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Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama

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Abstract

Mangrove stands of differing species composition are hard to distinguish in conventional, coarse resolution satellite images. The new generation of meter-level satellite imagery provides a unique opportunity to achieve this goal. In this study, an IKONOS Geo bundle image and a QuickBird Standard bundle image were acquired for a study area located at Punta Galeta on the Caribbean coast of Panama. The two images cover the same area and were acquired under equivalent conditions. Three comparison tests were designed and implemented, each with separate objectives. First, a comparison was conducted band by band by examining their spectral statistics and species by species by inspecting their textural roughness. The IKONOS image had a higher variance and entropy value in all the compared bands, whereas the QuickBird image displayed a finer textural roughness in the forest canopy. Second, maximum likelihood classification (MLC) was executed with two different band selections. When examining only multispectral bands, the IKONOS image had better spectral discrimination than QuickBird while the inclusion of panchromatic bands had no effect on the classification accuracy of either the IKONOS or QuickBird image. Third, first- and second-order texture features were extracted from the panchromatic images at different window sizes and with different grey level (GL) quantization levels and were compared through MLC classification. Results indicate that the consideration of image texture enhances classifications based on the IKONOS panchromatic band more than it does classifications based on comparable QuickBird imagery. An object-based classification was also utilized to compare underlying texture in both panchromatic and multispectral bands. On the whole, both IKONOS and QuickBird images produced promising results in classifying mangrove species.

Keywords: IKONOS; QuickBird; Mangrove

1. Introduction

Mangrove forests are highly productive ecosystems that typically dominate the intertidal zone of low energy tropical and subtropical coastlines (Kathiresan & Bingham, 2001; Lugo & Snedaker, 1974). The constituent species in these forests are often differentially distributed with distance from the water's edge, forming zones of differing species composition perpendicular to the intertidal gradient. Mangrove habitats and the organisms they support are of significant ecological and economic value. At the same time, their health and persistence are seriously threatened by coastal development projects and various forms of non-renewable exploitation (Ellison & Farnsworth, 1996; Farnsworth & Ellison, 1997; Saenger et al., 1983). Thus, there is an increasing need to monitor and assess mangrove forest structure and dynamics, both to gain a better understanding of their basic biology and to help guide conservation and restoration efforts. The ability to accurately map mangrove species with the tools of remote sensing would greatly assist in this effort.

Satellite images have not been extensively used for mapping mangrove species due to the limited spectral and spatial resolution of conventional imagery. Given the small patch size of some mangrove species, spatial resolution plays a more important role than spectral resolution in discriminating different mangrove species. Previous research indicated that accurate discrimination among mangrove species was not possible with conventional satellite data, but was possible using images from an airborne sensor such as CASI (Green et al., 1998). The recent launching of

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so-called "Very High Resolution" (VHR) satellite sensors provides a new opportunity to map land cover types at a much higher spatial resolution than with previously available sensors. In the VHR category, there are two major commercial sources of imagery: IKONOS images from Space Imaging and QuickBird images from DigitalGlobe. The IKONOS 2 satellite, launched in 1999, provided the first publically available VHR satellite images, while even higher resolution images became available from the QuickBird satellite in 2001. There have been several classification studies examining IKONOS spectral information in conjunction with its spatial texture information. Wang et al. (submitted) found that, with an integrated usage of pixel and object-based classification methods, mangrove species can be mapped with high accuracy. Franklin et al. (2001) found that second-order texture values extracted from a panchromatic IKONOS image effectively increased separability among nine Douglas fir forest age groups. When comparing an IKONOS image with other conventional satellite and airborne remote sensing images (TM, SPOT, CASI, etc.), Mumby and Edwards (2002) found the enhanced spatial resolution of the IKONOS image could deliver greater thematic accuracy in mapping marine environments. To date, however, very few studies have examined the suitability of QuickBird images for mapping land cover types, or compared IKONOS with QuickBird images in this regard. Given the vast amount of potential applications using VHR data, it is necessary and worthwhile to compare the effectiveness of these two types of images for mapping different land cover types.

An exhaustive comparison of IKONOS and QuickBird spectral and spatial quality is beyond the scope of this paper. In this study, we focus on mangrove species mapping and compare the two image types from the following three perspectives: (1) their spectral quality using subjective visual inspection and overall spectral statistics, (2) their classification effectiveness using multispectral bands with and without panchromatic bands, and (3) their classification effectiveness with inclusion of texture information.

2. Study site and data preparation

2.1. Study site

The study was conducted in mainland mangrove forests near the Smithsonian Tropical Research Institute's Galeta Marine Laboratory (9°24′18N, 79°51′48.5W) at Punta Galeta on the Caribbean coast of Panama, approximately 8 km northeast of the city of Colón.

