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Comparison of Pixel-based and Object-oriented Classification Methods for Feature Extraction in Coastal Zone of Central Konkan, Maharashtra, India

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Abstract: *The coastal zone has unique geographic setting and socio-economic characteristics that differentiates it from other areas in terms of land use/land cover and its spatio-temporal pattern. Thus, the traditional way of satellite image classification may not deliver proper results. This research attempts to investigate an appropriate method of image classification especially in coastal zones. Two (Pixel-based) image classifiers, viz. Maximum Likelihood Classification (MLC) and Object-oriented Image Classifier were tested and compared using two moderate resolution imageries (Landsat TM and IRS P6 LISS III) and one high resolution imagery (Worldview-2 Digiglobe). The accuracy of classification of both methods was evaluated using reference data sets derived from high-resolution satellite images and field investigation. The comparison was performed in a statistically precise way in order to validate the appropriate method of classification, according to the resolution of images. It was observed that the level of classification, in terms of number of classes, increases with the level of spatial resolution. The worldview dataset when subjected to Object-oriented Classification technique yields higher level of accuracy of almost 95% (= 0.91). As compared to this, the level of accuracy drops down to 86.06% (= 0.84) when the same image is subjected to MLC technique. However, overall accuracy is better in case of moderate resolution images when MLC technique is adopted instead of Object-oriented Classification.*

Keywords: *Pixel-based classification, object-oriented classification, kappa statistics*

Introduction

Availability of digital images at varied scale has led the user community to demand for rapid but reliable service of the end products. This demand has led the scientific community to constantly develop new techniques of image analysis and representation. As the multispectral imageries with higher spatial resolution like, IKONOS, Quick Bird and WorldView-2 were made available, the level of complexity essential for digital image processing changed significantly. Conventional techniques of image processing, that is processed pixel-wise, may not be suitable for high resolution imagery as these are obtained from the components characterised by higher frequency along with horizontal layover that are produced by off-nadir look angles (Chen *et al.,* 2008). Walter (2004), and Im and Jenson (2005) developed new algorithms for the analysis of such high-resolution images. These algorithms primarily consisted of marginal information, like neighbourhood correlation images, and also dealt with shape, size and texture of pixel region (Syed *et al.,* 2005).

Land surveying and monitoring is feasible using remote sensing technology that proves to be a better approach for the extraction of land use/land cover (LULC) information. According to the purpose and size of the study area, imageries with varied spatial resolution were chosen for the research. Most of the researchers have often preferred satellite data with medium-resolution like the Landsat TM or ETM+ or IRS 1C/1D/P6 over the high-resolution images. Though the moderate resolution images give substantial results for the classification procedures adopted, they lack in the delineation and extraction of features in detail. For example, at times it is necessary to differentiate between the dense and sparse settlement in a rapidly growing urban center or identifying the different species of vegetation along the coast.

Image classification is performed to extract differentiated classes or theme categories and developing interpretable maps from raw remotely sensed digital data. Pixel-based Classification is either a supervised classification, unsupervised classification or some combination of the two (Enderle and Weih, 2005). These pixel-based measures consider the spectral characteristics of each pixel within the selected area, instead of spatial or contextual information (De Jong *et al.,* 2001). Now a days, higher spatial resolution images are available which gives more precise results of LULC classification (Dwivedi *et al.,* 2004).

Currently, for the classification of moderate resolution images, pixel-based methods are used. Many researchers have used Landsat images for LULC identification. Toulios *et al.* (1990) have employed the Landsat data to perform thematic mapping of W. Messinia, Greece for understanding landuse patterns which show several land use classes and mapped it precisely. The major problem in this technique is due to similar reflecting properties, several classes are difficult to categorise because of their confusing nature.

To overcome this problem, new approaches are often sought that would probably increase the classification accuracy (Chen *et al.,* 2008). One of the approaches is Object-oriented classification which has gained significant importance in recent times due to the availability and more employment of higher resolution data in change detection studies. Recent articles have focused on the usage of such datasets and adopted the Object-oriented approach of image segmentation for obtaining better classification of their study areas. Im *et al.* (2008) used 'correlation image analysis' and 'image segmentation' based on object-based change detection which increases the classification accuracy up to 90%. Working on object based classification of high-resolution satellite images, Poomani and Sutha (2020) concluded that the HRSVM-CNN method was able to produce better classification results than the exiting classification methods. According to Laliberte *et al.* (2004) and Jensen *et al.* (2006) LULC can be successfully achieved by employing the Object based approach. A number of researchers have also reported the occurrence of 'salt and pepper effect' in the output images where the high resolution data sets were treated with the pixel based methods. (De Jong *et al.,* 2001; Campagnolo and Cerdeira, 2007). It was also observed that this particular 'salt and pepper effect' would lead to imprecision in the classification output (Van de Voorde *et al.,* 2004; Gao and Mas, 2008). Since last decade, the experts from the geoinformatics fraternity have tried to develop innovative classification technique which is fully automated (Blaschke *et al.,* 2000). It is also thought to improve the flaws and drawbacks encountered during the usage of pixel based techniques (Csatho *et al.,* 1999; Marpa *et al.,* 2006).

