EXAMINING THE RELATIONSHIP BETWEEN VEGETATION INDICES DERIVED FROM UNMANNED AERIAL VEHICLE (UAV) AND PLANETSCOPE HIGH RESOLUTION SATELLITE IMAGERY IN A SOUTHERN AFRICAN DRYLANDS ECOSYSTEM

By

Amelia Carol Bradshaw

A paper submitted in partial fulfillment of the requirements to complete Honors in the Department of Earth and Ocean Sciences.

Approved By:

Examinig Committee:

Narcisa Pricope, Ph.D.
Faculty Supervisor

Joanne Halls, Ph.D.

Zachary Long, Ph.D.

Cuixian Chen, Ph.D.

Doug Gamble
Chair, Department of Earth and Ocean Sciences

Honors Council Representative

Director of the Honors Scholars College

University of North Carolina Wilmington

Wilmington, North Carolina

April 2019
Abstract

Dryland ecosystems, which cover around 40 percent of the world, are essential to the livelihoods of millions of people. These ecosystems are threatened by climate change, which ultimately affects the productivity of dryland vegetation. This study utilizes two different remote sensing platforms, Unmanned Aerial Vehicle (UAV) and PlanetScope satellite imagery, to determine if these platforms can be classified in synchrony to inform vegetation analysis at the community scale, then across time. To do this, three vegetation indices were calculated, then used to classify the images, using three different classification methods. These included a productivity-only decision tree, a productivity and structure-based decision tree, and an unsupervised classification. It was discovered that there were differences in the two sensors that made a pixel-based analysis difficult, especially attempting to utilize the same classification method for both image types. As a result, no classification method yielded classification accuracies as high as expected, given the very high resolution nature of the imagery, concluding that the two platforms do not have a strong relationship to inform pixel-based analysis across larger extents or different temporal scales. This was due to discrepancies between the sensors, both in spectral and spatial resolution. Future studies would benefit by focusing on an object-based approach for classification, as these classification methods have yielded better results for classifying very high resolution imagery.
Acknowledgements

I want to thank the National Science Foundation for providing the funding for this research, through Grant #1560700, “Land Systems Dynamics, Vulnerability, and Adaptation in a Transfrontier Conservation Area”. I also thank Dr. Narcisa Pricope, my advisor for this project, for her support and advice throughout this process. I want to thank Steele Olsen as well, for his support in the initial stages of this research and his work involving UAV imagery collection and processing. In addition, I want to thank the team at the University of Louisville, Dr. Andrea Gaughan, Dr. Forrest Stevens, and Nicholas Kolarik for aiding in collecting and processing the UAV imagery collected in 2017 and 2018.
Introduction

Drylands habitat is a vital, yet highly sensitive ecosystem that covers approximately 40 percent of the Earth’s surface. Drylands include not only desert systems, but other vegetation communities such as shrub and grassland (Lu, Kuenzer, Wang, Guo, & Li, 2015). These ecosystems are classified by rainfall, or the lack thereof. An aridity index, which is the ratio between average precipitation and total annual potential evapotranspiration, is used to define drylands. An environment with an aridity index of less than .65 is considered a dryland (Behnke & Moritmore, 2016, p. 2). Rainfall in these environments is highly variable, though climate change is exacerbating these conditions, causing major changes in vegetation regimes and biodiversity loss (Cui, Gibbes, Southward, & Waylen, 2013; Gaughan & Waylen, 2012). This in turn affects the animals and humans who live in these ecosystems and utilize their local plant communities for food and other resources. Assessing the human vulnerability to environmental change in these regions is an important part of understanding how dryland systems function and change through the course of time, and how these changes affect those who live in these environments.

To understand human vulnerability in the environment, one must consider how humans interact with the landscape around them, and how the landscape in turn responds to these impacts. The study of coupled human and natural systems (CHANS) aids in the investigation of vulnerability to environmental and climate changes. CHANS are systems where humans interact with the natural components in their environment and form a reciprocal relationship with nature. These relationships create different effects in the environment, including complex feedback loops, nonlinear patterns of change such as
thresholds, and temporal effects such as time lags between initial human interaction and the effect on the landscape (Liu et al., 2007). We are just beginning to understand and measure these various interactions in CHANS, as this area of research requires a multidisciplinary approach between ecological sciences and social sciences, and the systems at play in these human-environment interactions are very complicated. These linkages are critical to assessing vulnerability, as even small changes in either the environment itself or the way humans interact with the environment can create cascading effects in the landscape, which in turn can increase the vulnerability of these systems.

Vulnerability is defined as the degree to which a system or a component in the system is likely to experience harm due to exposure to a kind of hazard or stressor (Turner et al., 2003). However, focusing just on stressors to attempt to understand impacts on systems is insufficient, as this ignores the vital factor of the system itself, which has its own interactions with the stressor, along with how humans interact with the stressor and the system (Turner et al., 2003). Rather, we must consider an array of elements to begin to understand vulnerability. These include not only the variety of stressors, but also the exposure of the coupled system to hazards, the sensitivity of the system to exposure, the system’s resilience to the hazard, and the system’s adaptations after the stressor. The dynamics of the hazards and the systems they affect must be examined at multiple scales in order to gain a fuller understanding of how the hazard has affected the entire system, from the local unit to the regional scale or beyond (Turner et al., 2003). This understanding of vulnerability as a complex interaction of the hazard or stressor and coupled human and natural systems is the framework used to inform the greater project of assessing vulnerability in the drylands environment of southern Africa.
To begin to study the vulnerability of a given community within the context of a larger dryland system, we must examine one of the key points of dryland vulnerability, which is precipitation variability and how this factor affects vegetation productivity. Small shifts in precipitation can create major impacts in the landscape, which affects household vulnerability (Gaughan et al., 2015). Internationally, drylands are known for their highly variable precipitation regimes, and this precipitation variation drives vegetation productivity and vegetation community change, specifically in more arid environments (Behnke & Moritmore, 2018, p. 8). Vegetation productivity can be used as a proxy for vulnerability in these environments, revealing the fluctuations in precipitation over time, as productivity is a reflection of water availability (Pricope, Gaughan, All, Binford, & Rutina, 2015).

Vegetation productivity can be estimated by calculating vegetation indices from various remote sensing platforms, including satellite imagery and imagery derived from unmanned aerial vehicle (UAV) sensors. Vegetation indices are derived from wavelengths plants are known to reflect and absorb in varying quantities, depending on their chlorophyll levels, leaf water storage, and leaf structure. These indices produce measures of vegetation greenness, which are then used as proxies for a variety of plant productivity measures, such as gross primary productivity and leaf area index (Jiang, Huete, Didan & Miura, 2008). Though many vegetation indices have been created, several have become dominant due to their reliability. First is the normalized difference vegetation index or NDVI, developed by Tucker in 1979 (Weber, Schaepman-Strub, & Ecker, 2018). The NDVI is a ratio index that compares red wavelength to near infrared wavelength to determine greenness.
\[ \text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \]

The NDVI has shown to have a strong correlation to absorbed photosynthetically active radiation (APAR), which has led to this index being used in estimates of aboveground net primary productivity (Kerr & Ostrovsky, 2003). There are several problems with the NDVI, including decreased accuracy in areas with highly reflective soils, its sensitivity to atmospheric scattering, and issues related to large leaf area indices and high greenness, which can lead to oversaturation in the derived index (Jiang et al., 2008). This oversaturation at high greenness values can lead to underestimations of productivity in areas of dense vegetation (Gu, Wylie, Howard, Phuyal, & Ji, 2013). Due to these issues, other vegetation indices have been developed, to overcome problems encountered with NDVI.