Three tree species comprise the canopy of the forest study-areas. They are: black mangrove (*Avicennia germinans*), white mangrove (*Laguncularia racemosa*), and red mangrove (*Rhizophora mangle*). Red mangrove forms a pure or nearly pure stand at the seaward fringe. About 10–20 m from the water's edge, white mangrove joins the canopy, forming a nearly even mixture with red mangrove in the low intertidal. Black mangrove joins the canopy in the mid-intertidal, creating a mixed canopy of the three species, and gradually comes to monopolize most upper intertidal stands. White mangrove may disappear completely from the canopy in the upper intertidal, or occur only as scattered individuals or small stands (Sousa, unpublished data).

Although the average crown size of a particular species varies from site to site within our study area, reflecting variation in average tree size, generally speaking, the crowns of mature canopy, black mangroves, which dominate upper intertidal forests, are the largest, with average crown area ranging from 209 to 362 m^2. By comparison, the average crown areas of mature canopy, white mangroves in these upper intertidal forests range from 164 to 231 m^2. In lower intertidal, mixed red/white forests, white mangrove crown areas are smaller still, ranging from 90 to 141 m^2. Red mangrove crowns in these low intertidal stands are of intermediate size, with average areas ranging from 127 to 241 m^2. The crown areas of fringe red mangrove trees are comparable, averaging 238 m^2.

Within mature interior stands, the species also differ in crown height. In the upper intertidal, white and black mangroves attain average crown heights of 24 and 23 m, respectively. In lower intertidal red/white forests, white mangroves reach average heights of 22 m, while red mangroves average 16–18 m in height. Thus, in low intertidal, mixed-species stands of red and white mangroves, crowns of the latter species tend to be emergent, with red mangrove forming a lower sub-canopy.

2.2. Data preparation

The image products we compared were purchased from the respective companies' archival collections. The IKONOS Geo bundle product consisted of one panchromatic image at 1-m resolution and one multispectral image at 4-m resolution, which were acquired on 2000-06-13 at 15:24 p.m. local time (© 2001, Space Imaging, all rights reserved). The images were radiometrically corrected by rescaling the raw digital data transmitted from the satellite. Since no dynamic range adjustment was requested in the production process, the original radiometric accuracy is retained and pixels in the image were recorded in 11 bits. Geometric correction was applied to the images to remove image distortions introduced by the collection geometry. The QuickBird standard bundle product consisted of one panchromatic image at 0.7-m resolution and one multispectral image at 2.8-m resolution, which were acquired on 2002-07-28 at 15:52 p.m. local time (© 2002, DigitalGlobe, all rights reserved). Similar to the IKONOS images, the QuickBird standard imagery was radiometrically corrected, sensor corrected, and geometrically corrected. Pixels were also recorded in 11 bits. The specifications of spectral wavelengths and spatial resolutions for both IKONOS and QuickBird imagery are listed in Table 1.

Table 1
Spectral and spatial resolution of IKONOS and QuickBird images

	Panchromatic (nm)	Blue (nm)	Green (nm)	Red (nm)	Near IR (nm)	Spatial resolution
IKONOS Geo	450–900	445–516	506–595	632–698	757–853	1 m (Pan), 4 m (Multi)
QuickBird Standard	450–900	450–520	520–600	630–690	780–900	0.7 m (Pan), 2.8 m (Multi)

View/illumination geometry is one of the factors that cause targets' reflectance to vary (Epiphanio & Huete, 1995). Since the two images used in this study were acquired at different times and sensor locations, we examined the corresponding metadata and found the following sun-sensor parameters. First, the sun elevation angle and azimuth angle are similar for both images: 59.1° and 59.6° for IKONOS, 65.4° and 64.5° for QuickBird, respectively. This similarity largely removes the effect caused by different illumination conditions. Second, regarding sensor view direction, the IKONOS image was collected with an azimuth angle of 99.22° and elevation angle of 64.25°, whereas QuickBird image was collected with an azimuth angle of 227.22° and elevation angle of 86.89°, respectively. Although nearly all the targets at the Earth's surface exhibit anisotropic behavior, data acquired by sensors positioned in either the backward or forward directions in the solar principal plane should be avoided because of the hotspot and forward scattering peak associated with specular reflectance (Kimes, 1983). In this study, the view directions for both IKONOS and QuickBird did not fall in the solar principal plane. In addition, both view angles are high. Therefore, only small variation in reflectance due to anisotropy would be expected between the two images. The relatively complex canopy structures of mangrove trees further reduces anisotropic bias.