Object-oriented Classification procedure involves 'partitioning satellite imagery into

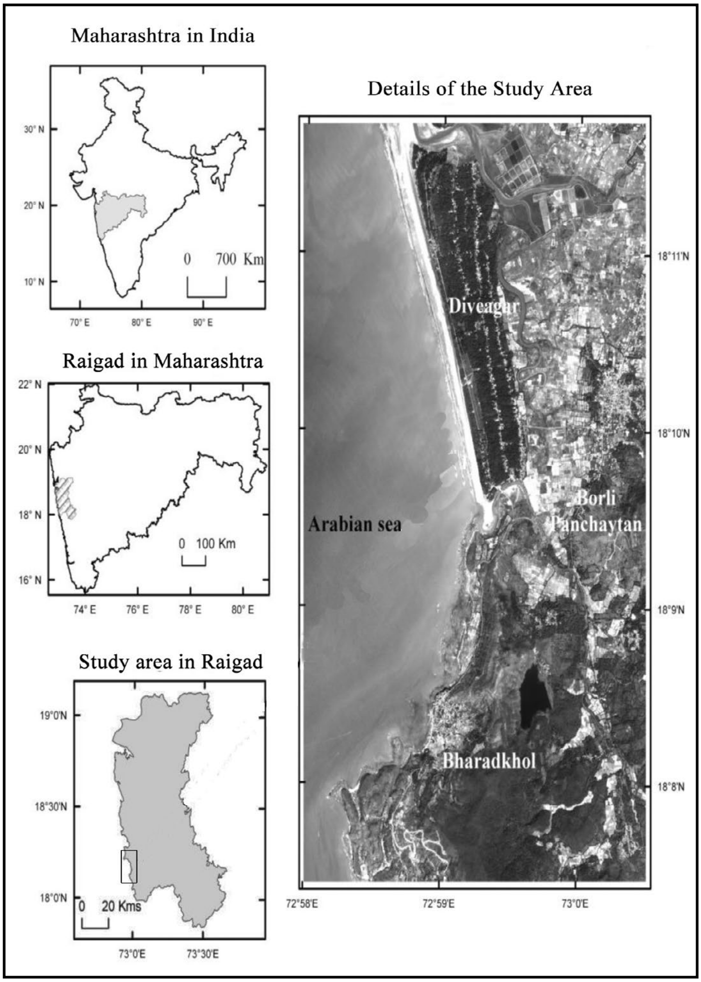

Figure 1. Location of the study area

meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scale. It analyses both the spectral and spatial/contextual properties of pixels and performs a segmentation process and iterative learning algorithm to achieve a semi-automatic classification procedure that promises to be more accurate than traditional pixel-based methods' (Blundell and Opitz, 2006; Hay and Castilla, 2006). Significant advantages are observed when the 'Object Based Image Analysis' involving 'multi-resolution image segmentation techniques' is used to analyze high resolution imagery. This technique divides the image into homogeneous regions which are obtained by considering various properties like, texture, shape, size and certain topological characteristics along with the spectral properties. Finally, 'image segments' are obtained by hierarchically arranging the features as 'image objects' (Benz *et al.,* 2004, Blaschke, 2005).

The present paper attempts to explore the suitability of a proper classification technique for the imageries from Landsat TM, IRS-P6, and WorldView-2 for the dynamic coastal region. Traditional pixel-based approach along with the recent approach of Object-oriented classification is adopted for both moderate and high-resolution images.

Study area

The study area forms a narrow belt of Central Konkan coast from the state of Maharashtra in India. This region is gifted with number of natural and manmade assets that have attracted attention of scientist communities. The region under study represents a peculiar estuarine-creek environment. The study area extends from 18°7′ N to 18°12′ N and 72°58′ E to 73°01′ E (Fig. 1). It covers the coastal settlements of Diveagar in the central part of the image and Bharadkhol to the south. Diveagar is a typical coastal settlement which stretches for five kilometers parallel to the coast. Two coastal streams jet out into the sea bordering Diveagar — one towards the north and other towards south. Built-up structures are surrounded by plantations of coconut, beetle nut, areca nut etc. Towards the seaward side of the settlement an extensive dune covered with dunal plantation (Pandanus odorifer and Casuarina) is observed. Towards east of Diveagar settlement, lies another major settlement- Borli Panchayatan. Bharadkhol settlement lies towards south of Diveagar and has a rocky coast.

Data and methods

Data

The data sets used for the present work relates to different satellites and sensors of different spatial resolution. Table 1 gives details of the satellite data chosen for the research. Landsat TM data of 2010 was downloaded from the USGS website (https://earthexplorer.usgs.gov/). The IRS-P6 LISS III data (2008) was obtained from National Remote Sensing Centre (NRSC), Hyderabad. The Worldview-2 DigiGlobe data was provided by Digital Globe Incorporated, Longmont Colorado, USA. Certain preprocessing steps were carried out before dealing with the actual classification. For the Landsat TM and IRS P6 images geometric corrections were applied in order to make them geometrically correct for further analysis. Image to image registration was carried out in ERDAS imagine 2010 software for performing the geometric corrections. All images were re-projected to Geographic Latitude/Longitude with the WGS 84 spheroid and datum.

