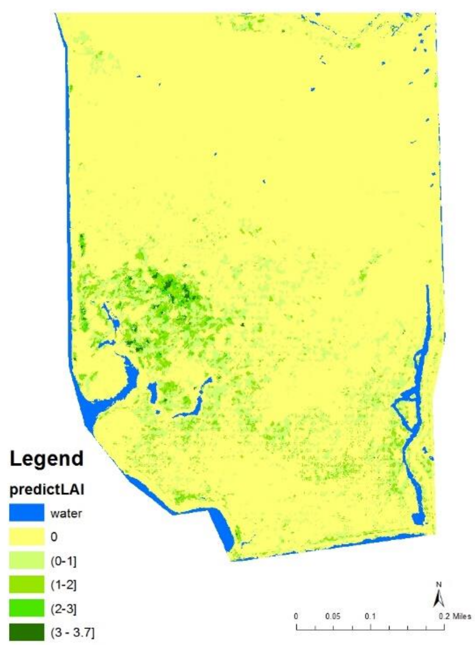

Figure 6. Map of LAI across the site.

LAI patches

The two figures below show the range of patch sizes for tumbleweed and pickleweed. There were 2037 total tumbleweed patches and 2516 total pickleweed patches. Both species appear to have maximum number of patches occurring at 10 square meters. Tumbleweed had a greater proportion of its patches under 10 square meters than pickleweed did.

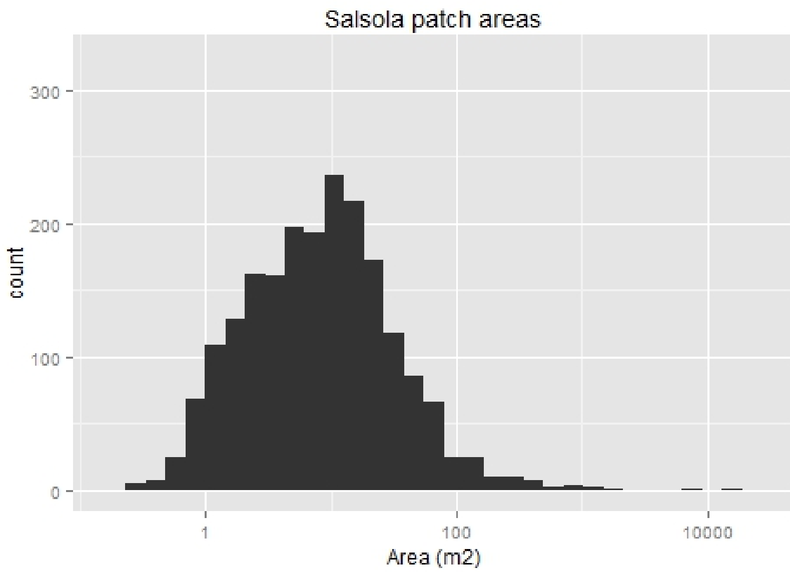

Figure 7. Distribution of tumbleweed patch sizes on log scale.

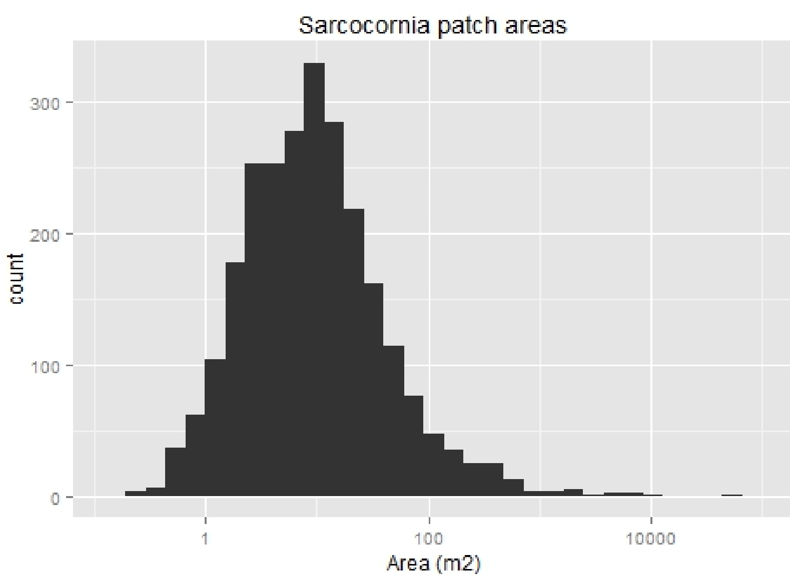

Figure 8. Distribution of pickleweed patch sizes on log scale.