Although neither image was ortho-rectified, the geometric distortions due to relief change can be ignored given the minimal elevational relief of the mangrove habitat (W. Sousa, unpublished data). With the exclusion of a terrain factor, it was reported that IKONOS Geo products would display a 15-m circular error with 90% confidence (CE90) while QuickBird Standard products exhibit a 23-m CE90. To register both images for the purpose of comparison, ground control points were chosen throughout the entire scene. Some of the points were centers of canopy gaps that appeared in both images. The rest of the control points were located at distinctive positions along a road and bridge. Field GPS reading were input to conduct geometric correction for the IKONOS and QuickBird images. This registration procedure achieved sub-meter accuracy. Matched subsets of the two images that covered the same study area were selected for the final comparative analyses.

The study area is the site of a long-term investigation (since 1988) by W. Sousa of the patterns and mechanisms of mangrove forest regeneration. This study includes regular ground measurement of forest inventory in permanent plots as well as GPS mapping of a variety of forest features. Based on this background information, a total of seven land cover types were chosen for the classification, including three different types of mangrove canopy, rainforest, gap, lagoon, and road. Since the goal of our study was to compare the images with respect to their suitability for distinguishing the species composition of mangrove forest canopy, we focused our efforts on the three most common canopy types in the study area. These are (1) pure red mangrove canopy, typical of fringing stands at the water's edge, (2) low to mid-intertidal, mixed canopy of red and white mangroves with whites usually emergent, as described above, and (3) pure black mangrove canopy typical of many upper intertidal sites. Henceforth, we will refer to these three canopy types by the short-hand titles: red, white, or black canopy.

To compare classification performance of the IKONOS and QuickBird images, spatially consistent training and test samples were first delineated on top of both images with the aid of the abovementioned field information. This procedure insured that the spectral signal in the samples corresponds to the same ground target. Given the patchy distribution of mangrove species, we used polygon tools to define both training and test samples. Separate training and test samples were chosen across the study area and the number of samples for each land cover type was listed in Table 2. All the samples were selected from areas where no cover type changes had occurred over the 2-year span. In addition, all training and test sample sites were revisited on the ground to confirm accuracy of measurement. Data collected as part of an environmental monitoring program at the Smithsonian Tropical Research Institute's Galeta Marine Laboratory, located immediately adjacent to the study forests, confirmed that the two images were acquired under very similar environmental conditions, characteristic of the

Table 2
Training and test sample size for IKONOS and QuickBird images

Image sources	Sample types	Red mangrove	Black mangrove	White mangrove	Gap	Lagoon	Rainforest	Road
IKONOS	Training	141	367	215	173	159	258	55
	Test	213	227	219	73	132	227	46
QuickBird	Training	305	519	455	218	334	538	108
	Test	424	479	399	170	287	449	99

early rainy season. Thus, we feel confident that temporal environmental variation is not confounding our comparison of the two images.

3. Methods

3.1. Overall comparison

As an overall comparison of image spectral quality, descriptive statistics for each band were assessed in both images. A total of five statistics were considered in this comparison: minimum grey level (GL) value, maximum GL value, mean GL value, standard deviation (S.D.) of GL value, and entropy.[1] Among these statistics, S.D. and entropy are the two most informative and indicate how much spectral detail is present in the whole image. A large S.D. value means that the pixel value frequency distribution has more dispersion, while a large entropy value represents a large amount of disorder exists among the pixel values. Using the method introduced by Moddemeijer (1989), we constructed a band-wise histogram of the probabilities of occurrence (P_i) for digital numbers (i) associated with individual pixels, and then calculated entropy as follows:

$$\text{Entropy} = \sum_{i=1}^{\max} -P_i * log_2 P_i$$

To make a visual comparison, we linked IKONOS and QuickBird images using their spatial coordinates. This ensured that the same locations were under examination at each test. The comparison took place in many sub-areas across the whole scene, canopy type by canopy type, and with a focus on color saturation and texture coarseness. The purpose of this visual comparison was to gain an intuitive idea of the spectral and spatial quality of each image.

3.2. Classification based on spectral information

Maximum likelihood classification (MLC) has proven to be the most robust classifier in the field of Remote Sensing, as long as spectral information in each class meets the normal distribution criteria (Bischof et al., 1992). We adopted the MLC method in this study to help us compare the performance of the two different images. With a total of five bands available for each type of image, we conducted a matching pair of classification tests on each of the images. Each test used a different band selection. In the first test, only the four multispectral bands were fed into the MLC. The results from this test provided a comparison of classification performance using only the images' multispectral bands. In the second test, the panchromatic band was added into the classification process together with the multispectral bands. To conduct this second classification test, some preprocessing of the images was required. Panchromatic images of IKONOS and QuickBird were resampled to 4 and 2.8 m, respectively, and stacked with their multispectral image counterparts, resulting in two five-channel images at a spatial resolution of 4 and 2.8 m. The results from this five-layer's classification were used to compare the contribution that panchromatic bands brought to overall mapping accuracy, thereby serving as an indirect comparison of the classification performance of panchromatic bands with IKONOS and QuickBird images.