One of the major problems with the NDVI is the decreased accuracy seen in regions with soils that are highly reflective. It has been discovered that the NDVI showed inconsistent relationships with the biophysical canopy properties, affected by the soil beneath the canopy and the moisture content of the area. To counter these deficiencies, Huete devised the soil-adjusted vegetation index or SAVI in 1988 (Jiang et al., 2008).

\[ SAVI = (1 + L) \times \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red} + L} \]

The SAVI also utilizes the near infrared and red wavelength bands, but adds a soil adjustment factor to the equation, the coefficient L. L is added to account for the non-linear near infrared and red radiative transfer through the canopy of a vegetated area, thus correcting the influence of background reflectance values seen in the NDVI. (Jiang et al., 2008) This index was also further modified, spurring the development of indices.
including the transformed soil-adjusted vegetation index (TSAVI) and the optimized soil-adjusted vegetation index. (OSAVI)

Another approach to solve issues found in the NDVI was the creation of the enhanced vegetation index, or EVI. The EVI was created with high biomass regions in mind, to decrease issues of index saturation and reduce the influence of the canopy background in order to develop a true estimation of the vegetation itself. This index also sought to reduce the influence of atmospheric scattering through adding coefficients to the various bands used in the equation (Jiang et al., 2008).

\[
\text{EVI} = G \frac{\text{NIR} - \text{Red}}{\text{NIR} + C_1 \text{Red} - C_2 \text{Blue} + L}
\]

The EVI uses the standard near infrared and red bands, along with the blue band, which is used to correct for the influence of aerosols on the red band. Several coefficients are added to the equation, including a gain factor, G, two coefficients, \(C_1\) and \(C_2\), to aid in atmospherically correcting the three bands used, and \(L\), a soil-adjustment factor (Jiang et al., 2008). The EVI has been further modified for sensors that lack a blue band. This version, the EVI2, removes the blue band from the equation, modifies \(G\) to 2.5, \(L\) to 1, and reduces the coefficients used to one, with a value of 2.4 (Jiang et al., 2008).

\[
\text{EVI2} = 2.5 \frac{\text{NIR} - \text{Red}}{\text{NIR} + 2.4 \text{Red} + 1}
\]

Through the creation of the EVI2, it was discovered that the red and the blue bands have a close, stable relationship, which demonstrates that the blue band had little influence in correcting for atmospheric influences in the first EVI equation. Instead,
removal of this band proved to not be problematic, and the EVI2 can be used as a substitute for the EVI (Jiang et al., 2008).

Vegetation indices have been used to study vegetation on a variety of scales, ranging from worldwide monitoring using coarse spatial resolution satellite platforms such as the Advanced Very High Resolution Radiometer (AVHRR) or Moderate Resolution Imaging Spectroradiometer (MODIS) to regional and local mapping using satellites with finer spatial resolutions, such as Landsat, Sentinel, and PlanetScope (Jiang et al., 2008; Weber, Schaepman-Strub, & Ecker, 2018; Puliti, Saarela, Gobakken, Ståhl, & Næsset, 2018; Houborg & McCabe, 2018). These satellites, ranging in resolution from one kilometer to three meters, aid in determining general trends in productivity over a region. To extract more specific vegetation data, including species differentiation and the patterns of vegetation over smaller regions, such as an agricultural area, a remote sensing platform with a much finer spatial resolution is needed. In recent years, unmanned aerial vehicles, or UAVs, have become popular in fine-scale vegetation analysis. Used extensively in agriculture, forestry, and viticulture, UAVs allow for operator-determined flight dates and times, instead of relying on set satellite acquisition times. UAVs are also relatively inexpensive, allowing for efficient data collection. Another major advantage of UAVs is their ability to derive three-dimensional models of the surface they image, allowing for structural analysis that can aid in applications such as forest inventories (Puliti et al., 2018). These factors make the use of UAVs very appealing for both commercial purposes and scientific inquiry.

Though UAVs have the advantage of a-la-carte data collection, UAVs have spatial limitations. Batteries on UAVs often are limited to around an hour range, with
decreases in battery life seen with heavier UAV payloads or poor weather conditions. This creates a limit in spatial extent of a single UAV-powered flight, making large-scale spatial analysis difficult. UAVs are also limited by time. As this technology depends on operator deployment without any publicly available UAV imagery database, historical imagery is not available. To study the historic trends of a region, one would have to utilize satellite imagery in conjunction with UAV imagery analysis. In the past several years, various studies from around the world, focusing on differing applications for vegetation analysis, have worked to study the relationship between UAV imagery and satellite imagery, to determine if the two can work together to inform analysis. The results of these studies show a range of applications and results, revealing the complexities of analysis between the two platforms.

One major study conducted by a team of Chinese scientists led by Tian focused on the use of UAV and WorldView-2 imagery to study the leaf area index (LAI) of the Dandou sea mangrove forests in the Guangxi province of China (Tian et al., 2017). The team utilized three different versions of the NDVI, the average NDVI, the vegetated specific NDVI, and the scaled NDVI to determine LAI, then compared the LAI for the two remote sensing platforms. An overall performance comparison was conducted as well (Tian et al., 2017). The results showed that the UAV’s seven centimeter pixel size picked up an enormous amount of spectral information, making the calculated NDVI values far more variable than the pattern of NDVI values seen in the WorldView-2 two meter pixel (Tian et al., 2017). On the other hand, the sensor on board of the WorldView-2 satellite has a far greater spectral response function than the MicaSense RedEdge sensor loaded onto the UAV. This increase in the breadth of wavelength interpreted by
the WorldView-2 sensor as red or near infrared caused the NDVI response to differ between the sensors (Tian et al., 2017). Analysis confirmed that the mean NDVI values indeed differed for each sensor between each land cover type studied, making a direct comparison between the two platforms more difficult. UAV imagery presented much higher variability compared to the WorldView-2 imagery due to the small pixel size of the UAV sensor picking up background soil and water reflectance values with ease. Though UAV imagery is noisier compared to satellite imagery, with extreme high and low values not necessarily representing specific land cover types, ultimately this high variability aided researchers, allowing them to create better classifications of imagery. In this case, the LAI created by the UAV was more accurate, based on field measurements recorded by a LAI-2200 Plant Canopy Analyzer (Tian et al., 2017). When looking at species variation within plots, the WorldView-2 satellite was more accurate due to a far greater spectral response function. This wider range in wavelength made for a more accurate NDVI value that was able to differentiate between species of plants within the mangrove forest, instead of simply the LAI alone. This study demonstrates that UAV and satellite imagery have their own strengths and weaknesses, which can be leveraged together to inform scientific analysis.

