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# An Evaluation of Unmanned Aircraft System (UAS) as a Practical Tool for Salt Marsh Restoration Monitoring, San Francisco Bay, CA

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Master of Science in Environmental Management

This Master's Project

**An Evaluation of Unmanned Aircraft System (UAS) as a Practical Tool for Salt Marsh Restoration Monitoring, San Francisco Bay, CA**

by

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# Abstract

Salt marshes in the San Francisco Bay area provide essential ecosystem services from critical habitat to buffering coastal flooding and are the focus of substantial ecological restoration, necessitating improved restoration monitoring approaches. Metrics such as land cover classification, bare ground elevation, and vegetation height provide an understanding of the functionality and health of tidal wetlands. Unlike traditional monitoring methods, which rely on time and labor-intensive field surveys or macroscale remote sensing techniques, unmanned aircraft systems (UAS) provide site specific high spatial resolution data that is comparable to satellite and manned aircraft derived imagery. I compared published literature and provided primary data analysis to evaluate the ability for UAS to provide useful monitoring metrics for salt marsh restoration. I employ UAS derived point cloud data to analyze 3-dimensional (3D) data and find that UAS data can provide elevation and hydrological modeling in addition to vegetation height metrics. My comparative review findings suggest that UAS technologies can be deployed towards salt marsh monitoring using multiple approaches to increase overall accuracy of these collected data. Using basic visible spectrum data, I achieved an overall accuracy of 73% land cover classification, and with more powerful sensors and computing, upwards of 90% accuracy can be achieved. UAS provide a temporarily flexible way to collect data, providing restoration ecologists more options and freedom to target specific temporal environmental characteristics. With functional data acquisition capabilities and a greater flexibility in temporal resolution, UAS show promise as a practical tool for salt marsh restoration monitoring.

# Chapter 1: Introduction

San Francisco Bay area salt marshes and coastal wetlands serve as important ecological resources. The region is home to many endemic and endangered marsh species having evolved within the specific climate and habitat types of the Bay Area (Spautz et al. 2006). In addition, the Bay Area is a key stop over spot for great migrations of avian species. These seasonal species rely heavily on functioning wetland systems and respond well to restoration of salt marsh habitat (Athearn et al. 2009). Salt marsh degradation and coastal development is adding more stress to these species causing a widespread effect on ecological systems all along the Pacific coastline.

San Francisco Bay has dramatically changed since the start of western development. Prior to the modern era, the bay was lined with approximately 220,000 ha of tidal marshland (Williams and Faber 2001). Today only a small fraction of tidal wetlands still exists with much being fragmented and providing poor ecosystem services. Due to the deteriorated condition of tidal wetlands in the Bay Area and a new understanding of the importance of these systems as buffers to climate change, there has been a push for salt marsh restoration.

Over the past 40 years, tidal wetland restorations have been implemented in the Bay Area with varying degrees of success. Most importantly, however, the definition of success has also changed in response to monitoring unanticipated evolution of these restorations (Williams and Faber 2001). These revolutions in salt marsh restoration can be attributed to a more developed understanding of the system brought on by decades of restoration monitoring.

Traditional methods of salt marsh restoration monitoring require trained biologists to collect data in situ. This method is effective at collecting very detailed data about the biotic and physical characteristics of sampling locations. With developments in airborne and satellite technology, remote sensing has become an additional tool that can provide much greater insight into site conditions over landscape levels (Zhang, M. et al. 1997). The benefit to this approach is the relative ease of data collection and the sheer amount of data available for analysis. In addition, remote sensing allows for more advanced temporal analysis such as comparison of salt marsh loss over multiple years (Campbell et al. 2017)

The most recent advancement in remote sensing monitoring technology is the implementation of unmanned aircraft systems (UAS). Colloquially known as “drones”, UAS systems are small and portable aerial platforms that allow restoration practitioners to gather their own data. Examples of the benefits of this technology are the ease of access, relatively low entry level costs, repeatability, and high image resolution (Ridge and Johnston 2020). The advance in this technology makes real time data collection over natural ecosystems easier than ever to collect and is gaining traction as an informative tool in the environmental field.

In this study, I aim to address following question: can remote sensing using imagery, collected by UAS, effectively monitor success metrics for salt marsh restoration within the San Francisco Bay area? I evaluate the effectiveness of UAS through two main sub-questions. Firstly, can UAS provide enough spectral and spatial resolution to develop a functional land cover classification of salt marsh environments? Secondly, can UAS provide similar data to established Light Detection and Ranging (LiDAR) data to effectively capture 3D metrics of salt marsh environments?

I have gathered evidence to answer my questions by reviewing and comparing primary published literature. I further support these published studies with my own data analysis using UAS aerial data collected over the Corte Madera Ecological Reserve in Marin County, CA. I share these data analyses as proof-of-concept sections within my discussion sub-sections (land cover classification, UAS derived DTM, bare earth model, tidal channel modeling, and vegetation height metrics) to support evidence from the primary literature. However, current constraints of UAS limit its use as a full replacement for field-based or satellite-based imagery collection. Lastly, I provide recommendations as to the practical implementation of UAS technology today to monitor salt marsh restoration practices.

# Chapter 2: Background

## Salt Marsh Restoration

Coastal ecosystems have evolved with diurnal tide cycles that dictate the structure of vegetation habitats. Restored salt marshes are often returned to these tidal inundations after long periods of being cut off by levees (Williams and Orr 2002). In salt marshes, tidal inundation frequency and severity are related to small changes in elevation(Cahoon and Reed 1995). High marsh and low marsh vegetation communities may only be separated by small increments in elevation (Moffett et al. 2012). However, the low marsh has evolved mechanisms to deal with daily inundation twice a day for extended periods of times; whereas, high marsh communities can only tolerate infrequent inundation  (Silvestri et al. 2005). Low marsh species tell of different evolution pathways than established high marsh communities due to their different abilities to stay submerged in saline waters (Pennings and Callaway 1992). Plant communities, directly impacted by frequency and level of inundation create mosaic patterns that can be used as indicators of elevation, hydrology, and even soil conditions (Millard et al. 2013). In the San Francisco Bay region, Pacific cordgrass (*Sporobolus foliosus*, formerly *Spartina foliosa)* dominates the low marsh habitat where pickleweed (*Salicornia pacifica)* dominates the mid-marsh habitat. Each community has unique traits that allow it to survive at specific tidal inundation levels. In turn, each community hosts different ecosystem services such as habitat for specialized species or ability to mitigate storm surge (Feagin et al. 2010, Rosencranz et al. 2018). Understanding the spatial distribution of these habitat types allows practitioners to better design restorations to achieve the most functionality.

Salt marsh restoration project design are often influenced by the goals of the stakeholders. Often these restorations aim to provide ecosystem services through both habitat improvement and economic benefit for humans (Teal and Weishar 2005). This may include fishery restoration, habitat preservation, storm surge mitigation, or erosion control (Staszak and Armitage 2013). In addition, salt marsh restoration has been seen to increase the uptake of carbon dioxide, a potent greenhouse gas, through a process known as carbon sequestration (Wang, F. et al. 2021). Mature and diverse vegetation communities are better suited to provide these services than new and homogenous restorations. Composition of salt marsh vegetation communities can reflect changes to salt marsh ecology from primary succession after initial restoration to a more mature system. Understanding small changes in elevation, salinity regimes, soil conditions, and hydrology can lead to a better understanding of restoration end goals (Pennings and Callaway 1992). Combing data gathered about salt marsh condition and the needs of the stakeholders ultimately determine what constitutes successful salt marsh restoration.

A restoration with storm surge mitigation might seek to have a large mid-marsh zone with complete bands of low marsh at the shoreward edge. This would create two different habitat types to provide wave attenuation during storms (Anderson and Smith 2014). Alternatively, a restoration targeting reintroduction of salt marsh harvest mice (*Reithrodontomys raviventris)* might target mid-marsh habitats with non-fragmented pickleweed as a dominant vegetation type (Bias and Morrison 2006). Monitoring physical metrics at these restorations allow practitioners to evaluate the success of the restoration and provide adaptive management quickly to adjust the restoration to align with project goals. Quick and reliable monitoring data is crucial to ensure restoration success.

## Monitoring Restoration Success

### In-Situ Field Monitoring

Traditional ground surveys require trained biologists to navigate the salt marsh site on foot to record data. Field biologists take measurements of vegetation and use instruments to record other physical data which are extrapolate over the entire project site to determine salt marsh conditions. Field based observation techniques are often slow, hindered by difficult navigation, and may not accurately convey data over the entire study site. Standardized vegetation survey methods utilize quadrat-based ground measurements and *in-situ* GPS measurements (Espriella et al. 2020). In addition, time, effort spent, and cost usually limit the repeatability of these surveys. For example, in the 1990's it was estimated that the median marsh monitoring cost in the Northeast United States was over \$3,000/acre, ranging from \$2,000/acre to \$90,000/acre (Louis Berger and Associates and United States. Environmental Protection Agency. Region, I 1997) In addition, *in-situ* data collection over entire marsh complexes can take weeks or months of effort. During this time, vegetation communities and characteristics can change seasonally making data difficult to accurately compare without remote sensing (Smith et al. 1998). These limitations culminate in fewer repeated surveys and less accurate spatial data, however, provide more detailed species level identification.

Considerations for the damage done during *in-situ* monitoring must also be considered when choosing to conduct field surveys over remote sensing techniques. Salt marshes are sensitive environments that can be easy disturbed by humans, particularly in California where 90% of salt marshes have been lost. Field techniques require invasive entry into marshes that leave footprints, disturbance of vegetation communities, and potential negative effects on salt marsh specific fauna.

# Remotely Sensed Monitoring

## *Land Classification*

Remote sensing, using aerial imagery has changed the way ecologists study landscape level ecosystems. This study of the Earth's surface from an aerial perspective allows for large scale environmental monitoring. Metrics, such as land cover classification provide more complete details about site wide conditions that may be missed with boots on the ground surveys. Land cover classification helps to build a picture of the vegetation characteristics over the entire site within one snapshot in time (Sanchez-Hernandez et al. 2007). This allows the stakeholders to visualize overall site conditions, not just extrapolated data from a few data points. When viewing project sites using an aerial view, the monitors can more easily visualize changes in vegetation communities, habitat evolution, and even impacts from stressors such as sea level rise (SLR).

Remote sensing of salt marsh vegetation communities has become a more efficient way to collect information for land cover classification. Remote sensing uses data, obtained by satellite or aircraft above the study area in an efficient and non-invasive manner (Yeo et al. 2020). Using spectral signatures (specific reflected wavelengths of light), vegetation textures, analyst prior knowledge, and specialized software, these data can be analyzed by comparing like values and assigning them a classification. Often this requires input from the analyst to provide training samples in a technique known as supervised classification (Keuchel et al. 2003). Once training samples are determined, programs such as ArcGIS Pro can be employed to automatically assign each pixel of an image a value as compared to the training sample. This is repeated over the entire image, resulting in a land cover classification map.

Currently, pixel-based classification and object-based classification are the most common types of analysis. Pixel-based classification compares values of a single point of data to surrounding pixels. These pixels, a collection of single squares, contain data values for reflected light energy such as the visible or infrared spectrum. Software that can conduct land cover classifications compare the values of each pixel to the next to determine similarities or differences (Figure 1). Object-based classification groups similar pixels together into segmented images then compares these segments to the training samples to assign a classification value. Basic light sensors can detect in the visible light spectrum represented by Red, Green, Blue (RGB) spectrum. This is like a digital camera that captures images in the same way the human

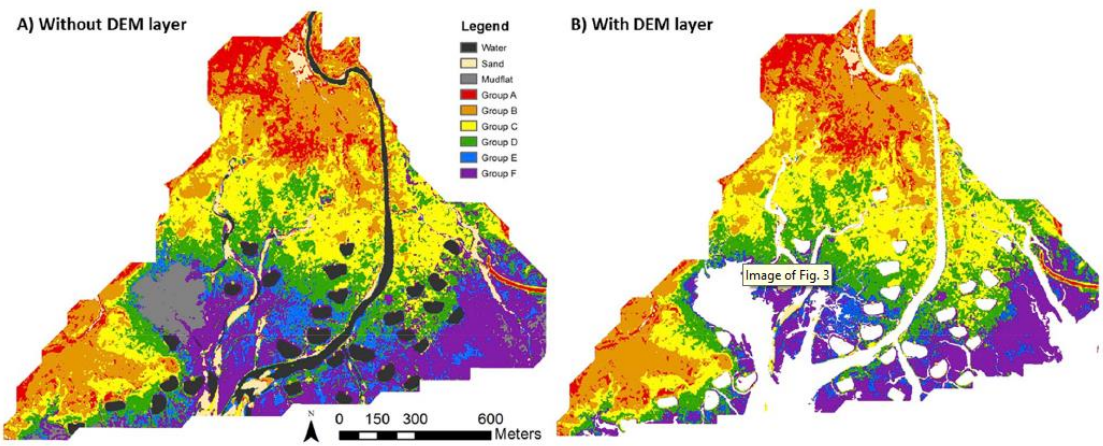


*Figure 1: A satellite based remote sensing technique for land cover classification over salt marshes. Using site specific knowledge, training samples are created and fed into the software during a supervised classification analysis. A Digital Elevation Model (DEM) can add another layer of data to increase accuracy. (Yeo et al. 2020)*

eye and brain see the world. Employing RGB to conduct these land cover classifications, data from three spectral bands are used differentiate the pixels from each other. Multi-spectral provides even more bands to conduct the analysis which usually provides more accurate classifications. Each pixel or group of pixels are analyzed and compared over an entire project site using these methods.

One advantage to aerial based observations is that data can be collected over entire project sites at one time. This eliminates the need to extrapolate data over the project area and provide more a more complete spatial assessment. In addition, these surveys are repeatable with relative ease without taking large amounts of field time. Being able to repeat surveys as a time series allows the user to better understand salt marsh trends and change over time (Campbell and

Wang 2020a). This is especially important to understand the long-term impacts of anthropogenic stressors on a salt marsh complex. Land cover classification time series provides data to evaluate change in vegetation communities, biomass, and disturbances. Understanding these impacts allows stakeholders to assess change and risk factors affecting salt marshes (Campbell and Wang 2020b). Remote sensing technologies provides researchers and restoration practitioners an effective and repeatable method to develop land cover classification.

### *Three-Dimensional Data*

Three-dimensional monitoring is a useful dataset to better understand site conditions for salt marsh restoration. Traditional monitoring for 3D data is collected using LiDAR technology which employs active laser light from the sensor and records reflection times (Dubayah and Drake 2000). 3D data provides vertical detection points of an object in relation to the ground, the sensor, and other separate data points. By comparing these values to each other, valuable information such as ground elevation, slope, and vegetation heights can be measured. Examples of practical applications for this would be to understand where optimal elevation for tidal vegetation plantings can take place or to monitor and track soil erosion on exposed marsh edges. With SLR adaptation and resiliency as the basis of salt marsh design, understanding vertical structure of marshes is important. By analyzing 3D data over time, soil movement and erosion, accretion rates, vegetation communities, and above ground biomass (AGB) can be derived providing a better understanding of salt marsh changes.

Resilient salt marsh design focuses on maintaining a functional marsh system ahead of sea level predictions for the future. Salt marshes exist at specific elevations in relationship to tidal waters. As average tidal waters rise, salt marshes migrate both horizontally and vertically through accretion of sediments, deposition of dead organic matter, and landward migration. Understanding the 3D characteristics of salt marshes is more important to their recovery now more than ever, as available sediment loading in the SF Bay has dropped 36% in recent decades; although accretion rates are currently keeping pace with SLR through accumulated organic matter (Schoellhamer 2011, Callaway et al. 2012). Due to prior land use, urbanization, and management practices, many current tidal wetlands have little to no room for landward migration (Feagin et al. 2010). Island marshes may suffer from slowed accretion rates from fewer suspended sediments and often are impacted by erosion. Sound restoration design must take these factors into account to plan for the environmental conditions of the future and to develop a system that can adapt with fewer human interactions.

# Remote Sensing Platforms

## Orbital Platforms

Large orbital remote sensing platforms such as, Landsat 8 satellite system, carry advanced sensors that can capture large amounts of high-resolution data. Modern technology allows for high resolution aerial imagery, between 1-90 m pixel size (Timm and McGarigal 2012). Image resolution is extremely important in achieving high accuracy during data analysis. At 1 m pixel resolution, it is possible to achieve 87% classification accuracy in salt marsh environments (Timm and McGarigal 2012). However, having too large of pixel resolution may not be able to detect small initial changes of restoration such as sparse recruitment of vegetation seedlings. These small changes may take years to develop into large enough features to be detectable if the pixel resolution is too large.