To quantify the classification success of the different image types, we generated an error matrix based on the test samples and computed Kappa ($\hat{K}$) values and their variances. Pair-wise Z tests were used to statistically compare classification success using the different image types. As a complement to the Kappa value, overall accuracy for the seven land cover types is reported as well. Since the classification of mangrove canopy composition is the overall goal of our study, we compared user and producer accuracy for the three canopy types.

3.3. Classification with inclusion of texture information

High spatial resolution embodied in IKONOS and QuickBird images provides a unique ability to incorporate small-scale textural information in the classification process. Texture is the visual effect caused by spatial variation in tonal quantity over relatively small areas (Anys & He, 1995). We expected that small-scale spatial variability would help discriminate those canopy types that were hard to distinguish from spectral information alone. We employed two different methods to separately evaluate the classification performance of spatial information embodied in panchromatic and multispectral bands of the IKONOS and QuickBird images. In the first method, a spatial texture analysis was conducted on the panchromatic band alone. First-order and second-order texture statistics were explored separately. For first-order texture, local variances computed at different window sizes were extracted from the panchromatic band and associated as supplemental bands with other spectral bands to be run in the MLC classification method. For the second-order texture, classification was based on a feature set of three texture statistics (see details below). In the second method, texture information in both the multispectral and panchromatic bands was considered using an object-based classification method. For both methods, the contribution of spatial information to classification for each of the two images was compared using the error matrix and pair-wise $\hat{K}$ tests, as described earlier.

Below, we describe in greater detail the two methods by which we evaluated the influence of textural information on the accuracy of classification using the different image types.

[1] Entropy is a measure of the disorder of a system. It is related to the amount of information a system contains. It is frequently used in the field of signal processing, physics, information theory, and statistics.

3.3.1. Maximum likelihood classification with first- and second-order texture information from the panchromatic band only

In practice, texture associated with a pixel in an image is assigned by considering GL vector occurrence frequency in a local neighborhood (usually a rectangular) centered on that pixel. Texture of a specific order is extracted based on the dimension number of GL vectors under investigation. For example, a first-order texture is calculated based on the frequency of only one GL in the neighborhood while a second-order texture is based on the frequency of one pair of GL. Textures of different order, ranging from one to nine, have been proposed by different researchers (Anys & He, 1995; Wang & He, 1990). Since a higher order texture requires extra computation time, first- and second-order textures are the mostly commonly used and have been integrated into most commercial remote sensing software. In this study, we calculate both first- and second-order textures to help evaluate classification performance of the two different images.

For the first-order texture, a local variance was calculated with six different rectangular window sizes of 3, 5, 7, 9, 11, and 21. Then variance for each window size was coupled with the four multispectral bands and classified with MLC to compare texture effectiveness between the two images.

Fourteen different statistics, summarized from a grey level co-occurrence matrix (GLCM), have been extensively used in past studies to represent second-order texture (Haralick et al., 1973). Many of these statistics are correlated. In order to reduce redundancy and minimize the dimensionality of feature space for classification purposes, Clausi (2002) recommended using only three statistics: contrast, correlation and entropy. In this study, we adopt this feature set. Three variables affect the classification performance of the extracted feature set: (1) window size: i.e. at what neighborhood the GLCM will be built, (2) displacement vector: i.e. at what spatial distance and in which direction do we look for the co-occurrence of a pair of GL, (3) GL quantization level, i.e. based on how many quantized GL levels we observed co-occurrence. In this study, to extensively compare the texture embedded in IKONOS and QuickBird panchromatic images, we set window sizes separately, at 5×5, 11×11, and 21×21, and quantized the GLs separately at 1024, 256, 128, 64, 32, and 16. Displacement vectors at four directions (0°, 45°, 90°, 135°) with a spatial distance of 1 pixel were used to produce an averaged value for each texture statistic. MLC was carried out on this feature set and the $\hat{K}$ value was used to compare texture effectiveness of the two images.

3.3.2. Object-based classification

Since the GLCM method is only effective for extracting texture from one band, in order to compare the overall texture performance underlying multispectral bands as well as the panchromatic band within the two images, we used an object-based classification. Basically, the implementation of an object-based classification can be divided into two stages: segmentation and classification. In the segmentation stage, based on all five available bands described in Section 3.2, spectral homogeneity was calculated and used as a criterion to segment the whole scene into separate objects. In the second stage, classification was carried out based on the synoptic information at the object level, rather than at the original pixel level. Object-based classification was implemented in eCognition™ 3.0 software. Since scale parameter is an important variable for defining the break-off value for spectral homogeneity, it has to be determined before segmentation. From our previous experiments, 25 was identified as the optimal scale parameter for the study site (Wang et al., submitted). Hence, we used this value to segment both the IKONOS and the QuickBird image. In the same manner, comparison was made based on the $\hat{K}$ value derived from the error matrix.