Another study that sought to establish a link between UAV and satellite imagery was a forestry-based assessment conducted by Dash, Pearse and Watt in 2018. Researchers used herbicides to induce a controlled level of stress on mature *Pinus radiata* trees, then used both UAV and RapidEye imagery to determine which produced the best measure of tree stress. The goal was to link the two platforms in order to enhance the positives of both for better analysis of tree stress (Dash, Pearse, & Watt, 2018). The team
used the NDVI, the green NDVI, and the red edge NDVI to compare the imagery captured by the UAV and the satellite. The UAV imagery was resampled, then regression models, including Random Forest, were used to examine the relationship between the indices derived from the different platforms. It was found that the UAV imagery was more sensitive to changes in tree stress, specifically for smaller stands of trees that were effectively lost in the five meter RapidEye pixel (Dash et al., 2018). While this study confirmed that NDVI and red edge NDVI are the best indices to detect plant stress, the importance of these indices differed by platform. NDVI showed greater predictive power for the UAV imagery, while red edge NDVI was the better predictor for RapidEye imagery. The researchers concluded that the RapidEye sensor’s broader bandwidth for the red edge wavelengths (which encompass the optimum wavelength for plant stress detection at 700 nm) can lead to the UAV-derived red edge NDVI being less useful for tree stress studies because the sensor on this UAV had a narrower bandwidth for the red edge that did not include 700 nm (Dash et al., 2018). Despite the differences in the spectral response of both sensors, the two did exhibit correlation based on the derived indices. The NDVI and green NDVI both showed a linear relationship, while the red edge NDVI revealed a second-order polynomial relationship. The researchers concluded that the sensors were complimentary and could be used together to monitor plant health in the realm of forestry (Dash et al., 2018).

With the precedent set by prior studies focused on the relationship between UAV and satellite imagery, the goal of this study was to further this vein of research and examine the relationship between UAV and PlanetScope satellite imagery. Investigating the relationship between the two platforms could lead to a greater level of study, as
PlanetScope’s daily observation of the earth and 3 meter spatial resolution can aid in temporal analysis, a limiting aspect of data collection using UAV platforms. I hypothesize that productivity and structural metrics will show no statistical difference between the platforms, allowing the two to be analyzed in conjunction to inform greater spatial and temporal analysis of the region. To do this, I have utilized three common vegetation indices, the NDVI, the SAVI, and the EVI2, and examine the relationship between the UAV and the satellite imagery through these indices. If a positive relationship is seen, both images will be classified with the same method to allow for future large-scale analysis of the study area through satellite imagery.

**Methods**

**Study Area**

The imagery for this study was collected in the Kavango-Zambezi Transfrontier Conservation Area (KAZA) in southern Africa (Figure 1). This large wildlife conservation corridor spans over five countries: Angola, Botswana, Namibia, Zambia, and Zimbabwe. The goal of this conservation area is to conserve wildlife at the regional scale through cooperative efforts between nations (Gaughan and Waylen, 2012; Schultz, Shapiro, Clevers, Beech, & Herold, 2018). The precipitation and subsequent vegetation growth in the conservation area follows a gradient from north to south, with the northern portion of the region being wetter, with more dense vegetation growth, while the south is considerably drier (Cui et al., 2013; Schultz et al., 2018). Precipitation is generally variable throughout the conservation area, with the highest annual variability seen in the southern portion (Cui et al., 2013). Through this region flows three major rivers that
affect the landscape and the livelihoods of the inhabitants of the area. These rivers, the Okavango, the Kwando, and the Zambezi, flow from the northern areas with abundant rain into the south, providing water that is vital for both humans and animals (Gaughan & Waylen, 2012).

The strong climate variability seen in the southern portions of KAZA have led to major changes in vegetation structure. Southern Africa’s precipitation regime is strongly affected by the El Nino/Southern Oscillation (ENSO) cycle, the inter-tropical convergence zone (ITCZ), and the sea-surface temperatures of the Indian Ocean, a major source of moisture for southern Africa (Cui et al., 2013; Gaughan & Waylen, 2012). Over the past few decades, these global climate cycles have begun to change, causing higher air temperatures and longer dry periods. These fluctuations have led to landscape degradation in the southern African savannas, characterized by changes in vegetation communities, namely a decrease in variation in vegetation and a move toward a shrub-dominated landscape (Cui et al., 2013). These changes impact the residents of the area, both human and animal. With humans gathering close to the rivers of the region to provide water for themselves, along with their livestock and crops, conflicts with wildlife become common during the dry season when water is exceptionally scarce (Gaughan & Waylen, 2012). Precipitation variations also negatively affect the conservation goals of this region, as a changing landscape will impact the wildlife of the region, making it increasingly difficult for humans and wildlife to coexist. Knowing the possible impacts on both humans and wildlife due to climate variability, studying these trends at small and large scales over the course of time will help to keep KAZA a healthy, well-functioning conservation area for all residents.
Figure 1. Study Area map for the KAZA region. The top panel shows the entire conservation area, represented by the red outline. Selected UAV sites for 2017 and 2018 are shown in the lower two panels, with sites represented by color-coded rectangles.
Study Methodology

Field Data Collection and Initial Processing

Data was collected in the field over the course of several visits to the KAZA region. The first trip where UAVs were used as a form of data collection was in 2017, where the team of researchers traveled to Namibia to conduct the first systematic acquisition of imagery. 60 sites were randomly selected, representing a variety of land cover types, ranging from dense woodlands to open grasslands and agricultural areas. These sites were selected using a stratified random sampling protocol. The first stratification was by country context, the second by community, the third by the centroid of the community, and the fourth by proximity to roads of varying degrees of use (Olsen, 2017). UAV flights were conducted during peak sunlight hours when at all possible, to avoid excessive shadow that would obscure the images. Calibration data for each flight was collected using a radiometric calibration target. UAV imagery was collected according to a flight path planned in the Pix4D software for each site. The flight design was a double overlapping grid with 80% image front overlap and 70% image side overlap for sites 200 by 200 meters (Olsen, 2017). A DJI Mavic Pro drone was used to collect both the RGB imagery that would be used to derive the digital surface and terrain models, while an externally mounted Parrot Sequoia Multispectral Sensor was used to collect multispectral imagery in four bands, green, red, red edge, and near infrared. Along with the UAV imagery, ground control points and vegetation transects were collected at each site, using Open Data Kit Collect, to ensure proper ground validation for the UAV data (Olsen, 2017). Three ground control points were taken along the diagonal of the 50 meter long transect, one at the center and one at either end of the transect. These were
demarcated on the ground using brightly colored markers that could be seen in the imagery collected by the UAV (Olsen, 2017). 2018 data collection followed a similar process, with modifications to the vegetation transect collection protocol. The study area was expanded to include 42 randomly selected sites in a communal area of Botswana.

