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Comparison of two classification methods for vegetation mapping in Palau

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COMPARISON OF TWO CLASSIFICATION METHODS FOR VEGETATION MAPPING IN PALAU

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ABSTRACT

COMPARISON OF TWO CLASSIFICATION METHODS FOR VEGETATION MAPPING IN PALAU

By Julie K. Andersen

The goal of this thesis is to test and develop a classification method using IKONOS imagery to produce a vegetation map for the tropical islands of Palau. Two methods of classification are tested and compared: the use of per-pixel based classifications and segmentation-based classification. Existing research on this subject shows no current consensus on the best method of classification for tropical Pacific vegetation. The two different classification methods were compared visually to determine the suitability of IKONOS imagery to map diverse tropical vegetation on the islands of Palau.

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CHAPTER 1: INTRODUCTION

BACKGROUND ON REMOTE SENSING IN TROPICAL VEGETATION

Remote Sensing involves the collection of information about an object or geographic area from a distant vantage point using specialized instruments (Jensen, 1996). Remote sensing can be as simple as looking across a valley and stating what is on the other side, to visual interpretation of aerial photographs, to the use of highly specialized sensors orbiting high above the earth. For the purposes of this study the distant vantage point is near-earth orbit and the specialized instrument is a sensor mounted aboard a satellite. The sensor is used to measure the reflectance values of light in different portions of the spectrum.

In instances when remote sensing is used in tropical coastal ecosystems, which are intricate and geographically complex, high-resolution data must be used to accurately rectify these features (Chauvaud, Boushon, & Maniere,1998). For the purposes of this study two different methods of remotely sensed data classification are employed.

The first method studied is unsupervised classification. Unsupervised classification is a traditional scientifically sound method used to classify remotely sensed data using a per-pixel approach. An unsupervised classification is dependent on the data itself for the definition of classes. This method is used when less is known about the data before classification. The analyst's responsibility, after classification, is to attach meaning to the resulting classes (Jensen, 1996).

The next method is segmentation. Segmentation involves using an algorithm to group (or segment) portions of the image into areas of like pixels. The groupings can then be labeled with a corresponding class value.

This study is to test two classification methods including, unsupervised and segmentation as a base for classifying, and mapping the diversity of vegetation types found on Palau by using high-resolution satellite imagery. Previous vegetation maps exist for Palau but are in need of updating. Updated maps will be used for resource management, change detection, and to identify resources at risk. The Republic of Palau and its diverse vegetation have undergone much change and have potential large scale land use changes in their near future. Work was also completed to determine if the newly developed classification based on satellite imagery is comparable with the previous classification based on aerial photo interpretation. Obtaining a new vegetation classification that does crosswalk with the previous classification allows for study of the land use changes and patterns that emerge across the landscape over time.

LOCATION OF THE STUDY: PALAU

This study was conducted in The Republic of Palau. Palau is located between the Philippine Sea to the west and the Pacific Ocean to the east. Palau lies in the South Pacific and covers an area of 458 sq km (CIA World Factbook, 2006). The islands of Palau run roughly from north to south, covering about 125 miles (Galibrath, Bendue,& Friary, 2000). A map showing Palau and surrounding islands can be found in Appendix A.

In order to map the diversity of vegetation on Palau, this study compares a spectrally based per-pixel classification with a spatial object oriented classification each using a different software package: ERDAS Imagine and eCognition respectively. Additionally fieldwork and preprocessing of the imagery were also studied.

The following chapters provide background information on the Republic of Palau, an overview of previous vegetation mapping efforts and methods used, as well as the current classification methods used for mapping, followed by a discussion of the current mapping approach, findings, and limitations.

CHAPTER 2: BACKGROUND

PALAU

Palau is one of the most varied, compact physical environments to be found in any ocean. Palau's flora and fauna are one of the richest in Micronesia (Levy, 2000). Palau is considered the westernmost archipelago in the Caroline chain, consisting of six island groups totaling more than 300 islands, including the World War II battleground of Beliliou (Peleliu) and the world-famous rock islands (CIA World Factbook, 2006). The six archipelagos of the Caroline chain, from east to west, are the Belau (Palau) Archipelago, Yap Islands(s), Fais Island, Chuuk (Truk) Archipelago, Pohnpei (Ponape) Island and Kosrae Island (Fosberg, 1980). The Carolines lie in the humid equatorial region, where the climate is very warm and wet year round (between 3000 and 5000 mm mean annual rainfall).

The Republic of Palau only recently gained independence in 1994 after a 12-year compact of free association with the United States (CIA World Factbook, 2006). Palau's population is roughly 20,579 people (CIA World Factbook, 2006). The capital and largest town, Koror, is also located in the State of Koror. The State of Koror has a population of about 14,000 (as of 2004) and contains about 90% of the population of the country. The town of Koror has a population of 11,200 (Wikipedia, 2006). Based on Palau's size and population, there are roughly 43.93 sq km per person in Palau.

The largest continuous land mass in Palau is Babeldoab, the second-largest island in Micronesia (Levy, 2000). Babeldoab is 27 miles long, has a land area of 153 sq miles or 398 sq km and makes up 87% of the nation (Galibrath, et al., 2000). The vegetation in

Palau is highly varied due to both limestone and volcanic geology. Variety lends itself to a highly diverse and complex association of vegetation types. Babeldoab, volcanic in origin, is thickly vegetated and many of the differing vegetation types are found here. The area south of Babeldoab and Koror is riddled with hundreds of tiny umbrella-shaped islands called the Rock Islands which were formed from the weathering of ancient uplifted reefs (Levy, 2000). The rock islands are of a different soil type (limestone) than Babeldoab as well as some of the other outlying islands. Babeldoab is mostly volcanic and supports a 700-foot-high volcanic center, fringed with mangrove forests (Levy, 2000).

Presently, southern Babeldoab is, in essence, a suburb of Koror (Levy, 2000). However, owing to the poor roads the rest of Babeldoab remains an island of villages and open space (Levy, 2000). Work is underway to develop a paved road circling the island of Babeldoab which is sure to bring changes to much of the large island. Conservation groups are concerned about the environmental effects of the road itself and the influx of population it may bring (Levy, 2000). Early stages of this road construction can be seen in a portion of the satellite image used for this study in Figure 2.1.

Ongoing road construction as seen in Figure 2.2 was observed at the time of field survey in March of 2005. Projected completion for the 53 mile road is during 2006. Once the road is completed, a newly constructed capitol on the eastern side of Babeldoab as seen in Figure 2.3 is set to begin operation. The new capitol is located about 20 km northeast of Koror. This influx of governement jobs will draw some people away from Koror and bolster the area around the new capitol.

The single most defining factor guiding land use change for the future of Palau is the redistrubution of settlement and jobs due to the completion of the compact road. Outside investors are already looking to develop parts of Palau that are currently undeveloped and covered in vegetation. Having a current land use map is imperative to help guide Palau's growth.

Figure 2.1. Signs of Road Construction Observed on Satellite Imagery

Figure 2.2. Road Construction Observed in Palau, March 2005

Figure 2.3. Palau's New Capitol Building in Melekeok

VEGETATION OF PALAU

The mature vegetation of the Caroline Islands (to which Palau belongs) is generally dominated by broad-leaved evergreen species (Fosberg, 1980). The original vegetation of Palau is generally thought to have been forest with some areas of savanna in places of impeded drainage, but human activities over time have greatly expanded the savannas (Fosberg, 1980.) Much evidence of the shift away from forested land in the nation of Palau. The people who settled the islands have a long-standing history of food plant production including taro, tapioca, papaya, banana, and coconut. The need for suitable growing areas results in the clearing of forest lands to make way for agroforestry. A typical pattern observed in Palau is the clearing of a forested parcel of land, often in a flat, low-lying area near a water source. This cleared land is then planted with crops. A family or network of people from the nearby village or town usually does the planting and farming. If the family continues to work the parcel, it remains in an agroforest state. However, as some members of the family or village move toward the urban areas of Koror, the cropland is often abandoned and will revert to either grassland or marsh. In time, the forest may begin to encroach on these cleared properties. However, before this happens, one of the members of the family usually decides it is time to take up farming once again or may even lease the property to be cultivated by others. The pattern that emerges is often agroforestry to grassland or marsh and then back to agroforestry. Cleared for crop production rarely revert to a forested condition. When this occurs it is usually a mass of tangled thick secondary vegetation until the tree species present can grow to size. This was observed especially in areas that had once been cultivated as coconut plantations. Coconut farming was at its peak during the time of Japanese occupation of Palau, however; it is no longer a factor in the exports of Palau. Much of the landscape of Palau changed after the Japanese left the islands shortly after World War II, abandoning many cultivated areas. Remnants of these abandoned areas were originally classified in 1987 as secondary vegetation. At a more recent visit to Palau in 2005, it was observed that few areas of secondary vegetation remain. The species composition is similar to that of upland forest and much of the tree species have grown to a larger size class and resemble the upland forest type more than that of a distinctly separate secondary vegetation type class.

Much of Palau has changed, is changing, or has the potential for change.

CHAPTER 3: PREVIOUS MAPPING METHODS AND SOFTWARE

The first step in mapping was to first analyze the previous classification (Cole, Falanruw, MacLean, Whitesell, & Ambacher, 1987) before attempting to design a new classification scheme. The previous classification broke the islands into four general classes: forest, secondary vegetation, agroforestry and non-forest. Descriptions of the species present in each class and overall characteristics of the classes can be found in the Vegetation Survey of the Republic of Palau (Cole et al., 1987). An overview of the 19 classes present in the historic classification is presented in Table 3.1. Historically the forested classes and coconut plantation type were also further subdivided into size and density classes (Cole et al., 1987.)

Table 3.1. Classification Scheme 1987.

Forested Classes
Upland Forest
Swamp Forest
Mangrove Forest
Atoll Forest
Casuarina Forest
Limestone Forest
Rock Island Subtype
Plantation Forest
Palm Forest
Secondary Vegetation
Agroforest
Agroforest with Coconuts
Coconut Plantation
Non Forest Classes
Marsh
Grassland or Savanna
Strand
Cropland
Urban
Barren
Water

Preliminary analysis of the historic classification was performed to determine if all of the historic classes were present in the IKONOS image. Upon visual inspection, the classes of atoll forest, casuarina forest, and limestone forest (non-rock island type) were present only on the outlying islands of Kyangel, Peleliu and Angaur. These areas are not covered in the satellite image. Classes found only in the outlying areas were eliminated from the classification scheme.

The methodology used by Cole et al. to classify Palau's vegetation was based on aerial photograph interpretation. Aerial photographs were taken at a scale of 1:10000 during 1976. The minimum mapping unit for the project was 1 acre. Fieldwork was completed in 1985. Vegetation types were identified by examining the photos stereoscopically for differences in tone, texture and pattern. The accuracy of the vegetative typing depended on the age and quality of the photographs, the skill and training of the photo interpreter, and on comparisons of potential types to actual field characteristics (Cole et al., 1987).

Aerial photograph interpretation as a form of remote sensing is useful visually and spatially, but no spectral information is available. The advantage of modern remote sensing is the availability of both spectral and spatial information, with the ability to use a computer to do much of the analysis. Image processing software, allows for spatial patterns, tone and texture to be separated by the computer, leaving the identification of the classes to the interpreter.

CHAPTER 4: METHODS

SOFTWARE

Two different image processing software packages were used to conduct the study: ERDAS Imagine version 8.7 and Definiens e-Cognition version 3.1. Bundled features of the software packages, segmentation algorithms, were applied using both ERDAS Imagine and Definiens eCognition. The USDA Forest Service Remote Sensing Applications Center (RSAC) developed the segmentation algorithm used by ERDAS, while the eCognition algorithm is a commercially available product from the Definiens Company. Though the Forest Service Application is free, a copy of ERDAS Imagine and license are also needed to run the algorithm. Both products require an initial monetary investment, though the eCognition software package is considerably more expensive than the ERDAS package. The USDA Forest Service supplied both products; otherwise cost for the project would have substantially increased.

IMAGERY

The USDA Forest Service (FS) provided November 2000 IKONOS satellite imagery for the study. IKONOS produces 1-meter black-and-white (panchromatic) and 4-meter multispectral (red, blue, green, near infrared) imagery (Space Imaging, 2006). The 4-meter multispectral imagery was used in order to run classifications using image-processing software.

Most of the preprocessing, such as georeferencing or bringing the map into alignment with a map projection, was done at the Pacific Northwest Laboratory in Portland, Oregon, before the study began. Unfortunately, the imagery still included approximately 20% cloud cover. This limitation was possible to overcome because IKONOS imagery includes enough information to remove all non-vegetated classes from vegetated classes. Once this is complete, it is then possible to separate the clouds from other non-vegetated features.

Creating a ratio of band four to band one was used for removal of cloud cover in ERDAS Imagine software. This ratio separates vegetation is separated from cloud, urban and barren areas. This occurs because clouds present high radiances in the visible band and very low radiances in the thermal channels, so the highest ratio values are closely related to cloud cover (Karteris, 1992). This worked well in ERDAS to separate the clouds and other non-vegetated classes. However, further work was needed to separate the clouds from urban and barren areas, which tend to reflect similarly. This was achieved by using the eCognition segmentation algorithm; the clouds were separated into their own polygons by the computer. Both programs are suitable for the purpose of cloud removal, though eCognition was better suited for the final step of removing the clouds from other non-vegetated features.

Removal of the clouds did not address the fact that the area under the clouds would still require classification. For the purposes of this study the area was simply classified as clouds. If classes are desired under the clouds, use of another image that is cloud free in those areas is recommended. Another IKONOS image, taken during the same month, would retain consistency; however, this would substantially increase the cost of image acquisition and may not be possible given the weather and satellite patterns.

Resolution of satellite data refers to the capability of a remote sensing system to resolve adjacent objects or conditions in the recorded imagery (Gao, 1999). Each IKONOS pixel captured by the sensor represents an area 4m by 4m on the ground. Choosing the IKONOS platform was a step towards trying to classify vegetation at a higher resolution. In the past Forest Service land cover classification was often done using Landsat thematic mapper images, which only have a 30m resolution. The idea behind using finer resolution for Palau was that in an area with such diverse vegetation, a higher resolution would be needed to capture the diversity in the different vegetation type covers.

The 4 bands provided (red, blue, green, near infrared) cover specific areas of the spectrum and have a particular bandwidth. Table 4.1 which shows both the spectral and spatial resolution for all four bands is developed from the Space Imaging website at http://www.spaceimaging.com/products/ikonos/index.htm

Table 4.1. IKONOS SPECTRAL BAND CHARACTERISTICS

Band	Spectral Resolution (μm)	Resolution (m)
Blue	0.45-0.52	4x4
Green	0.52-0.60	4x4
Red	0.63-0.69	4x4
Near IR	0.76-0.85	4x4

Using IKONOS imagery instead of Landsat TM data in order to achieve higher resolution does mean giving up the additional wavelength regions at 1.55-1.75 and 2.08-2.35 μm. Gao, 1999 used these longer wavelengths to achieve higher accuracy of mapping mangroves. Mangrove is one of the desired classes to map on Palau.