4. Results

4.1. Comparison of overall spectral quality

Table 3 lists the spectral statistics derived from each band in the IKONOS and the QuickBird image. It is readily observable that the standard deviation and entropy values of IKONOS image bands are consistently higher than those of QuickBird bands, including two frequently used vegetation reflectance bands, green and NIR bands. Since the quantization level is 11 bits for both IKONOS and QuickBird images, the higher SD and entropy value of the former means that the IKONOS image captured a richer, more detailed spectral reflectance for the same ground target. Intuitively, this finding can be related to a visual effect, that IKONOS utilizes more enriched color and looks more vivid than QuickBird image. Visual examination of the images confirmed this difference for all three mangrove canopy types as well as rainforest. In contrast, visual examination of texture coarseness, conducted on top of the two images' panchromatic bands for each mangrove canopy type, gave a

Table 3
Band spectral statistics for IKONOS and QuickBird images

Band	Min	Max	Mean	S.D.	Entropy
IKONOS image after removing lagoon					
1 (Blue)	0	730	318.5746	84.47042	3.667
2 (Green)	0	958	314.1516	86.0434	4.532
3 (Red)	0	910	186.6714	53.30962	4.263
4 (NIR)	0	1369	699.5516	241.647	6.3
5 (Pan)	0	1130	415.0652	139.023	5.756
QuickBird image after removing lagoon					
1 (Blue)	0	520	190.0258	50.16941	3.478
2 (Green)	0	933	253.2666	69.29446	4.419
3 (Red)	0	774	116.7564	34.27773	3.988
4 (NIR)	0	1266	597.0977	206.1689	6.175
5 (Pan)	0	1302	340.6839	115.067	5.601

somewhat different result. Fig. 1 presents a snapshot of three types of mangrove stands taken from the two images. The QuickBird image of fringing red mangrove stands (Fig. 1(a)) appears to exhibit more textural roughness than the IKONOS image (Fig. 1(b)). In contrast, there does not seem to be much difference in discernable texture between images of canopies in mixed red/white stands (Fig. 1(c) vs. 1 (d)) or in stands dominated by black mangroves (Fig. 1(e) vs. 1 (f)), both showing a clustering circular pattern. The fact that higher resolution panchromatic QuickBird images (0.7 m) do not consistently reveal higher spatial detail than IKONOS images (1 m) is probably related to differences in canopy morphology among the three different kinds of mangrove stands. Fringing red mangrove stands are monospecific, with crown areas of intermediate size. Such characteristics might be expected to minimize textural variation. However, red mangrove trees exhibit considerable reiteration of form (i.e. repetition of tree architecture) as they grow. When a leader is damaged or killed, it is readily replaced by an orthotropic lateral branch (Tomlinson, 1986). As a result, within a given crown, several leader complexes can develop, producing a more open, broad, and irregular canopy. It may be that the slightly finer spatial resolution of the QuickBird image better captures this small-scale heterogeneity in the red canopy than does the IKONOS image. The branching patterns of black and white mangroves are more diffuse and irregular, and neither species exhibits the strong reiteration of architecture seen in the canopy of red mangroves. Thus, their crowns may not show much variation in texture at spatial scales that would be differentially detected in the two types of images.