All UAV flight images were processed in Pix4D software by research colleagues at the University of Louisville. Using the structure-from-motion algorithm embedded in Pix4D, for each of the 102 sites, we created a multispectral orthomosaic, a digital terrain model (DTM), and a digital surface model (DSM) from the imagery collected. Structure-from-motion (SfM) is a concept similar to stereoscopic photogrammetry, where multiple overlapping, offset images can be used to construct a three-dimensional structure of an area (Westoby, Brassington, Glasser, Hambry, & Reynolds, 2012). In the case of SfM, these images do not need the network of 3D positioning targets needed in traditional stereoscopic photogrammetry. Rather, features are automatically extracted from overlapping images and iterative bundle adjustments are used to create the SfM-derived three-dimensional image (Westoby et al., 2012). Most processing defaults were left, save for a few with special considerations. Alternative calibration was used, as this setting is optimal for nadir images with accurate geolocation. Full image scale was used to compute additional 3D points. Though this setting is more computationally intense, the additional points are very helpful in image processing compared to the results from the default half-image scale. Window matching size was increased to 9 by 9, to improve the accuracy of the densified points. Again, this is more computationally intense than the default, but yields a more rigorous result (Kolarik, 2018). Finally, triangulation raster interpolation, based on Delauney triangulation, was used to create the output raster. This
creates a more detailed, though less smooth, raster product compared to inverse distance weighting processing and is recommended by Pix4D for agricultural areas or other areas where high detail is needed, such as our own (Kolarik, 2018). Due to issues in GCP reliability at the fine spatial scale of the UAV imagery, GCPs were not included in 2017 processing. Rather, it was concluded that the UAV on-board GPS was sufficient for proper image rectification. Initially, multispectral images were radiometrically calibrated, but it was discovered that the calibration cards for the associated bands were collected incorrectly for 2017. After this discovery, imagery from both 2017 and 2018 was reprocessed, leaving the multispectral imagery radiometrically uncalibrated.

In conjunction with the UAV imagery, Planet satellite imagery was utilized. Planet Labs is a commercial satellite imaging company that collects satellite data through three major sensors, PlanetScope Doves, SkyStat, and RapidEye. The goal of Planet Labs is daily collection of imagery covering the entire planet (Planet Monitoring). PlanetScope is the daily collection sensor array, with over 120 Dove satellites imaging the earth daily (Planet Imagery and Archive). These satellites collect at a spatial resolution of 3.0 meters, with a four band spectral resolution, comprising of red, blue, green, and near infrared bands (Planet Monitoring, Table 1). For this study area, I was able to utilize imagery that coincided spatially with the UAV flight sites. Though the dates of collection were not exact, I ensured that the images were collected within a few weeks of flights. For 2017, I used PlanetScope images for June 2 and June 4 and for 2018, I utilized a single image from June 6 of that year for analysis. PlanetScope 3B analytic image packages are orthorectified and corrected to surface reflectance values by the company, utilizing sensor telemetry and a sensor model for the latter. The 16-bit surface reflectance file provided in
the package contains the surface reflectance corrected image. (Planet Imagery Product Specifications).

<table>
<thead>
<tr>
<th>Sensor Type</th>
<th>Spatial Resolution</th>
<th>Spectral Resolution</th>
<th>Spectral Wavelength (nm)</th>
<th>Temporal Revisit</th>
</tr>
</thead>
<tbody>
<tr>
<td>UAV Parrot Sequoia +</td>
<td>.10 meters (depending on sensor altitude)</td>
<td>Green, Red, Red Edge, Near Infrared</td>
<td>530-570, 640-680, 730-740, 770-810</td>
<td>As operator determines</td>
</tr>
<tr>
<td>PlanetScope</td>
<td>3.0 meters</td>
<td>Blue, Green, Red, Near Infrared</td>
<td>455–515, 500–590, 590–670, 780–860</td>
<td>Daily</td>
</tr>
</tbody>
</table>

Table 1. This table shows the specifications for both the UAV and the PlanetScope sensor used in this study.
Imagery Analysis

Initial analysis of the UAV and PlanetScope imagery was conducted in both ArcGIS Pro and ENVI. Due to issues with ENVI reading and processing PlanetScope imagery, PlanetScope vegetation indices were calculated in ArcGIS Pro, then exported to ENVI in an ENVI-readable format. Final UAV analysis was conducted in ENVI. Of the many flights available, an initial sample of eleven flights were chosen, seven from 2017 and four from 2018 (Figure 1). These sites were chosen based on land cover type, so a variety of local land covers, such as grassland or shrub-dominated, were included for analysis. Only images with a low degree of tree shadow were included. For both imagery platforms, three different vegetation indices were calculated, the normalized difference vegetation index (NDVI), soil-adjusted vegetation index (SAVI), and the enhanced vegetation index 2 (EVI2), described above. Coefficients in the SAVI and EVI2 were kept uniform between platforms.

After the vegetation indices were calculated, PlanetScope images were clipped to the extent of the UAV imagery. UAV imagery was then rescaled to 3.0 meters using nearest neighbor resampling to allow for analysis between the two platforms. The UAV and PlanetScope images were stacked, then scatterplots were produced to analyze the relationship between the vegetation indices for the two platforms. The sites with the best relationship between the UAV and the satellite imagery were used to conduct vegetation classification (see Appendix A). For each year, 2017 and 2018, two sites (A230 and A242; A2200 and F4003 respectively) were tested. Of these sites, only the NDVI values showed a strong linear correlation, so classification analysis was performed for only the NDVI index images.
Classification of the imagery was performed using three methods: a classification based on productivity values only, a classification that combined vegetation structure and productivity, and an unsupervised ISODATA classification. First, histograms of both the UAV and the PlanetScope NDVI values for each site were analyzed to determine natural breaks in productivity values (Figure 2). Four classes were created by this method. The highest productivity category included NDVI values above 0.6, the middling productivity category included values between 0.45 and 0.6, a low productivity category from 0.3 to 0.45, and finally a very low productivity category for values below 0.3. These breaks were used for both PlanetScope imagery and UAV imagery to maintain classification consistency, applied through a decision tree classification method which produces binary “yes” and “no” decision values that can be further subdivided to produce finer classifications (Figure 3).
Figure 2. The above figure is an example of the histogram of the NDVI values for site A2200, with band 1 representing a UAV image and band 2 representing a PlanetScope image. The UAV value range extends further at the low and high end than the PlanetScope index values, which remain constrained in the middling range. The correlation between histograms informed the productivity breaks used in both decision tree classifications.
Figure 3. This figure shows the productivity-only decision tree classifier used for this classification.
The second classification scheme combined vegetation structure measurements derived from the UAV and productivity measurements from both platforms. First, UAV digital terrain models and digital surface models were used to provide a classification of vegetation structure. The digital surface model is a three-dimensional model of the flight area that records shape, height, and location of all structures in the area, including trees and shrubs, along with any built objects on the landscape. The digital terrain model is another three-dimensional model that can be derived from the UAV sensor, but only records the actual ground surface of the area, leaving out trees and other elevated structures. Thus, subtracting the digital surface model from the digital terrain model can create estimates of plant height. This analysis was performed through band math, then the difference image was resampled to 3.0 meters to facilitate analysis between the resampled UAV imagery and the PlanetScope imagery.