Increasing the spatial resolution in exchange for less spectral resolution may actually make it harder to classify some of the classes.

In cases where vegetation cover is patchy, the finer resolution will reflect more of the patches and create more noise and speckle in the classifications. Using a lower resolution can essentially average out this noise. However, lower resolution imagery often averages too much information. When forest type cover is highly complex and patch sizes are small, some of the desired classes can become averaged together loosing much of the actual on the ground distribution. IKONOS' limited bandwidth did not provide for much separation of the desired classes, which may have been alleviated if using a platform with a greater amount of bandwidth as well as better spectral resolution had been used.

As mentioned in the previous section, IKONOS imagery is better at capturing smaller patches of vegetation than traditional LANDSAT imagery. This finer resolution brings with it much noise often relating to confusion between classes. The noise was analyzed by determining if it was present consistently across the entire image, or if it was localized in certain areas. This helped to determine if the noise was a product of the image or if it was related to the distribution of the vegetation. The vegetation in many of the classes is highly complex in arrangement, often including some of the same species in different classes. This caused areas of different vegetation types to reflect at similar values. In addition, the image itself did contain more noise than had been seen in lower resolution images used in other non-related studies. Thus the IKONOS image was noisy because the vegetation was noisy but it also included some noise due to the higher resolution of image itself.

The IKONOS Image provided was taken in November of 2000, but not provided for study until 2004. This proved to be problematic, as a field survey could not be conducted until 2005, five years after image capture. This means that when visiting the islands, some of the observed data may or may not be present in the image taken five years earlier. Examples of this include cleared areas, recently planted areas, and burned areas.

In order to overcome this, if an area was recently disturbed it was noted on the field datasheet, but not used in the actual classification of the image. Additionally the image was taken in November, while the on the ground field survey was performed in March. This was due to researcher and funding availability. Some of the vegetation changes seasonally. For some of the vegetation, what appears to have a full crown upon visiting in March, which would definitely influence the sensor, may not actually have the same amount of foliage in November. Many of the forest types in Palau are not usually dominated by a single species, but by a complex association of species. Vegetation that may appear to be of an aggregate type of forest in November may not appear aggregate in May, due to different peak seasons for the species that make up each forest type. Additional studies of the changes in vegetation within each forest type would be needed to determine if this factor significantly affects the classification process. However such a focus is outside the scope of this thesis.

TIME OF YEAR AND RAINFALL

Rainfall amounts vary from November to May, potentially affecting how the remote sensor captures vegetation. Typical rain forest climate still prevails in Belau (Palau). This rainfall gradient shows up in the vegetation (Fosberg, 1980). The average monthly rainfall can be seen in Figure 4.1.

The time of year of the image, November 2000, was neither the highest nor the lowest month for rainfall for the islands of Palau. November 2000 also did not deviate significantly from the average November data across multiple years. Essentially November is an average time to collect the imagery. However during the month of November, the satellite sensor will not capture the vegetation classes when they are at

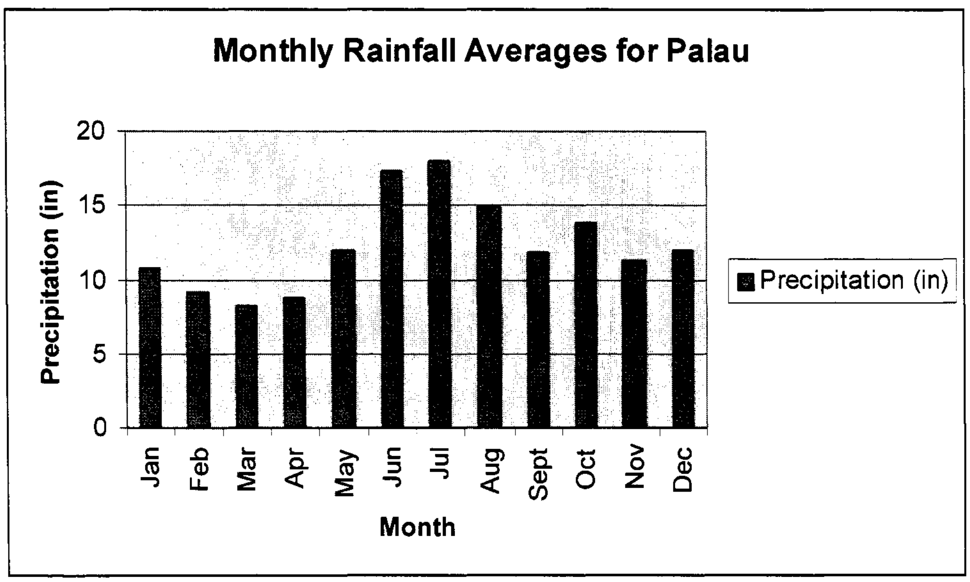

Figure 4.1. Monthly Rainfall Averages for Palau

their peak moisture levels, which is during the months of June and July. Nor will it reflect the vegetation when it is at its lowest amount of available moisture in the months of March and April. Thus some difference between what was observed by the sensor in

November would be different that what was observed on the ground in March. This suggests that the classes that are most affected by changes in moisture may not be best suited for capture by the sensor during a median moisture month such as November. However, trying to obtain a cloud free image during the peak rainy season could prove problematic. Comparing reflectance values for the November image to one taken in March or April for classes most affected by available moisture does warrant further study.

Though rainfall may have something to do with vegetation distribution on the islands the difference may also be attributed to a combination of factors, including the geologic substrate and the difference from the continental floristic source areas (Fosberg, 1980). Given the image availability, and researcher availability, the study was conducted with these limitations in mind.

The IKONOS image has a limited bandwidth, but initial work separating out vegetation from non-vegetation yielded positive results in two different software environments. Some additional problems to work around were the time of year of the image, the age of the image and the "averageness" of the image. Looking at rainfall data, allows the analyst to determine if the month and year used are representative of a typical year, however on the ground observations may differ from sensor observations due to the time lag in collection of on the ground data, as well as the difference in the vegetation during the year.

ANCILLARY DATA LAYERS

Imperative to the study was collection of both primary and ancillary data layers. The primary data layer was the IKONOS 4 Band, 4-meter imagery discussed previously. Additional data layers were also obtained, both through manipulations of the original image as well as individual acquisitions. Additional data layers were used for quality control, forest type classification and validity testing

Data layers created from the IKONOS Image included a Normalized Difference Vegetation Index (NDVI). The NDVI image was created using the following formula:

$$NDVI= NIR - Red/ NIR + Red$$

ERDAS Imagine was used to compute the NDVI Image. When using ERDAS for this purpose IKONOS is not a valid sensor type listed in the available menus. Thus, LandsatTM was selected as the sensor type, since it uses the same band combinations to calculate the index. Float single was selected for the output file type. This is because NDVI is dimensionless as it is a ratio between two bands (De Jong, Sluiter, Zeijlmans, & Addink, 2006). The NDVI image was used to determine the amount of biomass and chlorophyll content of an area. An excerpt of the NDVI image can be seen in Figure 4.2. These parameters make it possible to distinguish areas of vegetation from non-vegetation.

Another vegetation index that was created from the IKONOS Image was a Tasseled cap Transformation. ERDAS Imagine uses coefficients created by Horne in 2003 to compute the transformation. Interpretation of the tasseled cap image was best achieved when setting the bands to 1, 2, 3 (RGB). When viewing the image as such, Layer 1 (red) represents the brightness component (indicates areas of low vegetation and high reflectance). This is a good measure of soil: the lightest and brightest areas are soil or barren areas as seen in Figure 4.4. When viewing the tasseled cap image, these areas appear pink and have an above average brightness value. Layer 2 (green) illustrates the

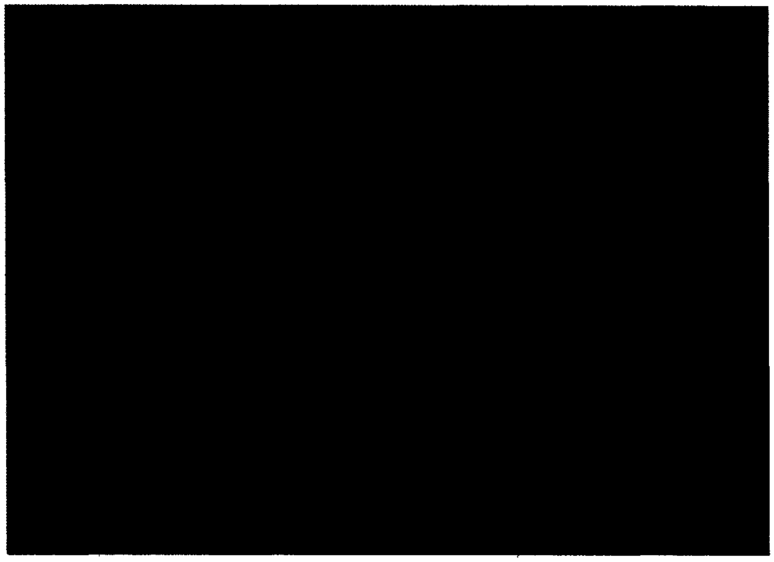

Figure 4.2. NDVI Image of Downtown Koror. Green represents vegetation, while black represents an absence of vegetation.

Figure 4.3. Satellite View of Downtown Koror. Even though this is the most urban area in all of Palau, it is highly vegetated in the NDVI image of Figure 4.2. This reflects the high percent cover of vegetation present both on the ground and in the imagery.

greenness component (indicates vegetation) the lightest and brightest areas are vegetation. When viewing the tasseled cap image in Figure 4.5 these areas appear yellow in color and have a high brightness value. Layer 3 (blue) shows the wetness component (indicates water or moisture) these areas in 4.6 appear to be dark in the image and have a low brightness value.

Figure 4.4. Tasseled Cap Image, Layer 1. Bright pink areas show a high reflectance value with little vegetation, indicating a barren area. The barren areas in the figure above are associated with the building site of the new Capitol located in Melekeok.

Figure 4.5. Tasseled Cap Image, Layer 2. The bright yellow color is a highly vegetated area of Palau. Mangrove, rock island, upland and grassland cover are each present. This illustrates that although the Tasseled cap image easily identifies areas of vegetation, it is not adequate to distinguish between different types of vegetation.

Figure 4.6. Tasseled Cap Image, Layer 3. Note the dark area in the upper left, this area is especially dark and can thus be identified as a water feature.

The tasseled cap transformation was extremely useful in determining areas of soil and bare ground, as well as determining buildings and urban areas. The transformation provided useful to pick out water features from the surrounding classes. However, the vegetation classes were still lumped essentially into a single entity- having a bright yellow appearance with high brightness values. At times the brightness within the vegetated areas did vary, but significantly or consistently enough to separate individual classes within the vegetated areas. Additional data layers were acquired to see if any of these layers might yield additional findings.

The US Forest Service Pacific Northwest Laboratory provided a digitized soil map of Palau. This digitized map was obtained from a soil survey performed by the The US Department of Agriculture's (USDA) Natural Resources Conservation Service (NRCS), formerly Soil Conservation Service (SCS), which leads the National Cooperative Soil Survey (NCSS). The NRCS is responsible for collecting, storing, maintaining, and distributing soil survey information for privately owned lands in the United States (Natural Resources Conservation Service, 1995). Palau was included in this soil survey as it was once viewed as a trust territory of the United States. The soil maps are produced from different intensities and scales of mapping. The three soil geographic data bases created are the Soil Survey Geographic (SSURGO) database, the State Soil Geographic (STATSGO) data base, and the National Soil Geographic (NATSGO) database. The Palau soils information was retrieved from the SSURGO soils database. The SSURGO database provides the most detailed level of information and was designed primarily for farm and ranch, landowner/user, township, county, or parish natural resource planning and management (Natural Resources Conservation Service, 1995). Using the soil attributes, this data base serves as an excellent source for determining erodible areas and developing erosion control practices, reviewing site development proposals and land use potential; making land use assessments and chemical fate assessments; and identifying potential wetlands and sand and gravel aquifer areas (Natural Resources Conservation Service, 1995). Using NCSS mapping standards, soil maps in the SSURGO data base are made using field methods. Surveyors observe soils along delineation boundaries and determine map unit composition by field traverses and transects. Aerial photographs are interpreted and used as the field map base. Maps used by the NRCS for soil mapping in Palau used scales ranging from 1:12,000 to1:63,360. Typically scales are 1:15,840, 1:20,000, or 1:24,000. The maps, along with comprehensive descriptions, produce an attribute and spatial database for NCSS publications (Natural Resources Conservation Service, 1995). The soils map proved interesting to use, as it contains encoded data and a large relational database is needed to decipher the meaning of the different codes associated with each soil polygon. Though the soils information was complete, forest types did not stay true to any one-soil type, with the exception of the rock island forest type. It was found primarily and exclusively on limestone soils. An excerpt from the soils map can be seen in Figure 4.7.

Figure 4.7. Screen Capture of the SSURGO Soils Data Layer. The brown polygons in the above image are all of a limestone soil type. Rock Island Forest type is confined to this soil type.

When viewing the original satellite image as seen in Figure 4.8 it is not always easy to pick out vegetation types. One particular vegetation type, the rock island forest type, did not look significantly different from surrounding vegetation cover, nor did it exhibit any special spectral characteristics that were enough to distinguish it from surrounding vegetation.