Orbital platforms often carry multiple sensors that can detect a high range of spectral imagery. Prior to a component failure in 2019, Worldview-4 Satellite was able to collect data in the panchromatic wavelengths as well as multispectral in RGB and near infrared spectrum (Satellite Imaging Corporation 2021). More bands of light detection allow for more accurate identification of land features and can allow for more advanced analysis such as vegetation indices, spectral transformation used to enhance vegetation properties for comparison (Abdou et al. 1996). For example, different species of trees have unique spectral signatures that can be used to differentiate each species from one another (Al-Ali et al. 2020). With more data bands, ranges of spectral wavelengths, spectral differences are more easily detected. The more data available to be used in the program's classification, the more accurately it can differentiate between cover classes.

These larger commercial platforms allow for more cost-effective monitoring over large scales than field monitoring. The shortcoming of these data is related to scale. At small scale restoration site, finer resolution is often required to detect early growth in mudflats. Worldview 3 data has a resolution of 1.24 m in eight bands of multispectral data (Al-Ali et al. 2020). Planet Labs, a modern multi-satellite commercial company, can provide 3.7 m multi-spectral resolution with its most up to date satellites (Planet Labs Inc. 2021). This advance in technology is a great achievement but may still not be enough resolution to differentiate small new vegetation at the sub-meter scale. Real world marsh restorations often introduce vegetation plugs that range in the centimeter resolution ground coverage spaced out under half a meter (Hammond 2016). These plugs may take years to grow into patches of 0.5 m in diameter making them difficult to detect until several years after installation. Several years may be too long to wait to implement adaptive management to achieve restoration goals or to fulfill funding requirements.

In addition to spatial resolution, temporal resolution is a major hurdle. Satellite and aircraft systems can be expensive to task; thus, redirection of these assets is less likely. For instance, for a given year of flights, there may only be a handful of suitable images addressing geography, weather, tidal cycle, and growing season. Often, satellite imagery does not capture a salt marsh project site during optimal low tidal inundation or optimal atmospheric conditions (Campbell and Wang 2020a). This leads to inaccurate land cover classifications and analysis of land cover area (Espriella et al. 2020, Campbell and Wang 2020a). As satellite technology advances, this hurdle may lessen but for now this is the reality of these platforms.

More modern systems such as Planet Labs platform are based off hundreds of small micro-satellites that can provide almost daily monitoring (Planet Labs Inc. 2021). This platform provides a better temporal resolution but as previously noted, may not grant enough spatial resolution. Until satellite technology can provide both very high spatial and temporal resolution together, these platforms still have major deficiencies that make them impractical for smaller site-specific salt marsh restoration.

## Unmanned Aircraft Systems

Unmanned Aircraft Systems can be employed today to achieve extremely high levels of spatial resolution and can be deployed to collect real time data. These systems comprise of both aerial flight platforms and light detecting sensors, communication units, and data sharing software. The aerial platforms are small, portable, and deployed at will making data collection very flexible and easily repeatable (Vergouw et al. 2016). The advantage of UAS to provide centimeter level spatial resolution while being able to collect temporally targeted data provides a great benefit to restoration practitioners. This technology sits perfectly between the very specific in situ monitoring and the broad scales of satellite platforms.

Two main components of UAS determine the usefulness in data acquisition. First, the UAS GPS accuracy greatly affects the spatial accuracy for vegetation classification. Modern consumer grade UAS have sub-meter accuracy. DJI advertises a 0.01 m horizontal and 0.015m vertical position accuracy for its mapping specific consumer drone (DJI 2021). Using ground control points allows for further calibration and reduces positioning error of UAS imagery by comparing ground-truthed GPS locations to the collected imagery (Martínez-Carricondo et al. 2018). This process allows for calibration of highly accurate positioning. The second component that affects data accuracy and capability is the sensor system used to record data. Many entry level consumer grade UAS only come equipped with a sensor capable of recording in the visible spectrum. Data constricted to RGB are limited in scope as compared to multi-spectral and LiDAR acquisition.

Several styles of UAS exist, including fixed wing and multi-rotor, which carry a wide array of light detecting sensors. Common off-the-shelf UAS systems bridge the gap between recreational flying and scientific data collection. These often are equipped with accurate GPS locators, the ability to collect data autonomously, and entry level RGB light capture sensors. The benefit to these systems is that costs are relatively low due to their commercial applications. Advanced systems increase the capability of UAS by extending flight times, increasing sensor resolution, and allow for capture of different light spectra including multi and hyper spectral and LiDAR.

Unmanned Aircraft Systems also include the software that allows for easy data recording and transfer. Modern consumer grade UAS can be fully automated using basic smartphone applications such as Pix4D and DroneDeploy. These software take the users' parameters and control the aerial platform to collect images without user input during flight. Post processing of these images often requires both UAS specific software and already established remote sensing software such as ArcGIS Pro.

UAS systems can provide high spatial resolution while providing flexibility in data acquisition timing. This is beneficial to collecting high quality data for land cover classifications and 3D data. UAS collect a series of imagery and combine them together using specialized software. Much of this process is automated by third party software which makes this technology more accessible to a wide range of consumers. The process of overlapping individual photos into one large image is known as photogrammetry (Fraser et al. 2016). A 0.018m ground resolution orthophoto can be achieved using photogrammetry and aerials collected from a UAS (Boon et al. 2016). This resolution translates to each square pixel having a width of 0.018 m (1.8cm). This is greatly improved on Worldview-3 imagery where each pixel is 1.24 m (124 cm) in width.

One important note is that UAS relies on small battery packs for power. The limitations in battery technology often limits flights to 20 mins of less. Large scale surveys might not be possible or may be inefficient with constant changing and charging of batteries. The time and resources required to employ UAS over large landscapes greatly limits its ability at these large scopes. A possible fix to this problem is using multiple UAS at the same time. However, this does increase the cost to operate. At large scales UAS may not bring any additional effectiveness to data acquisition compared to satellite data which is why UAS would be limited to small site-specific projects.

# Chapter 3: Methods

## Literature Review

I conducted a literature review of primary published literature of the usage of UAS as a tool environmental monitoring. Journal articles and conference briefings were gathered using academic search engines such as Scopus and Google scholar to identify peer reviewed literature. Journals were evaluated for rankings on Scimago to ensure the quality of these articles. I conducted a literature synthesis to evaluate my sub-questions and incorporated my own original data analysis of UAS imagery for a subset of remote sensing topics. I present these data as proof-of-concept sub-sections within my discussion to highlight real world application of UAS technology for salt marsh restoration.

## Study Site

UAS data acquisition was conducted over the Corte Madera Ecological Reserve (CMER) in Marin County, CA (Figure 2). Total area cover was 36.25 ha and focused on the linear shoreline habitats. The UAS flight was conducted over open mud flat, open water, salt marsh, and upland transition zone. The flight was coordinated to coincide with a low tide to ensure that water levels would not cover marsh habitat. Typical vegetation found within the salt marsh portion of the study area include Pacific cordgrass (*Sporobolus foliosus)*, Pickleweed (*Salicornia pacifica)*, Saltgrass (*Distischlis spicata)*, and Gumplant (*Grindelia stricta)*.

Corte Madera Ecological Reserve is a salt marsh complex comprised of a series of natural and restored salt marsh habitat situated at the mouth of Corte Madera Creek. Once part of an interconnected series of tidal creeks and coastal wetlands, CMER now is mostly isolated as an ecological reserve without any significant nearby tidal wetlands. It is situated in a mostly urbanized landscape with highly impacted upstream ecosystems and high erosion pressure from shoreward ferry traffic. Some areas of CMER have a mixed series of land use history, including diked rangeland and filled tidal marsh (Friends of Corte Madera Creek). CMER has undergone many phases of tidal marsh restoration ranging from the 1970s to a recent conversion of filled wetlands back to tidal action in 2020.


*Figure 2: Study Area located within the Corte Madera Ecological Reserve, Marin County, CA. This is a portion of a salt marsh with much of it in different phases of passive restoration.*

## Data Acquisition

All UAS data was generously donated to my project by the San Francisco Estuary Institute (SFEI). Flight permission was applied for by SFEI and granted by the California Department of Fish and Wildlife (CDFW). The UAS was piloted by Pete Kauhanen, MA., FAA permitted drone operator (part 107) and GIS manager with SFEI. In addition, Mr. Kauhanen conducted the post flight data analysis and quality control via the Site Scan software. This involved manual adjustment of ground control points (GCP) based upon LiDAR data as well as in situ surveying provided by the CDFW observer.

I chose to conduct this study with an RGB equipped UAS to highlight the entry level consumer grade platforms that small scale restoration projects might employ. Advanced sensor systems could increase the performance of UAS data with a tradeoff of increased purchase pricing. Small scale restoration projects might not have the funding or ability to employ these professional level tools. Data collection was conducted in September 2019. SFEI employed a consumer-grade DJI Mavic 2 Pro with a stock RGB visible spectrum sensor. This unit had a vertical position accuracy of +/- 0.1 m and a horizonal accuracy of +/- 0.3 m.

Automated flight and image capture were conducted using the Site Scan flight control application. Still images (780 in total) were captured over the study area and later imported to the Site Scan mapping software. The ortho-mosaic image was georeferenced using 11 GCP and had a mean RMS horizontal error of 0.006m. The output coordinate system was WGS 83/ UTM zone 10N. Average pixel resolution was 1.45 cm. Point cloud data generated 118067701 3D densified points with an average density of 1013.62 points/$m^3$.

Data were transferred tome in January 2021, and I conducted further analysis in the spring of 2021. Vegetation analysis was conducted within the ArcGIS Pro program. 3D point cloud analysis was converted and analyzed within the LAStools software and further analyzed within the ArcGIS Pro program. Data used to produce figures within this paper include geo-rectified ortho-mosaic imagery with three bands in the RGB light spectrum and a 3D point cloud dataset.

## Vegetation classification

### Training Samples

To train the ArcGIS software to automatically identify different land cover types, I created training samples to capture a range of spectral signatures unique to my pre-defined cover classes (Schmidt 2017). Training samples are vector format polygons that shared similar spectral signatures within cover classes (Oldeland et al. 2021). I defined class groups by employing my in situ experience and observational knowledge of major vegetation classes and land cover types within the study site and my knowledge of salt marsh ecology (Table 1). I converted the UAS derived ortho-mosaic imagery into a false color manipulation to highlight vegetation compared to other unique spectral signatures. I used this false color image and personal knowledge of the study site to create training polygons that represented each cover class. Signatures were compared to each other by graphing spectral values for the three RGB bands. Any training samples demonstrating spectral overlap were merged to streamline the process. Specific training samples from different classes that display too similar spectral signatures values were re-evaluated for accuracy and either redrawn or removed. I did this to remove training samples that could lead to misclassification. This was repeated until differences in unique samples were less apparent. The samples were converted into vector files to be used in the image classification.

*Table 1: User identified vegetation cover classes. Cover classes were determined using user knowledge of the site conditions, in situ observations, and general knowledge of SF Bay area salt marsh species*

| Land classification cover types |
|---|
| Water |
| Mudflat |
| Cordgrass |
| Cordgrass/Pickleweed |
| Pickleweed |
| Other wetland vegetation |
| Gumplant |
| Other Upland woody shrubs |
| Unvegetated surface |
| Upland transition zone |

## Classifying Land Cover

Utilizing the training samples, I ran two methods of classification to assign a class value to each pixel according to its unique spectral signature. Once complete, a project wide land cover classification was produced. Two methods were chosen to improve the chances of developing an accurate vegetation classification for the site using only RGB imagery: pixel-based and object-based classification (figure 1).

### *Pixel-Based Classification*

I converted the training samples into unique a spectral signature file. This process takes the spectral signatures found within the vector shape of the training sample and records that value as a classification value. These signature files were then used in a classification process that analyzes the ortho-mosaic image pixel by pixel using a standard maximum likelihood classification method (Otukei and Blaschke 2010). Once complete, I conducted an accuracy assessment using 300 randomized points. These points were manually verified against aerial imagery and knowledge of the site and salt marsh vegetation (figure 3).

### *Object Based Classification*

Using the classification wizard within ArcGIS Pro, I analyzed the imagery data using an object-based classification approach. The classification wizard segmented the imagery into like groupings of pixels based upon similar attributes (Figure 3). I chose to set my maximum pixel per object at 300 to increase resolution but still provide adequate pixels per object to not oversimplify the land cover classification. The tool then compared the training sample spectral signatures to the segmented objects using a support vector machine approach to produce a classification of the study area (Oldeland et al. 2021). I had the option to manually reclassify mis-classified objects within the wizard but chose not to due to the scope of this project and the lack of field verified sample points. Typically this step would be done to correct any misidentifications that the user could positively identify. Finally, an accuracy assessment was conducted using 300 randomized points (Figure 3).

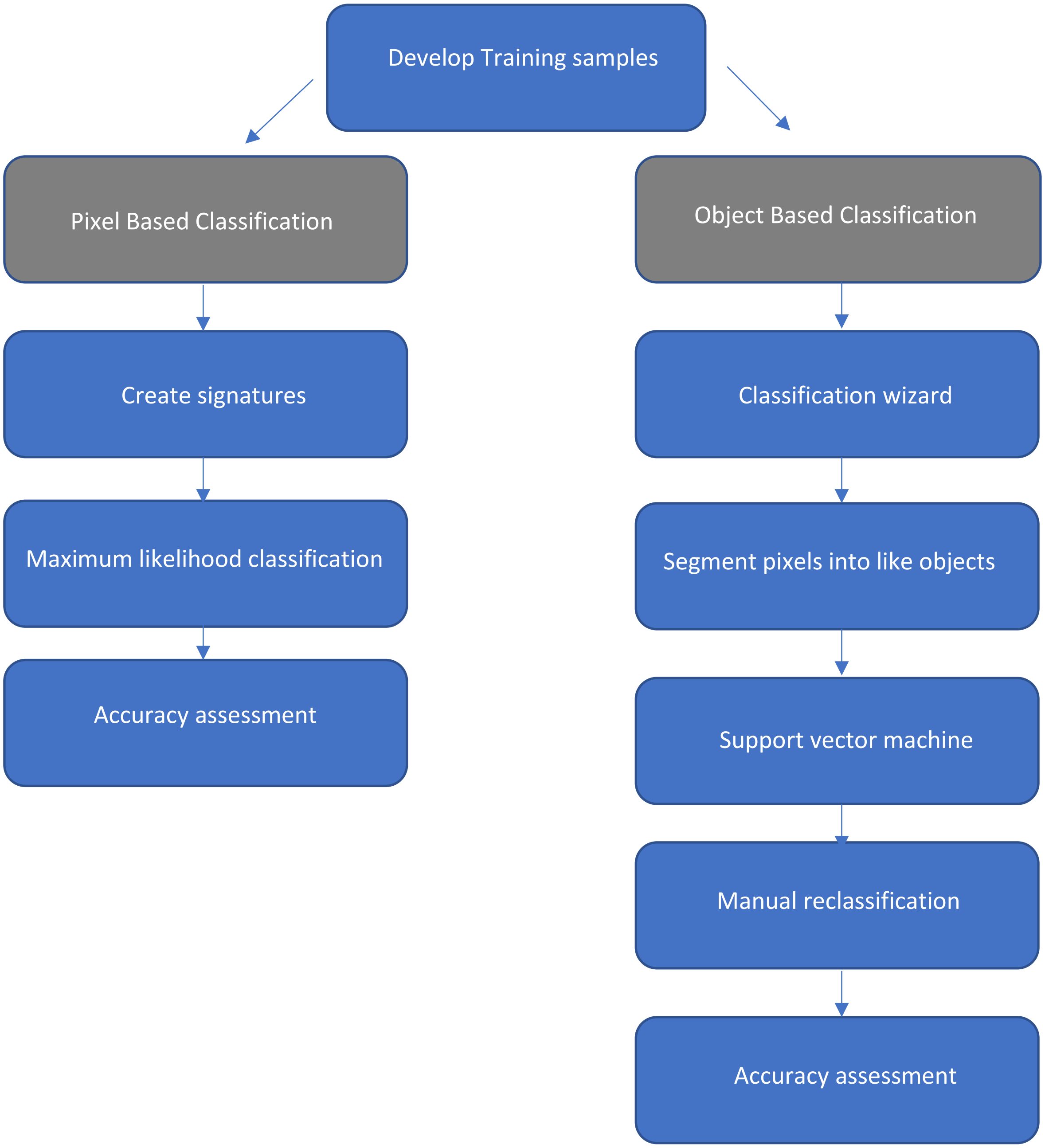


*Figure 3: Vegetation classification process. Two separate processes were chosen to increase potential for accurate vegetation classification. Both pixel-based and object-based methods are established remote sensing techniques for this purpose.*

## 3D data analysis

Three-dimensional data analysis is a powerful tool to evaluate the vertical structure and condition of salt marsh restoration. LiDAR, the established method to capture 3D data, has been used to develop monitoring datasets such as elevation modeling. Active laser light return times are calculated and used to model point clouds (Dubayah and Drake 2000). Similarly, UAS imagery can be used to develop points clouds using photogrammetry. The results of this technique can be used to calculate vertical distribution of points which provides enough detail to create surface elevation models (Dai et al. 2018).