DISCUSSION

Remote sensing is increasingly being used in natural resource management, in part because of technological advances that have made tools more accessible to the average researcher and because of the potential and efficiency of remote sensing tools. This study utilized the spectral data in a high-resolution aerial photograph for upland marsh vegetation classification and for leaf area index (LAI) prediction. The results suggest that a reasonable classification accuracy of 83% can be produced using spectral data and the Bayes classifier algorithm. On the other hand, the best multiple regression model for predicting LAI had an adjusted R-squared value of 0.42, which indicates some relationship exists between LAI and spectral variables, but not enough to predict LAI reliably. Consequently, the sampling design and model will need further refinement. As previous studies have found, remote sensing methods show promise in management settings. The high classification accuracy suggests that very high resolution imagery can be used for change detection in wetland landscapes. If there is a shift from field methods to more remote methods to measure and manage wetland environments, wetland managers can better preserve the fragile landscapes.

Marsh vegetation classification and patch areas

The four supervised classification methods produced accuracies between 75% and 85%, so there are substantial differences in classification capabilities. The Bayes classifier method produced the highest overall accuracy of 83%. Depending on where ground truth points are selected, a classification may be more accurate or less accurate. From a quick overview of all the error matrices, pickleweed tended to be the most misclassified. There were difficulties distinguishing actual pickleweed from all of the vegetation categories, particularly from dry vegetation. For the Bayes method, there were also significant difficulties distinguishing actual dry vegetation from other green vegetation. One explanation for the difficulty with classifying pickleweed is that I included both younger, forest green pickleweed as well as older, purple pickleweed in the class ‘pickleweed’. Because both green and dead pickleweed patches were presented in the mapped area, this class exhibited higher spectral variation, so it is difficult to select representative samples for discriminating it from other vegetation types.

In terms of distribution, most pickleweed does not occur near water or roads, unlike tumbleweed. Pickleweed appears to be more widespread, from northwest to central to southwest portions of the site. There is a large monospecific pickleweed patch in the center of the site. Tumbleweed, on the other hand, tends to occur nearer to bodies of water throughout the southern part of the site. There is also an extensive patch of tumbleweed on the southeast portion of the site. Similarly, other green vegetation occupies a large swath of the western portion of the site. Pickleweed and tumbleweed tend to coexist at the confluence of these two species and other green vegetation. This suggests that the boundaries of large patches may be susceptible to multispecific competition. Tumbleweed has established itself well in the southeast portion of the site and appears to be spreading northward and westward (based on patch distribution and comparison with 2013 observations by Dronova (unpublished)). If it can outcompete pickleweed or other native vegetation, then larger tumbleweed patches can potentially develop from the current distribution of monospecific patch boundaries.

I expected tumbleweed patches to be more variable in area than pickleweed patches because tumbleweed is a non-native species in the process of invading. Mean patch areas were similar between the two species: pickleweed had an average patch size of 28.3 square meters, whereas tumbleweed had an average of 20.7 square meters. Pickleweed had a maximum patch size of 56,000 square meters, more than three times the maximum tumbleweed patch (16,000 square meters), however. Standard deviation of pickleweed patch size was 1160 square meters, compared to tumbleweed's 385 square meters. If I exclude the maximum pickleweed patch, pickleweed's standard deviation becomes 329 square meters. Contrary to what was expected, the area of tumbleweed patches did not have a noticeably larger standard deviation than that of pickleweed patches.

LAI model

The LAI model I created aimed to predict LAI values from a mixture of spectral data and vegetation indices calculated from the raw spectral values. I used backward elimination regression in R with three sets of variables: raw, log, and squared values. The best model was a log-transformed model using the features log(brightness), green divergence, log(max difference), and mean red layer, log(standard deviation), and GNDVI. The adjusted R-squared value of the model was 0.42 and the AIC value was 41.12. The models I produced using the different sets of variables all had R-squared values within 0.05 of 0.40, which suggests that there may be a limitation presented by the values in the dataset. I only used spectral data from a 4-band (R, G, B, NIR) photograph to produce a regression model. The future work in this direction may benefit from including soil moisture data, elevation data, or potentially using hyperspectral imagery to predict LAI more effectively. Overlaying the classification map on the LAI map, tumbleweed appears to have slightly higher LAI than pickleweed, which may be explained by the fact tumbleweed grows taller than pickleweed on average.