In the instance of rock island forest, using the SSURGO soils data layer alone, made it easy to identify potential areas of rock island forest type. This particular forest type is confined to areas of limestone soils. The limestone soils are extremely steep and rocky and prove unsuitable for most development. Little disturbance to the vegetation covering this particular type of soil has occurred. Using the soils data layer to identify areas of limestone soils, made it was easy to identify rock island forest type. When field visiting the islands, the local NRCS representative stated that the rock island

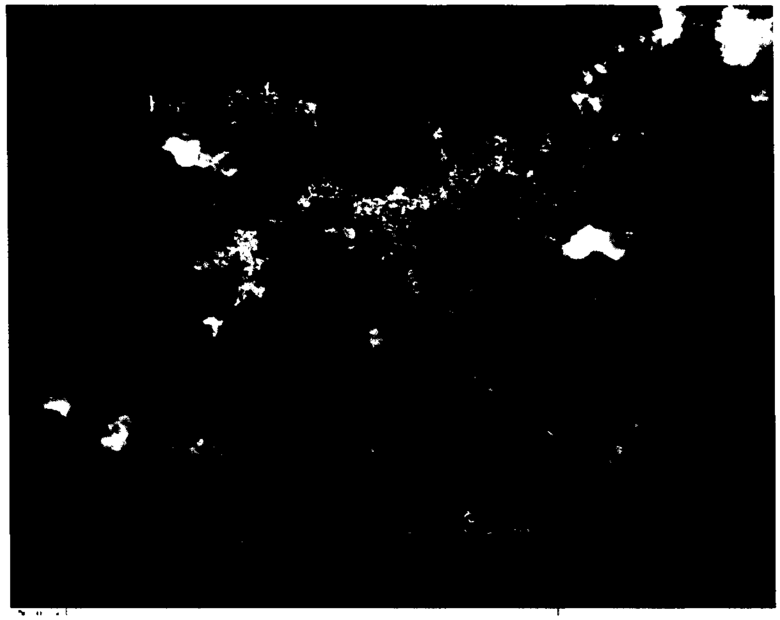

Figure 4.8. Satellite View of the Same Area Shown in Figure 4.7. Although areas of vegetation are evident (in green), It is not easy to find any areas of distinctly different vegetation types.

forest type did not stray from the limestone soils and that the composition of the rock island forest type did not seem to change significantly from island to island. Though the species composition may vary by the amounts of individual species, it seems to always be composed of the same types of species of vegetation. When visiting, little effort was given to try to break apart the known areas of rock island forest type into more than one class. Evidence of rock island forest outside of limestone soil was sought after, but not found to occur. Using the SSURGO Soils data layer to identify this particular forest type class was deemed acceptable. A portion of the final classification based on soils is seen in Figure 4.9.

An additional data layers included digital raster graphics of topographic maps. The maps are geo-rectified digital copies of United State Geological Survey maps compiled by photogrammetric methods from aerial photographs taken 1968-1971. The

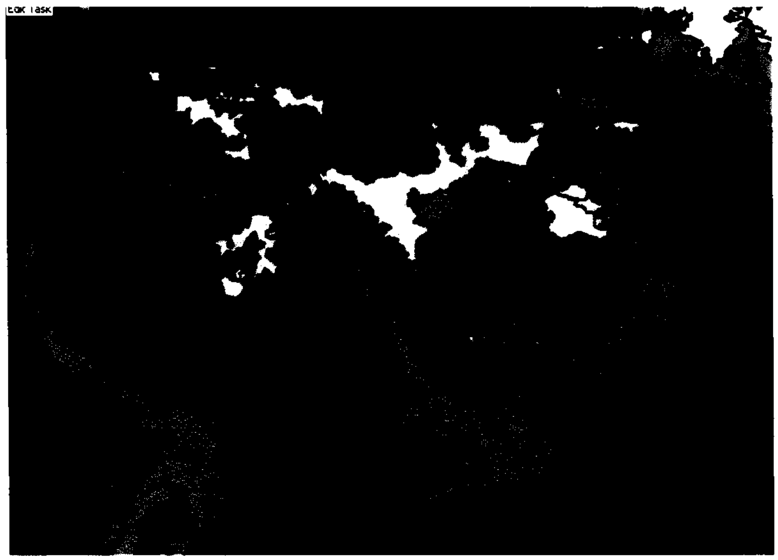

Figure 4.9. Rock Island Forest Areas Shown in Brown. This determination was made using the limestone soil type from the SSURGO soils data layer shown in Figure 4.7.

maps were also field checked in 1980 and the final maps were edited in 1983. The topographic maps were useful references to determine topography. The topographic maps were especially useful for the rock islands. Though possible to determine areas of rock island based on soil type alone, the soils map was not all-inclusive or the area covered by the IKONOS image. Looking for similar types of land formations like those identified as rock island in the soils layer, made it possible to find these similar types of land formations in areas not covered by the soils layer. The maps were also useful in confirming areas of suspected mangrove forest type. The maps were used mostly as a validation aid and for their topographical data. Similar data could also have been obtained from a digital elevation model; however, there are known reliability problems with the current DEM available for Palau. An excerpt from one of the topological maps can be seen in Figure 4.10.

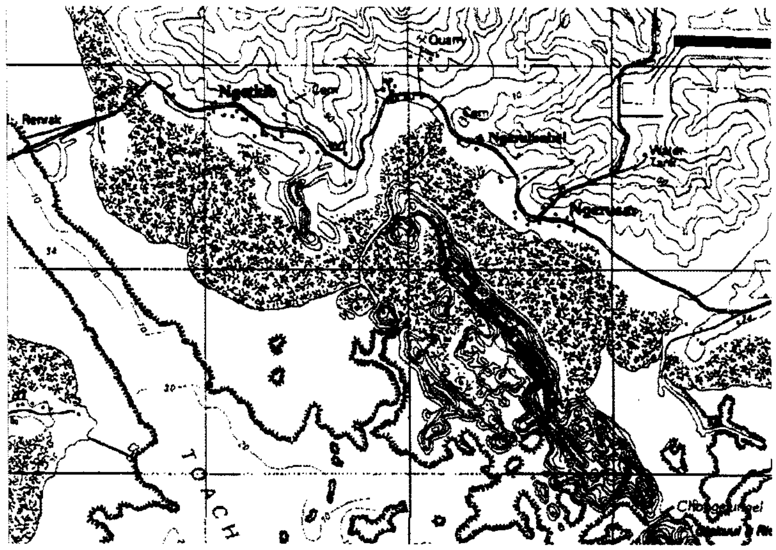

Figure 4.10. Topographic Map. Steep contours in the lower right indicate rock island forest found on steep limestone soils. Mangroves are shown ringing the water in a dark green pattern while the wider contours in the upper portion of the image need further classification.

Building a Geographic Information System (GIS) in order to utilize ancillary data layers proved useful to map the vegetation of Palau. Each layer was useful for either direct classification or for validity checking of assigned classifications. This software package allows the user to turn layers on and off, overlay the layers and make layers transparent as needed. Through extensive visual interpretation the GIS was a much-needed tool in order to classify Palau.

THE NEW CLASSIFICATION SCHEME

The USDA Forest Service proposed a new classification scheme for Palau based on the 1987 USFS vegetation survey results by Cole et al., *Vegetation of the Tropical Pacific Islands* (Mueller-Dombois & Fosberg 1998), preliminary comments from Palau foresters, and previous experiences of vegetation classification using IKONOS imagery for Guam, American Samoa and the Commonwealth of the Northern Mariana Islands (CNMI). A crosswalk between the two schemes is presented in Table 4.2.

Next, initial questions regarding the proposed scheme were generated in order to resolve some of them before the field visit in March of 2005. Initial questions included: Is the new scheme adequate? What forest types need to be divided added to or deleted? After generating some initial questions, the next step was to study and understand each class contained in the scheme. Literature review, web searches, and discussions were conducted to identify key species for each class, view pictures of the representative classes and vegetation as well as note any representative information about a particular class. Upon inspection of the classes, specific class questions did come up. Examples include: Is there a minimum size for cropland? Does the grassland class need further separation? Does upland forest need further separation? Obviously the proposed classification scheme needed revision in order to present classes that could be identified in the vegetation as well as in the remotely sensed imagery. An important step was to generate some initial classes based on the imagery alone. Having these classes present when field visiting would help to determine if the classes identified by the computer actually correspond to any of the classes identified in the classification scheme.

Table 4.2. Crosswalk Between Previous and New Classification Schemes

Palau Vegetation Class (suggested)			Crosswalk to USFS Survey Class
Level 1	Level 2	Level 3	
Forest			
	Upland Forest on Volcanic Islands		Upland Forest
		Interior Upland Forest	Upland Forest
		Ravine Forest	Upland Forest
	Limestone Forest		Limestone Forest
		Pisonia Forest (only on Fanna Island)	Limestone Forest
		Rock Island Forest	Rock Island Forest
	Atoll Forest		Atoll Forest
		Casuarina Forest	Casuarina Forest
	Wetland Forest		
		Mangrove	Mangrove Forest
		Swamp Forest	Swamp Forest
	Leucaena Stand		Secondary Vegetation
	Agroforest		Agroforest
		Coconut Plantation	Coconut Plantation
		Other Agroforest	Agroforest
Rangeland			
	Grass/Shrub		
		Savanna Complex	Grassland/Savanna
		Strand Vegetation	Strand
		Urban Vegetation	Urban/Secondary Vegetation
		Other Shrub/Grass	Secondary Vegetation
	Marsh Wetland		Marsh
	Cropland		Cropland
Developed			
	Urban Built-up Land		Urban
Barren			
	Cleared Land		Barren
	Sandy Beach and Bare Rocks		Barren
Water			Water

UNSUPERVISED CLASSIFICATION

An unsupervised classification was selected for the first attempt to classify the IKONOS image. The unsupervised classification was conducted using similar techniques to those used by Liu, Fischer & Donnegan, 2005 to classify Guam, American Samoa, and CNMI. These methods can be found online at: http://www.fs.fed.us/r5/spf/fhp/fhm/landcover/islands/index.shtml

Software for preprocessing the imagery was used before classifications were run. Discussion with Liu via email was conducted to identify any known areas of weakness. Liu also asked questions that helped to further refine the new classification scheme for Palau. During his field survey of Guam, Leucaena was observed in such abundance that a new class was created to capture the vast stands. His question was whether or not Leucaena was also present on Palau, and if so, did it warrant its own class? (It does not). His experience in classifying other tropical islands provided a guide that was useful in determining which layers to use during unsupervised classification.

The first classification was run using ERDAS Imagine on the raw IKONOS remotely sensed data. This classification was run to determine if any immediately obvious classes were present in the imagery before utilizing some of the enhanced data layers such as the tasseled cap or NDVI layers. In order to perform this classification, clouds were removed from the original image and then the image was classified into 15 classes using the ERDAS ISODATA algorithm. Using this technique enabled some classes to be distinguishable from others. Urban and barren areas as well as grasslands were distinctly different from the surrounding forest. Mangrove areas also showed promise as a separate class. An excerpt of this resulting classification can be seen in Figure 4.11. The yellow and green areas indicate grasslands, while the bluish purple areas to the left represent mangroves. Dark areas within the image are either roaded or barren while the darker areas to either side are ocean. However, the area on the right side of the image is a jumble of many classes and colors. Much of Palau was also a similar jumble of classes. While the preliminary unsupervised classification showed promise for some classes, it also contained many confused classes. This may have been a result of noise in the original image; however, it was also possible that the vegetation was indeed so diverse that it appeared as a jumble of classes to a high-resolution remote sensor. In order to determine if this was the case, a comparison was made with the historic vegetation map. When viewing the historic map, the areas containing jumbles of pixels were not small patches of intermixed classes, but usually one larger class. This indicated that either extreme change had occurred on the islands of Palau, or a problem with the new classification.

Some of the confusion may have been due to the fact that the original image was noisy. A possible cause for some of the confusion may have been the angle of the sun at the time of image capture. Testing to see if the image was picking up a difference in east side versus west side vegetation due to the orientation of the sun at the time of capture was possible by zooming the image to the islands south of Koror. As mentioned in the previous chapters, the islands south of Koror are known as the rock islands and exhibit distinct vegetation based on the limestone soils. However, when viewing a portion of the classified image over this area, a distinct difference is observed in east side versus west side vegetation. This can be seen in Figure 4.12.

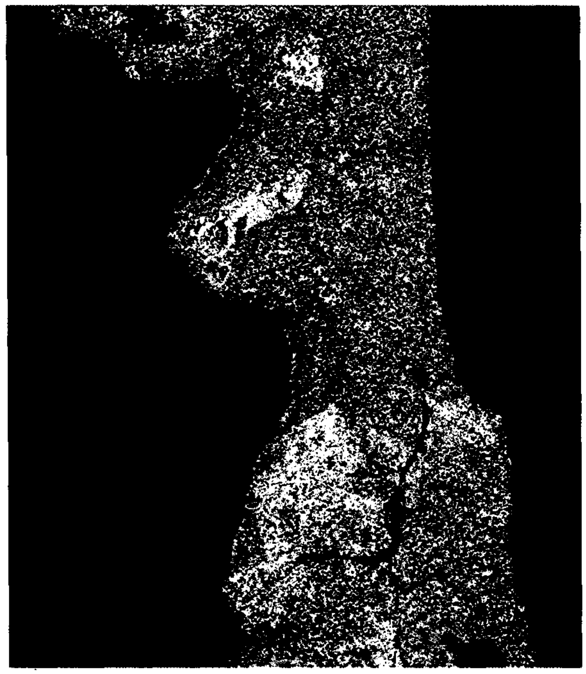

Figure 4.11. Unsupervised Classification. Yellowish-green areas are grassland while bluish purple areas on the left are mangrove classes. Note the confusion of classes on the right hand side of the image.

Figure 4.12. East Side vs. West Side Vegetation. Blue represents Ocean. The darker reddish purple is east side vegetation, while the lighter colors represent west side vegetation.

Perhaps the rock islands are different west side versus east side, but perhaps the imagery was the actual problem. Additional classifications were run in hopes of obtaining a less confused classification. Results from the different classifications were similar. Attempts to increase the number of classes and then combine made the image appear even more pixelated initially making it difficult to combine classes. Distinguishable classes were best preserved in the15 class range. However the number of classes needed for level three of the proposed classification scheme was 13, and the 15 classes that were obtained in the classifications did not seem to match up particularly well with the proposed classification scheme.

A Principal Components Analysis (PCA) was run to eliminate noise in the imagery. PCA is often used as a method of data compression. It allows redundant data to be compacted into fewer bands—that is, the dimensionality of the data is reduced. The bands of PCA data are non-correlated and independent, and are often more interpretable than the source data (Jensen, 1996; Faust, 1989). Based on the statistics behind principal component analysis, the most data should fall in the first few principal components. In order to determine which principal components to use to both retain valuable data and eliminate the noise, scatter plots were created. An example of the scatter plots of the principal components of Band 1 compared with bands 2, 3, and 4 of the IKONOS image can be seen in Figure 4.13. When viewing each component as a scatter plot, you can see where the pixels are distributed.

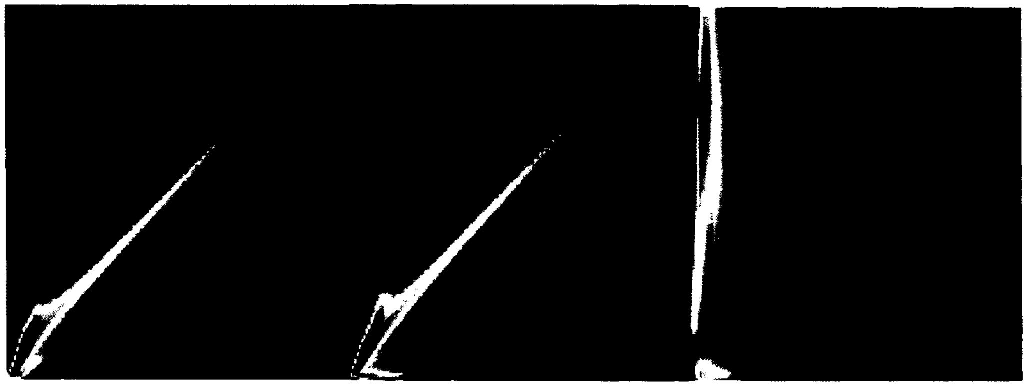

Figure 4.13. Scatter Plots of the Principal Components. Band 1 is compared with bands 2,3 and 4 respectively.