Elevation modeling is a key tool used in the restoration design process. There are similar modeling terms that are often used interchangeably or are often confused with each other. In Table 2, I defined key terms of elevation models often derived for environmental monitoring.

*Table 2: General key 3D models derived from point cloud data (GIS Geography 2021)*

| General 3D elevation models | | |
|---|---|---|
| Digital Elevation Model | DEM | 3D representation of only the land surface elevation above mean sea level |
| Digital Terrain Model | DTM | Similar to a DEM, this layer represents land surface elevation, but is differentiated using augmentation by vector data that includes natural features such as ridges or rivers |
| Digital Surface Model | DSM | 3D representation of elevation including surface features such as trees, buildings, and other features |
| Normalized Digital Surface Model | nDSM | Derived from the difference of DSM and DEM (DSM-DEM) to determine the height of a feature above the land surface |

### Digital terrain modeling

A bare earth model or digital terrain model (DTM) was developed using point cloud data gathered using the UAS and analyzed using the Site Scan software (Esri 2020). Ground points were isolated from the point cloud and used to create a raster (Figure 4). Void space was filled between ground points using a natural neighbor interpolation method.

Using this same data, I applied a hillshade technique to the DTM and assigned a single unique color scheme to the model. The hillshade tools creates a shaded relief by artificially considering an illumination source. This creates a shadow effect giving 3D texture to the visual model.

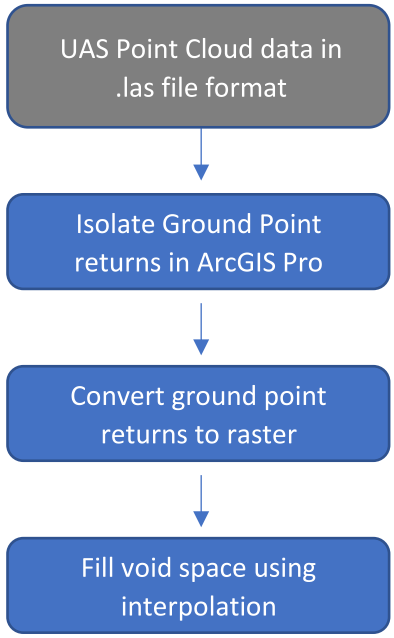


*Figure 4: DTM modeling requires ground points to be filtered out using ArcGIS Pro software*

## Digital surface modeling

I created a Digital Surface Model (DSM) using a dense point cloud provided by SFEI (Figure 5). Using ArcGIS, I filtered out surface points within the point cloud representing the topmost surface. These points were converted into a raster using a natural neighbor interpolation method to fill in voids between points.

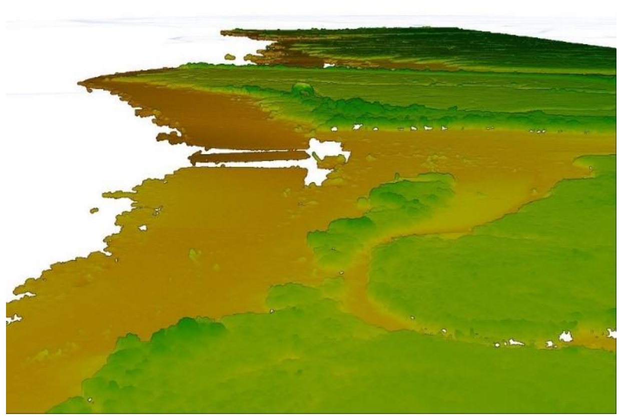

*Figure 5: Three-Dimensional view of DSM point cloud developed from UAS data points*

## Channel modeling

Understanding channel formation and placement helps restoration practitioners evaluate the maturation of restoration projects. LiDAR is typically employed to determine stream locations and watersheds on upstream riverine systems. The same technique that is applied to that modeling can be used to determine tidal channel locations within a marsh. UAS derived point clouds can be employed in much the same way to predict channel locations. This allows practitioners to develop these models using one UAS dataset instead of relying of traditional LiDAR returns.

Using tools within ArcGIS Pro, channel networks can be modeled (Figure 6). The DTM raster was cleaned up and sinks removed using the Fill tool to create a depressionless DTM. Flow direction was then calculated by calculating negative change in z-value over distance. Next, flow accumulation was calculated. This used the flow direction to determine the number of pixels that would drain into each other pixel. The ArcGIS con tool allowed me to set a number value to a channel network and a null value for everything else that is not within the channel. For instance, a raster value of 1 = a channel network and a value of 0 = background non-channel. Lastly, a stream channel was created into a vector feature class allowing me to visually see channel networks and incorporated into other land modeling.

Tidal channel order could also be determined using a similar method (Figure 7). This allowed me to clean up the data, eliminating small and short primary unconsolidated depressions. Flow accumulation is again calculated. This raster data was queried to remove smaller values to the accumulation layer. The raster calculator determined all values above and below my determined threshold, being a value of 75 for this modeling. Values above were given a new value of 1 and the rest a value of 0. This reduced the number of possible tidal channels to represent the major channel complexes instead of small unconsolidated channels. Using the stream order tool in ArcGIS Pro, the raster results and flow direction were used to create a raster layer of stream order according to the amount of cell values running into each tidal channel cell. This raster then was then converted into a feature class polyline.

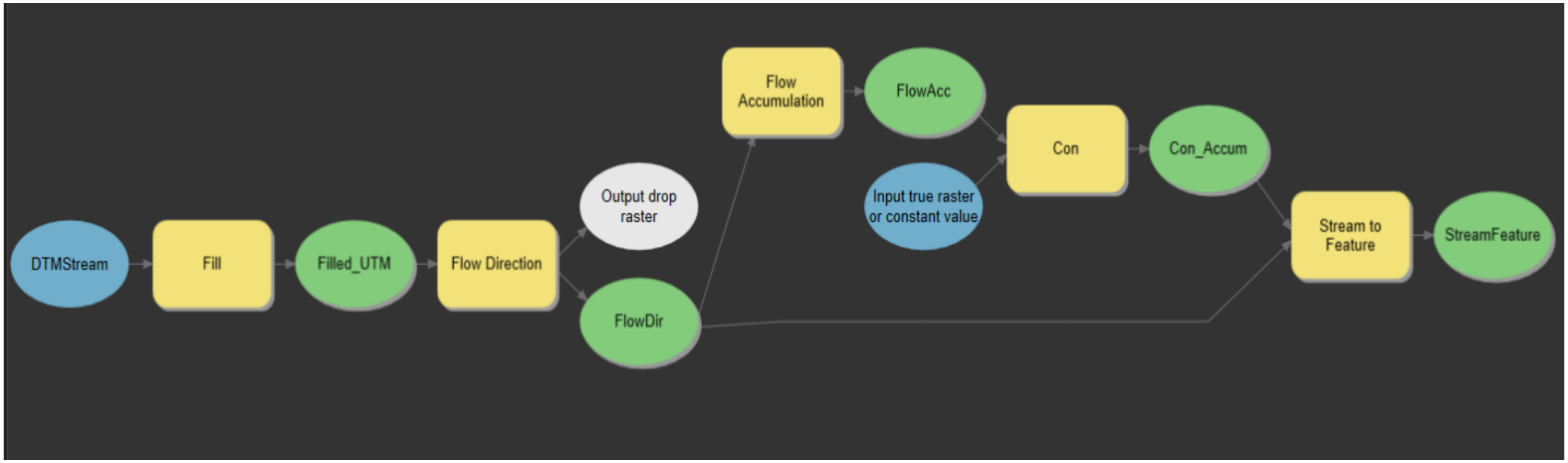


*Figure 6:ArcGIS Pro workflow for channel prediction. Outcome product is a layer file of predicted channelization networking within the marsh complex based upon flow direction between individual pixels.*

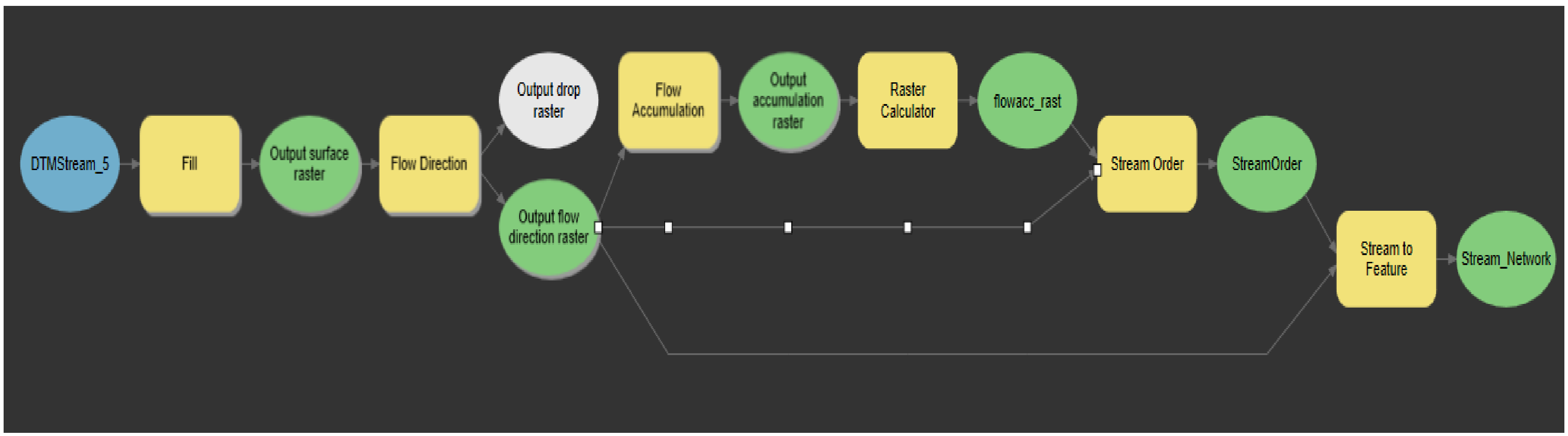


*Figure 7: Stream order calculation methodology. This method requires user input to create a tidal channel layer. To present only lower order channels, higher order predicted channels can be removed during the process to provide only data on major channels complexes*

## Estimating vegetation height

Using the DSM and DTM raster layers, a new nDSM raster was be created estimating vegetation height. These two datasets were needed to determine vegetation height. The DSM related to the topmost surface, including the top of vegetation biomass. The nDSM or height of vegetation was calculated using DSM-DTM (Pinton, Canestrelli, Angelini et al. 2020). Using Inverse Distance Weighted (IDW) interpolation, point cloud data were then transformed into a raster value (DiGiacomo et al. 2020). The smoothed raster values represented the top elevation of detected vegetation. I changed the symbology to a stretch type and manipulated to display height differences more clearly.

# Chapter 4: Classification of Land Cover

Land classification monitoring is a useful tool for to understand the pre-conditions and evolution of salt marsh restoration projects. Classifying land cover provides insight into the change of cover classes such as the spread of planted salt marsh vegetation in newly constructed wetlands. This metric is important as a monitoring tool because vegetation cover is directly linked to salt marsh vegetation health and resiliency. In an era of SLR, this is especially important because vegetation presence and succession is directly linked to tidal inundation (Olff et al. 1997). Understanding land cover classification is an essential tool that allows restoration practitioners to better understand the system as it changes over time and to inform adaptive management should the restoration need it.

## *Vegetation Classification: Case Study*

The case study that I conducted produced two separate land cover classification maps, pixel based (Figure 8) and object based (Figure 9). Both maps produced differentiation of major cover types. Basic RGB UAS data was successful in creating these classifications. Further analysis and computer modeling changed the outcomes and accuracy levels. For restoration practitioners looking to gauge vegetation trends UAS can provide useful amounts of information.

The first method, pixel based supervised classification, produced a more detailed analysis (Figure 8) because each pixel is treated as a unique data point when comparing to the training samples. However, this level of detail can create a "salt and pepper" effect where many differently classified pixels dot the landscape (Weih and Riggan 2010) and create a more fragmented classification that can provide a more detailed but ultimately less useful map for restoration practitioners.

When examining the map produced, vegetation zonation is clearly demarcated (Figure 8). Cordgrass and Cordgrass/Pickleweed are the dominant feature classes which anecdotally matches my vegetation knowledge of the site conditions. In addition, the major channel complex is easily distinguishable from the surrounding marsh plain. The level of detail provides a great overview of the current site conditions and can easily be employed by practitioners.

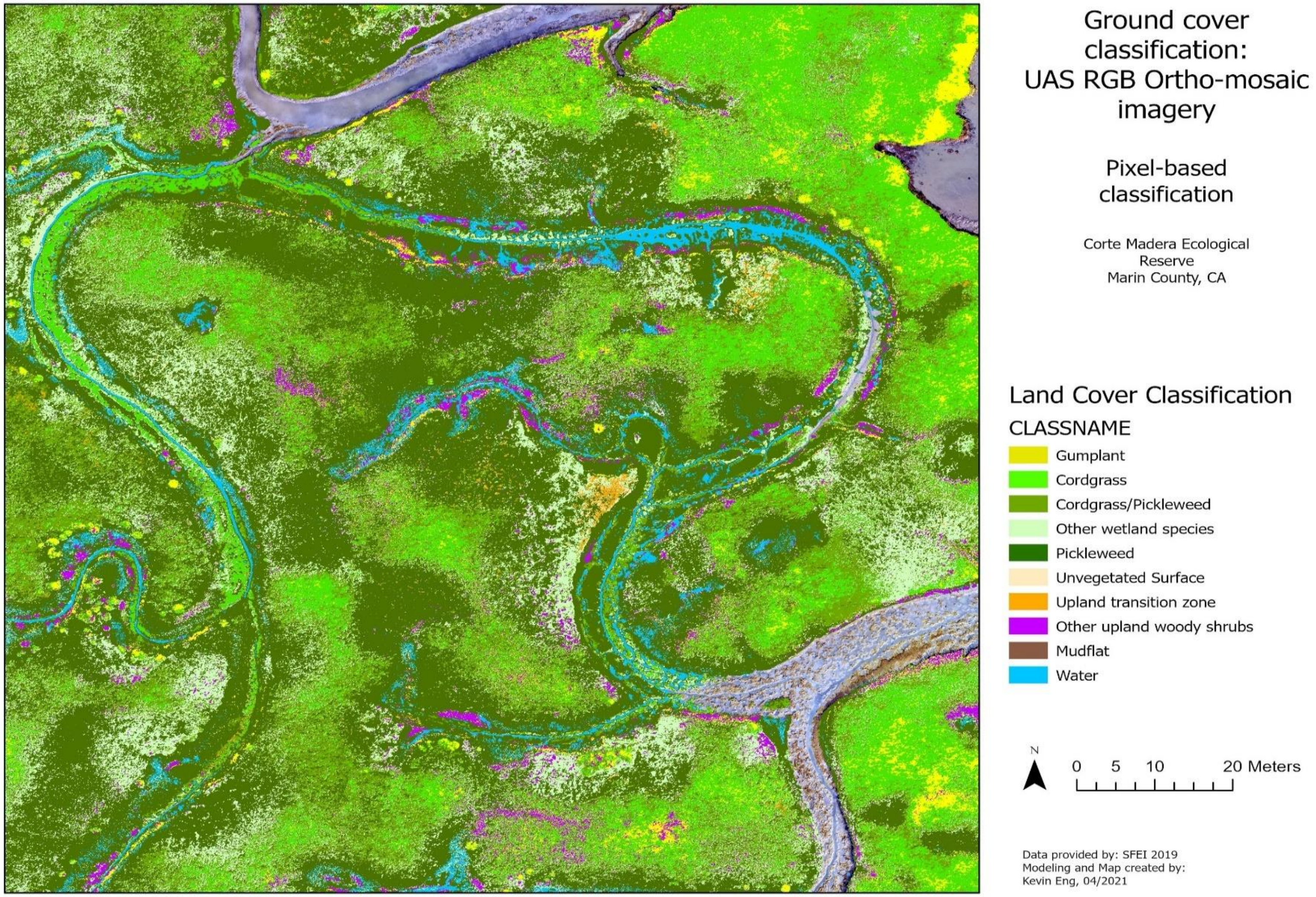


*Figure 8: Pixel based land cover classification conducts analysis on a pixel-by-pixel basis. This can create a highly detailed classification which provides more data for vegetation comparison but may overwhelm users with too much information needed for landscape level decision making.*

