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Classification of Terrestrial Materials and Vegetation Using Remotely Sensed Multi-Spectral Data at the Atlantic Undersea Test and Evaluation Center (AUTEC) Main Base on Andros Island, Bahamas

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Abstract
The classification of vegetation and materials—both natural and man-made—in the terrestrial environment was conducted using high-spatial-resolution, multi-spectral satellite imagery obtained from the IKONOS-2 sensor. The results of three supervised classification techniques, the Maximum Likelihood Classifier (MLC), the Spectral Angle Mapper (SAM) classifier, and Mahalanobis Distance classifier, are presented. Ground truth data were used to compare the statistical accuracy of the different classifier techniques to determine which classifier provided the best overall results. Based on the results of the statistical comparison, producer accuracy, omission error, and commission error, it was determined that the MLC provided the best overall classification. This technique was then optimized using the training data sets, and the process was implemented over the entire area of the satellite image. One site from within the image was selected for a final ground truth comparison to determine the overall improvement of the optimized classifier.

Introduction
AUTEC is a Department of Defense (DoD) test and evaluation facility that supports deep-water, littoral, and terrestrial training and test and evaluation operations. The DoD recognizes the importance of preserving the natural resources and ecosystems that are present in and around military installations by adherence to established federal, state, and local environmental regulations. The DoD is committed to protecting our natural resources while maintaining operational readiness through training and testing at its facilities. The assessment of these environments is critical for operational reasons and for purposes of monitoring these natural resources.

AUTEC has completed baseline environmental assessments of its littoral environment in and around its main base using multi-spectral satellite data and LIDAR bathymetric data to classify the materials observed within the satellite imagery. The advantage of using remotely-sensed (satellite) data instead of conducting conventional field surveys is that remote sensing provides timely, accurate, and complete coverage of a study area in the most cost-effective manner.

The focus of this paper is the classification of vegetation and natural and man-made materials within the approximate 1-square-mile terrestrial region in and around AUTEC's main base for purposes of environmental planning and for identification of training and testing areas within the terrestrial and littoral environment. The analysis and results for the littoral region are presented in a separate paper.[1]

In the past, satellite sensors, due to their spatial resolution, have been able to provide information on only a broad ecological scale, with accuracies typically on the order of 55 to 70 percent using the LANDSAT thematic mapper or SPOT XS data.[2] With the advances in image processing technology and the advent of new satellite sensors (i.e., IKONOS-2 and QuickBird), the ability to spatially resolve and classify finer scale habitats has dramatically improved.

The methodology presented in this paper utilizes high-spatial-resolution IKONOS-2 data to conduct supervised classifications of the AUTEC terrestrial environment for the purpose of defining vegetative species and natural and man-made materials using various spectral classifiers, ground truth image data, and in-situ field data to evaluate the classification results.

Study Area

AUTEC is located on Andros Island in the Bahamas, approximately 177 nautical miles southeast of West Palm Beach, FL. Figure 1 depicts AUTEC's location with respect to Florida and the major Bahamian Islands. The AUTEC main base, located on the eastern side of Andros Island, is approximately 1 square mile in area. It comprises both developed and undeveloped areas. The developed areas consist of paved surfaces (such as roads and a heliport), buildings, and cultivated areas (such as a baseball field), and a capped landfill. The undeveloped areas consist of undisturbed vegetation of both indigenous and non-indigenous invasive species. The vegetation species on the main base are representative of the vegetation species across the island; therefore, the classification techniques employed in this study are applicable to the island as a whole. The vegetation on the main base includes many tree species—like the mahogany tree (*Swietenia mahogoni*) and silk cotton tree (*Ceiba pentandra*)—that are protected by the Bahamian Government. The Australian pine tree (*Casuarina equisetifolias*) is considered to be one of the most prevalent invasive species in the Caribbean. The Australian pine competes with and displaces native plant species, such as the mangrove tree. The mangrove ecosystem and other beach habitats have been altered because of the encroachment of the Australian pine.[3]

Figure 1. AUTEC, Andros Island, Bahamas

Data Sources

The IKONOS-2 data for the main base was acquired from Space Imaging Corporation. IKONOS-2 imagery can sometimes be obtained from the Commercial Satellite Imagery Library archives for certain locations; however no data were available for the AUTEC main base. The IKONOS-2 data used in this analysis were acquired on 25 April 2000. The data were provided in both panchromatic and multi-spectral image (MSI) formats. The MSI data consist of four spectral bands—blue, green, red, and near-infrared. The data were provided in Universal Transverse Mercator (UTM) coordinates and had an X-Y spatial resolution of 4 meters by 4 meters.