The lack of an ellipse shape in the scatter plots shows that the data is not normally distributed. Additionally the plot of bands one and four in the example above show the most separability. The high correlation between bands 1 and 2 shows that in the principal components image, those two bands are highly redundant as their values are tightly distributed linearly along a central axis. Scatter plots provided information that may not have been derived visually from the original images. After looking at the scatter plots, the principal components of band 1 were selected for the next round of classifications.

A layer stack based on the principal components was then created by combining the first principal components from band one with band 2 of the tasseled cap image indicating greenness, (which should show changes within the different vegetation classes), the NDVI image for band 3 and the Near Infrared from the original image (which is also known to be useful in vegetation classification). Include the near infrared band is redundaant since bands one and four of the principal components showed the most separability. This band was selected for inclusion because vegetation differences often show up in the infrared portions of the spectrum. This stacked image relies on the principal components of the original image as well as data derived from two different vegetation indices and information from the near infrared part of the spectrum know to be useful in vegetation classification.

The classification produced from the layer-stacked image was not significantly better than the first classification. It had some strengths at identifying mangrove swamps, but one of the classes in a known mangrove area was also found in grassy areas indicating that either mangrove reflectance levels are similar to grass, or that perhaps the sensor is actually picking up moisture amounts in the vegetation and that when wet, the grassy areas, may reflect similar to the wet mangrove areas. Because the two classifications were so similar, incorporating spatial values into the classification was determined to be the next step.

A low pass filter algorithm in ERDAS Imagine was used to include spatial information into the classification. A 3x3 and 5x5 mean filter was applied to the original image as well as the principal component image, and the images were reclassified. This was successful at reducing some of the noise in the images, but also created another problem; in places the classifications were too smooth, resulting in loss of road networks, and creation of new classes along boundaries. Noise, or an extreme speckling of different classes was also still prevalent. Noise is a problem often associated with using high-resolution data, especially in areas of high diversity. Additional classifications involving minor modifications to try and eliminate residual classes around clouds were also performed. This was done to get true classes of vegetation with minimal effect from moisture levels around cloud features. Experimental classifications involving different layer stacks with both more and less dimensionality did not yield classifications that were any less noisy, or better suited to separating vegetation classes. After running many classifications with little to no significant differences, the classifications were examined to determine which ones were best suited to use in the field study.

Classifications involving the low pass filter seem to contain less noise, which indicates that the spatial patterns in the image contain valuable information. Those classifications using either a 3x3 filter were best suited to reduce some noise without smoothing out important features such as roads, urban areas and waterways. One commonality among all of the classifications was that all seemed to identify classes near water features. Vegetation may exhibit change near water bodies, but uncertainty arose as to whether or not the observed effect was due to actual changes in the vegetation or changes in moisture levels alone that the imagery may have captured. Efforts to eliminate moisture effects were made by choosing to use the greenness layer of the tasseled cap image rather than the moisture layer. However trying to eliminate moisture effects proved difficult as vegetation changes may or may not occur based on moisture amounts. Consideration was given as to whether what was observed was due to vegetation class changes, or changes due to changes in moisture content. Basically some parts of the forest may contain more moisture than others, but not change forest types.

None of the classifications yielded small isolated classes. Either large individual class was present or many different small isolated pixels were present. Some of the classes in the proposed classification scheme were expected to be very small isolated areas within the imagery, such as small patches of cropland or plantation forest. Not finding any small isolated classes meant that either those classes were no longer present, had changed or additional classification was needed. If additional classification was needed, additional ancillary layers may be the key to identifying these areas, or perhaps even manual coding of these classes may be necessary.

Preliminary review of the classifications seemed to indicate that many of the forest type classes identified in the classification scheme did not seem to have homogeneous spectral values in the image. Fieldwork was needed to determine if these classes were distinct across the landscape. The unsupervised classifications appeared to be useful in identifying some of the classes, but may prove unsuitable for identifying other additional classes in the imagery. Unsupervised classification is useful only if the classes can be interpreted. It did not appear that some of the jumbled areas of the image were going to be interpretable. This raises serious concerns as to whether or not the areas of jumbled pixels were going to be classifiable using an unsupervised classification alone.

After initial questions and review, a new proposed classification scheme was created for use when field visiting Palau. Initial questions helped refine the proposed classes as well as provide a guideline of questions to investigate during the field visit. A series of unsupervised classifications was created using ERDAS Imagine. The classifications were inspected visually and compared with known facts regarding vegetation distribution across Palau. Two of the classifications were picked for beta testing during the field survey. Some of the vegetation types contained within the classification scheme appeared to be noticeable in the unsupervised classification.

However, when other classes were not immediately discernable, concerns about the suitability of the unsupervised classifications were raised. These concerns, questions and assumptions were documented in order to prepare for the field survey and visit to Palau in March of 2005.

FIELD SURVEY METHODS

In order to further investigate the proposed classification scheme as well as the unsupervised classification schemes, a field visit to Palau was scheduled for March17-April 1, of 2005. One of the local foresters was scheduled to provide transportation, navigation and assistance for the trip. The objectives for the field visit were to gain knowledge about the different types of vegetation, identify major species, work on the proposed classification scheme and collect as many possible GPS points to use in understanding the unsupervised classification and to use as potential training data for a supervised classification. The main objective was to gather enough points to provide a wide cross section of each class identified in the classification scheme. The final objective of the field visit was to use the knowledge gained from the trip to produce a new vegetation map for Palau.

In order to best sample the islands of Palau, it was necessary to identify a sampling strategy. A random stratified by road access sampling procedure was identified for each of the classes that were expected to be present. Polygons from the historic vegetation map that either contained a road or were within 1000' feet of a road were selected. From these polygons random points were created using a random number generator in excel. Visual inspection of the random points reveled that some of the classes had more points than others. Also, some classes historically were much larger than others. Thus a class-by-class assessment was done to determine if additional points were needed in each class. The larger the historic land area covered by a class, the more sampling points were established. This was planned in order to help determine the answer to the question, do some of the larger classes need to be split into more than one class, or are their forest types similar enough to retain the original class designation? During this stage of visual inspection, an attempt was made to add at least 10 additional sample points per class. The additional sample points were added based on the largest polygons of a particular class that did not already have a sampling point contained within them. An effort to use the centroid of these polygons was made. In addition, an inspection of the historic map with the unsupervised classification was made. If an area of like pixels could be identified in the historic classification, and one historic class covered the same area, an attempt to sample the location was made by designating a sample point. Only vegetated classes had sampling points established as it appeared easy to separate urban and water features in the imagery using techniques outlined in Chapter 3.

Smaller classes that did not cover large areas made it difficult to identify at least 20 sample points per class. In these cases, as many possible points as could be identified in the stratified area were established. A good example of this was in the palm forest class. Only one polygon had been identified by the historic classification. By selecting a sampling point in this polygon, all of the available sampling points had been covered. If the polygon had been larger, however, additional points could have been added. Once initial plot selection had been made, a total of 208 potential survey points had been identified covering 12 of the historic classes. Given a study timeline from Monday, March 21 to Friday April 1st provided for 11 total days of fieldwork. The goal was to try and visit 20 points per day in order to meet the goal of the 208 initial study points.

Before actual fieldwork could begin, a field datasheet was developed to identify variables of study. An example of the datasheet can be seen in Appendix 2. Each point was numbered 0-208, with a space to record the observers' names, the GPS location of the point, the time spent averaging the signal and the precision of the signal. The most important data collected was an observation by the Palauan field staff of the current forest type. Space was provided for both the primary forest type, as well as a secondary forest type for points that straddled two separate conditions. Observations were then recorded as to the dominant overstory species and the size class of the plants in the overstory, identified as tree, shrub, forb, or grass. This step was to help identify the species composition within the classes was highly variable, or if it was somewhat predictable. An average canopy height was then recorded using a clinometer and estimated in meters. A Density observation was then made selecting from High Density of greater than 70 percent crown cover of main canopy, Medium percent crown cover of 30-70 percent, and Low Density of crown cover less that 30 percent. These values were taken directly from the previous classification in order to remain consistent. A percent slope was then recorded using the clinometer and also an aspect was taken using a compass set to true north. The next observation that was recorded was the extent of the class. Choices included were subplot (58.9 foot circle), hectare (185.1-foot circle), or beyond estimated in meters. This variable was supposed to help in pixel assessment. If a point barely covered an area roughly 60 feet across, the point should appear as a distinct pixel value with many different pixels surrounding the point, which could help to explain much of the noise in the imagery. However, if the forest class of the observation point were noted to extend for miles beyond, the point should then appear as one pixel values surrounded by similar pixel values which would show that the noise in the imagery is due to something other than the distribution of different forested classes. This did not eliminate the problem that noise in the image could still be accounted for by the diverse distribution of vegetation within a single class, which would also appear as a point with one pixel value surrounded by pixels with different reflectance values. The next variables recorded were the original class that the point was assigned to (to help monitor if particular classes were undergoing more change than others) as well as noting if it was still the present class, or if the point is now a new class, what the new class should be. Finally a notes section was added at the bottom to record any notes pertinent to the observation point. Kashgar Rengulbai of Palau and Julie Andersen of the United States made all field observations. Points ranged geographically from the far northern state of Ngarchelong on Babeldoab to some of the southern most rock islands. At all field points a Cannon Sure shot digital camera was used to take photographs looking North, East, South and West from the center point. Using a feature of the camera, a sound file was recorded with each photograph identifying the point number, direction and any notable species or features present. This method made it easy to determine which pictures went with which photographs.

During the field survey efforts were made to ensure that points were measured in as vast an area as possible given the limitation of access. This was both for data integrity standards and to accommodate desires by the local governors that each of Palau's states be represented in the vegetation survey. Kyangel, Peleliu and Angaur could not be included in the classification, as their states were not covered by the IKONOS image. A four wheel drive vehicle provided by the Palau forestry department aided in gaining access to areas that would otherwise be impossible to access. In some cases where stone paths between villages had incorrectly been identified as roads, efforts to hike to points that were less than one half mile away were made. All GPS readings were made with a GARMIN GPS III. Efforts to average the readings for a count of 180 or greater were made. When poor GPS coverage was a problem, an offset from an area of better coverage was used to record the distance to the point center.

Beginning Monday, March 21, 2005, ten total days of fieldwork were completed. Given the distance between points and the condition of the roads some of the initial study points were not accessible without significant efforts. In an attempt to mitigate this problem, any points that we could not be reached by walking less than ½ mile were noted as no access. For each inaccessible point, the class that is was supposed to represent was noted and if possible substitution points were established. Using this method a total of 130 initial plots were visited and a total of 54 substitution points were visited for a total of 185 total sample points. The total number of plots by class can be seen in Table 4.3 Of the 15 classes that were sampled, 13 were vegetated classes. The other two classes were urban and water which were sampled in areas that had been vegetated in the previous survey. Areas in the unsupervised classification that had been identified as either urban or water were verified visually when driving from vegetation point to vegetation point.

Table 4.3. Number of Field Points by Current Class.

Agroforest	12
Cropland	13
Barren	4
Grassland	25
Mangrove	19
Marsh	17
Plantation	14
Rock Island	11
Strand	8
SV	5
Swamp	16
Up	20
Secondary Vegetation	12
Urban	8
Water	1
Total	185

Most of the work involved in post processing was in GPS data correction. In cases when the GPS receiver or the satellite configuration overhead was not cooperating with the field data collectors, an offset collection point distance was recorded. These two variables record the azimuth to the plot center from the offset location point as well as the distance in feet of the offset. This was adapted from the procedure outlined in the Field Instructions for the Inventory of the Pacific Islands (Forest Service 2005). In order to correct offset locations, some trigonometry was applied using a excel spreadsheet. The formula used in the spreadsheet software to correct for easting is as follows:

SIN(RADIANS(GPS Azimuth))*GPS Distance

This yields the amount in feet that is offset for the X, or easting axis. Additionally the conversion factor of 1 meter= 3.2808399 feet was used to find the amount in meters that was offset for the X or easting axis. This correction factor was added to the original UTM easting to arrive at the corrected easting and the actual location where plot data was collected. Only a slight modification to the formula was needed to correct for northing:

COS(RADIANS(GPS Azimuth))*GPS Distance

This yielded the amount in feet of offset for the Y, or Northing axis. The correction factor of 1 meter= 3.2808399 feet was again applied to yield the amount in meters that was offset for the Y (Northing axis). This correction factor was then added to the original UTM Northing to arrive at the corrected Northing.

If possible field staff waited for accurate readings at the actual plot location, but in order to save time and attempt the target goal of 20 field points per day, some plot locations were offset. Visual inspection to verify the plot locations followed after data correction. Only one field point was deemed unusable due to an error in GPS data collection. A map of the 185 field points can be seen in Appendix 3.

Results of the field survey provided instantaneous answers to some of our classification questions. The field study also created additional questions. *Merremia peltata* was present in abundance and at times did cover areas greater than 4 square m, which meant that it might show up as a distinct pixel, if not class of its own. Efforts to sample particularly large patches of *M. peltata* were made during the field survey, though only 5 locations were found where merremia was abundant enough as well as the primary species. Comparing spectral values of pixels to those in other forest classes showed that although distinctly different on the ground, the merremia patches were not distinctly different enough to be picked out with IKONOS data. However, given the limited abundance of merremia in Palau, it is recommended to field survey using a GPS to map individual polygons of Merremia and designate a separate class.

The classification that had been devised was adequate, but some modifications were needed. The original class of palm forest no longer applies, as it had been an isolated polygon of the introduced ivory nut palm, which has been cleared for an urban building site as seen in Figure 4.14. An additional question that was answered during the field visits was the minimum size required for cropland. Anything under 1 acre was not likely used for crop production on a commercial scale, but for either personal or family use. Cropland over 1 acre in size usually provided enough crops that at least some of the produce would be used outside the landowners immediate family or even sold as a product, so a minimum size of 1 acre was selected. Patches of cropland less than one acre in size are not separate classes in the new classifications. Trickier questions to answer were whether or not some classes needed further separation. Grasslands did exhibit some species differentiation between grass and fern cover. Points were taken in both the fern-dominated and grass-dominated areas of grassland areas, however the spectral signatures from the IKONOS imagery were not different enough to warrant separating the two into separate classes. If separating the two becomes important at another date, using a hyperspectral sensor in order to try and distinguish a portion of the spectrum in which the two differ more dramatically is recommended.