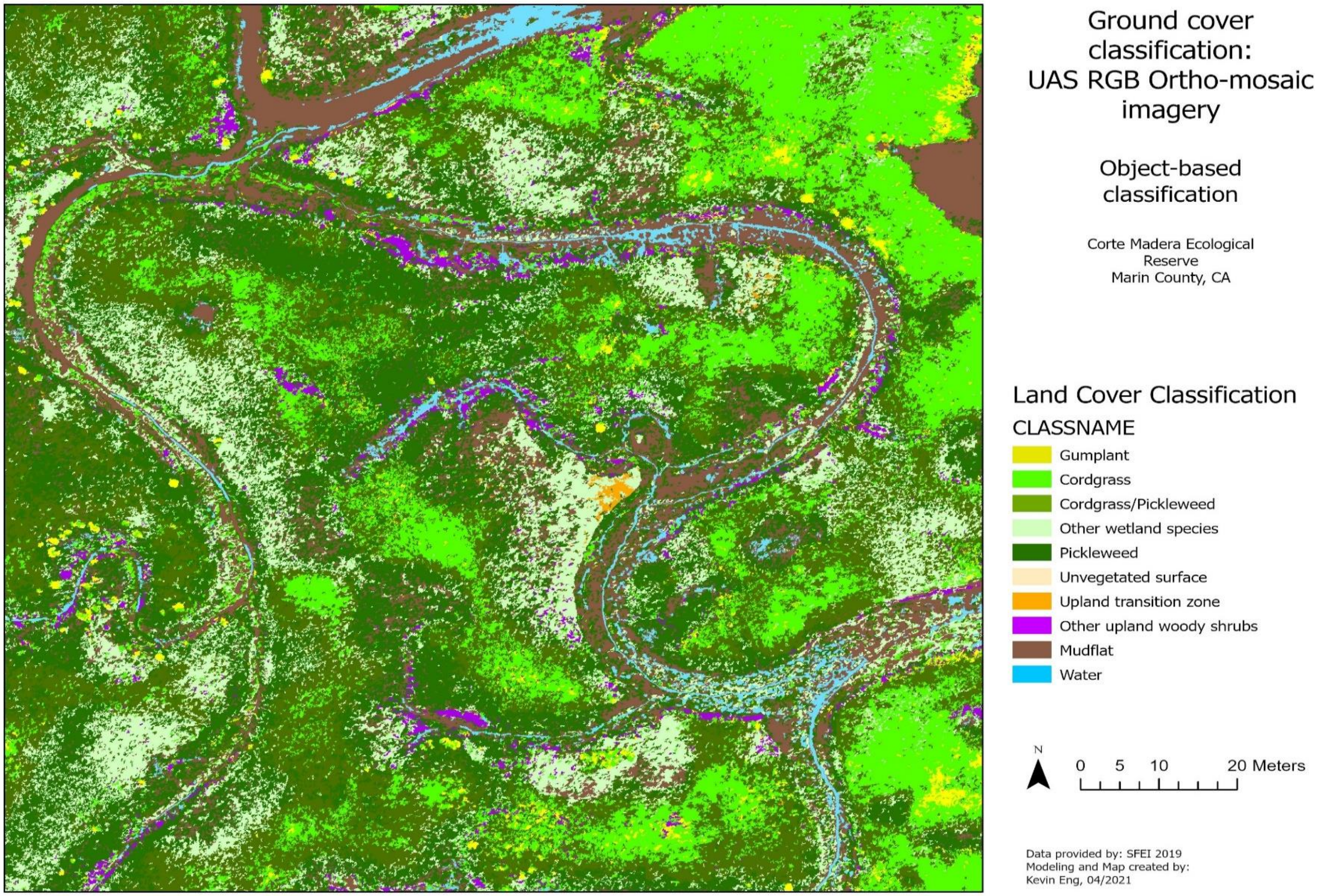


*Figure 9: Object-based classification conducts analysis on groupings of segmented pixels. This can create a more accurate classification than pixel-based classification. These accuracy results can be increased if more data, using multispectral imagery, is employed.*

The second classification method I employed was an object-based classification which groups like pixels together prior to classifying them (Figure 9). This mapping method produced more "other wetland species" classifications. This may better capture non-dominant species than the pixel-based classification. As before, the channel complex is clearly distinguishable as are differing land cover classes. This approach also provides great overview visual data that is useful to practitioners who would benefit from monitoring land cover changes over time.

High resolution RGB imagery alone can produce basic, yet, useful land cover classification. Pixel based and object-based classifications using only RGB imagery resulted in an overall accuracy of 62% vs 73%, respectively (Table 3). When examining the results of both methods, the greatest confusion of signatures is between pickleweed and mudflats. This is probably caused by similar spectral signatures, possibly from mud covering the low growing plants or just not enough data to more accurately distinguish between the two. Object-based classification is often seen to be more accurate when creating land cover classification maps, however, pixel-based classification provides higher resolution which is important if differentiation small species level individuals is important (Aldous et al. 2020, Correll et al. 2019, Michez et al. 2016).

*Table 3: Accuracy comparison between two classification methods. Using RGB only UAS data, the greatest accuracy was produced using the object-based approach. This is generally consistent with other published literature in similar habitat types.*

| Accuracy comparison: Object-based vs. Pixel-based | | |
|---|---|---|
| Method | Overall accuracy | Kappa value |
| Pixel-based Maximum Likelihood | 61.70% | 0.508 |
| Object-based Random Forest | 72.80% | 0.661 |

Certain cover classes have much higher accuracy when only using RGB. For instance, water, mudflat, upland transition zone and unvegetated soils all had over 90% accuracy where upland shrubs, cordgrass/pickleweed, and other wetland vegetation all had accuracy below 50% (Table 4). These results suggest that RGB values provide adequate data to conduct classification where signatures are unique such as bare earth. However, in more similar spectral profile classes, RGB has a difficult time differentiating between the classes. Multispectral data has been seen to improve upon these similar spectral classes (Boon et al. 2016, Fraser et al. 2016). Depending on the needs of the restoration project, RGB UAS data may provide enough information at a lower cost and easier entry into remote sensing data collection.

*Table 4: User accuracy by cover type. Water returns are assessed at 100% accuracy whereas upland woody shrub vegetation class returns are only 20% accurate.*

| Object-based classification: User accuracy by classification type | |
|---|---|
| Classification | User Accuracy |
| Water | 100% |
| Mudflat | 92% |
| Cordgrass | 70% |
| Cordgrass/Pickleweed | 44% |
| Pickleweed | 75% |
| Other wetland vegetation | 40% |
| Gumplant | 60% |
| Upland transition zone | 90% |
| Upland woody shrubs | 20% |
| Unvegetated soils | 90% |

## Benefits of UAS in Land Cover Classification

UAS can support field surveys by providing as needed aerial surveys. Just-in-time aerial imagery refers to imagery captured as close as possible to the optimal collection period for the project. Using these data in land cover classifications can provide similar land cover estimates to field based observations conducted concurrently. For example, Oldeland et al (2021) found that UAS object-based classification provided similar cover estimates to field based mapping of Sea couch grass (*Elymus athericus*), a native salt marsh grass to central Europe (Figure 10). Multispectral imagery was employed for this study and segments were limited to 20 pixels in size creating relatively small objects. This allowed for higher spatial resolution but can be time-consuming and require great amounts of computer processing power. The field-based estimation produced a 6.29 ha cover estimate of Sea couch grass while UAS imagery produced a 6.22 ha cover estimate within the same site boundaries. This is an important study comparing UAS remote sensing and in situ monitoring because it highlights drawbacks with both approaches. Field based monitoring tended to overestimate cover due to physical limitations of viewing vegetation over large polygons whereas UAS remote sensing tended to misclassify vegetation cover due to spectral variations (Oldeland et al. 2021).

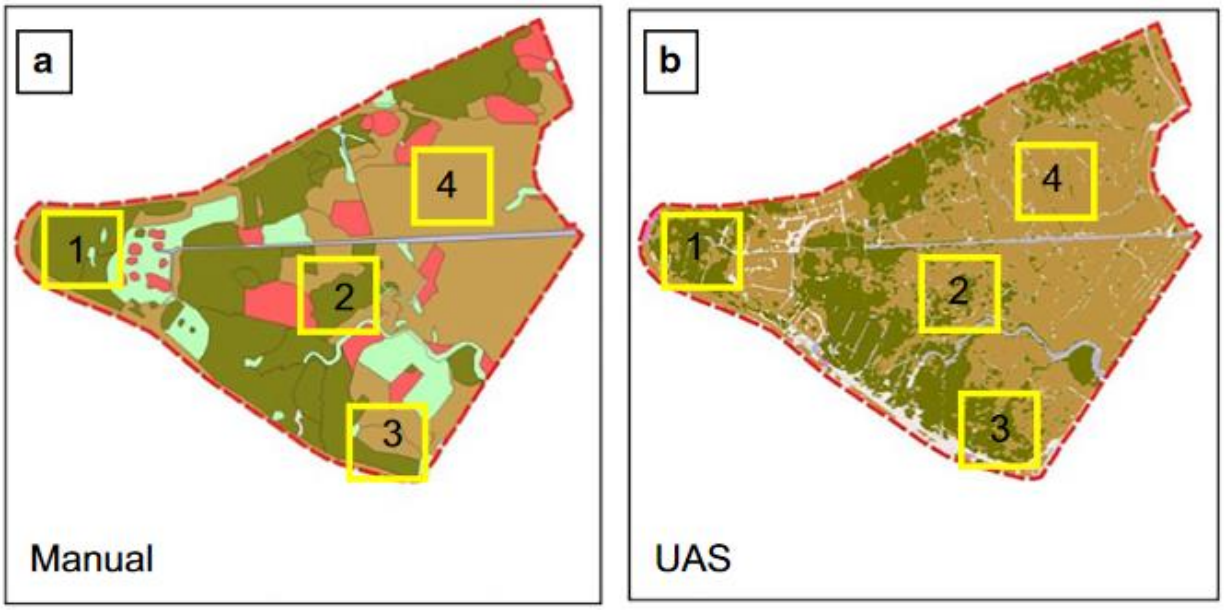


*Figure 10: Comparing manual vegetation cover mapping vs. UAS derived remote sensing. Manual vegetation monitoring is more generalized and can be subject to over estimation. UAS remote sensing is more detailed but is subject to misclassification of individual pixels. (Oldeland et al. 2021)*

## Needs Assessment for Upgrading From RGB

Project needs dictate the necessity for upgrading UAS platforms from the basic entry level. The specific goals of a restoration project will determine if RGB is sufficient or if commercial grade technology is required. If vegetation indices or more specific species level identification are required for the project, RGB alone may not be the technology required. However, if a monitoring project requires counting of individuals in of cover class, for instance woody salt marsh species compared to grasses, then RGB does provide enough data (Hassler and Baysal-Gurel 2019). Upgraded platforms can carry more expensive and specialized sensors such as multispectral or LiDAR. However, these sensors are very expensive compared to consumer grade electronics, often costing tens of thousands of dollars. The limitation of upgrade cost dictates the usefulness of UAS to restoration practitioners.

Vegetation classification using UAS is very dependent on the physical characteristics of the salt marsh being monitored. The more complex the system and species cover types, the less accurate the remote sensing is (Husson et al. 2016). However, in favorable conditions, high levels of accuracy are possible. Smooth cordgrass (*Sporobolus alterniflorus)* patches have been accurately classified with a 94% overall accuracy in China using UAS systems (Michez et al. 2016). This is especially true in environments where classes have very distinct spectral signatures, such as cordgrass compared to mudflat. Despite low-cost and simple sensors, RGB based UAS have obtained accuracies in land cover classifications comparable to UAS multispectral classifications (Daryaei et al. 2020). These findings occurred within studies done on terrestrial systems but advances in computer processing such as random forest algorithm contributes to improved accuracy (Daryaei et al. 2020). RGB sensors can detect differences in textures of vegetation cover. Textures can be used to identify specific species with high accuracy (Michez et al. 2016). The low cost of RGB sensors compared to multispectral creates a need to develop better software and techniques to evaluate classification types.

Multispectral data are more expensive to acquire but can be more useful depending on the research question. Instead of three bands of data of RGB, multispectral sensors usually capture between 5 and 12 bands (Hassler and Baysal-Gurel 2019). UAS can be fitted with these sensors which expand the detection capabilities of the platform to the same levels as satellite imagery (Al-Ali et al. 2020). The drawbacks are the cost of upgrade over entry level UAS and the limited battery life compared to orbital systems. UAS outfitted with multispectral sensors can cost $10,000 or more for the unit (MicaSense 2021). Small or single flight restoration projects may not warrant such a high cost. However, when the scale of the project, repeatability, or higher accuracy are needed, multispectral UAS data can be an invaluable asset.

The quality of UAS multispectral airborne data is closely comparable to handheld spectral sensors. These data have a strong 1:1 correlation to in situ reflectance values in wetland habitats (Figure 11) (Doughty and Cavanaugh 2019). This makes UAS detection of multispectral data highly accurate. Vegetation indices, spectral transformations of multiple data bands, enhance different contribution levels of each of those bands. Changing the intensity value of each band in a series of data bands allows different values to be highlighted in an easy to view manner. For example, the normalized difference vegetation index (NDVI) index calculates differences in near-infrared (NIR) and red reflected light energy. A healthier plant absorbs more red light and reflects more NIR. When a project relies on this level of detail, multispectral analysis is key to accurate analysis and requires upgrading from basic sensor technology.

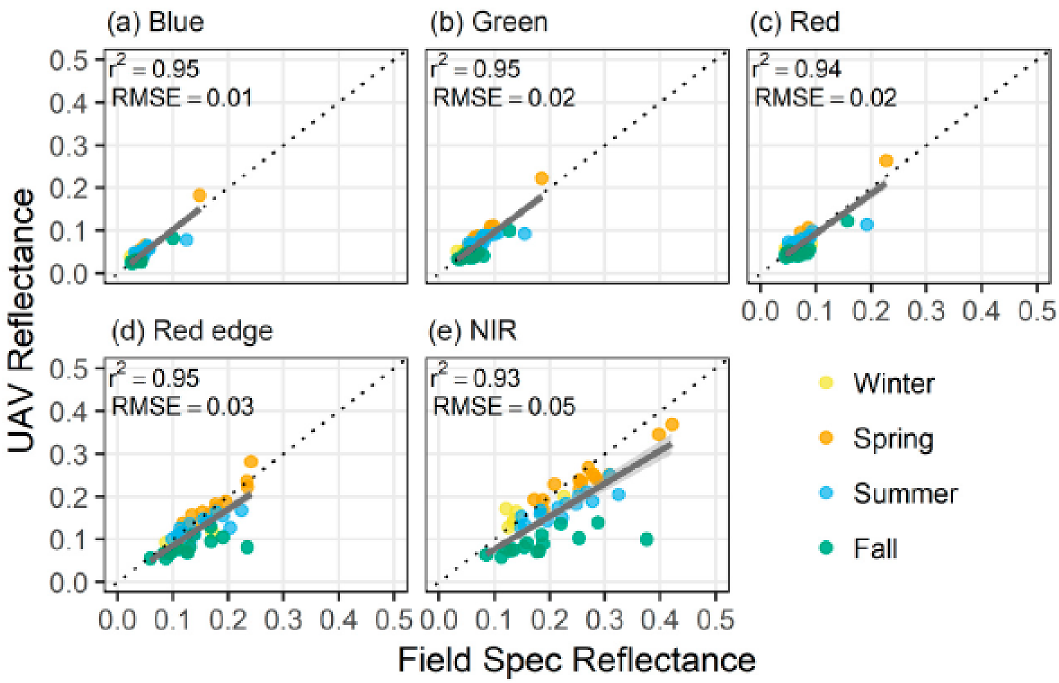


*Figure 11: UAS derived reflectance values show strong correlation to in situ reflectance values in the visible spectrums. This allows for accurate land cover classifications to be developed using spectral signatures. (Doughty and Cavanaugh 2019)*

# Benefits and Drawbacks of UAS Platform

UAS technology provide a great additional tool for ecological restoration monitoring. However, UAS are not a one stop shop for data collection. Additional benefits of UAS also must be weighed against drawbacks to this technology outside of cost. Negative aspects of UAS include limits in usability at large scales, additional expertise, and specialized software. Positive aspects include compatibility with established technologies and methodology, temporal flexibility, and a unique vantage for qualitative observations.

## Addition Expertise Needed

Acquisition of imagery leads to increased data collection time and expertise when employing UAS as compared to purchasing ready to use commercial satellite imagery. UAS requires the user to collect their own data, post process it, and conduct quality checks prior to analysis. This increases time and cost. The benefit of temporal and spatial resolution may outweigh the extra time and effort needed. This, however, is case specific according to project goals. As a new technology, software support development is crucial to lowering logistical costs and generalize this technology to a broader user base.