The ground truth data used for the comparison were obtained from two sources: a high-spatial-resolution mosaic photograph of the AUTEC main base and in-situ field surveys. The composite photograph was created from a series of low-altitude photographs acquired over a period of several days in October 2001. The relative spatial resolution of the photograph is on the order of 0.15 meter. The in-situ field surveys were conducted to develop the regions of interest for the classifier training data set and to develop ground truth sites for post-processing comparison. The geodetic positions and percent relative material coverages were collected at various ground truth sites.

Radiometric Corrections

The satellite sensor records the intensity of electromagnetic radiation reflecting from the earth's surface as a digital number (ND). For these arbitrary DN values to be meaningful, they must be radiometrically corrected and converted to surface reflectance values. Three steps are involved in the radiometric correction process of satellite imagery data:

1. The raw DN values for each band must be converted to spectral radiance at the aperture of the sensor. This conversion uses the calibration coefficients of the sensor to account for the "gain" and "bias" of the sensor in each band of the multi-spectral image.

2. The spectral radiance must be converted to apparent reflectance at the sensor. Reflectance is simply the ratio of the radiance recorded at the sensor to the irradiance from the sun, taking into account the solar elevation at the time of image acquisition. Radiance refers to the upwelling radiation leaving the earth's surface, whereas irradiance refers to downwelling radiation reaching the earth's surface from the sun.

3. The apparent reflectance must be converted to surface reflectance. This conversion corrects for the effects of absorption and scattering due to the atmosphere. Atmospheric corrections can be implemented using several different methods, most of which account for only the removal of path radiance. The atmospheric modeling method, which is the most complicated and sophisticated method to implement, was chosen because it compensates for both atmospheric absorption and scattering. The "Second Simulation of Satellite Signal in the Solar Spectrum (6S)" model[4] was used to implement atmospheric corrections to the IKONOS-2 data.

Ground Truth Data Collection

Supervised classification derives its name from the fact that the classifier compares the spectra from within the image to reference spectra. Reference spectra can be obtained from published spectral libraries that are available for both natural and man-made materials, as well as for vegetation. When the reference spectra have been obtained from a spectral library, the units of the image must be in surface reflectance. Reference spectra can also be obtained from within the image using ground control points (GCPs). Whenever ground truth data are available, the preferred approach is to use reference spectra derived from within the image. In the case of this analysis, the ground truth comparison site GCPs and the classification training data sets could easily be established.

An in-situ field survey was conducted in November 2002 to define areas of specific vegetation and to establish GCPs at these locations. The GCPs are geospatial reference locations where the material or vegetation has been identified and is distinct over an area of spatial extent that is greater than that of the spatial resolution of the satellite image. Table 1 presents a partial list of the vegetation GCPs that were collected.

Table 1. Vegetation Regions of Interest

Vegetation Type	Genus and Species	Lat (deg)	Lat (min)	Lat (sec)	Long. (deg)	Long. (min)	Long. (sec)
Mahogany	*Swietenia mahagoni*	24	42	9.2	-77	46	17.1
Mahogany	*Swietenia mahagoni*	24	42	25.0	-77	46	26.4
Australian Pine	*Casuarina*	24	42	36.2	-77	46	7.3
Australian Pine	*Casuarina*	24	42	8.4	-77	45	45.8
Mangrove	*Rhizophora mangle*	24	42	43.2	-77	46	14.6
Royal Poinciana	*Delonix regia*	24	42	28.9	-77	46	43.8

Because of variations in spectral reflectance with the seasons, the spectral signatures of the vegetation may be significantly different from the in-situ data because the latter were collected in November and the satellite imagery was acquired in April. For example, the near visual infra-red (NVIR) spectral reflectance of wet grass is significantly higher than that of dry grass.

The GCP location data were combined with the material identification data, coverage data, and extent data to generate an image-based spectral reference library for the materials and vegetation species of interest. These image-based reference spectra are sometimes referred to as regions of interest (ROIs). The ROIs relate the material classification to the spectral signature of the material. Figure 2 shows the ROIs for mangrove trees, Australian pines, asphalt surfaces, and other items of interest.