Using the previous classification to designate field sites allowed us to field test the existing vegetation map, as well as determine the relevancy of using the older map until a more suitable and current map could be produced. Initial findings were that

Figure 4.14. Site of Former Palm Forest Vegetation Site. Now converted to urban use.

the older map is still very useful but, some important changes were also observed. Many areas that were previously designated as swamp or marsh have become cultivated and are now agroforest or cropland. Additionally, some areas that were previously agroforest or cropland have been abandoned and are now reverting to grassland or upland forest types. An additional observation is that much of what was secondary vegetation has significantly recovered and can now be designated as upland forest, instead of secondary vegetation. Secondary vegetation for the purpose of this classification is an area that does not exhibit the traits of a well-developed upland forest. Often, secondary vegetation was instead dominated by a layer of colonizing plant species such as Macaranga, Hibiscus and/or Merremia without a well-developed canopy of larger trees in multiple layers. An additional observed change is the decline in coconut plantation forests. Since the previous survey no new plantations have been established and those that were previously established are not maintained. In many cases the natural vegetation or colonizing vines are moving in and changing the vegetation from that of a coconut plantation to upland forest or secondary vegetation. Also in places, people have cut the coconut to make way for agroforestry. Due to these changes, a likely decline in the coconut plantation forest type class as well as an increase in the upland forest type class is expected.

Though useful as training for the researcher and in initial observations, the field study was in no way comprehensive enough to produce a final classification without further work. The next phase of the study will involve compiling the field data and using the information gathered to attempt to train a computer-based software program to classify a satellite image into forest type classes. Based on field observation, some classes should be easier to differentiate than others. Mangrove forests were highly homogenous and seemed to form rather distinct boundaries and should prove easier to map. However some classes such as grasslands and marsh share common species and may appear similar in reflectance to a satellite and thus be harder for a computer to differentiate. In cases such as these, it may become imperative to utilize the ancillary data layers discussed in Chapter 3 in order to improve the classification.

Overall, the field visit was highly successful, as many representative stands of vegetation were visited. The field study also helped to refine the proposed vegetation classification scheme into one that better reflects the vegetation classes currently present in Palau. Additionally, areas of change were noted and further questions generated and potential difficulties identified.

SEGMENTATION

A classification using a segmentation algorithm in e-Cognition was conducted. This process uses both spectral values as well as spatial context of the pixels to one another to generate polygons with like values. Performing this step of the analysis was necessary to determine if per pixel based unsupervised classifications are not the best-suited method to use with high-resolution imagery of tropical island vegetation.

Using the Forest Service's Segmentation algorithm proved to be more difficult. First the executable files and other supporting files must be downloaded and installed on the user's machine. These steps were fairly straightforward and not too difficult to follow even for a novice user. Next the image to be segmented is selected and the user selects the option to run the algorithm. Input values for block size, spectral threshold distance and minimum region size are required. The image is processed in blocks and the user can set the processing block size. The larger the block, the faster the program will run and the output will have fewer "artificial" lines. However, a large block size also uses more memory, which may adversely affect the computer running image segmentation (Ruefenacht, Vanderzanden, & Morrison, 2002). Experiments were conducted using different block sizes, and though smaller block sizes would process faster, larger block sizes did produce a more useable result. A block size of fifty was better suited than a block size of five. A spectral threshold distance value is entered to limit region growth. Experiments were run to increase or decrease this number in order to change the average region size. The Minimum Region Size defines the size for the minimum region. The unit value is in pixels. All regions less than or equal to this value will be merged with the most similar adjacent region (Ruefenacht et al., 2002). A minimum block size of 50 was initially selected, but some variation of this was also tried to improve results. Once the user selects these values the algorithm is run and an Arc Info coverage is generated. However, upon trying to run the algorithm the first time, ERDAS error message was generated. Upon contacting Ms. Ruefenacht, the error message was attributed to using Windows XP. At the time of research, the algorithm was not supported for that environment. As the Forest Service upgrades to newer operating systems, the algorithm would need to be developed to match the operating environment. However until this happens, having only a windows 2000 based algorithm is limiting for non Forest Service based users. After acquiring access to a Windows 2000 based machine, work on segmentation was continued. The segmentation algorithm was still problematic when trying to utilize the original image. Ms. Ruefenacht thought that the problem might actually be with the image. As the background values were ocean (because Palau is an island environment, a large portion of the background values of the image were ocean) these values were causing the program to crash. A mask of the islands was created to remove the problematic background values. The ERDAS segmentation algorithm only worked when the original IKONOS image was subset to exclude background values.

A spreadsheet was generated to document the input values selected as well as observations of the resulting segmentation based classifications. An excerpt from this spreadsheet can be seen in Table 4.4.

Results from using the ERDAS Segmentation algorithm were unsatisfactory because the resulting polygons do not reflect the patterns found in the landscape patterns, but based on the reflectance values of the pixels in relation to the surrounding pixels. Examples of this directional artifact can be found in Figure 4.14 and 4.15.

Table 4.4. Segmentation Notes

Inputfiles	Band(s)	Block Size	Threshold Difference	Size	output file	Notes:
/subset	1,2,3,4	50	10	5	seg50_10_5	very small segment sizes
/subset	1,2,3,4	50	10	50	seg50_10_50	larger block sizes, but still very busy
/subset	1,2,3,4	50	10	500	seg50_10_500	better size, but grouped urban and forest
/subset	1,2,3,4	50	5	500	sub50_5_500	linear segments make no sense
/subset	1,2,3,4	50	1	500	seg50_1_500	you can tell the algorithm works left to right
/subset1	1	50	10	50	sub1_50_10_50	no difference from 2
/subset4	4	50	10	50	seg4_50_10_50	no difference from 2 or 6
/subset	1,2,3,4	500	10	50	sub_500_10_50	some difference from7
/subset	1,2,3,4	5000	5	50	seg5000_5_50	too much left to right
entireimage	1,2,3,4				50_10_50	wouldnotrun

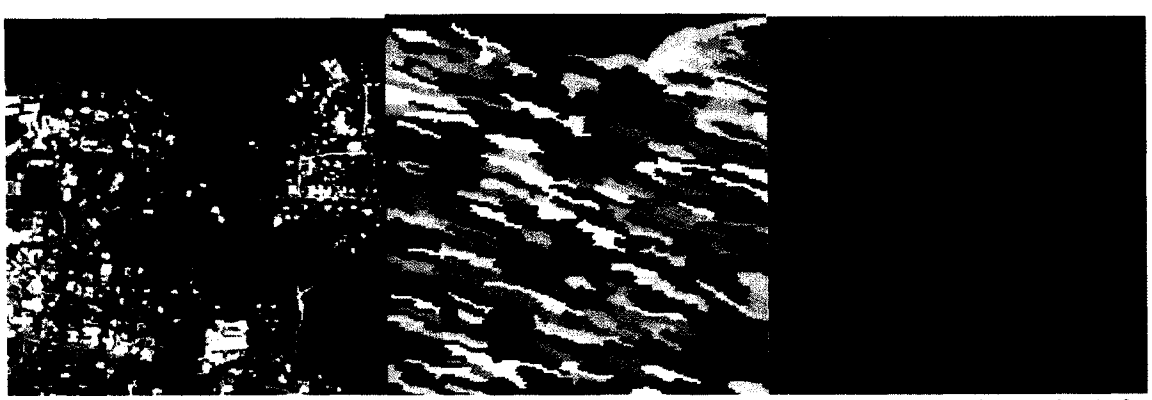

Figure 4.15. Initial Segmentation Attempts. A subset of the original image is on the left; the segmented image in the middle shows the left to right bias of the segmentation algorithm, while the image to the left shows an unsuccessful three-class reclassification.

In Figure 4.15, the segmentation algorithm is able to generate many polygons, but they do not capture the obvious patterning in the original image. The subset of the original image was chosen because it has a good mix of urban and vegetated areas, but the algorithm either grouped these areas together into many small polygons. In an attempt to reduce the number of polygons, the image was reclassified into 3 classes, which are shown on the right in Figure 4.15. However, the algorithm was not sufficient. This illustrates that the groupings created by the segmentation algorithm for ERDAS are not sufficient for even simplifying the image into three basic classes. Instead the three are lumped together unsuccessfully resulting in the useless classifications shown in Figure 4.15. Even attempting to group the segmented polygons by hand into three basic classes proved too difficult, as the initial groupings were too confused between the classes. Additional attempts to utilize the segmentation algorithm for ERDAS with different input parameters yielded similar unsuccessful results. Additional ERDAS segmentation correction attempts can be viewed in Figure 4.16.

Figure 4.16. Additional Segmentation Attempts. Here, utilizing different input values. Neither of the two outputs to the right resembles the patterns obvious in the original image on the left, and both reflect the left to right top to bottom bias of the algorithm.

Preliminary work with Segmentation in the ERDAS environment painted a bleak picture for the use of the spatial properties inherent in the IKONOS image. However, some algorithms are better suited than others for a particular type of imagery, thus an attempt was made to utilize the eCognition segmentation algorithm. This particular software package is much more cost prohibitive than the ERDAS software. Due to the economic constraints of obtaining a license for eCognition, only one attempt at segmentation could be run. The original image was brought to the USDA Forest Service Remote Sensing Laboratory in Sacramento, California. Zhanfeng Liu was then able to use the office copy of eCognition to run the algorithm on the original image. The patented eCognition segmentation algorithm creates image segments based on four criteria: scale, color, smoothness and compactness. These criteria can be combined in numerous ways to obtain varying output results, thus enabling the user to create homogeneous image objects in any chosen resolution (Definiens, 2006). Of the four parameters, the scale factor is the most important to set the size of output polygons. Zhanfeng Liu selected a scale factor of 50 based on his experience in mapping Guam. Color, smoothness, and compactness are all variables that optimize the segment's spectral homogeneity and spatial complexity. The balance at which these criteria are applied depends on the desired output (Definiens, 2006). Liu also selected the input parameters for these factors. The eCognition algorithm was then executed and the result was an ESRI shapefile. If licensing and software price were not an issue this is an area that could use further experimentation to try to determine the best values for each of the input parameters given the image provided.

The segmented image created by Liu was then compared to the ERDAS segmentation classifications in order to determine if the eCognition algorithm was any better suited for grouping polygons of like pixels when using the IKONOS image. An excerpt of the segmented image can be seen in Figure 4.17.

The eCognition segmentation algorithm was much better suited for the IKONOS Imagery. Most of the urban areas were visually separate from vegetated areas and water features fell into their own set of polygons. A few of the polygons had both urban and

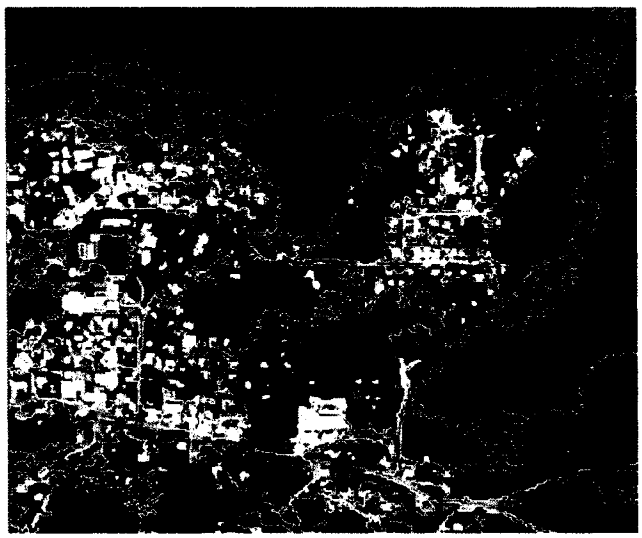

Figure 4.17. Subset of Segmented Image from eCognition

vegetated features in the same polygon, but overall the separation between the two was distinct. A simple three-class classification could be immediately made from the segmented image: urban, vegetation and water. If desired a fourth class could be added for urban/vegetation mix. Running only one session of eCognition was more successful than the many attempts with ERDAS Imagine. Though eCognition carries a higher price tag, the success of the segmentation algorithm alone may make it invaluable to Forest Service staff.

Once a useful segmented image had been obtained, the task was then to identify areas of known forest type covers and label polygons that cover those areas accordingly. This process is one that carries much subjectivity, as one researcher might label a polygon one forest type class, while another researcher may call it another. However, some steps to limit the subjectivity were in place. The unsupervised classification was successful at separating barren, urban, water, grass and to some degree mangrove features. Using the GIS software the per-pixel based classification could be placed below the segmented shapefile and those features from the unsupervised classification could be compared to their overlying polygons. When the two matched more or less, those features could easily be labeled. Some of the other classes from the proposed vegetation scheme though separable were not immediately apparent. Instead of trying to break the segments apart and automate their values based on any number of factors, it was proposed instead to use the GIS and the original image to essentially visually interpret the image. This idea was selected due to the time involved in trying to find the correct values in any number of layers needed to automate individual polygon class labeling. It is well known that remote sensing data of a higher spatial resolution increases visual interpretability (Munechika,Warnick, Salvaggio and Schott, 1993). Though automated labeling of polygons would be much faster than labeling by hand, that is only possible when the variables needed to automate the system are known. In the case of a Pacific island such as Palau, where the area to be interpreted is rather small, labeling the segmentation generated polygons by hand may prove faster. The researcher responsible must have knowledge of visual image interpretation as well as the ability to work within a GIS. Ancillary data layers can prove quite helpful in identifying specific class boundaries that can then be assigned to polygons in the segmented image.

Field collected data also proved useful in labeling of polygons. If a polygon contained a field point, the researcher can look at both field notes and the pattern within the polygon. If it is not unreasonable based on ground observations, and the polygon appears uniform in color and texture, it can be assigned the class of the ground point. However, in some cases the ground observations did not match the segmentation. A good example is a small area of cropland that was noted to extend only a few hundred feet in either direction, yet the segmented polygon enclosed an area that extended for miles from the ground point. This information was not useful for labeling s specific polygon, but the information did prove quite useful. It helped to determine if some classes were either not distinguishable based on spectral and/or spatial values alone, or that the scale factor selected was too large for a smaller sized class. Selecting a smaller scale factor to try to obtain a polygon more appropriately sized to the field observations would be a useful experiment to run. However, even after trying this experiment, some classes may not fall out into their own polygons at all. Thus, given the methods used those classes are not determinable from the IKONOS imagery. Additional transformations or combinations with other ancillary field data may be needed. For especially small classes with known extents, walking the boundaries with a GPS and importing the data, or by sketching in the boundaries from field observation will reduce processing time trying to locate the classes in the image.