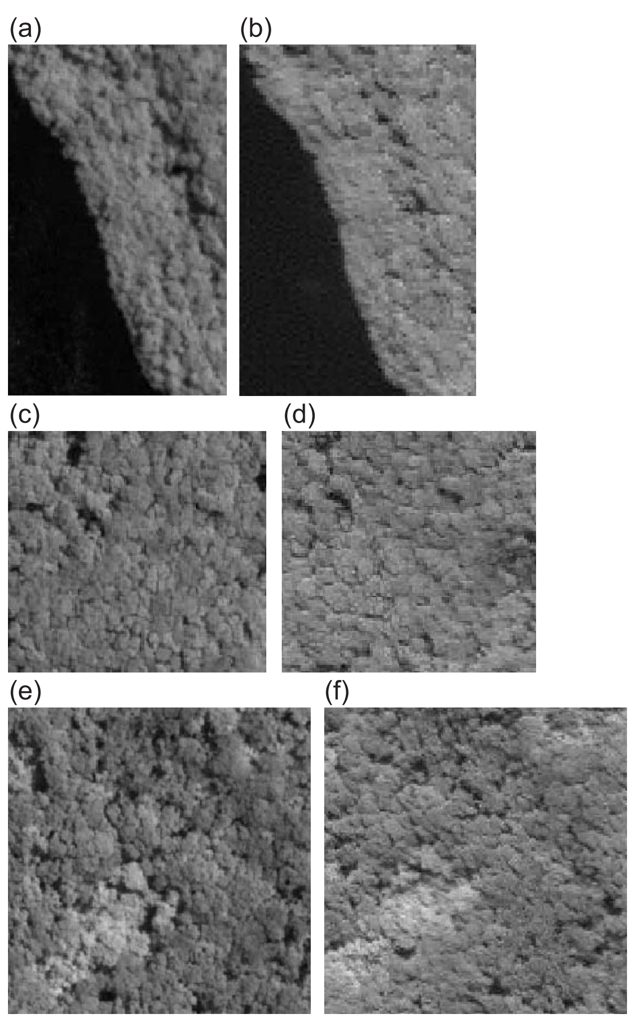

Fig. 1. Visual comparison of QuickBird and IKONOS images for three mangrove canopy types.

4.2. Comparison of classification based on spectral information

Table 4 presents the different classification results using multispectral bands with and without panchromatic bands for IKONOS and QuickBird images. When only the multispectral bands were employed to classify seven land cover types, classification based on the IKONOS image was slightly, but significantly, more accurate than classification based on the multispectral QuickBird image (Kappa Z statistics 1.98). Addition of the fifth, panchromatic band to the classification did not significantly change the accuracy of classification for either image type. However, the $\hat{K}$ value from IKONOS five channel classification was still significantly higher than that from the equivalent QuickBird bands (Kappa Z statistics 7.75). When the user and producer accuracies for each mangrove canopy type were examined, it was found that the IKONOS image was more accurate than QuickBird for red and black mangrove, but QuickBird achieved better accuracy for white mangrove.

4.3. Comparison of first- and second-order texture

The Kappa statistics obtained from the classification with inclusion of first-order texture (local variance at six different window sizes) are presented in Fig. 2. It should be noted that for the IKONOS image, inclusion of local variance improved the accuracy of classification achieved when only multispectral bands are used. The improvement was especially significant at window sizes of 21 (Table 5a). Conversely, when classification using the QuickBird image was compared before and after inclusion of local variance, $\hat{K}$ values were found to decline for all window sizes except 21 (Fig. 2, Table 5a). Apparently, first-order texture from the QuickBird image does not contribute as much as that from IKONOS towards distinguishing mangrove species. An indirect comparison of first-order texture derived respectively from IKONOS and QuickBird images follows. Given the fact that $\hat{K}$ value increases for IKONOS and decreases for QuickBird in most of the window sizes, it follows that first-order texture from the IKONOS image is slightly superior to that from the QuickBird image in separating mangrove species for our study area. This result is supported by a Z statistics test reported in Table 5b.

Table 4
Classification results' comparison using multispectral bands with and without panchromatic bands and pair-wise statistical tests of classification accuracy (kappa)

Data type	Bands selection	Overall accuracy (%)	Kappa statistics	User accuracy (%)			Producer accuracy (%)		
				Red	Black	White	Red	Black	White
IKONOS	multi only	75.3	0.7	57.7	66.4	83.9	68.5	71.3	88.1
	multi + pan	75.5	0.7	61.1	64.5	84.8	68.5	72.7	88.6
QuickBird	multi only	72.2	0.67	51.5	59.4	84.9	64.4	47.4	88.7
	multi + pan	73.43	0.67	54.9	57.3	86.7	65.1	49.9	91.2

Comparing pair	Z statistics	Confidence level (%)
IKONOS multi vs. QuickBird multi	1.98	95
IKONOS (multi + pan) vs. QuickBird (multi + pan)	7.75	99
IKONOS (multi + pan) vs. IKONOS multi	0	NS[a]
QuickBird (multi + pan) vs. QuickBird multi	0	NS

[a] Values under 95% confidence level are labeled as not significant (NS).

Results of classification based on three second-order texture statistics are reported in Fig. 3. In general, for all classifications, no $\hat{K}$ value exceeds 0.57, indicating that when only second-order texture information is utilized, neither the IKONOS nor the QuickBird image is sufficient for accurate mangrove species classification based on this level of textural information. Nevertheless, this fact does not prevent our comparison of the influence of second-order texture between the two images. For both IKONOS and QuickBird, as window size increases from 5 to 21, $\hat{K}$ value increases as well. Besides window size, another variable in this analysis is GL quantization level. Fig. 3 shows that second-order texture derived with different GL quantization levels performs differently. For example, at a window size of 21, a GL quantization of the IKONOS panchromatic image to 64 levels leads to a maximum $\hat{K}$ value of 0.57, whereas a GL quantization to 1024 levels results in a $\hat{K}$ value of only 0.41. Variation in the $\hat{K}$ value with different quantization levels also occurs on QuickBird images. To carry out an objective comparison, a statistical test was