## Scope, Scale, And Time

UAS have both benefits and drawbacks in relation to project scope, project scale, and time. Large satellite-based land cover classifications aim to generalize classes over the landscape. UAS provide the ability to focus on small areas within these generalized classes that would otherwise be missed or grouped into other classes by satellite data (Daryaei et al. 2020). The unparalleled spatial resolution is a major benefit to UAS. While not appropriate for large scale mapping, UAS are able to capture minute details and changes that would otherwise go unobserved (Boon et al. 2016). In salt marsh pannes, algal blooms can be misidentified as rooted salt marsh vegetation. Understanding the system and verifying with extremely high-resolution imagery can allow the analyst to correctly reclassify these areas. Combined with user background information and UAS derived imagery, anomalies can be better explained and monitored.

In addition to improved spatial resolution, the at-will repeatability of UAS flights provide higher temporal resolution that might be required in intensive monitoring projects or to better capture seasonal fluctuations that might be missed using ground surveys or satellite based imagery (Al-Ali et al. 2020, Daryaei et al. 2020). In salt marsh habitats, this is especially useful due to the diurnal cycles that can cover the marsh plain with water. Observations at different tidal inundations can provide great insight into appropriate elevation and hydrology for restoration design.

UAS can be implemented more effectively than satellite data due to the flexibility of flight times. For instance, knowledge of phenological stages of flowering plants can provide a more optimal timing for class differentiation of species if flowers are produced at seasonal times (Michez et al. 2016). In Bay Area salt marshes, Marsh gumplant (*Grindelia* sp.) produce bright yellow flowers in the fall which is very distinct from most all other salt marsh species. These distinct signatures can help to differentiate Marsh gumplant with higher accuracy.

Negatively, remote sensing using UAS data can produce unpredictable results stemming from data being collected from a distance. Land cover classification accuracy between cover classes often differ due issues such as similar spectral signatures, user error in identification of training samples, or corrupted data. For instance, classification using UAS for three species, *Impatiens glandulifera*, *Heracleum mantegazzianum*, and *Fallopia sachalinensis/Fallopia* *japonica* yielded a 72%, 97%, and 68% accuracy respectively (Michez et al. 2016). *Heracluem mantegazzianum* was accurately classified while the two other species were not. These inaccuracies do not provide great confidence in the entire classification model.

Selecting between satellite and UAS derived remote sensing is truly subject to the goals and requirements of the specific project. Scalability and resolution are the two main factors that drive the preference of one technology over the other. Many studies conducted within the past five years conclude that with current technology and limitations, UAS cannot outright replace satellite derived or in situ data collection but act as complementary technology (Hassler and Baysal-Gurel 2019, Al-Ali et al. 2020).

## Increase Benefit in Conjunction Other Remote Sensing Platforms

In the ecological restoration field, it is rare to only utilize one tool to gather all the necessary data for monitoring. Combing technologies and methodology often provide the most complete data. For instance, UAS data can improve the accuracy of satellite imagery analysis (Hassler and Baysal-Gurel 2019). The high resolution of UAS in smaller areas provides the ability for analyst to better identify land cover types which help to create training samples for satellite based remote sensing. In arid desert like habitat, UAS provide detailed training samples of riparian vegetation that would otherwise be misclassified on the landscape level (Daryaei et al. 2020). A scenario in salt marsh restoration for this technique would be to use UAS data to classify newly colonized vegetation communities that might be misrepresented as mudflats without vegetation. These data can be used to train larger satellite data over large restoration sites. This represents a multi-temporal combined with multi-sensor approach to remote sensing to improve overall accuracy.

## A Picture is Worth a Thousand Words

UAS provide the ability for restoration practitioners to gather data quickly and provide immediate feedback to address dynamic changes in salt marshes. UAS flights and analysis can provide almost real time data that is essential to deal with adaptive management issues (Papakonstantinou et al. 2020). In addition to quantitative data collection, video and still images acquired during UAS flights can provide reference photos, qualitative observations, and inform remote sensing users about ground conditions (Boon and Tesfamichael 2017). Restoration projects rely on land cover classifications; however, funders and stakeholders respond to visual aids. A major component to successful restoration is continued public support. Visuals, both images and video, are a powerful tool to provide qualitative observations (figure 11).

*Figure 12: Qualitative observations are equally as important to restoration managers. Stakeholders and practitioners often acquire more positive feedback from a simple aerial photograph than statistics and numbers. Restoration of salt marshes is a balance of scientific study with achievable goals set by the public (Kerr 2019)*

Understanding your project goals will determine the usefulness of UAS to you. In consideration of land cover classifications, cost and efficiency are best evaluated by scale. Satellite data is more cost effective in large land classifications at broad scales. The cost and effort per acre are reduced. However, if the goal of the project requires more detailed information at smaller scales, than UAS can provide better value. Perhaps, then the best scenario at this time is a combination of the two technologies where UAS can help to improve satellite data by filling in the finer scale details.

# Chapter 5: Three-Dimensional Data Monitoring

Salt marsh evolution prior and post restoration success depends heavily on ground elevation compared to tidal waters. Diurnal tidal cycles flood marshes with saline water, transport and deposit sediments, and control habitat structure and development. These functions are directly linked to the resiliency of salt marsh habitats to stressor such as SLR (Kirwan and Guntenspergen 2010). In addition, frequency of inundation controls vegetation colonization and elevation range (Silvestri et al. 2005, Balke et al. 2016). Three-dimensional data monitoring and remote sensing can provide insight into these ecosystem functions over site wide scales.

UAS technology is the newest and rapidly evolving method for 3D data collection. More traditional remote sensing techniques using LiDAR technology, provide high accuracy while providing data over the entire study site (Collin et al. 2010). The drawbacks to LiDAR are costs involved with manned aircraft surveys and difficulties in repeated monitoring events. UAS technology provide reasonable 3D results as compared to LiDAR and can be a reliable alternative method for data collection (Yuan et al. 2018).

In this section, I aim to address the question whether UAS can provide enough high-quality 3D data to help restoration practitioners better understand the vertical structure of salt marsh restorations. Data analysis that is useful for improving the understanding of the vertical structure of salt marshes includes ground elevation and elevational relationships, hydrologic feature modeling, and vegetation characteristics. Using UAS point cloud data, I provide proof of concept evidence to validate published literature for these applications of 3D data sets:

- Bare earth modeling
- Marsh surface elevation
- Hydrological feature monitoring
- Vegetation height

Comparing my findings to published literature I seek to give clear examples of the usefulness and benefits of UAS technologies for improved monitoring of salt marsh restoration.

## Marsh Surface Elevation Monitoring

Understanding marsh elevation for restoration of marshes is important as a preemptive design measure in addition to tracking sediment accretion. Salt marsh vegetation is adapted specifically to certain elevations where tidal influences have greater or lesser effect (Silvestri et al. 2005). Surface elevation modeling is a remote sensing technique that connects individual data points to create a continuous surface model. Digital elevation models can predict vegetation classes of salt marshes according to presence at specific surface elevations. Restoration ecologists often employ surface elevation modeling to better understand the system and track changes over time.

### Lidar Technology

LiDAR data provides detailed vertical points that can be used to create highly accurate elevation models. These data are generally gathered using specialized equipment aboard aircraft tasked for general projects and over large land areas. GPS accuracy, along with closely calibrated equipment, allow for accurate positioning ranging from 0.5 m to 3 m horizontal accuracy depending on platform and data analysis methodology (Getmapping 2021). Remote sensing using LiDAR data is a cost-efficient tool to evaluate ground elevation over large landscape levels when compared to field-based methods. Examining the estimated cost difference between field-based data collection to LiDAR remote sensing in forest ecosystems shows that LiDAR's average cost is $2.29 / acre for 90,000 acres while field based study's average is $2.46/ acre for 5,280 acres (Hummel et al. 2011). Although, not directly comparable due to scope, LiDAR does provide an advantage when conducting landscape level monitoring.

### Drawbacks to Manned Aircraft Based LiDAR

Although LiDAR based elevation models are ubiquitous in the environmental management field, the technology is not without fault. The drawbacks to manned aircraft LiDAR systems are scope dependent cost, resolution, and poor laser penetration in dense vegetation (Hladik and Alber 2012). LiDAR imagery requires specialized equipment, manned aircraft, correct weather windows and tidal conditions to be optimally implemented. The logistics and inherent cost to bring these systems online for small projects hinders repeatability. Often LiDAR data are very broad and expand over large land areas for multiple projects and do not specifically target single project boundaries. For instance, only two publicly available LiDAR data sets from

USGS are available for my study area, 2014 and 2020 (United States Geological Survey 2021). It is not uncommon to have only one LiDAR dataset available for an entire restoration project, limiting collection of useful monitoring data.

Salt marshes are affected by environmental variables, many of which are difficult to predict. For instance, erosion due to wind driven wave action can change as-built surface elevations. Without repeated elevation modeling, it is difficult to determine the true extent of elevation loss prior to vegetation establishment. Real time data allows practitioners to evaluate this disturbance and mitigate the process immediately (Pethick 2002). Ultimately, this can culminate in salt marsh restoration failure or the need to spend more money. For instance, it would be difficult to measure the rate of yearly marsh loss due to shoreward erosion within my study area using LiDAR due to lack of annual LiDAR data. Marsh loss would need to be calculated and averaged using the 2014 and 2020 datasets or augmented with less precise visual estimations using aerial imagery. This could lead to an incomplete record of meteorological effects on erosion. California experienced a high amount of precipitation in 2017 after years of draught. Without yearly data, there is no way to determine if increased high tides brought on by intense flash urban runoff during this period increased the rate of erosion. Not being able to fully understand this stressor would set up for less than desirable erosion mitigation efforts to curb further erosion pressure.

LiDAR data acquisition often aim to gather elevational data over large landscapes which limit the vertical resolution due to data storage and processing limitations. Manned aircraft LiDAR systems typically have a 1 m spatial resolution (Pinton, Canestrelli, Wilkinson et al. 2020). High vertical spatial resolution is extremely important in remote sensing analysis of salt marsh environments. While a 1.0 m accuracy provides great resolution on the landscape level, it may not be suitable for salt marsh habitats where micro changes in elevation (e.g., 10 cm) can change habitat communities.

In addition to temporal and resolution issues, LiDAR data collection is currently not as accurate as in situ measurements due to physical limitations of laser penetrance of dense vegetation canopy. Salt marshes often included both bare ground and short dense vegetation. Due to the density of these low-lying vegetation and small differences in height off the bare earth, LiDAR returns may confuse vegetation with ground points (Wang, C. et al. 2009, Pinton, Canestrelli, Wilkinson et al. 2020). When this happen, the top of vegetation is misidentified as the ground surface culminating in over estimation of elevation modeling and an underestimation of vegetation surface elevations (Zhou et al. 2018, Pinton, Canestrelli, Wilkinson et al. 2020). At salt marsh restoration sites, this underestimation poorly captures the true condition of the site. Elevation derived metrics such as vegetation height and biomass are then less desirable to evaluate marsh restoration success.

To overcome for these limitations, LiDAR-derived DEM data must be corrected using algorithms or manual methods. Hladik and Alber (2012) published a study where overall mean error using LiDAR data for salt marsh vegetation elevation modeling was 0.10 m with individual species having errors up to 0.27 m (Table 5). After correction, mean error was reduced to 0.01 m as compared to in situ ground sampling points. (Hladik and Alber 2012). These corrections are important but are usually unique to each situation and require field verification to determine if they are accurate.

In addition to penetration issues for low lying vegetation, tall grass species also display underestimation error. Taller grass species are less dense at the very top of their biomass. This reduced density makes it difficult for LiDAR laser beams to hit individual blades of grass and provide accurate returns, especially when spatial resolution is too broad.

*Table 5: Unmodified vs. corrected vegetation heights. Mean accuracy errors displayed by marsh species. Different species have differing errors due to physical characteristics preventing accurate LiDAR penetration to ground. (Hladik & Alber, 2012)*

| Cover class | Mean (m) | N | SD (m) | SE (m) | RMSE (m) | FVA (m) | 95th percentile (m) | *p*-value |
|---|---|---|---|---|---|---|---|---|
| *Unmodified DEM* | | | | | | | | |
| Tall *S. alterniflora* | 0.27 | 66 | 0.15 | 0.02 | 0.31 | 0.61 | 0.52 | <0.001 |
| Medium *S. alterniflora* | 0.09 | 62 | 0.06 | 0.01 | 0.11 | 0.22 | 0.18 | 0.007 |
| Short *S. alterniflora* | 0.03 | 72 | 0.04 | 0.01 | 0.05 | 0.10 | 0.10 | 0.073 |
| *S. virginica* | 0.04 | 49 | 0.05 | 0.01 | 0.07 | 0.13 | 0.14 | 0.024 |
| *D. spicata* | 0.05 | 10 | 0.03 | 0.01 | 0.06 | 0.11 | 0.09 | 0.001 |
| *B. maritima* | 0.04 | 15 | 0.04 | 0.01 | 0.05 | 0.10 | 0.10 | 0.032 |
| Salt pan | 0.01 | 26 | 0.04 | 0.01 | 0.04 | 0.07 | 0.06 | 0.815 |
| *J. roemerianus* | 0.10 | 35 | 0.08 | 0.01 | 0.13 | 0.25 | 0.24 | 0.007 |
| *B. frutescens* | 0.12 | 15 | 0.09 | 0.02 | 0.15 | 0.29 | 0.24 | 0.001 |
| Overall | 0.10 | 350 | 0.12 | 0.01 | 0.16 | 0.31 | 0.37 | <0.001 |
| *Modified DEM* | | | | | | | | |
| Tall *S. alterniflora* | 0.05 | 66 | 0.18 | 0.02 | 0.18 | 0.36 | 0.33 | 0.691 |
| Medium *S. alterniflora* | −0.03 | 62 | 0.06 | 0.01 | 0.07 | 0.13 | 0.06 | 0.068 |
| Short *S. alterniflora* | −0.03 | 72 | 0.04 | 0.01 | 0.05 | 0.10 | 0.04 | 0.131 |
| *S. virginica* | −0.01 | 49 | 0.05 | 0.01 | 0.05 | 0.10 | 0.08 | 0.515 |
| *D. spicata* | −0.02 | 10 | 0.03 | 0.01 | 0.03 | 0.07 | 0.02 | 0.168 |
| *B. maritima* | −0.01 | 15 | 0.03 | 0.01 | 0.03 | 0.06 | 0.04 | 0.981 |
| Salt pan | −0.03 | 26 | 0.04 | 0.01 | 0.05 | 0.10 | 0.02 | 0.416 |
| *J. roemerianus* | −0.06 | 35 | 0.08 | 0.01 | 0.10 | 0.19 | 0.07 | 0.125 |
| *B. frutescens* | −0.01 | 15 | 0.09 | 0.02 | 0.08 | 0.17 | 0.12 | 0.799 |
| Overall | −0.01 | 350 | 0.10 | 0.01 | 0.10 | 0.19 | 0.17 | 0.494 |

LiDAR technology is a great tool for large scope landscape level data collection. This is extremely valuable for broad level environmental monitoring which can aid in salt marsh restoration design and monitoring. However, the drawbacks to LiDAR technology leave room for an intermediate technology that can improve on deficiencies based on the scale of projects.

## UAS Point Cloud Technology

UAS technology provides a useful tool that bridges the gap between difficult to gather in situ monitoring and more broad scoped manned aircraft LiDAR technology. These newly developing technologies provide benefits that increase the data gathering potential for smaller scale projects while still achieving an overall remote sensing approach. Ultimately, the benefits of UAS compared to more traditional collection methods dictate that accuracy versus scale or cost must be weighed when considering the use of UAS.

Unlike LiDAR, UAS produce 3D point cloud data by comparing many overlapping still photos from different viewing angles in a process known as photogrammetry. This is the process of obtaining 3D spatial relationships between points by measuring and interpreting photographic images in relationship to each other(Dai et al. 2018, Fraser et al. 2016). This process relies on passive reflectance of light back to the UAS sensor which makes it less powerful than LiDAR which employs targeted laser light.

UAS platforms provide enough spatial resolution to produce 3D data that can be developed into DTMs. UAS data, using Structure from motion (SfM) photogrammetry, a common form of UAS photogrammetry, can provide detailed point clouds of the mud surface (Dai et al. 2018). The points attributed to surface elevation can be filtered out and then converted into a single rasterized layer representing ground elevation. Accuracy is dependent on sensor resolution and flight elevation. Spatial accuracy has been published consistently under 10 cm of horizontal error with one study finding a 7.5 cm accuracy when compared to GPS-RTK in situ monitoring (Dai et al. 2018). UAS point cloud data's horizontal accuracy is limited by several factors including limitations to light penetrance, detection of fine plant matter, sensor resolution, and image overlap during flight.