Methodology

In order to perform classification of the coastal areas of Diveagar, two approaches are taken into consideration. The general methodology adopted for the study is depicted in figure 2. Both the data sets, moderate resolution and high-resolution imageries, were subjected to supervised classification (pixel based) and Object-oriented (object based) methods (Fig. 2)

Table 1. Satellite data used for the Study

Satellite	Sensor	Spatial resolution (m)	Spectral resolution	Date
IRS P6	LISS III	23.5	Bands- 4 Green, Red, NIR, MIR	14 February, 2008
LANDSAT	TM	30	Bands - 7 Blue, Green, Red, NIR, MIR, TIR, MIR	14 November 2010
Worldview-2	Digiglobe	2	Bands - 8 Coastal, Blue, Green, Yellow, Red, Red Edge, NIR1, NIR2	1 November 2010

PIXEL-BASED CLASSIFICATION

One of the major types of pixel-based classification is supervised classification which classifies the pixels of unknown identity with the reference of pixels of known identity. In this process, the known pixels are known as samples which are collected through ground surveys and field investigation. Considering every pixel as an individual unit, these are compared with one another and to those of known identity. A group of similar pixels is identified which creates one thematic class. Final output will be thematic map which contains several classes and represented with color or symbol.

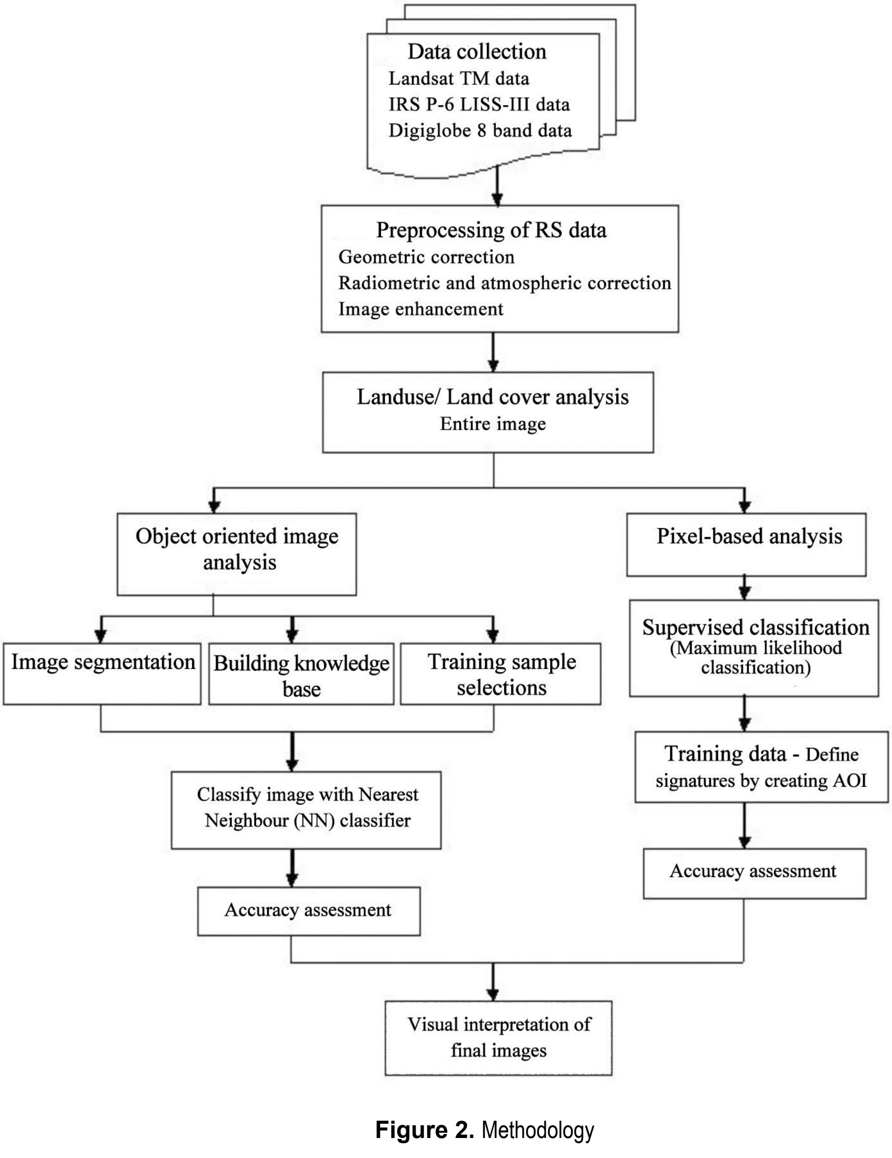

Figure 2. Methodology

Pixel-based classification of the images was thought necessary as this would enhance the land use type in coastal areas of Diveagar and surrounding region, which is important for extraction of natural and anthropogenic features. While classifying an unknown pixel, the Maximum Likelihood Classifier (MLC) assesses variance and covariance of the spectral response pattern of every class. It is assumed that the distribution of the data set being trained is Gaussian. Hypothesis of normality is generally sensible for the distribution of common spectral responses. 'Under this assumption, the distribution of a category response pattern can be completely described by the mean vector and the covariance matrix. With these parameters, the statistical probability of a given pixel value being a member of a particular land cover class can be computed. The resulting bell-shaped surfaces are called probability functions and there is one such function for each spectral category' (Lillesand and Kiefer, 1994).