Upland Forest is a large class found last in the imagery, as it is covers areas of vegetation on the volcanic islands that do not fit into the other classes. Upland forest as described by Cole et al. is the most species diverse. This could be due to its nature as a catch-all class. The upland forest type could use further subdivision into smaller classes. The high diversity and limited time made that possibility outside the realm of this study. A suggested way to accomplish this task would be to follow the example of Zhanfeng Liu in the classification of Guam and begin by separating the class into areas of interior and ravine upland forest. This separation could be performed using either the topographic map layer or DEM if desired. At lower elevations on the volcanic islands, areas along ravines will tend to be either dominated by swamp or mangrove forest types, which will cause some confusion.

Limestone Forest can be easily identified when combining the soils data layer with the segmented image. Though Rock Island Forest type is a subset of the limestone forest class, it was the only limestone forest identified in the current vegetation map. This is due to the area covered by the IKONOS image. If a larger image were to be obtained it would be useful to look for areas of limestone forest outside of the boundary of the rock islands. However, at this time, as the imagery only covered limestone forested areas of the rock islands, only rock island vegetation is noted.

Wetland vegetation proved difficult to separate in some regards and not difficult in others. Mangrove proved easy to identify, thus it was identified as its own class. However both swamp and marsh were more difficult. In visual appearance marsh looks similar to both grasslands and upland forest. In cases where there was confusion with grasslands, upon closer inspection marsh often appeared smoother and greener and closer to water as in Figure 4.18. On the left is the original image containing areas of both grassland and marsh. However the marsh areas are smoother and a slightly different green than the surrounding grassland. Also note the proximity to water that plays a role in identifying marshy areas.

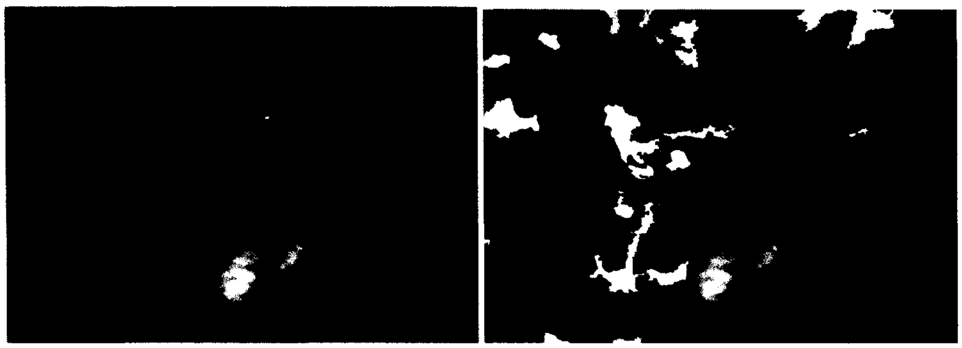

Figure 4.18. Before and after shot of Grasslands vs. marsh. Grasslands appear yellow, while marsh appear pink. Water appears blue.

Another problem encountered with marsh is that it is often converted to either cropland or grassland, thus it is not always a well-established distinctive class as at any given time it may be in the process of being converted or reverting from either crop or grassland causing some confusion. The swamp class proved the most difficult to extract from the imagery. At times it is identical in appearance to either upland or mangrove vegetation. The general idea is that swamp occurs slightly above the mangrove forests. According to Cole et al. the most common habitat for such forests is low-lying areas just inland of mangroves above tidal influences. However, when consulting the historic vegetation map and comparing it with the imagery, no true discernable difference between swamp and mangrove could be determined. In many of the low-lying areas, what was historically labeled as swamp is now absorbed into the mangrove class.

Table 4.5. Revised Classification Scheme

Palau Vegetation Classes			Crosswalk to USFS Survey Class
Level 1	**Level 2**	**Level 3**	
VEGETATED			
	Upland Forest on Volcanic Islands		Upland Forest
		Interior Upland Forest	Upland Forest
		Ravine Forest	Upland Forest
	Limestone Forest		Limestone Forest
		Rock Island Forest	Rock Island Forest
	Wetland		
		Swamp Forest	Swamp Forest
		Marsh wetland	Marsh
	Mangrove		
		Mangrove	Mangrove Forest
	Agroforest		Agroforest
		Coconut Plantation	Coconut Plantation
		Other plantations	Plantation Forest
		Cropland	Cropland
	Grass/Shrub Land		
		Savanna Complex	Grassland/Savanna
		Other Shrub/Grass	Secondary Vegetation
		Strand Vegetation	Strand
NONVEGETATED			
	Urban	Urban Built up land	Urban
		Urban Vegetation	Urban/Secondary Vegetation
	Barren	Cleared Land	Barren
		Sandy Beach and Bare Rocks	Barren
WATER	Water	Water	Water

In addition, areas along streams and waterways that reach into the upland areas did not appear significantly different from the surrounding upland forest. More inland areas that were once called swamp forest were absorbed into the upland class. Even though the swamp class was not spectrally, spatially or visually separable using the given research techniques, it does not mean it is not a distinctive vegetation class. In order to accomplish this task, a different remote sensor may prove useful. Certain types of forests such as mangroves and swamp forests are found to be spectrally more distinct on ATSR data than on sensors of similar spatial resolution (Eva, Achard, Mayaux, Stibig, & Janodet, 1999). Further research is needed to separate the swamp class.

Though the swamp class was extremely difficult to separate in the imagery, one class that did prove easy to visually identify on the IKONOS image was the mangrove forest. Using the GIS, it was possible to verify that areas of suspected mangrove from visual inspection were also labeled as areas of mangrove on both the topographic map as well and the historic classification. This was possible because in Palau, the mangrove forest occurs along lower portions of rivers and their mouths, on coastal mud flats, and on some offshore islets (Cole et al.,1987). Sometimes a visually suspect area was included in what was otherwise an obvious mangrove polygon. In these cases, it was possible to see if the "arm" of a polygon that looked visually different from the rest of the polygon was located at a low enough elevation with proximity to the sea or some other waterway. If it was near enough to the water, the arm of the polygon was left as a mangrove forest. However, if the arm extended too far up a steep slope, which would prevent inundation from the sea or was, too far from other water sources, it could be separated visually from the overall mangrove polygon and labeled with appropriately. This tells me that usually the software was able to distinguish mangrove forest, but at times, some type of misclassification did occur, but it was possible to remedy using visual interpretation and ancillary data layers.

Agroforest classes became any class created due to human influence. Thus the classes that were historically cropland, agroforest and all types of plantations are now lumped into level 2-category agroforestry. In the new classification at level three agroforestry and cropland remain lumped as agroforestry. This is because the two were historically separated by the presence of tree crop species. Those areas that had some element of tree crop were called agroforest, while those areas with only ground level crops such as taro were called cropland. However, even in the historic classification, it was rare to have patches large enough to be called cropland. During the field visit in 2005, few areas of human crop cultivation were observed that were totally devoid of any tree or tree like species. The normal pattern was a cultivated path of either taro or tapioca intermixed with papaya, banana, mangos and the occasional coconut or betelnut palm. Thus instead of trying to separate the two classes, they were lumped into one larger agroforestry class.

Plantation forests were also small in size and rarely distinguishable on the imagery, however, some remnants of historically larger coconut plantations were still present during the field visit. Though few of them were being actively cultivated the abundance and presence of coconut palms was enough that it changed the overall vegetation present. Coconut plantation was left as a separate class, and the smaller plantations of paperbark, acacia and teak were lumped into a generic plantation forest class. The latter classes were too small and not spectrally or spatial different enough to be distinguishable in the imagery. However, having visited the islands and taken GPS readings on site at many of the plantations made it possible to use the imagery almost like an aerial photograph to outline the extent of the field visited plantations. In order to better map these locations, it is recommended that the island forests take GPS units and manually map the plantations, as they are small in size and few in number. The larger coconut plantations were harder to pick out, as not as many of them could be field visited. However, a distinctive dark pixel speckle pattern is often seen in the imagery in areas of coconut plantation. An example of an area heavily covered with coconut and exhibiting a high degree of speckling can be found in Figure 4.19. In areas with high concentrations of coconut, this method worked well to pick out coconut plantations. However, in areas where coconut may only be scattered it was harder to distinguish if a dark pixel was due to either shadow (which also appears dark) or to the presence of coconut or some other factor entirely. If areas on the historic classification had been identified as coconut, an effort was made to look for the specking, otherwise, unless the speckling was highly obvious a new plantation had been directly observed in the field, no new areas of coconut plantation were mapped. Speckling often occurred within a polygon only partially. In these cases it was a subjective call as to whether there was enough speckling to call the entire polygon coconut plantation, or if the polygon was split into two classes. Ideally, the best was to delineate coconut plantation (instead of relying on speckle alone) would be to use higher resolution imagery. Examples include the panchromatic band of the IKONOS image to achieve higher resolution or using an even higher resolution sensor such as Digital Globe's Quick Bird sensor. At these higher resolutions, coconut palms are visible with the naked eye and can easily be selected from the imagery.

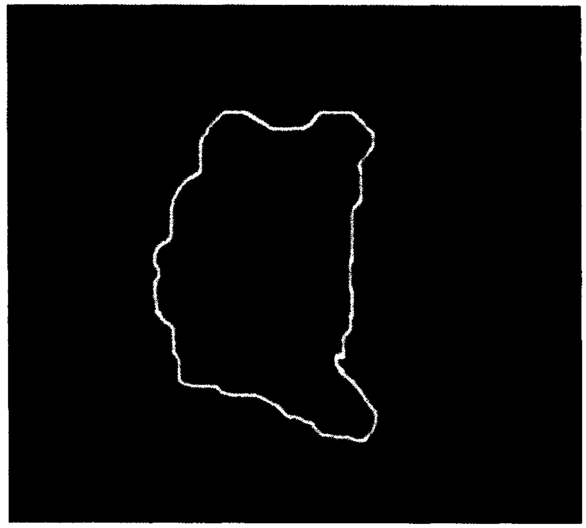

Figure 4.19. Coconut Plantation as Viewed in the Satellite Imagery. The area inside the yellow polygon illustrates the scattered dark pixels typical of coconut presence.

Grassland is a level two component in the new classification scheme. If desired the grassland class could be further subdivided into additional level three components. Some ideas for this separation include savanna, and/or a class for the fern dominated portion of the grasslands, another grasses/shrubs class, or perhaps pandanus present grasslands and those lacking pandanus. Though some spectral separation was seen within the grassland class, further work to better separate the grassland is recommended if desired by the island foresters, otherwise a simple grassland/savanna class is sufficient. IKONOS is well suited to extract grassland from both software packages.

A level three component listed on the new scheme is strand vegetation type. It is listed under grassland/savanna for lack of a better location. Perhaps this class should be elevated to a level two and carry its own distinction as it is often has tree species present and is really not much of a grassland whatsoever. The dominant species observed during the field visit were Barringtonia and coconut palms. Though the class was observed, it was not mapped as it a very narrow linear class, and many times not even wide enough to cover a single column of pixels. The class is quite small and not really distinctive enough to warrant mapping, but if so desired using a simple buffer around sandy barren areas on the landward side would identify potential locations for this class.

Level 2 urban class is currently mapped to include both urban built up and urban vegetation into one category. Using a simple mask of the areas currently identified as urban and then using NDVI should easily separate the two classes if desired. However for mapping purposes, urban vegetation was considered to be part of the overall urban areas and not mapped separately. The other non-vegetated class of Barren could also be further separated into cleared areas and sandy rocks and beach if desired. Visually looking at the locations of polygons currently labeled as barren and selecting only those that are mostly linear and follow the waters edge would manually separate the two barren classes if so desired. Some barren roaded areas may appear as strand when located alongside the shore, thus knowing the location of the road network is important to completing this task correctly. Currently and barren roaded areas that fell within a village, town or city were lumped with the urban class as part of the overall urban boundary of that village.

Finally water features were mapped into a class. Further separation of the water class into fresh and saltwater classes may be possible. However, that particular topic was beyond the scope of this project. Overall, segmentation when coupled with the image transformations, per pixel based classifications, and visual interpretation proved suitable to map most of the desired classes. Some classes are stronger represented than others, while some classes such as swamp could not be determined given the methods used. This does not mean that those classes cannot be extracted from the IKONOS imagery; it only means that additional work and study are needed.

CHAPTER 5: ANALYSIS AND DISCUSSION

The original intent of the study was to compare an unsupervised classification, and a segmentation based classifications using IKONOS imagery. Initial research indicated that one of these classifications would be better suited than the other, especially for particular vegetation types and in certain areas. However after conducting further research, the best classification for Palau is actually a hybrid of the two different classification techniques. However, after performing the unsupervised classifications and finding the classes so jumbled, the integrity of the spectral data values was questioned for many of the vegetated classes. This was hypothesized to be due to spectral overlap in the classes selected for use in the classification scheme. Further analysis was conducted to determine if this was true.

The first step in the analysis was to determine if vegetated and non-vegetated classes could be distinguished given spectral values alone. A normal probability plot, which plotted the vegetated values against the non-vegetated values, was used for this analysis. Inspection of the resulting graph showed that the vegetated and non-vegetated classes are separable based on pixel values alone for all four IKONOS band types. The best separability occurs in the red, blue and green bands, with minimal overlap in the IR band. This can be seen in Figure 5.1. In studying the probability chart, the red values do not follow a straight line indicating that the data is not normally distributed. Vegetation and non-vegetation were observed in the probablility chart to be seperable indicating that they are separable spectrally using IKONOS. However, the distribution pointed to a suspect distribution of the overall data values.

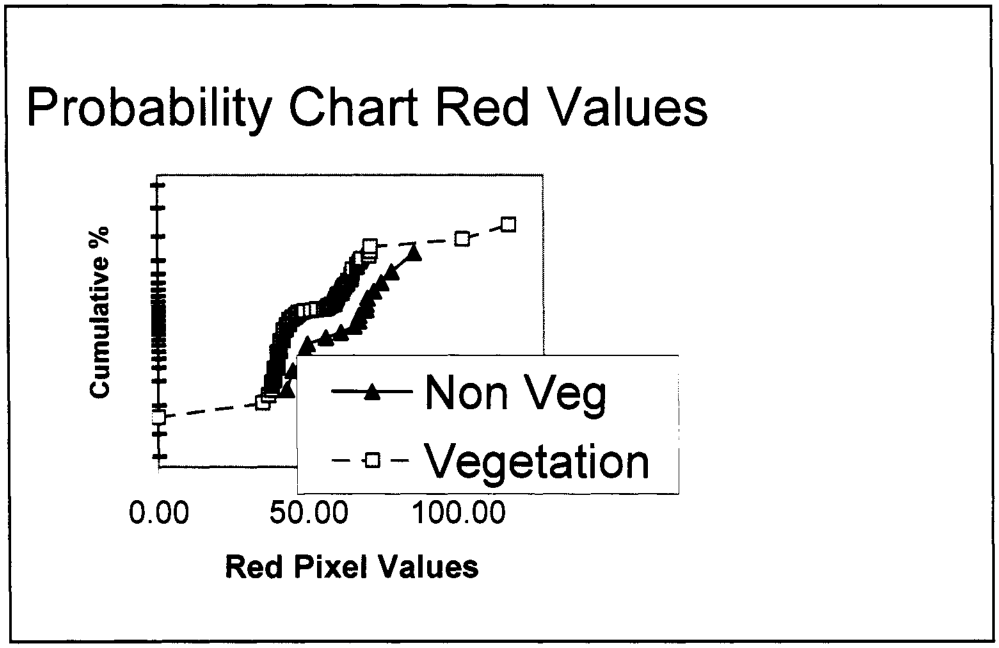

Figure 5.1. Probability Chart Red Values

In order to explore the distribution of data, the band values for the field collected data points were plotted against one another using Excel. The data points were grouped by class and then plotted using the four bands of the IKONOS Imagery for a total of six graphs. An example of one of these graphs can be seen in Figure 5.2. The collection of all six graphs can be found in Appendix D.