UAS point cloud data provides comparable elevation modeling results to LiDAR derived data, while improving temporal resolution. Although LiDAR is currently more accurate, image-based point cloud can still be useful for salt marsh restoration (Salach et al. 2018). UAS DTM can achieve a 0.29 m vertical resolution compared to 0.15 m LiDAR derived DEM. This allows for UAS DTM to have a 2.5 m contour while LiDAR can achieve a 1.0 m contour (Boon et al. 2016). In addition, in low vegetation systems, LiDAR derived DEM was seen to achieve a 0.11m root mean square error (RMSE) compared to UAS image-based results with a 0.14m RMSE (Salach et al. 2018). Here, RMSE is the comparison between the remote sensing derived DTM and the in situ DTM values determined using field-based measuring systems. These similar accuracies suggest that UAS DTM can be used as an alternative to LiDAR system.

The flexible nature of UAS data collection provides a benefit over traditional LiDAR. The ability for frequent repeatable data collection allows the users to take advantage of optimal temporal conditions to collect data. For instance, winter vegetation senescence can lead to better image penetration to the marsh ground surface for elevation modeling or avoidance of poor meteorological conditions to allow for better detection of the tops of marsh grasses when creating DSMs (Zhou et al. 2018, Malambo et al. 2018). UAS tools allow restoration practitioners to be more flexible and gather the necessary data on their schedule and be less reliant on third party data collection partners. This is especially important for 3D data collection that relies on manned aircraft rather than satellite data. Lastly, the continual evolution of sensor technology will soon allow for cheaper advanced sensors to be placed on unmanned aircraft at ever decreasing costs. This includes adapting LiDAR systems to UAS increasing detection capabilities but preserving UAS flexibility.

### *Proof of Concept: UAS Derived DTM*

I developed a UAS derived DTM to illustrate the ability of photogrammetry derived points clouds to collect 3-D data. Broadly, the DTM can show elevation changes and differences of the salt marsh bare ground surface while incorporating other vector data such as raised ridges. For instance, Tidal channel complexes are clearly identifiable by elevation values (Figure 13). In addition, the tops of levees, where the elevation is highest are easily distinguishable from the sloping edges (Figure 13). Higher elevation values are depicted by the orange colorization and a spectrum displays change in elevation to the lowest, displayed in dark green. Understanding elevational relationships provide management level data that can educate practitioners on appropriate locations for vegetation establishment, channel development, and slope transitions (Williams and Faber 2001).

My DTM model does highlight deficiencies of UAS data as mentioned previously. The resulting data show inaccuracies where the UAS was unable to detect points below dense vegetation. This is especially apparent where the DTM model clearly shows elevated surface where dense vegetation exists (Figure 13). This is most likely due to the inability to detect ground points below the vegetation at those locations. The modeling software automatically understands the lowest return values to be ground points. These points, which represent the lowest detections of the vegetation, are mistakenly incorporated into the raster development. These anomalies should be noted or manually corrected if this technology is to be employed.

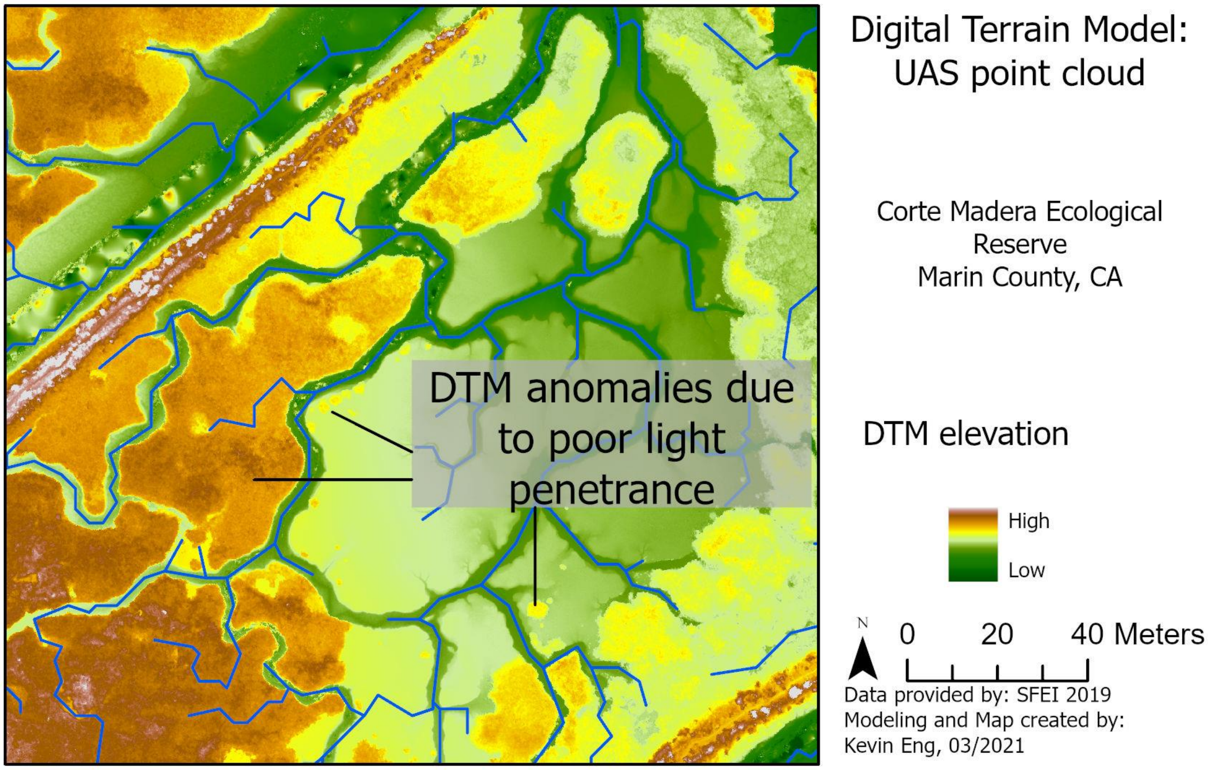


*Figure 13: DTM anomalies created by poor penetrance. UAS point cloud data is unable to detect true ground points under these patches of thick vegetation. The mis-identified points are included into the DTM raster layer but can be manually removed or filtered out with using additional data.*

## *Proof of Concept: Bare Earth Model Hillshade Manipulation*

I developed a hillshade manipulation of a bare-earth model, similar to DTM, to better visualize the underlying condition of the ground surface without vegetation cover. This manipulation provides an appealing visual representation of ground surfaces and soil attributes that would otherwise not be easily visible. In Figure 14, open mudflat is shown as a smooth surface. Evidence of soil erosion due to small tidal channel formation on the mudflat is highlighted as darker depressions. In addition, channel steepness and small topographic features are highlighted. The bank on the left side of the major channel is steeper with the right bank having a less steep elevation gain. This is important on its own to understand erosion and channel formation.

An ecologist would use these tools and knowledge of marsh vegetation to better plan for planting designs that would maximize survivorship and increase ecosystem services for the project goals. For instance, if habitat creation for California Ridgway's Rail (*Rallus obsoletus*) is a restoration goal to mitigate loss of habitat, then channel vegetation is critical for foraging habitat and cover from predation (Zhang, H. and Gorelick 2014, Rosencranz et al. 2018). Using the DTM and hillshade manipulation, channel edges can be better identified, and a planting design can be developed to encourage growth. Elevations that support Pacific cordgrass can be identified as compared to reference sites within the same marsh complex. This is a powerful tool that increases the site knowledge that may not be as readily apparent during in situ monitoring.

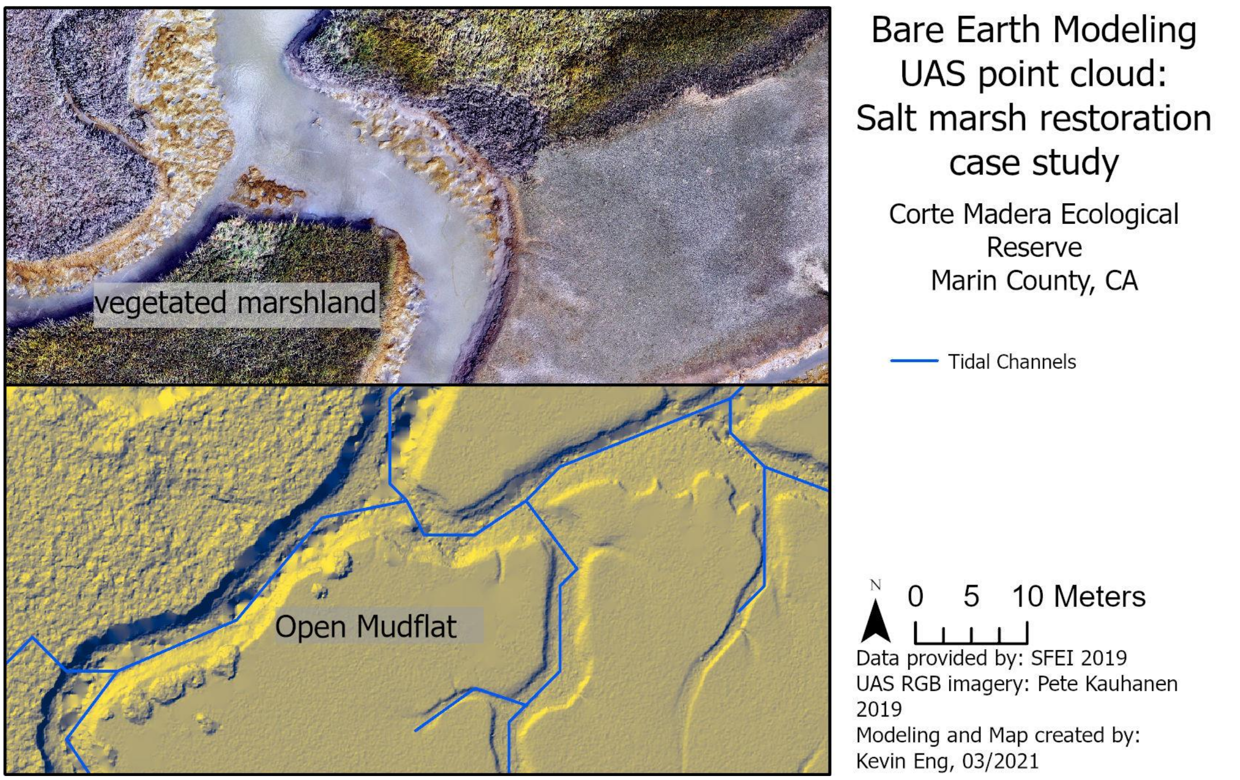


*Figure 14: Bare earth modeling can provide valuable information. Ecologists can use these data, combined with ecological knowledge to better design and monitor salt marsh restorations to meet project goals.*

## Slope Metrics

Employing DTM data, slope metrics can be modeled over project sites. An important marsh characteristic for salt marsh SLR resiliency is having a consistent slope from tidal mudflats to upland transition zones. As tidal waters rise, they flood over the landscape. Shallow slope floodplains are better suited to absorb tidal inundation and storm surge over larger horizontal distances. Manmade structures that emulate these natural landscapes are known as horizontal levees (Cecchetti et al. 2020). Gradual slopes allow for marsh vegetation to migrate up in elevation in response to SLR (Donnelly and Bertness 2001). Slope monitoring is critical to ensuring that horizontal levee construction meets the restoration goals.

UAS data provides a great opportunity to better monitor and understand restoration success when considering project area slope. UAS DTM provides comparable estimation for slope rise comparable to satellite-based analysis. Boon et al. (2016) demonstrated that UAS derived DTM predicted a slope of 1.77% over their study area as compared to a slope of 2.4% derived from google earth. The easy repeatability of UAS data collection allows practitioners to monitor season stresses that affect restoration projects, especially in early phases prior to widespread vegetation propagation. For example, the Sears Point wetland project, located in Sonoma County, CA, built raised earthen islands prior to restoration to tidal action (Sonoma Land Trust 2021). However, erosion rates of the island were higher than expected and required adaptive management to maintain these elevation heights (Figure 15) (Charles 2018). Although UAS technology was not employed, this would have presented an opportunity to employ this technology to great benefit.

*Figure 15: Adaptive management of raised earthen mounds to address wind driven erosion at the Sears Point wetland restoration, 2021. Pacific cordgrass is being planted to promote rapid vegetation spread over the earthen mounds within the site.*

## Hydrology Monitoring

Hydrological features allow for sediment transport throughout marsh complexes. As tidal inundation flood marsh plains, suspended sediments tend to settle near tidal creek banks. This elevates the areas adjacent to tidal channels at a greater rate than interior sections of marsh. If a marsh does not have adequate flow, sedimentation is limited to the shoreward edge and cannot make it to the interior of marshes. UAS derived surface modeling provides the ability to model channel system evolution. These data can inform stakeholders as to the progress of maturation for these younger restorations. As SLR intensifies, the interior of the marsh plain will continue to flood. This can lead to even more marsh elevation loss (Cornu and Sadro 2002). Eventually continued ponding will kill salt marsh plants that still require atmospheric air to live. This leads to even greater marsh loss due to the reduction of organic material introduced into the soil (Cahoon and Reed 1995). Understanding the hydrological connectively with restoration projects is vital for success.

UAS can provide useful data to monitor hydrological features such as creeks, tidal channels, and wetland boundaries. Salt marsh hydrology is the culmination on the interactions of diurnal tidal cycles, bringing in daily inundation, mixed with freshwater input from upland sources and precipitation. These processes shape and dictate the function of salt marshes, which in turn act as a buffer to stressors such as storm surge or anthropogenic pollutants (King and Lester 1995, Möller, Iris et al. 2014, Spencer and Harvey 2012). Modern day salt marsh restorations target this buffering ecosystem service as a design criterion making the monitoring of hydrological features very important.

### Tidal Channel

Using UAS point cloud data to evaluate tidal channel formation, the maturation of salt marsh systems can be monitored over time. Older remnant salt marshes in the SF Bay, such as China Camp in Marin County, CA, have a network of interconnected tidal channels (Fagherazzi et al. 2004). These channels provide a multitude of hydrological and geomorphological processes that help shape the productivity, vegetation structure, and resiliency (Wu et al. 2020). Diurnal inundation allows for low elevation channels to develop quickly where only extreme tidal inundation allows for higher elevation channel formation (Bayliss-Smith et al. 1979). Effective restoration designs should incorporate channelization and elevation metrics into their designs to jump start these important processes (Zeff 1999). Being able to monitor channel growth and spread is important in restoration practices as these provide important insight into the overall connectivity of the marsh.

UAS point cloud provide enough resolution between ground points to effectively model tidal channels. These 3D data, once analyzed, determine spatial relationships between points in the vertical axis (Ahmad et al. 2013). The modeling of tidal channels using UAS point cloud data is very similar to the common process of using LiDAR data to determine streams and watersheds. Understanding these relationships allow computer modeling to extrapolate the likely position of streams and channels relative to slope and probable water flow. This is extremely important in new marsh restoration where unvegetated mud surfaces are more prone to erosion and channel formation.

### *Proof of Concept: UAS Derived Tidal Channel Modeling*

Using UAS point cloud data, I created a feature layer that models tidal channels within the study area (Figure 16). The results are polyline representations of channel networks pictured in blue. My findings were evaluated by comparing the channelization model with aerial imagery of large channel networks. Overall, the UAS point cloud was able to predict the established channel network when compared to aerial imagery. Further field verification could help develop accuracy statistics but that was not within the scope of this project. Being able to accurately monitor channel network using UAS provides a useful tool to understand the evolution of salt marsh restoration with real time data. Restoration practitioners can use these data to inform restoration design and to give real time feedback for adaptive management of a restoration site.