In order to prepare classified image, supervised classification (MLC) was performed for all the images (Landsat TM, IRS image, and Worldview-2).

OBJECT-ORIENTED IMAGE ANALYSIS

The image classification in this technique starts with image segmentation wherein the image is divided into uniform, contiguous 'objects'. In eCognition 4 software, the smallest object contains single pixel which is known as a 'bottom-up region-merging' approach. (Baatz *et al.,* 2004). Every smaller object is merged into a larger object depending upon the color (spectral properties), scale, and shape (compactness and smoothness). In contrast to the moderate resolution imageries, high resolution imageries contain more information like shape and size (Guo *et al.,* 2017). The scale parameter is the most fundamental one that determines the size of the objects. If there is an increase in the scale parameter, the size of the objects is bound to increase. Though segmentation is initial and crucial process in Object-oriented classification, there are no well-known standards or fixed rules to determine the best parameters for segmentation (Chen *et al.,* 2008). The performance of object-oriented image classification is highly dependent on the segmentation accuracy. The best way to evaluate segmentation output is human interpretation and correction (Pal and Pal, 1993). Quantitative measures are developed to predict the level of over-segmentation and under-segmentation of regions. There are also certain techniques that enable the measurement of the inconsistency within the positions of the region boundaries.

Qualitative visual examination method was employed for the present study in order to find better segmentation results. In order to achieve an appropriate scale, comparison of the segmented objects with that of the uniform visual properties of the image was performed by involving various groups of possible parameters. The next step after the determination of the scale parameter was to modify other parameters iteratively to refine the object shape. As per DeKok *et al.* (1999), user specified scale or resolution of the expected objects regulates the process of segmentation. Thus, the accuracy and quality of the image classification in the Object-oriented technique actually depends on the best results achieved through the segmentation process.

During the classification process the nearest neighbor classifier was employed for the present work. The nearest neighbor classifier is treated as a 'soft classifier' and works on fuzzy logic.

ACCURACY ASSESSMENT

According to Campbell (2007), 'classification accuracy assessment measures the agreement between a standard assumed to be correct and a classified image of unknown quality'. The classified images obtained through running both Pixel based and Object-oriented processes were further subjected to accuracy assessment. It was observed that the overall accuracy obtained for the pixel based classification ranges between 83.20% and 86.06%. On the other hand, it ranged from 72.27% to 94.64% for the Object-oriented classification.

APPLICATION OF STATISTICAL METHOD TO ASCERTAIN THE DIFFERENCES IN CLASSIFICATION OUTPUT

Congalton and Green (1999) suggested the usage of Kappa analysis and application of 'pair-wise Z test' to ascertain the differences in the classification results. Other researchers like Dwivedi *et al.* (2004) and Zar (2007) have also employed this method to statistically verify the classification variations. Similar method was used to prove the hypothesis that 'the classification results obtained by using pixel-based and Object-oriented techniques yields significantly different results'. The Kappa coefficient is 'a measure of the agreement between observed and predicted values and whether that agreement is by chance' (Congalton and Green 1999). Usually, these values are scaled from 0 to 1. When a value is relatively close to zero it suggests that there are higher chances of agreement. The K-hat value is obtained by employing the equation 1.

$$\widehat{K} = \frac{P_o - P_c}{1 - P_c} \quad \text{.... Equation 1}$$

Where, P_o = actual agreement,

P_c = chance agreement

$$Z = \frac{\left|\widehat{K_1} - \widehat{K_2}\right|}{\sqrt{\widehat{var}(\widehat{K_1}) + \widehat{var}(\widehat{K_2})}} \quad \text{Equation 2}$$

Where, K_1 is the kappa coefficient for classification 1 and K_2 is the kappa coefficient for classification2 (Source: Weih *et al.*, 2010)

'Pair-wise Z' values along with their respective probability values were computed for each combination of two different