Once the difference image was created, breaks were created based on field measurements. Plants above 3.0 meters in height were classified as trees. Plants between 1.0 meters and 3.0 meters were classified as shrubs, while plants below 1.0 meters were classified as grasses. A decision tree was created where the difference image was classified according to these breaks, with all trees and shrubs classified based on height alone, regardless of NDVI. For land cover below 1.0 meters in height, NDVI was included to differentiate between grass and bare ground. For land cover below 1.0 meters in height, productivity values above 0.3 indicated grass. All submeter groundcover with NDVI values below 0.3 were classified as bare ground. This decision tree classification with the UAV-derived difference image were used for both UAV and PlanetScope imagery (Figure 4).
Figure 4. The above figure is of the productivity and structure-based decision tree classifier, created in ENVI.
The third and final classification method utilized an unsupervised ISODATA classification in ENVI. The image input was the NDVI image for both the UAV and the PlanetScope images. A minimum of ten clusters were created using twenty iterations of the ISODATA algorithm. ISODATA stands for Iterative Self Organized Data Analysis and is one of the more successful unsupervised classification methods, especially for complex imagery (Mitra, Mitra, & Santra, 2017). Clusters were generally grouped from lowest reflectance to highest for both platforms. Then, these ten clusters were reclassified into three ground cover classes, based on visual comparison of the very high resolution UAV imagery. Four classes were created from the ISODATA clusters; bare ground, grass, shrub, and tree. After completing all three classifications, the UAV and PlanetScope classifications for each site were compared using a T-test in Excel 2016. For each site and for each classification used, a two-tailed heteroscedastic T-test was performed on the pixel counts for the classification, to compare the UAV and Planet classifications.

Accuracy Assessment

An accuracy assessment was conducted on two selected sites, one for each year of collection. The two sites were A242 from 2017 and F4003 from 2018, both chosen for their visually apparent vegetation community classes that aligned with the four classes created through the classification methods in this study. First, regions of interest (ROI) were selected based on visual analysis of the original UAV imagery, to determine locations of trees, shrubs, grasses and bare ground cover. A mix of the single band greyscale imagery and derived NDVI values were used to determine these classes. After at least ten ROIs were created for each class, these ROIs were used to create a confusion
matrix in ENVI. Compiled confusion matrix results for both UAV and PlanetScope are shown in Table 3. These results focus on overall accuracies and Kappa Coefficients for each classified image. The overall accuracy is calculated by adding together the number of correctly identified class values, then dividing by the total number of values, while the kappa coefficient measures the agreement between classification values and truth values based on ROIs. A kappa coefficient of 1 represents perfect agreement, while a kappa coefficient of 0 represents no agreement (Calculating Confusion Matrices).

Results

When the first set of 2017 imagery was processed under initial calibration settings, a consistent difference was seen in UAV image values for all indices. Overall, there seemed to be a shifting up of the minimum value compared to the index values for Planet imagery. This issue was resolved by leaving the UAV imagery uncalibrated. Initial observations of the three indices showed some discrepancies between the Planet and the UAV imagery in terms of index range. The NDVI range was most similar between the two platforms, while the EVI2 was the least similar. Figures 5, 6, and 7 show scatterplots for the same site using three different indices, with the range for the UAV image on the x-axis and the range for the Planet image on the y-axis. The remaining scatterplots for the various sites are placed for reference in Appendix A. Correlation between the Planet and the UAV indices were strongest for the NDVI, showing a generally linear relationship compared to the SAVI and EVI2 relationships. This led to my aforementioned selection of the four sites, A230, A242, A2200, and F4003. The NDVI scatterplots for these four sites are included in Appendix A.
Figure 5. The above figure shows the NDVI scatterplot for site A230, with the UAV values falling on the x-axis and the PlanetScope values falling on the y-axis. For the NDVI, a generally linear relationship was seen compared to the two other vegetation indices.
Figure 6. This figure is of the scatterplot for the EVI2 of site A230, with the UAV values on the x-axis and the PlanetScope values on the y-axis. Note the differences in value range and the pattern of the values gravitating toward the left-hand side of the graph.
Figure 7. The above figure is of the scatterplot for the SAVI index of site A230, with the UAV values on the x-axis and the PlanetScope values on the y-axis. Though the value range for the two platforms are more alike than what was seen in the EVI2, the general trend of the scatterplot is similar, with values pushed to the left-hand side.
Classification Results