The development of ROIs through the use of GCPs, combined with the visual interpretation of the

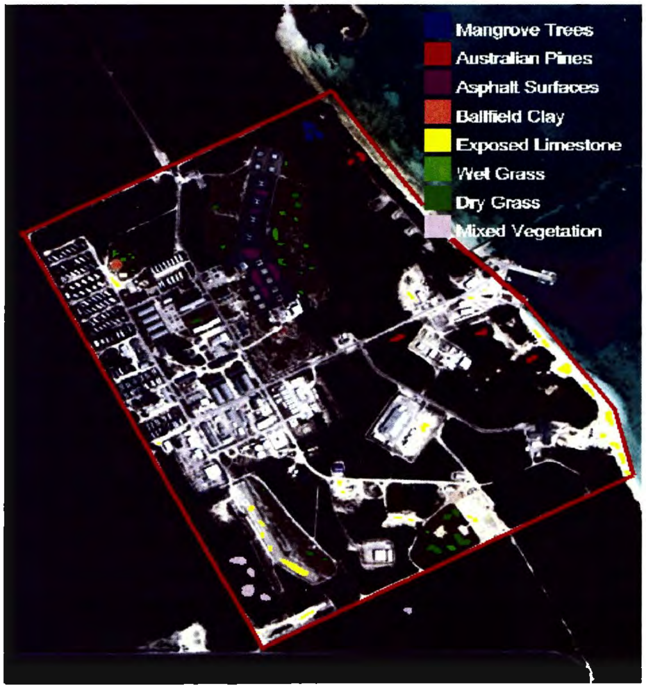

Figure 2. ROIs for Various Materials

image, is relatively straightforward. However, the possibility for the contamination of ROIs by pixels that do not represent the desired spectra signature does exist. The selection of pure material pixels was refined through the use of the N-dimensional visualization tool.[5] This tool plots the spectral response in one band against the spectral response in the other bands. From this visualization plot, one can see that pixels that correspond to the same material or vegetation type tend to cluster together. The clusters can then be isolated and new ROIs generated that represent unique spectral signatures. The mean spectral response for each of the ROIs was converted into a spectral signature that was used in the classification routines. Figure 3 shows the spectral signature for each material or vegetation species of interest that was extracted from the spectral image. The spectral response of some materials is very similar and, as a result, there is a potential for misclassification. In particular, the spectral responses for Australian pines and mixed vegetation are nearly identical.

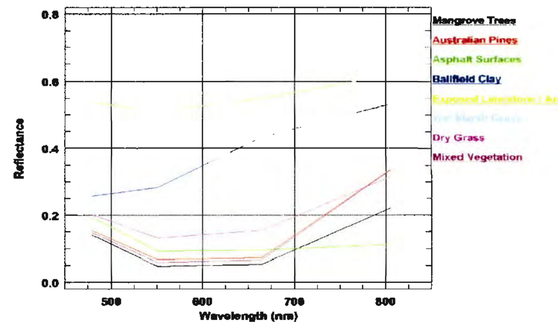

Figure 3. Spectral Signatures of Materials

Preliminary Classification

The decision to use supervised classification techniques rather than unsupervised techniques was based solely on the availability of ground truth data and the ability to identify the features and materials from within the image. A series of preliminary classification tests was conducted to evaluate which supervised classification technique provided the best results. These included the Maximum Likelihood Classifier (MLC), the Mahalanobis Distance classifier, and the Spectral Angle Mapper (SAM) classifier. The classification results were compared to ground truth data constructed from a combination of GCP data, coverage area information, and the high-resolution composite aerial photographic image.

The MLC is a statistical decision criteria classifier. It assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Each pixel is assigned to the class that has the highest probability (i.e., the maximum likelihood).[5] The threshold level for the decision criteria determines the classification rule. In the preliminary classification runs, the thresholds for all classes were set to zero so that all pixels within the image would be classified and no pixels would be undefined.

The Mahalanobis Distance classifier is a direction-sensitive distance classifier that uses statistics for each class or ROI. It is similar to the MLC, but it assumes that all class covariances are equal; for this reason, the Mahalanobis algorithm can be implemented more quickly.[5] The threshold level or distance threshold determines the classification rule. In the preliminary classification runs, the threshold distance was set to zero so that all pixels within the image would be classified.