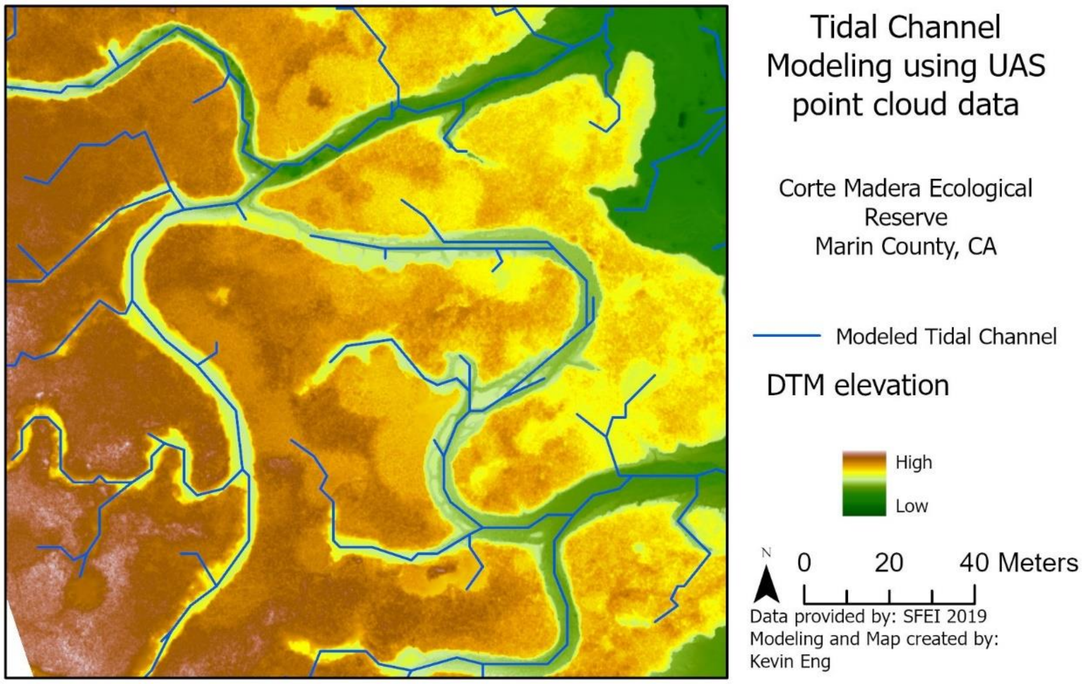


*Figure 16: UAS point cloud derived tidal channel analysis. Using ArcGIS Pro, waterbodies and watersheds can be predicted using terrain, slope, and flow direction.*

## Marsh Vegetation Height Monitoring

Monitoring height metrics for salt marsh restoration provides insight into productivity, resiliency, and ecosystem service potential. For restoration projects that target SLR resiliency and storm surge attenuation, height metrics play an important role. Relative tall canopy has a positive control on wave attenuation when compared to shorter salt marsh vegetation (Möller, I. 2006). In addition, height data can be used to compute above ground biomass (AGB). Understanding ABG can lead to predictions of productivity and carbon sequestration. Capturing multiple datasets over a short period of time can provide real time insight into marsh growth or degradation (DiGiacomo et al. 2020). UAS provide a perfect platform to capture multiple 3D datasets per growing season.

### UAS Point Cloud Derived Vegetation Height

UAS derived point cloud data can be used to determine height of salt marsh vegetation species. The results provide generalized trends but still suffer from light penetration of dense vegetation and detection of thin grass canopy. Published studies using UAS to determine salt marsh and grassland height metrics find that there is a consistent underestimation of height compared to in situ vegetation monitoring (Pinton, Canestrelli, Wilkinson et al. 2020, Yuan et al. 2018, DiGiacomo et al. 2020). A possible source for height underestimation for salt marsh species like *Sporobolus* spp. is that stem thickness and density tend to decrease with increased height. Fine leaf blades might not be detectable at the top of vegetation providing a source of error (DiGiacomo et al. 2020). These underestimations, however, have been seen to be consistent allowing the data to be corrected for increased accuracy. Like LiDAR corrections, manual or algorithm-based methods can increase the UAS vegetation height accuracy increasing the potential for suitable vegetation estimates.

### *Proof of Concept: UAS Derived Vegetation Height Modeling*

My vegetation height model, using UAS data, illustrates the ability of UAS to determine height variation of high marsh and transitional zone habitat (Figure 17). Height values of large woody shrubs were calculated to be 8m tall as detailed by the bright red colorization. Due to inaccuracies in short and dense marsh vegetation, this tool did not prove useful within the cordgrass/pickleweed plain within the constraints of this project and computing resources. Published studies, employing corrective algorithms or methodology to better detect ground surfaces, have illustrated the ability for UAS to achieve high accuracy in low marsh vegetation. The methodology employed in those studies are outside the scope and time frame of this project.

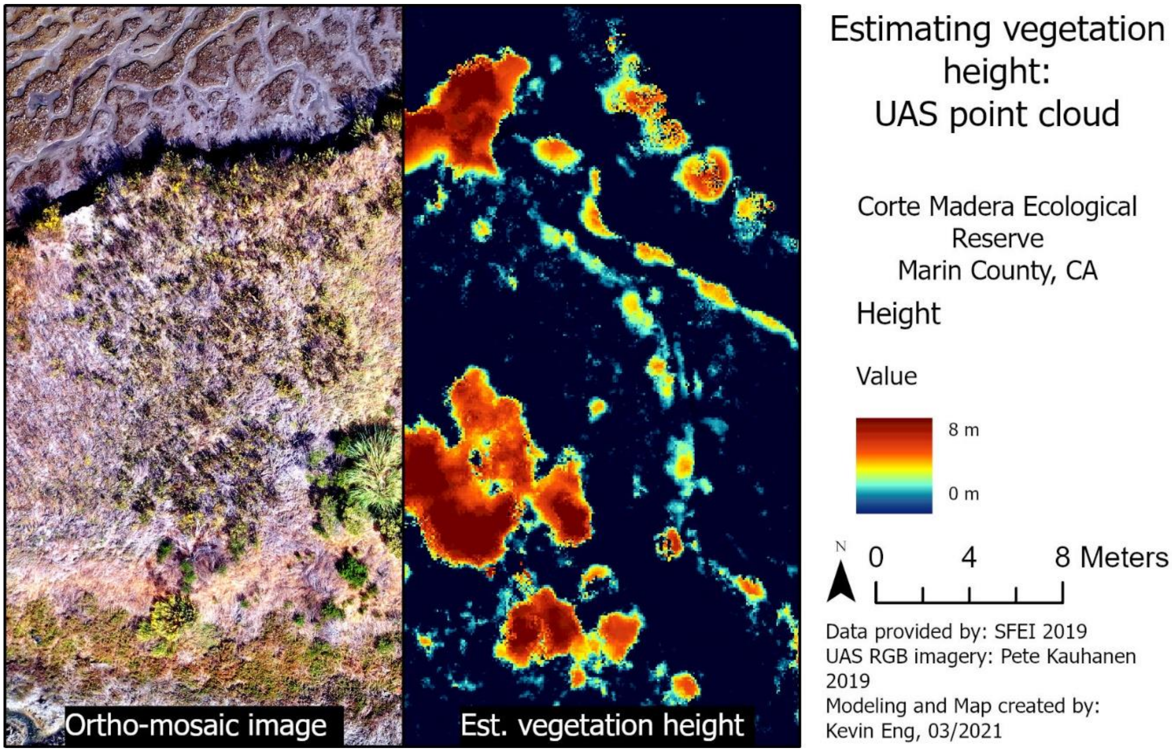


*Figure 17: High marsh and transitional zone shrubs heights can be calculated by subtracting the DSM from the DTM. The left side of the image displays the RGB UAS imagery of high marsh habitat. This habitat zone is dominated by woody shrubs and annual grasses. The right side of the image shows continuous imagery but displaying vegetation height estimates. Individual woody shrub height estimates show up clearly in the deep red color*

## Accuracy Correction of UAS derived DTM

Due to penetration limitations of dense vegetation and physical characteristics of grassland species, remote sensing techniques often require correction to resolve underestimation. Once complete, UAS height data becomes useful as a tool to measure vegetation height. This is traditionally executed by filtering out positively identified bare ground point cloud returns. Once a true bare earth DTM is created, mathematical algorithms can correct for discrepancies in vegetation height. These techniques are highly specific to the system they are analyzing. For restoration practitioners, this additional step to increase accuracy poses a management decision that must be made when comparing project goals, budget, and needs for data monitoring.

In a study by DiGiacomo et al. (2020), three methods to extrapolate true ground points were examined (Table 6). First, vegetation indices were used to filter out non-vegetated locations by comparing differing spectral signatures. Secondly, manually identification of bare earth provides similar values but requires user input and knowledge of the project site. Lastly, LiDAR bare earth returns are used, as is since they currently provide the most accurate bare earth data (DiGiacomo et al. 2020). However, as previously mentioned, these LiDAR data can be more expensive and difficult to acquire within the correct temporal parameters.

*Table 6: Methods for determining DTM to calculate vegetation height (DiGiacomo et al., 2020).*

| **Methods to overcome dense vegetation light penetration for remote sensing using UAS imagery** | | | | |
|---|---|---|---|---|
| Method | Result | r2 values comparing in situ to remote sensing | Mean Square Error (MSE) | Highlights |
| Filter out NDVI determined bare ground values | Provides point cloud data used in automated interpolation for DTM | 0.128 | 0.025 m2 | Least accurate but less variability in data |
| Manual idenitification of bare earth values | Provides user defined data used in automated interpolation for DTM | 0.181 | 0.045 m2 | Most labor intensive |
| LiDAR values to identify bare earth values | Uses addition LiDAR data to collect bare earth values | 0.295 | 0.045 m2 | Most accurate but requires a second data set |

Acquiring verified ground point data allows the user to query out false ground point returns that dense vegetation can create. Vegetation indices, such as NDVI, allows for detection of ground points compared to living vegetation. This is done by comparing green reflectance values. In salt marsh environments, non-detection of chlorophyll signatures (non-green) are assumed to be either dead vegetation or bare ground. These values, once queried from green vegetation, can be used to estimate areas of bare ground (DiGiacomo et al. 2020). The filtered ground points are then used to create a rasterized DTM. This technique, however, can lead to a loss of spatial resolution and smoothing over between ground points.

All three methods produce statistically similar results in predicting true stem height. However, with similar small $r^2$ values compared to in situ height measurements, all three methods suffer from underestimation of true stem height. Similar linear regression models of all three results indicate that all methods underestimate vegetation similarly. Multiple transformations and algorithms exist to correlate these data closer to true stem heights (Pinton, Canestrelli, Wilkinson et al. 2020, van Iersel et al. 2018, Yuan et al. 2018). Once transformed, the UAS point cloud method demonstrated similar predicted vegetation heights to that of the LiDAR (Figure 18).

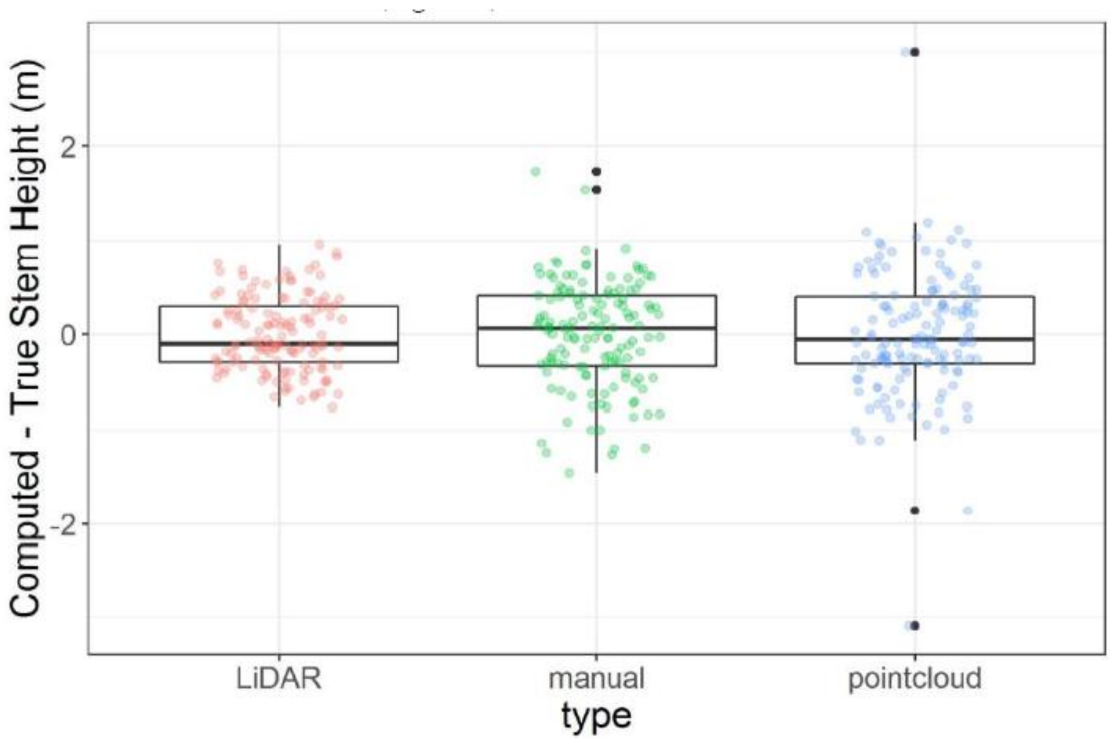


*Figure 18: Comparison of true stem height calculations between LiDAR, manual, and pointcloud derived DTM. All three show similar ability to compute true stem height. However, the spread of data points away from the mean is most limited in LiDAR data. (DiGiacomo et al. 2020)*

## Accuracy fluctuations in differing vegetation height classes

UAS point cloud data achieves better accuracy results for height measurements when individual specimens are clearly distinctive from the surrounding environment. Salt marshes are comprised of heterogenous vegetation communities that differ in average vegetation height. Frequently inundated zones tend to have short and dense vegetation whereas drier high elevation zones can support larger woody species (Moffett et al. 2012). It is possible that the low canopy and population densities of these woody species leads to more accurate vegetation height calculations. For restoration ecologists, understanding the average heights of larger woody species can provide insight into success metrics such as carbon sequestration, roosting habitat, and vegetation diversity.

A study by Fraser et al. (2016) illustrates that shrub vegetation height can be accurately measured in low-Artic environments. This environment shares similarities to salt marshes in that woody shrubs make up the tallest vegetation in an environment mostly dominated by low herbaceous species. Due to the lack tall vegetation in this habitat type, a very dense UAS point cloud is possible. By employing these point clouds of singular tall shrubs, an accurate height estimate can be made (Figure 19). In this study, the $r^2$ value is equal to 0.9636 with a S. E. of 0.08 (Figure 20). This result of close to a 1:1 remotely sensed height value compared to in situ measurements suggest that high accuracy is possible for Woody shrub species in open grassland environments.

Furthermore, if you combine height measurements with RGB imagery, a practitioner can more accurately evaluate vegetation classes by employing height as another classification value. As previously explored, RGB data can be used to identify vegetation classification. Using plant heights as an additional metric can increase the accuracy of consumer grade sensors on UAS only capable of RGB detection (Fraser et al. 2016).

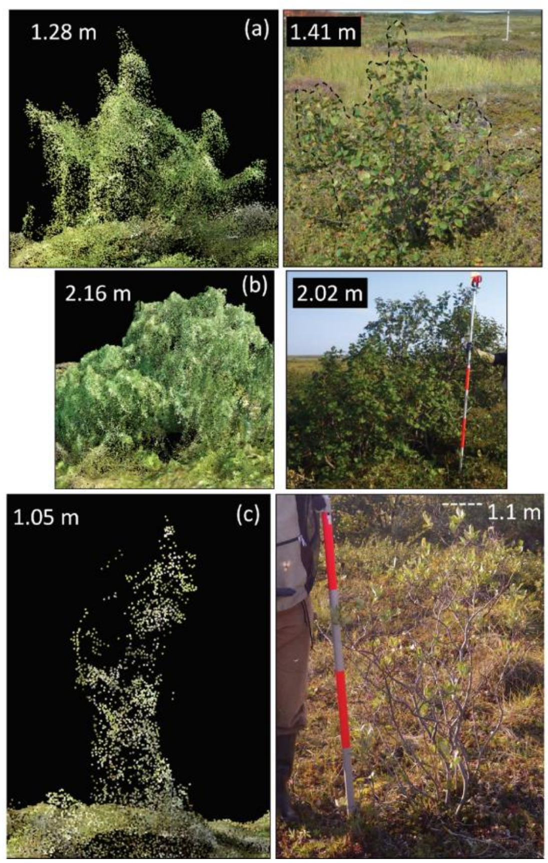


*Figure 19: Comparison of UAS point cloud data vs. in situ measurements of shrub species show similar height estimate using UAS derived imagery. The left photos are a visual representation of 3D point cloud data of these specific individuals. The right photos are in situ height measurement values (Fraser et al., 2016)*

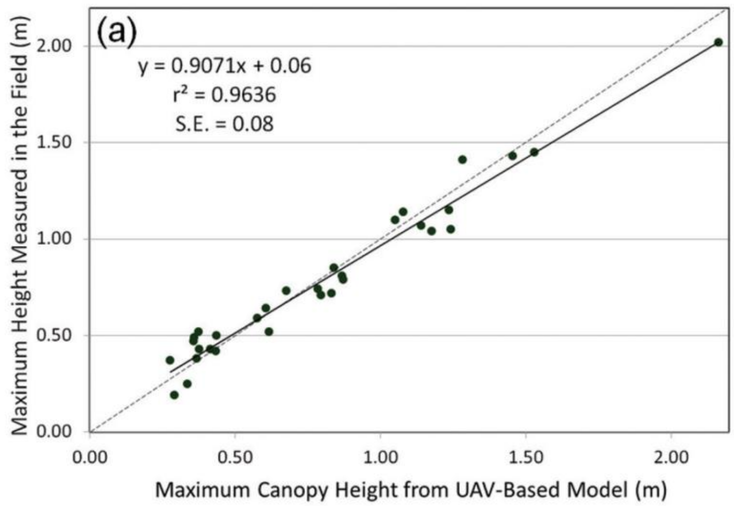


*Figure 20: The regression model illustrates that UAS based canopy height almost has a 1:1 relationship to field measured heights. This provides evidence that UAS can provide accurate height measurements for woody shrub species (Fraser et al., 2016)*

## Marsh vegetation Above Ground Biomass (AGB) monitoring

Above ground biomass is an indicator of success in salt marsh restoration as it conveys information regarding productivity, increases vegetation cover, carbon sequestration and resiliency to storm surge and SLR. Above ground biomass can be measured using in situ techniques; however, these are generally destructive to vegetation and can cause significant disturbance in the field. The technique is often extremely labor and time intensive requiring desiccation of plant material and measuring of dried tissue samples (Darby and Turner 2008). Remote sensing provides a way to create estimates of plant biomass on the landscape level. Although, not as accurate, these data can be analyzed over the entire study site and provide more generalized trends in productivity and carbon storage (Doughty and Cavanaugh 2019).