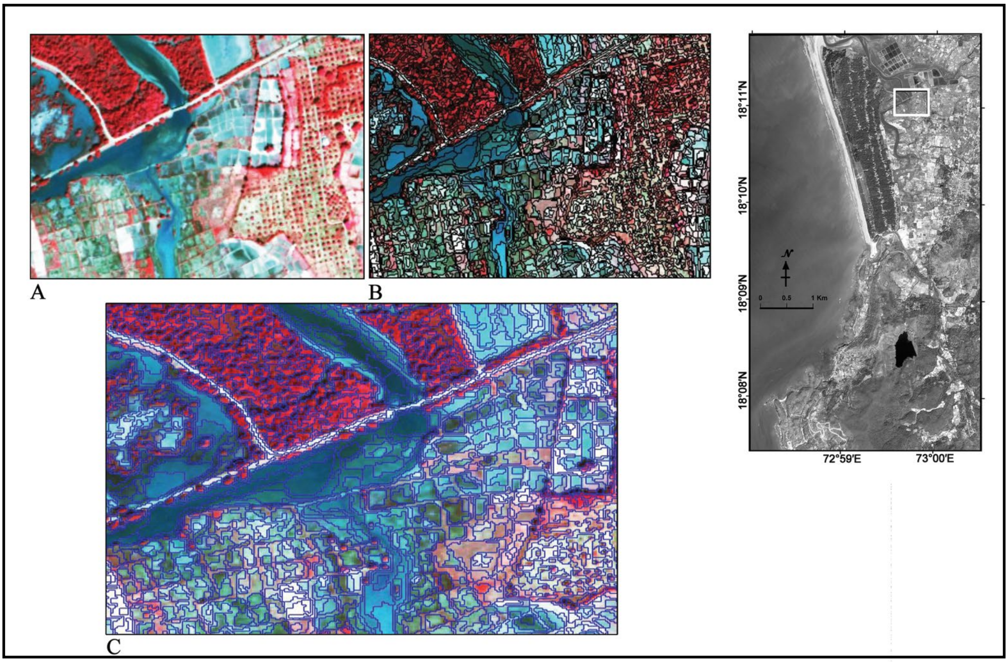

Figure 3. Image segmentation — where (A) original image, (B) segmented image, (C) segmented image with scale parameter 10

Table 2. Major land use classes considered for classification of images (*Marshy land is identified separately as wet sand and mangrove in worldview -2 dataset)

<table>
<tr><th colspan="3">Data used</th><th>Identified classes</th><th>Description</th></tr>
<tr><td rowspan="15">Worldview – 2 (13 Classes)</td><td rowspan="10">IRS P-6 (10 Classes)</td><td rowspan="8">Landsat (8 Classes)</td><td>Dense vegetation</td><td>Included the vegetation found along the hills</td></tr>
<tr><td>Kewda plantation</td><td>Included Kewda (Pandanus odorifer from Screw pine family) plantation along the coast</td></tr>
<tr><td>Water bodies</td><td>Rivers, lakes, ponds, ocean water, etc.</td></tr>
<tr><td>Dry sand</td><td>Sand deposits found along river mouth and beach</td></tr>
<tr><td>Built-up</td><td>Included the densely built-up as well as sparsely built-up area</td></tr>
<tr><td>Standing crop</td><td>Included all the agricultural fields</td></tr>
<tr><td>Barren land</td><td>Included the barren hill slopes, bare surfaces</td></tr>
<tr><td>*Marshy land</td><td>Included marshy land along the coast</td></tr>
<tr><td></td><td>Coconut plantation</td><td>Included all the coconut, palm trees commonly found in coastal areas</td></tr>
<tr><td></td><td>Sparse vegetation</td><td>Found in patches along the hills</td></tr>
<tr><td></td><td></td><td>Mangrove</td><td>Mangroves usually found over marshy areas along the coast</td></tr>
<tr><td></td><td></td><td>Wet sand</td><td>Wet sand deposits found along the beach</td></tr>
<tr><td></td><td></td><td>Fallow land</td><td>All the fallow land</td></tr>
<tr><td></td><td></td><td>Salt affected field</td><td>The fields having high reflectance, mostly water logged</td></tr>
<tr><td></td><td></td><td>Rocky coast</td><td>Bare or sparsely vegetated rock surfaces along the beach</td></tr>
</table>

classifications using equation 2. The null hypothesis suggested by Zar (2007) was applied which stated that 'with an application of two-tailed Z-test ($\alpha = 0.05$ and $Z\alpha/2 = 1.96$), if the p-value ≥ 0.025 (Z values < 1.96), then the classifications would not be considered statistically significantly different'.

Results and discussion

In this study, the eCognition software is used in order to attempt the image segmentation. The segmentation scale and shape factor are set as 10 and 0.5, while the smoothness was set as 0.3. The experimental area segmentation image is represented in figure 3. Object-oriented classification is used for extracting the features from the study by eCognition software; the results are compared with traditional classification method i.e. maximum likelihood classification.

All the image data sets were subjected to both the classification techniques. Depending on the resolution of the image the number of land use/ land cover classes obtained for each of the datasets varied considerably (Table 2). Landsat data with a resolution of 30m yielded only eight classes, whereas IRS, P-6 data with 23.5m resolution achieved ten classes. The worldview-2 data with the finest resolution of 2m had maximum number of classes (thirteen classes). While classifying the Landsat TM and IRS P6, level I and II classification is performed. In case of Worldview-2, classification is attempted up to level III. It was observed that the level of classification, in terms of number of classes, increases with the level of spatial resolution. It is quite natural but in case of coastal areas it is most essential because of variations in the spectral signatures for different classes.

Three parameters were thought to be crucial in this coastal tract that needed proper delineation: (i) proper identification of the settlement and understanding its pattern – clustered or interwoven with coastal plantation; (ii) identification and demarcation of mangrove vegetation and aquaculture ponds or other such structures; (iii) identification of general vegetation species observed in the coastal area.