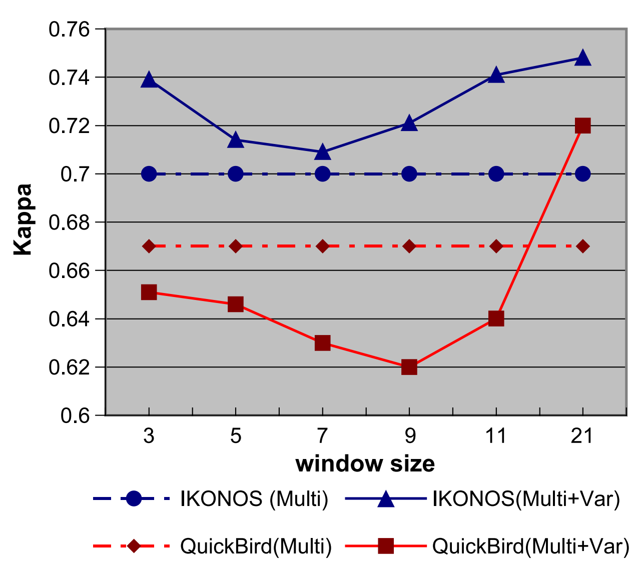

Fig. 2. Classification results with inclusion of first-order texture.

conducted comparing $\hat{K}$ values derived from IKONOS and QuickBird textures at the same window size and number of quantization levels. The test result is presented in Table 6. At a window size of 5 and quantization level of 128, the $\hat{K}$ value from the two images is not significantly different. When window size was set at 21 and quantization level was set at 1024, the $\hat{K}$ value derived from the QuickBird panchromatic image was significantly better than that derived from IKONOS image. Other than the above two cases, classification using second-order texture from IKONOS image outperformed the same classification using the QuickBird image.

Table 5
Comparison of the classification results with inclusion of the first-order texture

(a)

Data source	Window size	Kappa statistics (multi + variance)	Kappa statistics (multi only)	Z statistics	Confidence level (%)
IKONOS	3 × 3	0.739	0.7	1.8	NS[a]
(multi vs.	5 × 5	0.714		0.59	NS
multi +	7 × 7	0.709		0.34	NS
variance)	9 × 9	0.721		0.92	NS
	11 × 11	0.741		1.87	NS
	21 × 21	0.748		2.22	97
QuickBird	3 × 3	0.651	0.67	− 0.90	NS
(multi vs.	5 × 5	0.646		− 1.2	NS
multi +	7 × 7	0.63		− 2.17	97
variance)	9 × 9	0.62		− 2.78	99
	11 × 11	0.64		− 1.56	NS
	21 × 21	0.72		3.78	99

(b)

	Window size	Z statistics	Confidence level (%)
IKONOS vs.	3 × 3	4.75	99
QuickBird	5 × 5	3.55	99
	7 × 7	4.07	99
	9 × 9	5.28	99
	11 × 11	5.42	99
	21 × 21	1.37	NS

[a] Values under 95% confidence level are labeled as not significant (NS).

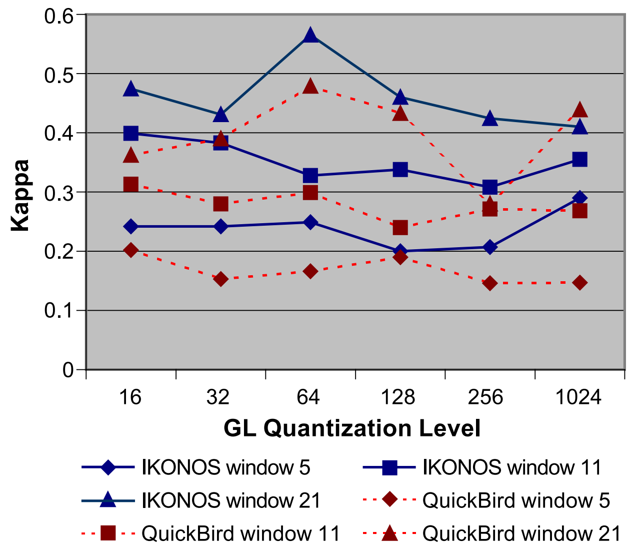

Fig. 3. Classification results with inclusion of second-order texture.