Multi-temporal and Multispectral UAS imagery provide the ability to better detect seasonal variations in AGB. Using an NDVI vegetation index, normally employed to understand vegetation health, seasonal biomass measurements can be determined. When compared to other indices, NDVI is shown to have the most accurate biomass estimate with and $R^2$ of 0.356 and a p-Value of $<0.005$ (Table 7) (Doughty and Cavanaugh 2019). By employing this technique, seasonal ecological patterns can be monitored within salt marshes (Figure 21). This is important in restoration practices where deviation from normalized patterns may indicate variations to salt marsh vegetation brought on by stress.

*Table 7: Equations to convert vegetation indices to Above Ground Biomass estimates. NDVI has the largest $R^2$ Value as compared to other vegetation indices. (Doughty and Cavanaugh 2019)*

| Index | Biomass Estimation Equation ($g\ m^{-2}$) | $R^2$ | RMSE ($g\ m^{-2}$) | $p$-Value |
|---|---|---|---|---|
| CIgreen | $519.1 \times$ CIgreen + 293.6 | 0.263 | 530.6 | <0.005 |
| CIrededge | $952.3 \times$ CIrededge + 730.9 | 0.112 | 582.6 | 0.009 |
| EVI2 | $2867.6 \times$ EVI2 + 566 | 0.244 | 537.5 | <0.005 |
| GNDVI | $3041.2 \times$ GNDVI − 175.3 | 0.302 | 516.6 | <0.005 |
| NRDE | $2686.2 \times$ NDRE + 682.9 | 0.115 | 581.6 | 0.008 |
| NDVI | $2428.2 \times$ NDVI + 120.1 | 0.356 | 495.9 | <0.005 |

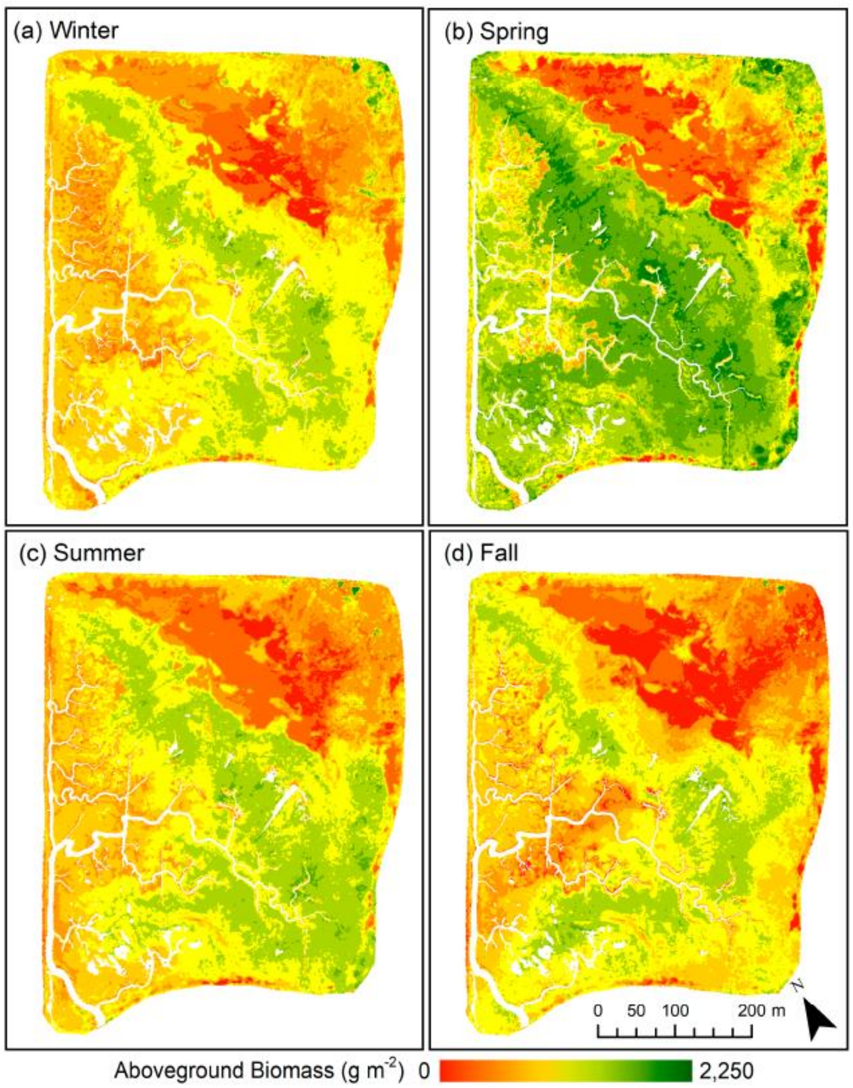


*Figure 21: Seasonal changes in AGB derived from NDVI index collected using multispectral sensors on UAS. Spring biomass is most abundant in salt marshes with these models due to increased green vegetation biomass in the spring season (Doughty & Cavanaugh, 2019).*

UAS multispectral imagery provides high resolution data that can better determine optimal elevations to produce maximum AGB. Compared to satellite imagery, UAS provides centimeter level precision compared to meter level. In salt marsh environments, significant changes to vegetation structure occur within this level of detection. For example, in Figure 22, peak biomass is estimated to occur at 1.6-1.8 m of elevation. For restoration projects aiming to increase AGB for habitat improvement or storm wave energy attenuation, understanding these target elevations is key to reaching project goals. Salt marsh design can target these elevations to ensure peak biomass.

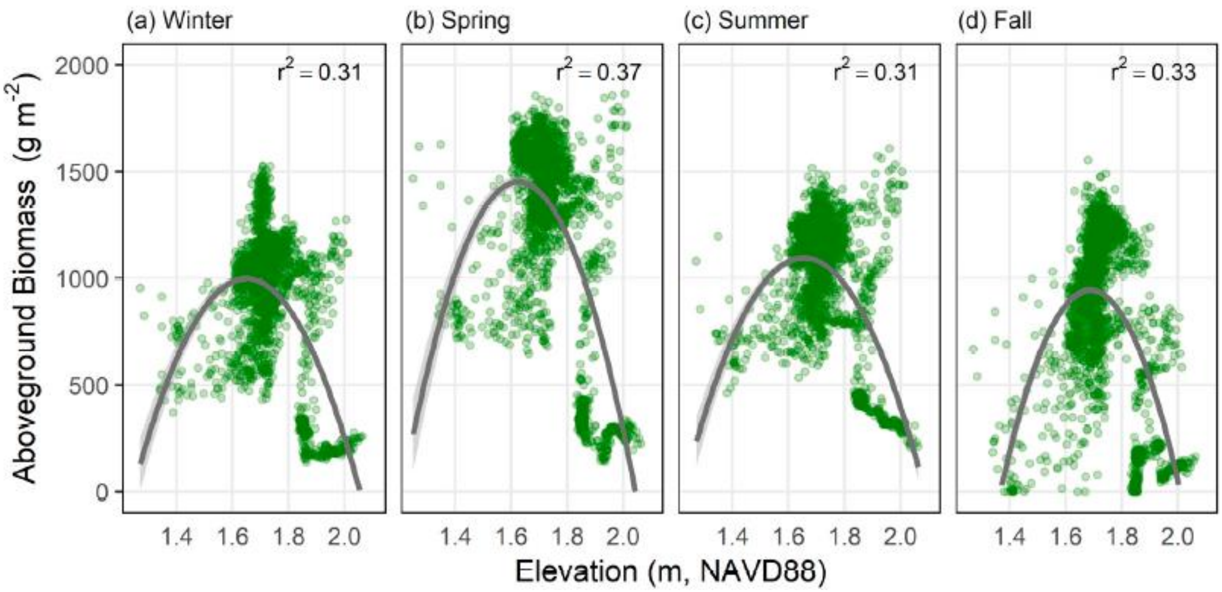


*Figure 22: Peak biomass, for all seasons, is congregated between the 1.6 and 1.8 m elevation. (Doughty & Cavanaugh, 2019)*

# Chapter 6: Recommendations for UAS application

UAS technology provide a new and relevant tool that can greatly benefit the ecological restoration practitioners. This technology provides a critical data collection technology that fits between in situ field surveys and large commercial grade aerial platforms. I present four recommendations for the usage of UAS that will allow for the best implementation of this new technology in salt marsh restoration.

1) Combining technologies to overcome deficiencies in entry level UAS technology:

If budget allows, combining multispectral and LiDAR sensors onto UAS platforms can provide high resolution and accurate data while providing the benefit of easy repeatability. Developments in sensor technology allows for more advanced sensors to be mounted onto smaller platforms. This increases the temporal and spatial resolution compared to manned aircraft systems and satellite platforms as UAS can fly at lower elevations which increases resolution (Fraser et al. 2016). Negatively, cost of data acquisition per acre is greatly increased due to expensive hardware. This can be compensated for if repeated flights are conducted, spreading out the cost hardware over multiple data collection events.

2) Flexibility of temporal resolution improves time dependent data quality:

UAS' main benefit is flexibility in data collection timing improving on temporal resolution. Field based monitoring is time intensive and often does not offer site wide data for a single point in time. Satellite and manned aircraft surveys are often difficult to task for specific small-scale projects limiting when data can be collected. UAS are portable and on demand which allow for flexibility considering seasonal changes, weather conditions, and tidal inundation.

UAS' on demand data collection allows for targeted vegetation sampling during optimal morphological conditions. For example, Gumplant in Bay Area marshes is difficult to detect in land cover classifications due to its similar spectral signature to other marsh vegetation (Li et al. 2005). In the fall, Gumplant has bright yellow flowers that make it more spectrally distinguishable. Targeted flights over the marsh complex during this time can allow for more accurate representation of Gumplant detection.

3) Repeatable monitoring surveys improve the understanding of the marsh system:

UAS' great strength is cheap and easy repeatable data collection. To fully utilize UAS and lower the cost per flight, restoration practitioners should employ this technology as often as possible to achieve their monitoring goals. Repeated data collection during different times of year provide data that captures seasonal changes that would otherwise be missed. Annual vegetation monitoring only captures a single snapshot of the marsh conditions. Multiple flights per year can capture different stressors or changes to the marsh. This is especially important in the Bay Area where our weather is dominated by wet cool winters and dry hot summers. Winter UAS flights can capture the effects of storms on the marsh while summer flights can capture the effects of hypersaline conditions.

UAS, when continually employed from the initial phase of restorations can overcome the limitations of line-of-sight detection through vegetation. To create more accurate DTM, UAS data collection would ideally take place prior to vegetation growth or during the winter season when ABG is at its lowest (Zhou et al. 2018). For example, many salt marsh restorations start with unvegetated mudflats after earth moving activities. This will allow for the best penetrance to the marsh ground surface allowing for accurate baseline DTM elevations. UAS flights should be repeated to better capture changes in height metrics. These data will help adaptive management, ultimately increasing restoration success.

The repeatable nature of UAS should be employed to capture external influences that can affect marsh vegetation communities. California experiences periodic drought conditions followed by periods of wet conditions. For instance, the Bay Area was in a historically long draught until 2017 when record rains fell. The impacts of these changes in rain affect vegetation communities by changing soil salinity. An invasive species prevalent in Bay Area marshes, Pepperweed (*Lepidium latifolium*), capitalizes in periods of lower salinity (Wigginton et al. 2020). This results in a large expansion during wet seasons. Frequently repeated aerial surveys with UAS will provide restoration managers much needed data on spread of this invasive allowing for more effective adaptive management.

4) Operational costs vary with scale of restoration projects:

UAS technology provide a range of capabilities that change operational costs according to need. Small scale salt marsh restoration projects would benefit from entry level consumer grade UAS while larger budget restorations will see better results from upgraded platforms. Upfront costs for UAS are a limiting factor to their widespread usage, especially when compared to the cost of one-time satellite imagery acquisition. This is a major consideration for a restoration project and must be evaluated prior to investment. Factors such as frequency of data collection, expertise to process UAS data, and staff time are all real-world logistics that determine the feasibility of UAS. An entry level consumer grade UAS and accompanying hardware generally costs about $2,000 USD. More advanced sensors can quickly add thousands of dollars to this.

Low budget projects can benefit from entry level UAS technology. Basic RGB data can provide trend data such as vegetation spread, height metrics, and information to aid in restoration design and adaptive management. High budget, regulatory, or academic salt marsh studies should employ multispectral UAS data to provide higher accuracy due to more available spectral data. The increase in cost is offset by the higher precision data that can lead to more robust analysis used in modeling, regulations, and academic study. Lastly, since most of the costs are upfront, the more frequently UAS are employed, the lower the cost per flight.

# Chapter 7: Conclusion

Salt marsh restoration is an increasing practice due to our ever-evolving understanding of their importance as ecological features and for their benefits to humans. In the San Francisco Bay, this is especially important as much of the historic salt marsh habitat has been cut off from tidal flow or filled. The Bay Area is high urbanized up to the water's edge which may cause significant issue with global climate change and SLR. Our understanding of tidal wetlands today has changed to where we understand their significance as a buffer from coastal flooding. The evolution of restoration practices can be linked to monitoring of successful and failed restoration attempts over the past 40 years. The evolution of monitoring of salt marsh restoration will allow us to evaluate restoration success, provide adaptive management, and continue to learn about these important processes.

The evidence collected in this study suggests that UAS technology is a valuable addition to more established monitoring techniques and technologies. While not being a complete replacement for technologies such as satellite imagery or airborne LiDAR, UAS provide similar results while being a more flexible data acquisition platform. UAS can be deployed at will of the practitioner to capture specific details of marsh restoration such as seasonal vegetation changes or differing tidal inundation. This is important to restoration practitioners who are more willing to have lesser quality data in trade for greater quantity and ease of access to repeatable data collection.

UAS technology can provide useful data to conduct land cover classifications over salt marsh environments. Entry level consumer grade UAS, outfitted with basic RGB sensors, can gather enough data to differentiate major land cover classes. Although these data may not contain enough information to detect species level classification, more broad classification mapping are highly useful. This is especially true when the desired data seeks to gain knowledge of metrics such as conversions of open soils to vegetated salt marsh. The potential to upgrade UAS sensors to include multispectral range increases the capability of the platform like top tier satellite imagery.

Using point cloud data processed by photogrammetry, UAS data can provide an alternative to LiDAR technology to capture 3D data. These data are dependent on passive light reflection to gather data points. Due to the need for direct line of sight, UAS photogrammetry suffers from the same setbacks as LiDAR. This ultimately does not improve on LiDAR, however, does provide comparable data. The flexibility in temporal resolution allows restoration ecologists to gather better ground data during the winter season when vegetation canopy is less dense. If UAS are employed at the very beginning stages of restoration where bare soils are the primary cover, light penetration does not affect the accuracy of the creation of DTMs. This creates an accurate baseline DTM to base all future height metrics on. The repeatability of data capture allows for real time changes to be captured during the restoration timeline, not when other large scale LiDAR acquisition is planned.

When determining if UAS technology is right for a specific project, it is as important to understand the limitations of this technology as with the benefits. This study identifies that UAS can excel when the spatial scope of the project is limited. This is due primarily with the physical limitations of battery size and time to acquire imagery over large landscapes. Generally, consumer grade UAS can fly for about 20 minutes on each battery. Multiple batteries are usually required to capture study sites. If a large study area is required, then satellite imagery is more efficient, although resolution is reduced. This is especially true if repeated monitoring events are not necessary. Modern commercial satellite imagery is becoming more readily available at ever decreasing costs. UAS can compete with these newer satellite platforms because they provide a higher image resolution which is often needed in small scale salt marsh restorations.

The future for UAS in ecological monitoring is quickly evolving as evident in the trajectory of published literature. Ten years ago, this technology was novel. Today, ever more complex studies are making UAS technology more practical for real world implementation. The next evolution in UAS technology will most likely be the user interface where persons with little training can gain the information that today only trained analyst can provide. UAS may not be a one stop replacement for in situ monitoring or other remote sensing technologies, however, it does provide an exciting tool that provides flexibility to restoration practitioners.

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