Figure 5.2 illustrates that the field collected data points are found in two distinct clusters. This indicates a bimodal distribution of the data. This bimodal distribution occurs in the red band of the imagery across all land cover classes. Each scatter plot displays a bimodal tendency whenever the red band is included. If the classes were each spectrally unique, clusters around each class with little overlap are expected. However, in viewing the pixel values plotted, no separable clusters and little to no distinction between vegetated land cover classes. Though the vegetated classes appear inseparable, the non-vegetative classes do show separability from both the vegetated classes, and from one another. Thus non-vegetated classes are separable in the IKONOS image using spectral values alone.

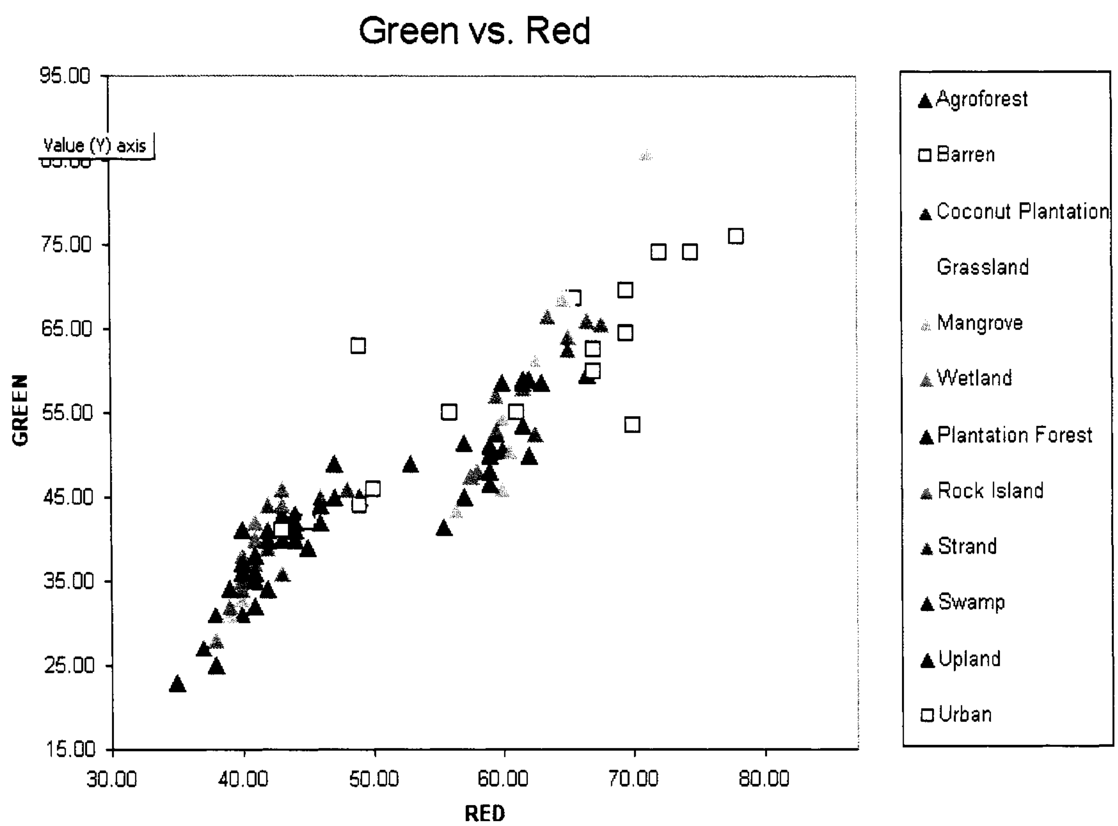

Figure 5.2. Red vs. Green Band Values by Class

Though the findings point to poor suitability of IKONOS imagery as a base layer for per-pixel based classification, the results may not be due to the imagery, but in the selection of sample points. Due to the limited time available for field sampling, the dataset is small and may not best represent the spectral values for the desired classes. This is a hypothesis worth mentioning, but every effort was made to secure the best possible field locations to represent to different classes. The idea that the problem lies with the field collected data and not the imagery is possible but unlikely.

After plotting the spectral values for the field collected data points, a supervised classification was not feasible. With the classes so confused, selecting credible training data within the image is too difficult. The plotted values also illustrate that spectral values alone are not enough to separate most of the classes in the imagery. Thus the segmentation avenue was pursued, and the field data points used as validity checking and interpretation of the segmentation based approach. Segmentation, which incorporates more spatial based data, did help to alleviate much of the confusion when trying to classify the vegetation based on spectral values alone.

CHAPTER 6: CONCLUSION

This study investigated classifying tropical island vegetation. The most robust method for classifying the vegetation of Palau was a segmentation-based classification using visual interpretation built on the foundation of a traditional per pixel-based approach. IKONOS is unsuitable to find all desired classes when only using spectral values. Two segmentation algorithms were tested and compared visually including one developed for ERDAS Imagine and one developed for e-Cognition. In this study, the e-Cognition algorithm performed superbly in comparison with the algorithm designed for ERDAS Imagine.

Segmentation eliminated some of the confusion in the image by delineating polygons that could be labeled manually. However, hand labeling was quite time consuming and highly subjective. Segmentation alone does not eliminate all of the confusion, and in some ways may tend to over designate a forest type class. A good example is the cropland/agroforestry class. Though patches of cropland vary in size, some of the polygons designated as cropland were much larger than they may have been on the ground. This is because the presence of a dwelling in an otherwise vegetated polygon was used to determine cropland. Basically the presence of a dwelling in order to tend to crops was used to make a class call, not any obvious change in the vegetation values or patterns within the imagery. Using a smaller scale factor may have helped to alleviate this problem. Segmentation provided a structure to work within, but visual interpretation of the image proved to be the most useful method to pick out some of the more difficult classes. Visually picking out many of the classes was not possible.

Sometimes a polygon had to be labeled with what amounted to an educated guess using all of the ancillary data layers and comparing it to the surrounding polygons. This method can lend itself to inherent classification errors. If relying on visual interpretation to define the troublesome classes is required, as it seems to be, obtaining even higher resolution imagery (either aerial or satellite) to be used in tandem with the IKONOS imagery may be the best possible solution. Though IKONOS is suitable for mapping tropical vegetation, it is by no means the best possible solution. The high diversity of the vegetation and high resolution of the sensor can cause undue confusion. At times less resolution, which averages the noise, might prove easier to work with. Additional work with hyperspectral imagery may find that classes that could not be determined by the IKONOS sensor are blatantly obvious to a sensor that covers a greater portion of the spectrum.

IKONOS imagery was best used to determine the classes of urban, barren, water, grassland and mangrove. Using the image for visual interpretation is possible to pick out areas of marsh, agroforestry, and coconut plantation with some certainty. Using ancillary data made it possible to locate rock island forest type. However, the class of swamp needs further work given the imagery provided. Mapping to level two of the classification scheme proved possible given the IKONOS Imagery. Further work to break out level 3 classes is warranted. Classes not covered by the image area will need to be looked at individually to determine if they can also be mapped using IKONOS.

Further studies that would benefit this research include an accuracy assessment. This step was not performed due to the lack of a sufficient number of spectrally homogeneous locations that had not already been used to help label the polygons in the final classification. Using the same points for both labeling and accuracy assessment would have introduced bias into the accuracy assessment. Utilizing external sample points, which are more spectrally separate for the desired classes is recommended. An example of field points that might be useable are the Forest Inventory and Analysis points installed on the islands of Palau. Additional studies using another type of imagery to extract the swamp class would be useful. Eva, Achard, Mayaux, Stibig, and Janodet (1999) found that certain types of forests such as mangroves and swamp forests are spectrally more distinct on ATSR data than on sensors of similar spatial resolution. This is an avenue worth pursuing. Further comparison of reflectance values during different parts of the year and the relation this plays out by classes most affected by available moisture does warrant further study.

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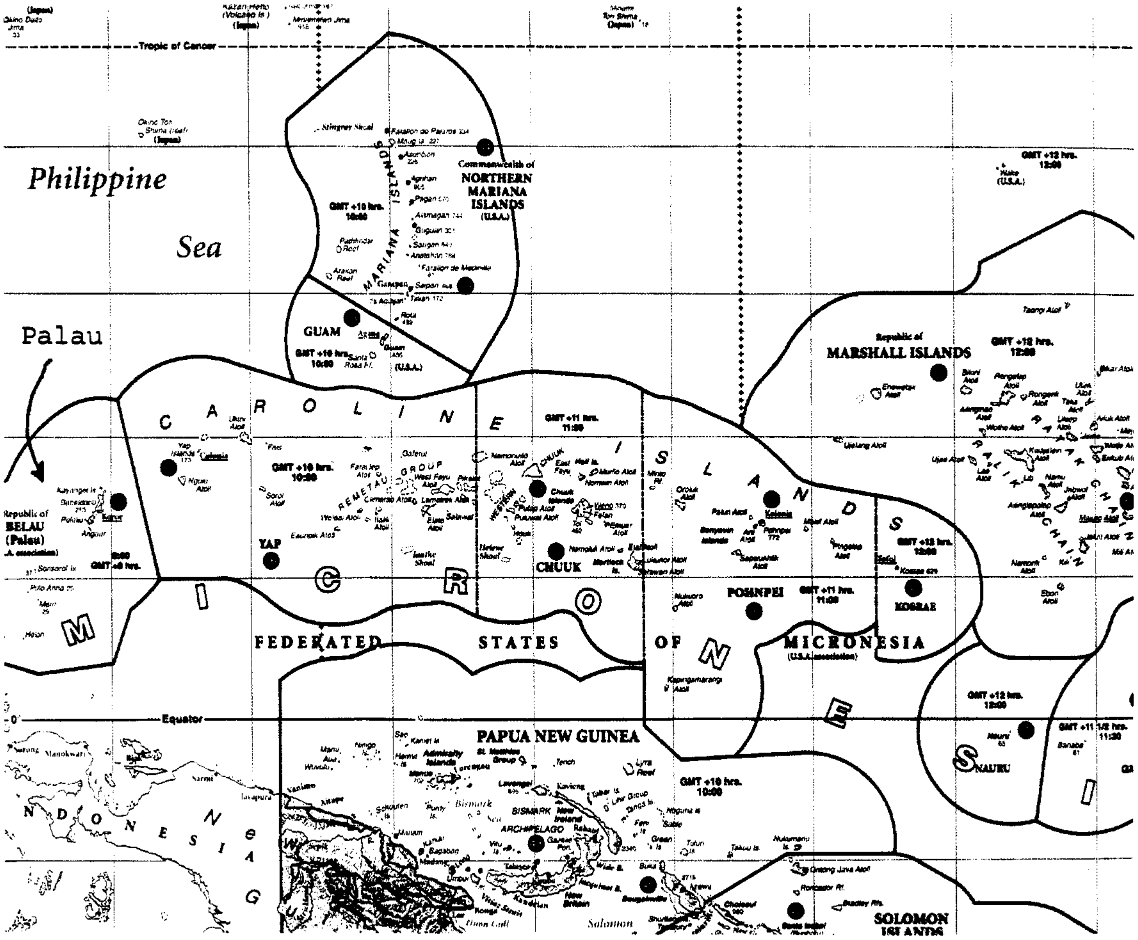
APPENDIX A. Map of Palau and Surrounding Area



APPENDIX B. Sample Data Sheet

Point # ________________________________

Recorded By:

____

____

____

GPS:

Unit	Garmin III
easting	________________
northing	________________
zone	________________
average:	________________
error:	________________
datum:	UTM/UPS, WGS 84

Primary Forest Type: __________________ (According to classification scheme)

Secondary Forest Type: __________________

Dominant Overstory:		Chose One:			
species 1	____________	Tree	Shrub	Forb	Grass
species 2	____________	Tree	Shrub	Forb	Grass
species 3	____________	Tree	Shrub	Forb	Grass
additional >3%	____________	Tree	Shrub	Forb	Grass
	____________	Tree	Shrub	Forb	Grass
	____________	Tree	Shrub	Forb	Grass

Canopy average height: __________________ Estimate in meters

Density:	High	Med	Low	Slope %	________
	71-100%	30-70%	0-29%	Aspect 0-359	________