Limitations and future directions

Marsh vegetation classification

The main limitation to this study were classification difficulties presented by spectral confusion. As noted earlier, pickleweed turned out to be difficult to distinguish from dry vegetation, most likely due to the inclusion of dead pickleweed in this study. Similarly a number of dry vegetation objects were misclassified as other green vegetation. Misclassifications reduce the classification accuracy, which in turn reduces the reliability of the classification rule set. The amount of data contained in the very high resolution imagery presented another difficulty in vegetation classification. Since the imagery is at a 15 cm resolution, it captures a lot of detail and noise in the landscape. While eCognition Developer can handle large amounts of data, the introduction of very 'noisy' imagery means there is more information for the software to sort through. Some segmentations and analyses take a long time to run because of the amount of data within an image. For management purposes, it would be ideal to split a landscape region into smaller more manageable pieces if working with sub-meter resolution photographs.

Also, the scope of this study was small in spatial extent. I worked with a marsh site around Suisun Bay that was 120 acres. I cannot say with confidence the classification methods can be applied to the rest of the wetlands in Suisun Bay. From working in the field and with the eCognition software, I realized the level of heterogeneity present on such a small scale. I conducted a pilot study on a subset of the aerial photograph before trying to classify the entire image and found that the classification accuracies dropped significantly when applying the pilot study rule set to the whole image. The goal when conducting a pilot study is to find a representative sample of the larger study sample. In the photograph of the site, this proved to be difficult. The uneven patchiness of the site meant that the subset would have to be virtually as large as the original image to capture the heterogeneity.

In future studies, one might obtain photographs taken at other times of the growing season. The image in this study was taken in August, which was late in the growing season for perennial pickleweed, but right in the middle of the growing season for oppositeleaf Russian thistle. Depending on what is the major plant(s) of concern, changing the time of growing season when the aerial photograph is taken may affect how well one can distinguish that plant from the rest of the landscape. In this study, the spectral signature from the Russian thistle was very distinct during August. As a result, I was able to produce an average of producer's accuracy and user's accuracy of 91%, the highest of all the classes.

LAI model

The goal was to create a multiple regression model that could predict leaf area index (LAI) across the extent of the site. I was only able to use 80 out of the original 112 data points, because some measurements were taken in areas of dry or dead vegetation. Since the site is not too large, the study could have benefited from taking more LAI measurements in the field. Another factor that may have affected the limited ability of the model to predict LAI is sampling effort. Our sampling effort consisted of 4 transects with evenly spaced points along each transect. Given that the site was inherently very heterogeneous, if an LAI measurement was taken at the boundary of different species patches, it may not have been representative of either of the patches. When I segmented the photograph using spectral data, the image object that contained the LAI point may have been comprised mostly of one species, instead of a combination of them. Thus, there might have been a discrepancy between the segmented image object and the LAI measurement that was supposed to represent that object.

CONCLUSIONS

This study suggests that remote sensing image classification algorithms are promising for applications in marsh landscapes to determine the distribution of *S. soda* and *S. pacifica.* Among the four supervised classification methods tested in this study, the most successful was the Bayes algorithm, which produced 83% classification accuracy. For the LAI model, spectral variables cannot predict LAI very well, but there is a promising relationship. To further develop this model, other physiological variables measured in the field should be included.

Depending on the applications of vegetation classification, one might opt for different spatial resolution of the input image data. This study has shown that sub-meter resolution photographs have good potential for classifying a heterogeneous marsh landscape broadly into vegetation types and even species like *Salsola soda* and *Sarcocornia pacifica*. A next step would be to figure out the appropriate level of resolution is suitable for one's analyses or studies. It is likely that, due to the level of heterogeneity of marsh sites like the one in this study, the image resolution cannot be too coarse, otherwise changes may not be detected.

In terms of distribution, *S. soda* and *S. pacifica* both have areas that are largely monospecific. Tumbleweed was concentrated in southeastern portions of the site, whereas pickleweed was concentrated in a long strip right across the center of the site. At the boundaries of large patches, however, multiple species were found. To monitor the spread of *S. soda,* one should focus landscape change studies in these bordering regions. Management implications are many, and this study is a small but encouraging stepping stone into more marsh studies using a combination of field and remote sensing methods.

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