The three classification methods consistently revealed that the two platforms showed dissimilar results. A classification based on productivity alone seemed to work fairly well for the UAV imagery, but the PlanetScope imagery tended to underestimate high NDVI scores across all four images. This was very apparent in sites with a large amount of vegetation, such as A230 or F4003, seen in figure 8 above. While the UAV was able to pull out the higher values that represent high productivity, Planet seemed to struggle to do the same. In areas with more variegated land cover, such as in A242, the UAV image reveals very fine differentiations in classification, while the PlanetScope imagery generalizes the classes a bit more. All T-tests for the productivity-based classifications showed no statistically significant correlation between the classified images, with all p-values hovering around 1 (Table 2). The accuracy assessment for both the UAV and PlanetScope imagery for the two sites demonstrated around a 50% overall accuracy, save for the F4003 UAV classification, which produced only a 25% overall accuracy. The kappa coefficients for all four images were below 0.25, demonstrating low agreement (Table 3).
Figure 8. The above figure shows the results of the decision tree classification method based on productivity alone. PlanetScope generally underestimates high productivity values, while the UAV classification is noisier, even at the same pixel size.
Table 2. This table compiles the results of the pixel-based T-tests for each classified image. The pixel counts are grouped by platform, while the T-test results for each site are presented below the first column associated with that site.
<table>
<thead>
<tr>
<th>Site and Classification</th>
<th>UAV Overall Accuracy</th>
<th>UAV Kappa Coefficient</th>
<th>Planet Overall Accuracy</th>
<th>Planet Kappa Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>A242-Productivity Only</td>
<td>(301/685)</td>
<td>43.9416%</td>
<td>(582/1153)</td>
<td>0.146</td>
</tr>
<tr>
<td></td>
<td>43.9416%</td>
<td></td>
<td>50.4770%</td>
<td></td>
</tr>
<tr>
<td>A242 Structure and Productivity</td>
<td>(544/1146)</td>
<td>47.4695%</td>
<td>(566/1146)</td>
<td>0.2249</td>
</tr>
<tr>
<td></td>
<td>47.4695%</td>
<td></td>
<td>49.3892%</td>
<td></td>
</tr>
<tr>
<td>A242 Classified ISODATA</td>
<td>(626/1153)</td>
<td>54.2931%</td>
<td>(565/1153)</td>
<td>0.3018</td>
</tr>
<tr>
<td></td>
<td>54.2931%</td>
<td></td>
<td>49.0026%</td>
<td></td>
</tr>
<tr>
<td>F4003 Productivity Only</td>
<td>(219/878)</td>
<td>24.9431%</td>
<td>(417/878)</td>
<td>0.2927</td>
</tr>
<tr>
<td></td>
<td>24.9431%</td>
<td></td>
<td>47.4943%</td>
<td></td>
</tr>
<tr>
<td>F4003 Structure and Productivity</td>
<td>(482/907)</td>
<td>53.1422%</td>
<td>(618/907)</td>
<td>0.5373</td>
</tr>
<tr>
<td></td>
<td>53.1422%</td>
<td></td>
<td>68.1367%</td>
<td></td>
</tr>
<tr>
<td>F4003 Classified ISODATA</td>
<td>(274/878)</td>
<td>31.2073%</td>
<td>(316/878)</td>
<td>0.178</td>
</tr>
<tr>
<td></td>
<td>31.2073%</td>
<td></td>
<td>35.9909%</td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Confusion matrix results for the UAV imagery are presented in this table.
The structure and productivity-based classification appeared to perform a bit better for both the UAV and the Planet imagery, with a greater level of differentiation seen in both due to the addition of structure. Utilizing structure to inform classification seemed to aid in uniting the two platforms, but this would be limited to sites flown by UAV, instead of allowing for a more expansive analysis of the region through satellite imagery. Additionally, the PlanetScope imagery shows the opposite trend as seen in the productivity-only classification method, where it is now underestimating the low productivity values that represent bare ground cover. In some instances, such as site F4003, the bare ground class is almost nonexistent in the PlanetScope imagery, while the UAV image was able to produce this classification (Figure 9). T-tests for this classification method also revealed that there was no statistically significant correlation between the images. Again, all p-values were around a value of 1 (Table 2). The accuracy assessment for both UAV and PlanetScope imagery for the two sites also demonstrated around a 50% overall accuracy for this classification method. The exception was the PlanetScope F4003 classification, which had an overall accuracy of 68% and a kappa coefficient of 0.5, representing middling agreement. The remaining three images all had kappa coefficients around 0.2 or 0.3, representing low class agreement (Table 3).
Figure 9. The above figure represents the structure and productivity-based decision tree classification results. In this classification method, PlanetScope generally underestimates low productivity values, while the UAV results remain noisy.
The third and final classification method, an unsupervised ISODATA classification, also revealed high discrepancies between the UAV and the Planet imagery. Even initial results with 10 unsupervised clusters showed that the UAV imagery was far noisier than the Planet imagery, even after performing resampling. As shown in figure 10, the initial ISODATA classes show a noisy and difficult to visually interpret UAV image, while the Planet image classes are far smoother, with classes that are easier to interpret popping out in the image. After using the greyscale green band UAV image and the UAV NDVI to inform class clustering, the two platforms still yielded different results in classification. Visually, they appear to be more similar and align with the visually observed land cover classes in the UAV imagery. This similarity would not carry over into the analysis, as no sites had a statistically significant relationship between the images, just as it was seen in the prior two classifications (Table 2). The accuracy assessment for both platforms varied by site in the case of the ISODATA classification. For site A242, both platforms demonstrated around a 50% overall accuracy and a kappa coefficient around 0.3, while site F4003 had only around 35% overall accuracy for both platforms and a kappa coefficient of 0.1, showing a very low classification agreement (Table 3).
Figure 10. The above figure represents ISODATA classification method performed on all images, with the clusters running generally from low productivity (Class 1) to high productivity (Class 10). Note the large amount of noise in the UAV imagery, while the PlanetScope classification has a smoother contour.
Figure 11. The above figure shows the ISODATA classification, reclassified into four classes by using the UAV imagery for visual analysis of classes. Overall, the ISODATA classification appears to fit the visual classification of the landscape well, with the two platforms showing a bit more agreement. Nevertheless, the UAV imagery is considerably noisier than the PlanetScope, which in turn affected statistical analysis.
Discussion

The results of the comparison of vegetation indices between the two platforms and the three classification methods used for the most correlated sites show considerable difference between the two sensor platforms. First, initial scatterplots revealed a poor relationship between the two platforms for the SAVI and the EVI2. Both of these indices had the greatest issues in scale correlation between UAV and PlanetScope imagery, along with unusual relationships seen in the scatterplots (Appendix A). This could be due to the use of coefficients in both equations that may be designed only for use with satellite imagery and do not transfer well to UAV imagery. Thus, the simple ratio equation of the NDVI proves to be the most useful index for this study, echoing its use in other UAV vegetation productivity studies (Tian et al., 2017; Dash et al., 2018; Böhler, Schaepman, & Kneubühler, 2018). Though the range in NDVI values differed between platforms, the values were similar overall, allowing for classifications to be performed.

The classification methods used revealed the differences between the platforms. Through general zones of an image were classified similarly, the details of the classes were often quite different. As seen in site A2200 for example, classifying based on productivity alone reduced the ground cover classification in the PlanetScope image. Similar effects on high values are seen in A242, where much of the area classified as highly productive in the UAV imagery is lost in the PlanetScope imagery. The overall accuracies for the productivity-only classification were approximately 40% to 50%, with one site, the UAV classification for F4003, having an overall accuracy of 24%. No images related to this classification method demonstrated high accuracy, with kappa coefficients below 0.3, indicating a low agreement between the classification and visually
classified ROIs (Table 3). While incorporating structural classes aided in classification of both platforms, these are specific to the UAV sites, as these structural estimates were based on structure-from-motion imagery derived from the UAV. This would prevent analysis over larger areas of PlanetScope imagery that lacks the structural data from a UAV flight. Also, the classifications were still not statistically significant, indicating that structure did not aid in classifying the image. The accuracy assessment demonstrated that this classification method had a moderate level of accuracy, around 50% for the classified UAV sites and nearly 70% for a classified Planet site. The agreement between classified images and selected ROIs was better for this classification method, with kappa coefficients between 0.2 and 0.5, reflecting a moderate level of agreement (Table 3). Finally, the ISODATA classifications showed the noise inherent in UAV imagery, as demonstrated in classifications shown in Figure 9. PlanetScope classifications, using the same method within the ISODATA algorithm, reveal smoother classifications that aligned with features in the landscape. In spite of this, the ISODATA classification method did not demonstrate high classification accuracies, especially for the site F4003, where both UAV and PlanetScope classified images have overall accuracies around 30%, with very low agreement (Table 3). This analysis demonstrated that the UAV platform has a problem with noise related to pixel size, which impedes classification and analysis on a pixel-by-pixel basis. Below, further consideration is taken for spatial and spectral differences between the platforms that ultimately make a pixel-based classification method difficult.
Spatial Considerations