The main problem(s) related to coastal feature extraction lies in the fact that settlements are often surrounded by dense coastal vegetation. The images acquired by the Landsat and IRS P-6 have medium resolution, so it is basically not beneficial for the mangrove identification. On the other hand, the higher resolution image like worldview-2 was able to precisely identify the vegetation along the coast, including

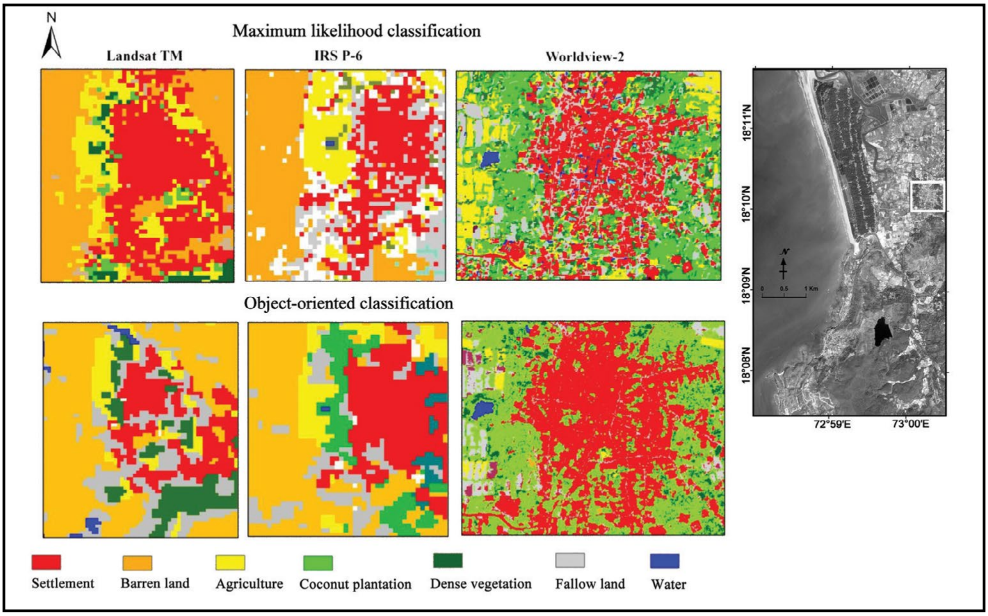

Figure 4. Settlement identification in Borli Panchayatan

plantations which create confusion in extracting them separately. Diveagar is having linear pattern of settlements which are parallel to the coast, with natural setup. Settlement pattern appears to have come up better for moderate resolution images using the MLC technique whereas it is clearer in case of worldview-2 dataset using Object-oriented technique. Due to high spatial resolution the clustered settlement of Borli Panchaytan surrounded by dense plantation is properly highlighted in figure 4. Visual appearance of Object-oriented classification is much smoother than MLC technique.

Another problem is related to the identification of mangrove areas and separating them from the dunal and other mangroves (Fig. 4). Mangrove vegetation is clearly visible in the figure 5c and 5d which is getting confused with the wet sand and aquaculture ponds in figure 5a and 5b, hence nomenclated as marshy land. This can be attributed to the resolution factor, but even in the high resolution dataset by using MLC method mixing of water bodies with built up structures and mangroves with other vegetation is observed. As against this segmentation technique appears to give better results as in figure 5D it is clearly seen that the water bodies are better demarcated and proper clusters of mangrove vegetation have been marked.

Vegetation along the coastal tracts often has a mixed pattern wherein the casuarina plantations are often intermingled with other coastal plantation. Diveagar area is peculiarly known for Kewda (*Pandanus odorifer*) plantation on the dunes. Figure 6d represents a peculiar scenario where various vegetation species are better classified and are easily identifiable separately. The patches of Kevada and coconut are clearly separated in the worldview image where Object-oriented Classification is performed. Aquaculture ponds present along the coast are also extracted properly using worldview-2.

The fields along the coast are mainly water logged due to tidal currents and mostly are salt affected having high reflectance in FCC. While performing Pixel-based Classification, the reflectance is similar with the built up class, so the classification accuracy reduces.

Table 3 represents the Kappa statistics along with the Z scores computed for the three types of datasets across the two classification methods. The worldview dataset when subjected to Object-oriented Classification technique yields higher level of accuracy 94.64% and   of 0.911. As compared to this the level of accuracy drops down to 86.06% (=0.84) when the same image is subjected to Maximum Likelihood Classification technique. On the other hand, the $\hat{K}$ shows a reversal pattern with the moderate resolution images (i.e. IRS P6 LISS III and Landsat TM). In both the classifications, the $\hat{K}$ is higher for Maximum Likelihood Classifier as compared to Object-oriented Classification.

In order to statistically ascertain whether the accuracies of the classified images are significantly different or not, Z-paired statistics is computed and their results are highlighted in table 4. Taking into consideration the fact that if the Z score values are >1.96 and the P (probability) values are <0.025 the classification methods should be significantly different in their accuracy level. When the MLC technique was employed for all the three data sets and the cross comparison was done (Table 4), it was observed that the classification results obtained for the MLC pairs of Worldview (WV) IRS, WV-Landsat (LS) and IRS-LS were not significantly different. On the other hand, when these same three pairs were subjected to only Object Oriented (OO) Classification technique it was noted that the results obtained for IRS and LS paired with WV yielded significantly different results. But interestingly IRS-LS pair with OO technique of classification does not show any difference in their results.