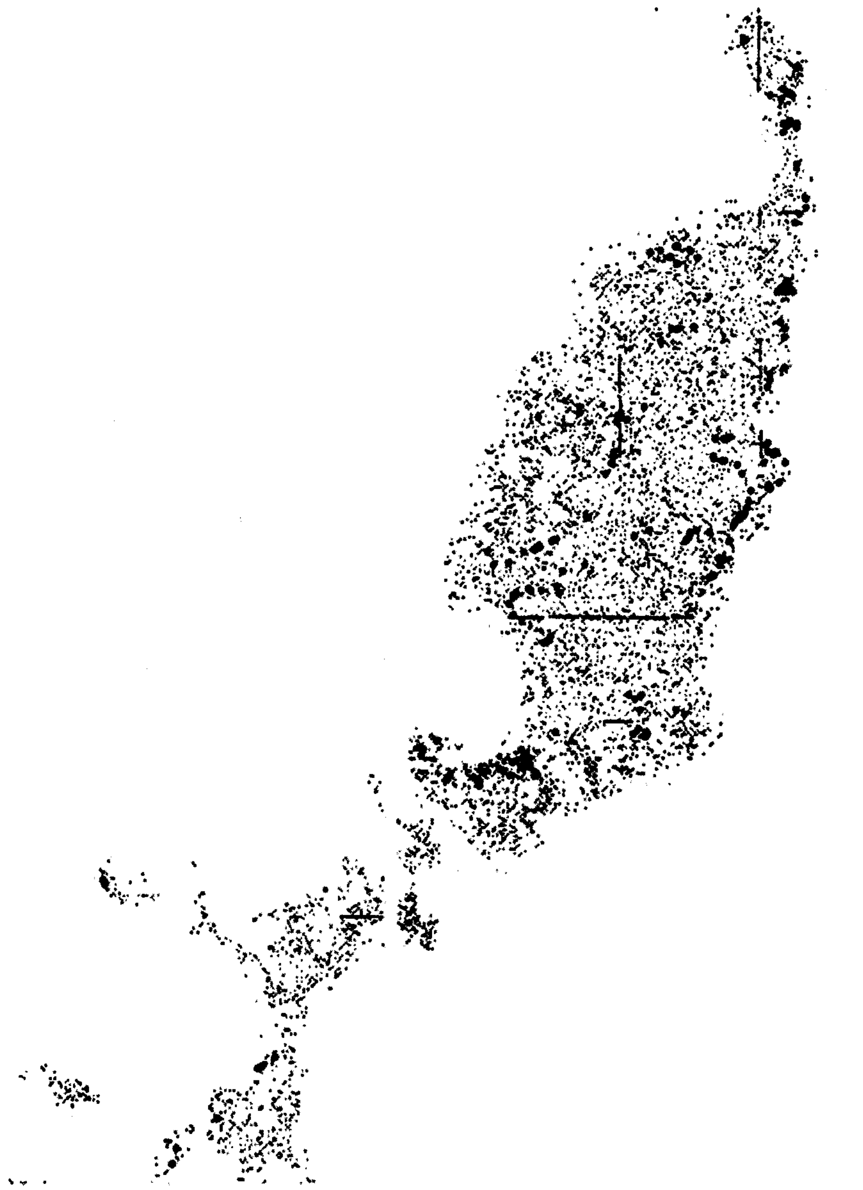
	Subplot	Hectare	Beyond-	Extent-meters:
Extent of the class:	Y/N	Y/N	Y/N	____________

Originally classified as: __________________________ Is this correct? Y/N

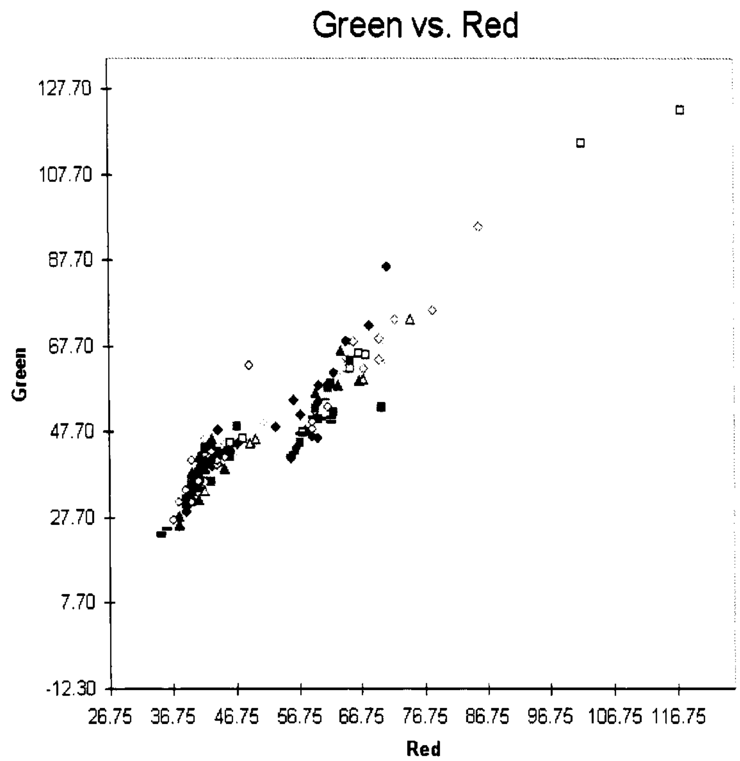
Should be: __________________________

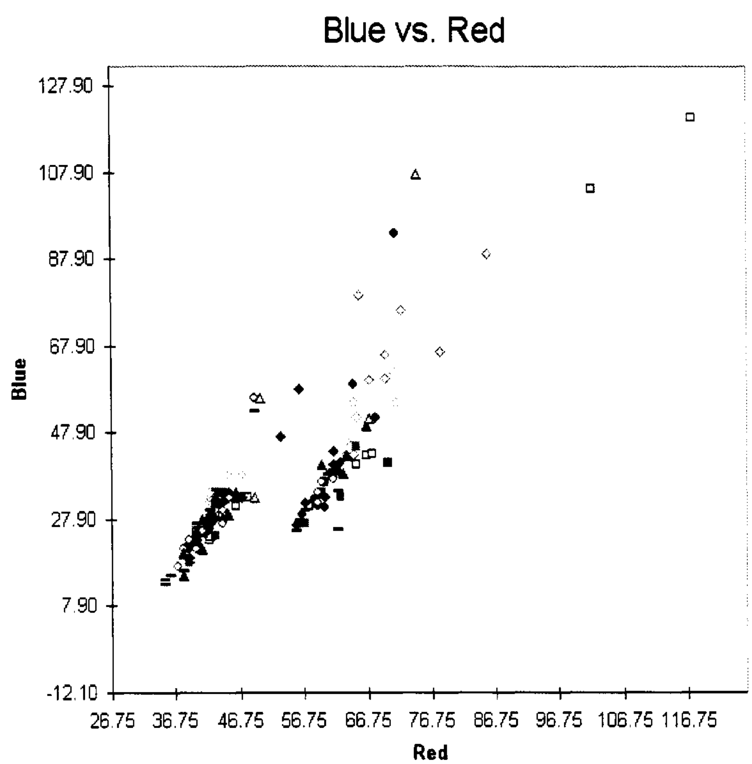
Notes:

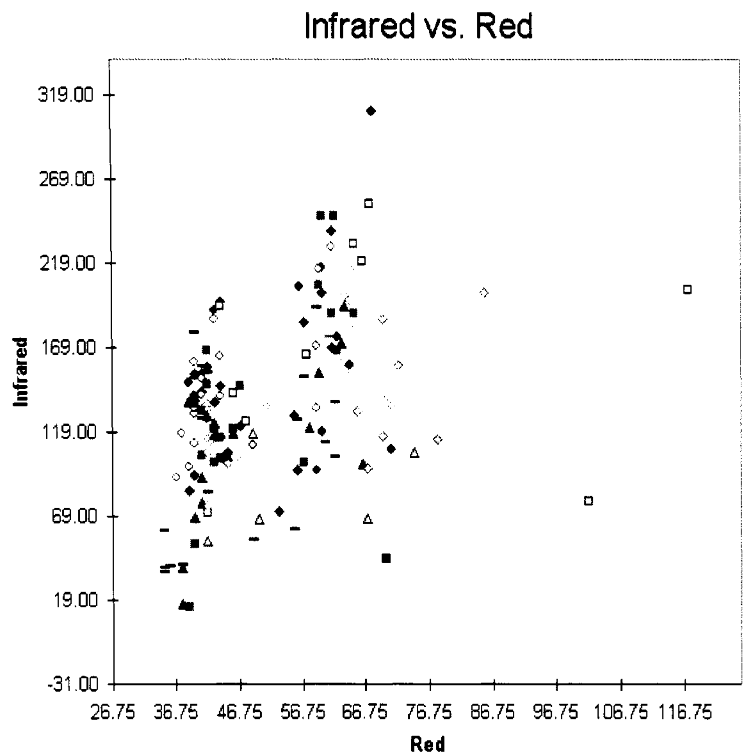
APPENDIX C. Location of Field Collected Data Points (in red)

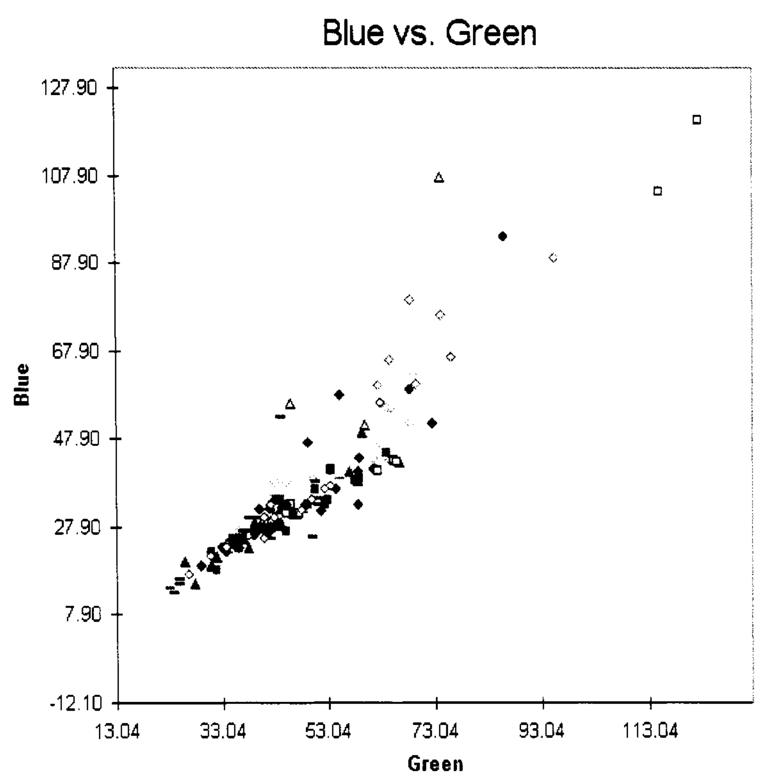


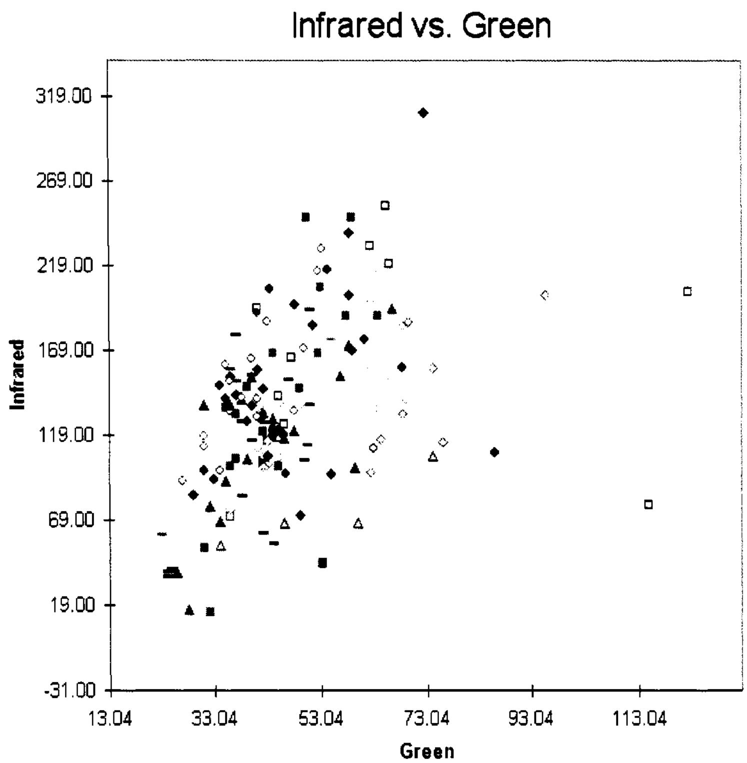
APPENDIX D. Graphed Reflectance Values for All Classes for All Four Bands

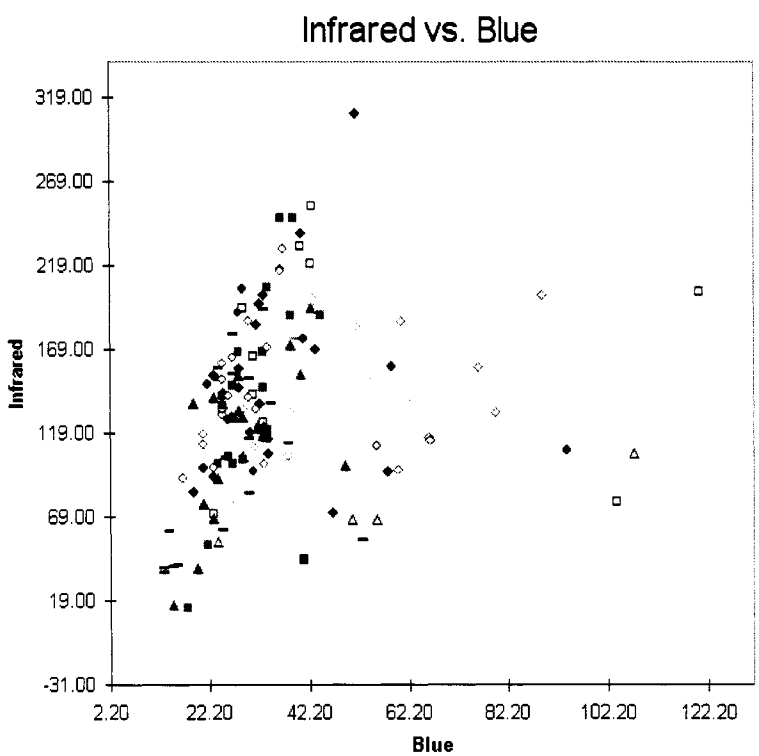





Infrared vs. Red
319.00
269.00
219.00
169.00
119.00
69.00
19.00
-31.00
Infrared
26.75 36.75 46.75 56.75 66.75 76.75 86.75 96.75 106.75 116.75
Red


Blue vs. Green
127.90
107.90
87.90
67.90
47.90
27.90
7.90
-12.10
Blue
13.04 33.04 53.04 73.04 93.04 113.04
Green


Infrared vs. Green
319.00
269.00
219.00
169.00
119.00
69.00
19.00
-31.00
Infrared
13.04
33.04
53.04
73.04
93.04
113.04
Green


Infrared vs. Blue
319.00
269.00
219.00
169.00
119.00
69.00
19.00
-31.00
Infrared
2.20
22.20
42.20
62.20
82.20
102.20
122.20
Blue

Agroforest	Agroforest/Cropland
Barren	Barren/Urban
Barren/Water	Cropland/Agroforest
Cropland	Grassland
Mangrove	Mangrove/Swamp
Marsh	Marsh/Swamp
Merremia	Plantation Forest/Coconut
Plantation Forest Mahogany	Plantation Forest- Other
Rock Island	Road
Secondary Vegetation	Shadow
Shadow/Road	Strand
Swamp	Upland
Upland Secondary Vegetation	Urban
Urban Vegetation	Urban/Agroforest
Urban Secondary Vegetation	Urban/Upland
Water	

Key to symbols in above graphs