The SAM classifier is a physically-based spectral classifier that uses an N-dimensional angle to match pixels to reference spectra. The algorithm determines the spectral similarity between two spectra by calculating the angle between the spectra and treating them as vectors in a space, with dimensionality equal to the number of bands. The length of the vector represents the brightness of the target pixel, and the angle represents the spectral feature. Thus, classification is based on the direction of the vector, not the length. As a result, this technique is relatively insensitive to illumination and albedo effects when used with calibrated reflectance data.[6] In the preliminary classification runs, the threshold angle was set to 0.1 radian.

Preliminary Classification Results

The classification routines were implemented over the area of the AUTEC main base. Three sub-areas were chosen for use in a statistical evaluation where ground truth data had been established. Each classifier was applied to the spectral image using the preliminary condition specified, and the results of each classification were compared to the ground truth data. The output classification images are presented in figure 4. The three ground truth comparison sites that were used in evaluating the processing techniques are indicated by black rectangles in figure 4. It is apparent from the classification images that all pixels were classified by both the MLC and the Mahalanobis Distance classifier, as specified by the initial threshold conditions. In contrast, the classification image for the SAM classifier shows undefined or unclassified areas within the image, as color keyed in black.

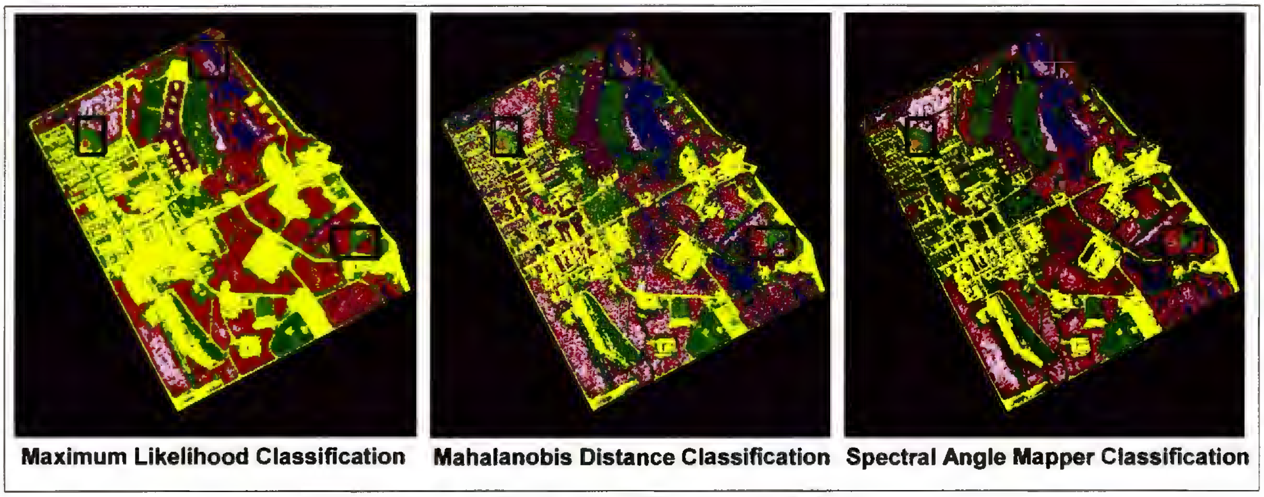

Figure 4. Preliminary Classification Results

An accuracy assessment was performed for all three sub-areas by comparing the predicted classification to the ground truth data. The error analyses were evaluated in terms of percent coverage by each class of material. The metrics used to compare the classification results were the *producer accuracy*, the *omission error*, and the *commission error*. Producer accuracy is defined as the number of pixels that were correctly identified divided by the actual number of pixels for that class. *Omission error* (under-classification) is defined as the actual number of pixels for a class minus the predicted number of pixels for that class, divided by the actual number of pixels for the class. *Commission error* (over-classification) is defined as the number of predicted pixels for that class that are incorrect divided by the total number of predicted pixels for that class. All three sub-areas from within the image were evaluated using these metrics. Table 2 presents the results for the area enclosed by the rectangle in the upper portion of each image.