4.4. Comparison of object-based classification

When texture information in both panchromatic and multispectral bands was used to aid object-based classification of mangrove species, IKONOS and QuickBird demonstrated almost equal classification effectiveness with $\hat{K}$ values of 0.69 (Table 7). It is worth mentioning that objects generated with the QuickBird image for mangrove stands had a smaller size compared to those generated with the IKONOS image. Recall that in the visual comparison section, mangrove canopy showed more texture roughness on the QuickBird image than in the IKONOS image. Thus, object-based classification did capture the texture differences underlying the two images, but a smaller object size for the QuickBird image did not contribute to a better classification result.

Table 6
Comparison of the classification results with inclusion of the second-order texture

	Window size	Quantized GL level	Z statistics	Confidence level (%)
IKONOS vs. QuickBird	5 × 5	16	7.19	99
		32	15.31	99
		64	15.42	99
		128	1.72	NS[a]
		256	11.08	99
		1024	26.28	99
	11 × 11	16	16.04	99
		32	18.95	99
		64	5.41	99
		128	17.95	99
		256	6.79	99
		1024	16.89	99
	21 × 21	16	20.96	99
		32	7.69	99
		64	16.3	99
		128	5.01	99
		256	26.4	99
		1024	– 5.64	99

[a] Values under 95% confidence level are labeled as not significant (NS).

Table 7
Comparison of the classification results using object-based classification at scale parameters = 25

Data type	Overall accuracy (%)	Kappa statistics	Kappa variance $\times 10^{-4}$	Z statistics	Confidence level (%)
IKONOS	73	0.69	1.5	0	NS[a]
QuickBird	74	0.69	1		

[a] Values under 95% confidence level are labeled as not significant (NS).

5. Summary and conclusion

This study compared the performance of IKONOS and QuickBird images, two popular VHR satellite images, in the classification of mangrove stand composition. The meter-level spatial resolution possessed by the two images lends itself to many potential applications in which detailed spatial information is essential. However, at the time of their purchase in 2002, the products differed considerably in price. The IKONOS image bundle was more than four times as expensive as the QuickBird image bundle, largely reflecting different minimum scene sizes required for purchase: 100 km^2 for IKONOS and 25 km^2 for QuickBird. This difference in price raises the question of cost effectiveness, especially for users needing to choose an appropriate image under a fixed budget. Both the promise of these two VHR image types for landscape mapping and their variable costs motivated us to conduct this comparison. Our study focused on imagery of mangrove forests on the Caribbean coast of Panama because, as described earlier, this habitat has been the subject of a long-term ecological study by W. Sousa. A central goal of this study is to map the distribution of mangrove stand types, as a foundation for experimental studies of the mechanisms controlling forest structure. We hoped to determine whether high-spatial resolution satellite images can substitute for relatively higher cost airborne images in obtaining a suitable classification map for mangrove stand types.

Three comparative tests were made in this study. By examining band spectral statistics and looking at sub-images of each image for the same location, a larger spectral variance and higher entropy value were found in both multispectral and panchromatic bands of the IKONOS image and a coarser texture was uncovered in the QuickBird image. The subsequent classification using multispectral and panchromatic images showed that (1) IKONOS multispectral bands delivered slightly higher classification accuracy than QuickBird multispectral bands, (2) for neither IKONOS nor QuickBird did the panchromatic band add discriminatory power when directly stacked with multispectral bands to be run in MLC. From the above two comparisons, it is clear that IKONOS demonstrated small but consistently higher spectral discrimination than QuickBird did for mangrove species at our study sites. The third comparison was of spatial texture. Results showed that: (1) with inclusion of first-order texture into the classification, for IKONOS, the classification accuracy was not significantly improved compared to multispectral classification except at window size 21. Whereas for QuickBird, accuracy actually dropped at three window sizes, with no improvements at other window sizes, (2) based on second-order texture features, classification from IKONOS outperformed that from QuickBird, and (3) IKONOS and QuickBird performed equally well when object-based classification was employed.

QuickBird was collected at a higher spatial resolution than IKONOS, 0.7 vs. 1 m at the panchromatic band and 2.8 vs. 4 m at multispectral bands. Visual judgment did validate the existence of a texture difference between the two images in which QuickBird is better than IKONOS. However, the results from first- and second-order texture classification did not support the expectation that QuickBird has an advantage over IKONOS in the spatial domain. This may be attributed to first- and second-order textural features lacking the sensitivity to capture the textural differences between the two images, which can easily be observed by a human being. Therefore, without an exhaustive test using various texture methods, it is hard to judge whether QuickBird or IKONOS image provides better texture-based discrimination.

In general, both IKONOS and QuickBird images presented promising results in classifying mangrove species. Spectral information played a more important role in classifying mangrove species than spatial information did. The IKONOS image provided slightly better classification than the QuickBird image for our study area. To evaluate whether IKONOS images are generally superior to QuickBird images for land cover classification, a more comprehensive set of paired images representing a variety of land cover types would need to be evaluated.

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