A cross comparison within the two

Table 3. Kappa statistics along with the independent Z scores for different classified images and techniques

Classified image data	Image classification method	Classification accuracy	Kappa statistic	Variance of kappa	Independent Z scores	Comparative Z score
Worldview II	Object Oriented	94.64%	0.911	0.000418	31.07	2.03
	MLC	86.06%	0.84	0.00081	29.52	
IRS P6 LISS III	Object Oriented	72.27%	0.755	0.00082	26.37	2.01
	MLC	86.11%	0.834	0.000713	34.1	
Landsat TM	Object Oriented	72.64%	0.705	0.000894	23.58	2.09
	MLC	83.20%	0.792	0.000849	27.18	

Table 4. Z-paired statistics and probabilities of different classification methods applied to different datasets. Z scores (Lower triangular matrix values) if > 1.96; p values (Upper triangular matrix values) if < 0.025. Then classification methods are significantly different in their accuracy level; otherwise methods are not significantly different in their accuracy level

		Classification method					
		Object oriented			Maximum likelihood		
		WV	IRS	LS	WV	IRS	LS
Object oriented	WV		<0.0001	<0.0001	0.021	0.011	0.004
	IRS	4.43		0.1131	0.0174	0.022	0.181
	LS	5.69	1.21		0.119	0.0064	0.0183
Maximum likelihood	WV	2.03	2.105	1.18		0.436	0.109
	IRS	2.29	2.01	3.22	0.15		0.131
	LS	3.34	0.91	2.09	1.23	1.12	

techniques adopted for these three datasets also provides an insight in to the differences in the results obtained. When each dataset was processed for different techniques it was observed that they yield statistically significantly different results. WV whether

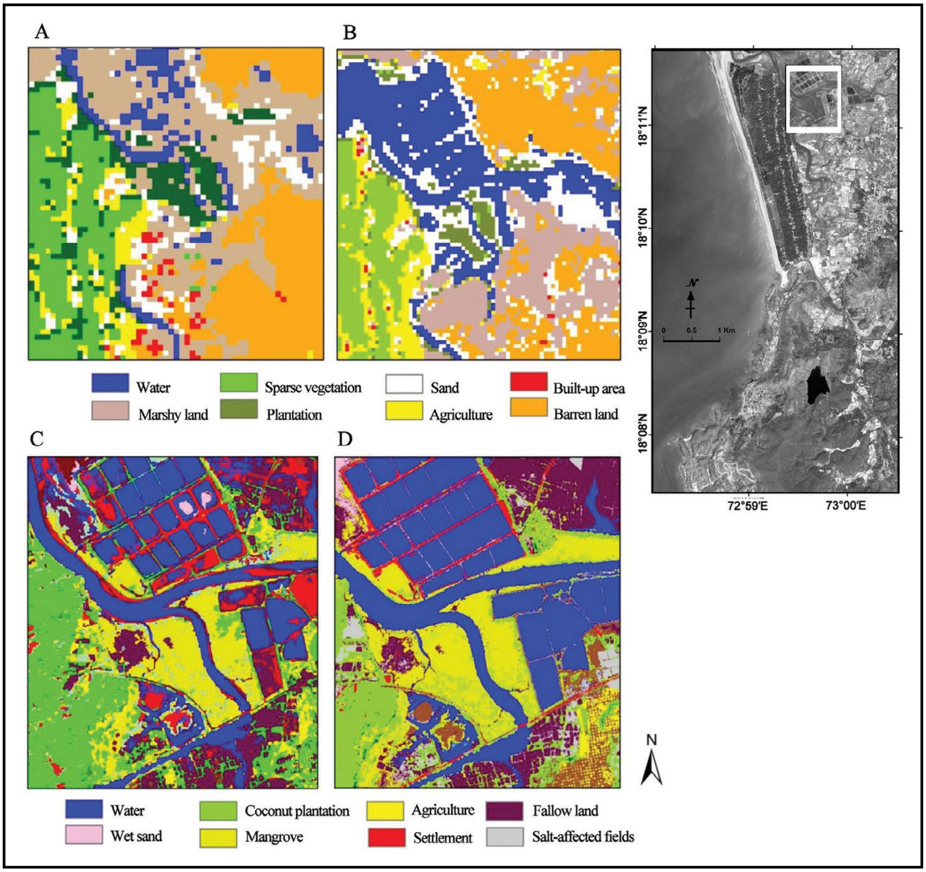

Figure 5. Mangrove identification — (A) Landsat TM image, (B) IRS P-6 image, (C) Worldview-2 image, (D) Object-oriented classification of Worldview-2 image

treated for OO or MLC and compared with IRS and LS with other technique also gives different results. But the situation changes when IRS and LS pair with different techniques are compared with their respective results. In this case the results are observed not to be significantly different from each other. This fact is also revealed from observing visually the outputs of the classification depicted in figures 4, 5 and 6.