A major difference between satellite and UAV platforms is spatial resolution. The UAV sensor used in this study had a spatial resolution of around 10 centimeters, while the Planet satellite image’s resolution is 3 meters. This is a considerable difference in pixel size, which also creates difference in how the two platforms record images. As Tian et al. (2017) noted, a very fine spatial resolution will cause greater variation in the reflectance values of a UAV image. This was seen in the massive range in index values for all UAV images in this study, as demonstrated by the histograms shown in figure 2. The large range is due to the UAV sensor picking up on minute details in the landscape, then recording these details in a small pixel. This leads to greater variation in the UAV image, despite the narrow bandwidth. Though a smaller range of possible wavelengths are recorded in a UAV sensor, the small pixel size records fine details in the landscape that would be averaged in a much larger pixel. This was seen the ability of the UAV sensor to better differentiate between plant and ground in an image compared to the WorldView-2 satellite image (Tian et al., 2017). This can be very advantageous when considering fine classes in imagery, but when analyzing averages of an index, this high variation can create issues. The more variable range of index values can create issues with classification, as I saw in this study. Though most values for the UAV NDVI were clustered near the same range of index values as the Planet image, the spread of index values in the UAV image were far greater. Ultimately, the greater variation and range within the UAV image makes the comparison of UAV and satellite imagery through pixel-based analysis difficult.
Overall, it appears that the greatest issue in comparing the two platforms in this study is in fact the very high resolution of the UAV imagery. When dealing with pixels that are mere centimeters wide, an enormous amount of data is collected, especially in comparison to even a high resolution satellite image, such as the 3 meter Planet pixel. Though the target data is collected, the small pixel size of a UAV also allows for the collection of noise, such as shadows in the image or gaps between trees (Lu and He, 2017). This was seen readily in the UAV imagery utilized in this study, with considerable shadowing around trees, along with canopy gaps leading to an excessive amount of ground cover visible in vegetated areas. This nearly excessive data collection leads to a heterogeneity within classes that make classification of imagery difficult from a spectral perspective. As stated by Lv, Shi, Benediktsson, and Ning, when classifying imagery, higher spectral resolution is more advantageous than higher spatial resolution for applications such as this study, where fine spectral differentiation is needed to determine vegetation productivity by plant type (2016). Higher spatial resolution increases variation within classes, which tends to make differing classes more spectrally similar, thus making classification on a pixel by pixel basis far more difficult. Rather, most UAV classification methods that have proven successful are object-based classifications such as Geographic Object-Based Image Analysis (GEOBIA) (Lu and He 2017). Objects are created through image segmentation, a type of spectral analysis that allows for the creation of segments based not on single pixel factors, but rather aggregated factors such as averages per band and variance within like segments, along with non-spectral attributes such as texture and geometry (Blaschke, 2010; Ruiz, Gussaelli, ten Caten, and Zanotta, 2018). This type of analysis works well for very high spatial resolution imagery such as UAVs, where objects
in the image are larger than the pixel size, thus made up of multiple pixels. Object based analysis has been used for many decades in a variety of image-based fields, but the advent of high-resolution satellite imagery in the early twenty-first century and the increased use of UAVs have led to many studies that focus on object-based analysis methods (Blashke, 2010; Lu and He, 2017; Alvarez-Taboada, Paredes, and Julián-Pelaz, 2017; Ruiz, Gussaelli, ten Caten, and Zanotta, 2018; Komárek, Klouček, and Prošek, 2018). For imagery with very high spatial resolutions, object-based analysis proves to be a far more useful classification method than pixel-based analysis, as was performed in this study.

Spectral Considerations

The results show some issues with spectral relationships at varying levels. First, the UAV imagery had to remain uncalibrated due to issues with field collection protocol in 2017. A few limited studies have focused on utilizing uncalibrated UAV imagery, with Bohler et al. discovering that uncalibrated imagery still could produce accurate results in crop classification of farm fields in Switzerland (2018). Interestingly, this study showed that the near infrared band was not as useful for crop classification as simply using the RGB camera (Bohler et al., 2018). Rather, the red band, whose upper end bandwidth was very close to the lower end of the NIR band in their sensor, proved to be the most useful for crop classification. Some species would benefit from the additional spectral information from the NIR, especially very similar species such as species of wheat. These results were interesting, especially given that most vegetation indices are based on the use of the NIR band, including all three I have worked with. Another agriculture-based study compared the uncalibrated RGBVI index to a calibrated NDVI index from a different
sensor, discovering that the two indices were strongly correlated (Bareth et al., 2016). This correlation was only seen in an experimental plot, while a true farmer’s field did not show such a relationship. The researchers think that this is due to the NDVI saturating at high values, while the uncalibrated RGBVI retained its ability to differentiate between crops even during the peak growing season (Bareth et al., 2016). These studies seem to demonstrate that uncalibrated UAV imagery should not create excessive issues in classification, though care must be taken when considering indices with NIR bands, both for calibrated and uncalibrated imagery.

When considering the relationship between UAV and satellite imagery, one must consider inherent differences in the sensors used on both platforms. UAV sensors are quite different in quality compared to satellite sensors for varying reasons. First, UAV sensors are mass produced for the general market, while satellite sensors are mounted on a single satellite that will observe the earth from the orbital platform. Satellite sensors generally have a greater range in spectral bands, though some, like the Planet constellation, have only four spectral bands. No matter the platform, satellite sensors have a much wider bandwidth than UAV sensors. As demonstrated in Tian et al.’s 2017 study of mangroves using UAV and WorldView-2 imagery, satellites have spectral bands that record a far wider range of wavelengths compared to UAV sensors. This can become an issue when performing analysis between the two platforms, as a narrow spectral band will miss important data a satellite sensor can pick up. An example of this was demonstrated in the study of forest health by Dash et al. (2018) where the narrow red edge band of the UAV sensor missed a specific red edge wavelength that has been found to be a signal of plant distress. On the other hand, the satellite did pick up this wavelength
because of the capabilities of its sensor (Dash et al., 2018). This is much the case in this study, where the Planet sensor has a much wider bandwidth compared to the Parrot Sequoia Multispectral Sensor that was used on the UAV. Planet’s bandwidth is nearly double that of the UAV sensor bands for the three bands the sensors share in common. (Shi et al., 2018; Parrot Sequoia +) The discrepancy in bandwidth between the two sensors can create issues in analysis. Trends may be seen in reflectance values and derived indices, but exact one-to-one spectral profiles would be more difficult to determine due to these inherent technological differences.