Table 2. Accuracy Assessment of Classification Routines

Material Classification	Producer Accuracy			Omission Error			Commission Error		
	MLC	MAH	SAM	MLC	MAH	SAM	MLC	MAH	SAM
Mangrove Tree	99.7	100.0	100.0	0.3	0.0	0.0	0.0	32.8	17.0
Australian Pine	100.0	48.3	60.5	0.0	51.7	39.5	3.9	0.0	0.0
Asphalt Surface	0.0	0.0	100.0	100.0	100.0	0.0	0.0	100.0	0.0
Ballfield Clay	100.0	100.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0
Exposed Limestone	51.2	4.7	4.7	48.8	95.3	95.3	0.0	0.0	0.0
Dry Grass	100.0	100.0	100.0	0.0	0.0	0.0	61.4	67.9	55.1
Mixed Vegetation	88.9	80.6	96.1	11.1	19.4	3.9	0.0	0.0	0.0
Undefined	2.8	2.8	100.0	97.2	97.2	0.0	0.0	0.0	31.1
Average	67.8	54.5	82.7	32.2	45.5	17.3	8.2	25.1	12.9
Weighted Average	8890	6900	8260	1110	3100	1740	N/A	N/A	N/A

Based on the results of the accuracy assessment, the SAM classifier produced the highest average producer accuracy and the lowest average omission error. However, the over-classification levels led to the concern that these results might be biased due to the absence of some materials within the image sub-area. To correct for this potential bias, a weighted average was calculated for the producer accuracy and the omission error to take into account the abundance of any material within the image. Based on the weighted average results, the MLC classifier produced the best overall classifications.

Classification Optimization

The preliminary classification results were derived using default classification criteria or minimum thresholds in order to evaluate the capabilities of several different classifier methodologies with respect to the specific image used. Based on the results of the preliminary classification, the MLC was chosen for classifier optimization. The optimization or tuning of the classifier implies the modification of classification rule criteria or, in the case of the MLC, the adjustment of the probability threshold for each material class. This process involved the modification of individual probability thresholds for each class of material for the three sub-areas of interest. The image was reprocessed using new classification criteria, and the results were compared to the earlier accuracy assessments. The goal in this optimization was to maximize the producer accuracy while minimizing both the omission and commission errors. A series of 12 optimization runs was conducted; the results are presented in table 3.

Table 3. Optimized Classification Results

Material Classification	Producer Accuracy	Omission Error	Commission Error	Weighted Results	
				Producer Accuracy	Omission Error
Mangrove Tree	98.2	1.8	0.0	3200	60
Australian Pine	100.0	0.0	0.3	3190	0
Asphalt Surface	100.0	0.0	100.0	0	0
Ballfield Clay	100.0	0.0	0.0	0	0
Exposed Limestone	11.6	88.4	0.0	50	380
Dry Grass	100.0	0.0	56.1	610	0
Mixed Vegetation	86.7	13.3	0.0	1560	240
Undefined	83.1	16.9	0.0	590	120
Sum	84.9	15.1	19.6	9200	800

The optimized results show a significant increase in the producer accuracy and a decrease in the omission error. The results also show an increase in the commission error; however, this error is due to the over-estimation of asphalt surfaces, which does not exist in the actual ground truth data and accounts for less than 0.1% of the classification. The weighted producer accuracy for asphalt surfaces is therefore equal to zero, and the overall weighted producer accuracy for the optimized classification is higher and the weighted omission error is lower.

Summary and Future Research

This paper has presented the results of terrestrial environment classification of vegetation and natural and man-made materials using high-spatial-resolution, multi-spectral satellite imagery and supervised classification techniques. The results obtained from the three supervised classification techniques—the Maximum Likelihood Classifier, the Spectral Angle Mapping classifier, and the Mahalanobis Distance classifier—indicate that the assessment of material classifications and vegetation abundance is an acceptable methodology, yielding a high producer accuracy. This methodology provides an assessment based on regional areas, avoiding results that could be skewed by unrepresentative fractions of the surveyed area. The methodology addresses the following concerns:

- ability to assess terrestrial materials and vegetation independent of site accessibility and weather,
- rapid assessment of terrestrial ecosystems in terms of generalized characterization of material composition,
- reduction in the number of in-situ field measurements required, and
- reduction of the vegetation abundance assessment studies.

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