It was observed that Object-oriented classified Worldview image was significantly different in its accuracy as compared to the rest of the classified images. Similarly, each image dataset when subjected to the two different classification techniques yields significantly different accuracy levels.

Conclusion

The study is mainly focused on the extraction of natural and anthropogenic features in the study area. Various species found along the coast such as coconut, palm, mangroves, Pandanus odorifer etc. can be delineated using high-resolution data (Fig. 6). Aquaculture ponds present along the coast are also extracted using Worldview-2. Trees planted along the borders of the farmland are quite effectively extracted from the worldview data by using the Object-oriented Classification technique.

While performing the Maximum Likelihood Classification of Worldview-2 pixels are considered in Object-oriented image analysis, segments are considered of same reflectance. Thus, Object-oriented

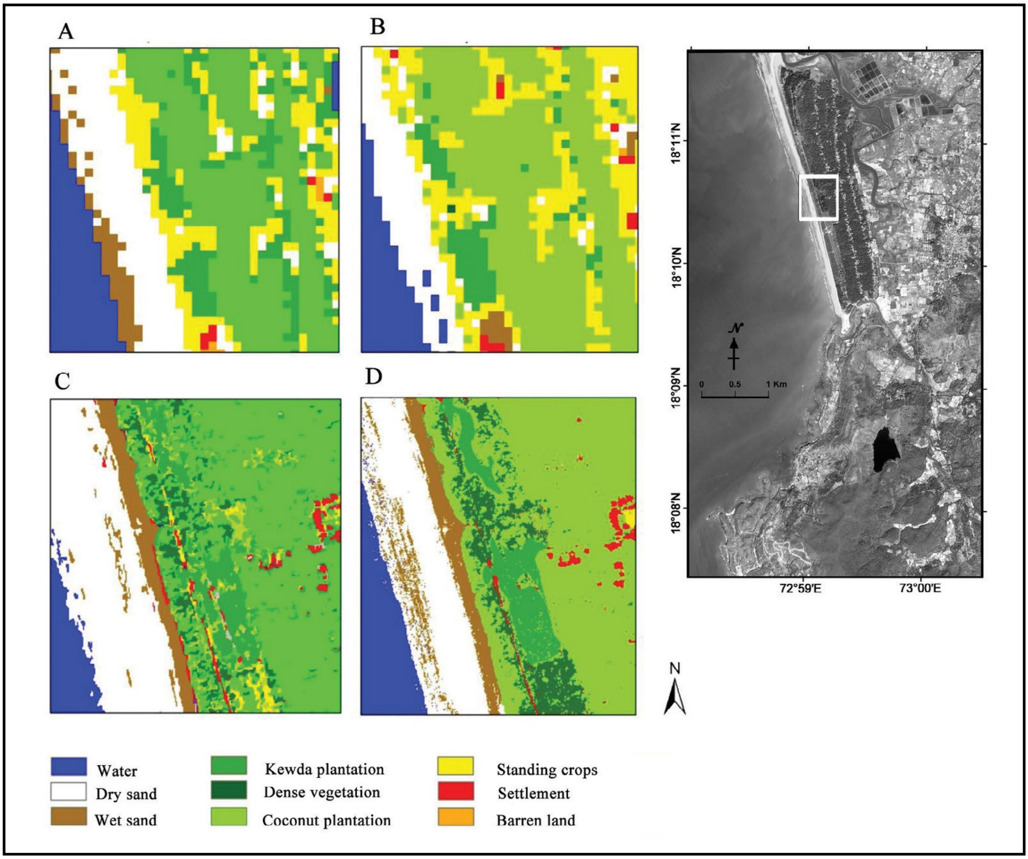

Figure 6. Vegetation species identification (A) Landsat TM, (B) IRS P-6, (C) Worldview-2, (D) Worldview-2 (Object-oriented classification)

Classification is more helpful in identifying the coastal settlements properly which are surrounded by plantation vegetation. In the segmentation process, shape, color, texture, etc. of the objects are taken into consideration, so it is favorable for the extraction of natural as well as anthropogenic features. Pixel-based Classification yields better results for moderate resolution images in extraction of settlements. Settlement pattern is clear with a better accuracy level using MLC technique than the Object-oriented analysis which appears to create more confusion of the built-up structures with other classes (Fig. 5). High-resolution image does not give appropriate results using MLC as there is confusion between barren and other classes with the built up areas. On the other hand, compact settlements are better represented without any mixing with the Object-oriented Classification.

Overall accuracy obtained for Object-oriented Classification is higher than that obtained using MLC technique for high-resolution data set which is statistically proven with Z-paired test. Overall accuracy is better in case of moderate resolution images when MLC technique is adopted instead of Object-oriented one. Thus, to summarize, it is observed that the Maximum Likelihood technique is best suited for moderate resolution images, but one has to rely upon Object-oriented Classification technique for high-resolution images.

Thus, it can be concluded that Object-oriented Classification technique is far better in case of higher resolution datasets as it is able to differentiate various coastal features and generate a high level of accuracy.

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