Due to differences in spectral response for UAV and satellite sensors, creating and comparing spectral indices can be difficult. First, in this study, both the SAVI and the EVI2 utilize coefficients to modify spectral responses in different bands to adjust for factors that may influence a vegetation index. The EVI and the EVI2 were both first utilized in MODIS imagery, with coefficients to adjust for soil and atmospheric influences (Jiang et al., 2008). The coefficients that correct for atmospheric influences would be useful for Planet imagery, but not for the UAV images. The SAVI utilizes a soil adjustment factor coefficient, but this coefficient may need to be modified according to sensor type, a consideration beyond the scope of my current knowledge. Additionally, some questions have been raised about the use of the SAVI in very arid landscapes with low vegetation cover, such as some of the areas in our own study with sparse vegetation. Ren and Feng discovered that six soil adjusted vegetation indices did not improve vegetation estimation in areas with 30% or less vegetation cover, namely due to low greenness of vegetation in arid areas leading to the soil adjustment factors underestimating the variability of plant greenness (2014). Overall, the NDVI, a simple
difference index, has proven to be a consistent, though imperfect, index for estimations of
greenness. This is demonstrated by the greater linear correlation between the two sensor
platforms in this study compared to the SAVI and the EVI2, which may either may be
inappropriate for UAV use due to unnecessary atmospheric correction factors or
coefficients that may need to be manipulated to yield an accurate result.

Comparing spectral indices derived from two sensor platforms reveals problems
in relation to aforementioned issues of differing bandwidth and variation in pixel
reflectance. In establishing a pixel-based index link between the two platforms, the
greater variation in index values for the UAV imagery made deciding productivity breaks
that would be appropriate for both platforms extremely difficult. The Planet-derived
NDVI had a far more compressed range due most likely to larger pixel size, along with
differences between sensors. Though resampling was necessary to establish to attempt a
direct comparison between the two platforms, this may have only increased the difference
seen in the UAV imagery, depending on the type of resampling method used. This was
discovered by Dash, Pearse, and Watt, who utilized cubic spline resampling in their
study. They found that resampling created differences in the three index values calculated
for all tree cluster sizes (2018). I utilized a nearest neighbor resampling method, which
maintains a better continuity between original values and the resampled values. This
method may have preserved the original pixel values to a greater degree than methods
that tend to smooth data and add error such as bilinear interpolation and cubic
convolution, but this may have instead maintained the variation that makes comparison
between the platforms more difficult. In addition, both Dash et al. and Tian et al.
discovered that different spectral indices performed better for each platform. Dash et al.
discovered that the NDVI performed better for the UAV imagery, while the Red Edge NDVI was a better choice for the RapidEye imagery (2018). Similarly, Tian et al. found that, of the three NDVI-based indices used, the average NDVI showed the highest accuracy in the WorldView-2 satellite, while the scaled NDVI was the most accurate for UAV imagery (2017). These studies reveal that attempting to utilize the same index for imagery classification, as I did in this study, may not be the best choice due to inherent sensor differences that affect accuracy for varying indices.

**Conclusions**

In this study, vegetation index-based pixel analysis was performed on UAV and Planet satellite imagery, in an attempt to examine the relationship between the two platforms based on shared derived characteristics. It was discovered that this relationship was not present, with no statistical significance seen in the comparing the three index-based classification methods used for both platforms. Accuracy assessment further confirmed this result, demonstrating moderate to low classification accuracy with generally low classification agreements. This confirms a null hypothesis, that there is indeed no similarity between the sensor platforms. This study confirmed what others have demonstrated, that the spatial and spectral differences between UAV and satellite imagery prove to be difficult to reconcile when comparing imagery derived from the two platforms, especially when attempting a pixel-based analysis. Instead, for UAV imagery in particular, object-based analysis performs best for classification of imagery. In future studies, improvements to the methods presented here can be made. Increasing the sample size of images used in the study would be helpful, especially with a focus on adding multiple land cover types. Here, most land covers were dominated by shrubs and trees,
with few agricultural areas or open grasslands used, as these images demonstrated the least correlation between the UAV and the Planet imagery. Analyzing more sites may help in this, allowing future researchers to determine if a stronger relationship could be seen in other land cover types. Utilizing object-based analysis of the UAV imagery would be especially helpful, though carrying this type of analysis over to a lower resolution satellite may present some issues. If a similar pixel-based study utilizing indices was performed, using different vegetation indices may be helpful in analyzing the relationship between sensors. These could include indices without satellite-derived coefficients, given the stronger relationship seen with the NDVI, which lacks those coefficients. Finally, working with other classification methods, such as Random Forest or other machine learning classification algorithms, may provide more robust classification results that may aid in analyzing the relationship between the sensor platforms.

This study has demonstrated that sensor differences can create problems in analysis that must be considered when working with two largely different platforms. Rather than a simple one-to-one comparison, the differences between UAV and satellite imagery make examining relationships between the two difficult, though not entirely insurmountable. Future studies utilizing differing classification methods and indices may be able to examine this relationship in greater depth. With an increase in UAV research across the globe, there is much hope for the field. UAVs provide an excellent source of information for scientists that satellites cannot provide and though the amount of data UAVs record can be exceptionally challenging to work with, properly harnessing this technology can greatly add to our scientific knowledge in remote sensing. This study shows some of the pitfalls of working with UAV imagery, hopefully helping others to not
only consider these issues, but inspiring them to continue the work needed to overcome these problems in their analysis.
References


Calculate Confusion Matrices. (n.d.) Retrieved from
https://www.harrisgeospatial.com/docs/CalculatingConfusionMatrices.html

Cui, X., Gibbes, C., Southworth, J., & Waylen, P. (2013) Using remote sensing to


Ren, H. & Feng, G. (2014) Are soil-adjusted vegetation indices better than soil-
doi:10.1111/gfs.12152


sustainability science. *Proceedings of the National Academy of Sciences, 100*(14), 8074-8079. doi:10.1073/pnas.1231335100

Appendix A

The following images represent the scatterplots for all sites considered in this study. For each image, the UAV image values align with the x-axis, and the PlanetScope image values align with the y-axis. Colors range from blue to red, with red colors indicating more data points.

**A230**

NDVI
A230_EVI2_3m_stack.dat

Layer (ROI R...clip.dat)

Layer (Resiz...12_3m.dat)
A234

NDVI
EVI2
SAVI
A239
NDVI
EVI2

A239_EVI2_3m_stack.dat
A242
NDVI
EVI2
SAVI
A310
NDVI
EVI2

A310_EVI2_3m_stack.dat

Layer (ROI R...clip.dat)

Layer (Resiz...AV_3m.dat)
F401
NDVI
A2002_EVI2_3m_stack.dat
A2200

NDVI

A2200_NDVI_3m_stack.dat
EVI2

A2200_EVI2_3m_stack.dat

Layer (ROI R..._clip.dat)

Layer (Resiz..._clip.dat)
F4000
NDVI

F4000_NDVI_3m_stack.dat
F4003
NDVI

![F4003_NDVI_3m_stack.dat](attachment:image.png)
SAVI

F4003_SAVI_3m_stack.dat