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Change detection studies in coastal zone features of Goa, India by remote sensing

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Digital remote sensing data of SPOT-1 (Nov. 1990), IRS-1C (Jan. 2001) and IRS-1D (Jan. 2003) have been subject to maximum likelihood classifier (MLC) to carry out change detection studies in the coastal zone of Goa. The classified images were evaluated on both homogeneous and heterogeneous regions in terms of confusion matrix as well as by field validation. The classification results of these multi-temporal data reveal that MLC gives an average accuracy of 85.69, 77.66, and 88.43% for 1990, 2001 and 2003 images respectively, and the corresponding kappa coefficients are 0.89, 0.84 and 0.86 respectively. Results of MLC indicate that there is an increase in urban land, vegetation and water body reduction in barren land and sandy beach along the coastal zone of Goa. The urbanization is attributed to tourism boom-related activities.

Keywords: Coastal zone of Goa, land cover, land use, maximum likelihood classifier, kappa coefficient.

GOA, the smallest state in India with an area of 3702 km², lies in the west coast. Goa is the prime tourist destination of India, and the tourism industry is growing rapidly. Associated with this growth, changes could be detected in the land-use, especially along the coastal belt such as construction of buildings, environment-friendly industries, resorts, breakwaters, minor harbours, expansion of a major port, etc. Goa has been experiencing a lot of changes in its land-use patterns. It has become necessary to detect the changes happening around this region as this may help determine the level of stress that the coastal zone of Goa is facing. Literature review points out that no study had been carried out to detect the changes that have occurred along the coastal zone of Goa other than the environment and sustainable local development of coastal area study¹. Increasing tourism appears to drive land-use/land-cover changes in Goa². Coastal geomorphic features, sediment transport and coastal vegetation (mangroves) have been studied using remote sensing data^{3,4}. As Goa is one of the global tourist destinations of the world, more development is expected along the coastal zone, and subsequently there will be changes in the land-use/land-cover pattern in the coming years.

In the present study, an attempt has been made to carry out change detection analysis for the coastal zone of Goa. For this purpose, available cloud-free remote sensing data have been subjected to digital image processing techniques as they provide a wealth of information due to synoptic coverage and repetivity. Change detection involves the use of multi-temporal datasets to derive land-cover changes between the dates of imaging. Types of change vary from short term to long term. Change detection procedures require data of the same or similar sensors. Influencing environmental factors should be considered in change detection procedures. Spatial and spectral resolution of recent satellite sensors gives high-quality satellite images. Remote sensing data having good spectral and spatial resolution are extremely useful for mapping land use and land cover⁵. Areas surrounded by aquatic systems are important for their contribution to the hydrological cycle⁶. Several image processing techniques have been developed in the last three decades to process and analyse remote sensing images and extract meaningful information⁷. Different land-cover types in an image can be classified using image-classification algorithms having spectral features. Methods based on spectral variations are robust when dealing with data captured at different times of the year⁷. The most common means of expressing classification accuracy is preparation of a classification confusion matrix⁸. These matrices compare the relationship between known reference and classified data on category-by-category basis. The classification procedures can be supervised or unsu-

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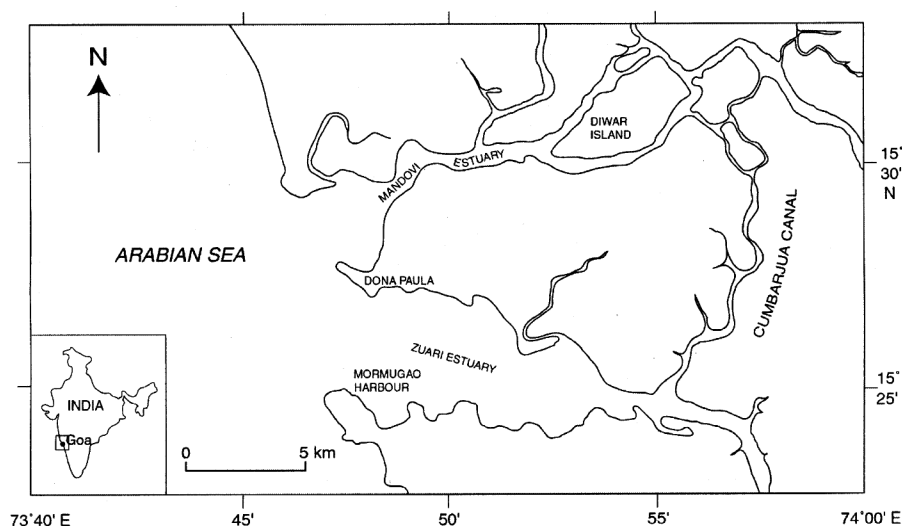


Figure 1. Area of study.

Table 1. Details of satellite data

Date of pass	Satellite and sensor	Bands (μm)	Pixel resolution (m)	Radiometric resolution (bits)
25 Nov. 1990	SPOT-1 (HRV)	0.50–0.59 (1) 0.61–0.68 (2) 0.78–0.89 (3)	20.0	8
19 Jan. 2001	IRS-1C (LISSIII)	0.52–0.59 (2) 0.62–0.68 (3) 0.77–0.86 (4)	23.5	8
31 Jan. 2003	IRS-1D (LISSIII)	0.52–0.59 (2) 0.62–0.68 (3) 0.77–0.86 (4)	23.5	8

pervised. In supervised classification, each measurement vector is assigned to a class according to a specified decision rule. Classes have been defined on the basis of representative training samples of known identity. The kappa coefficient indicates how each classification differs from a random classification of the cover types⁹. An analyst uses his/her experience of ground survey, image interpretation and historical data at the training stage. In the unsupervised scheme, no human interaction is involved, except providing some basic parameters. In this study, digital remote sensing data of SPOT-1 (November 1990), IRS-1C (January 2001) and IRS-1D (January 2003) had been subject to maximum likelihood classifier (MLC). Change detection analysis was carried out using digital image processing technique to map various coastal land-use and land-cover changes that have occurred over a period of time.

The study area is bound by the Mandovi–Zuari estuarine system (lat. 15°23'21.75" to 15°33'36.67"N and long. 73°47'42.43" to 73°58'46.27"E; Figure 1). The zone comprises of estuaries, sandy beaches, land-use and land-cover features. Tropical climate prevails and air temperature

varies from 21 to 33°C. Humidity ranges between 75 and 95%. The average annual rainfall is around 250 cm. Rivers in this region originate from the Western Ghats and flow towards the west and meet the Arabian Sea.

False colour composites (FCC) of three imagery (Table 1 and Figure 2) and topographical maps (48E, 48E/14 and 48E/15) of Survey of India have been utilized for the present study.

The features of the study area are categorized with the help of spectral values. The maximum likelihood decision rule is based on the probability that a pixel belongs to a particular class. The basic equation assumes that these probabilities are equal for all classes, and the input bands have normal distributions. After evaluating the probability value in each category, based on the threshold, the pixel would be assigned to the most likely class, labelled as 'unknown'. All imageries used in this study are subject to radiometric and atmospheric corrections by National Remote Sensing Agency, Hyderabad, which is a nodal agency for distributing satellite images in the Indian region. These satellite data have been registered and resampled to geographic coordinates and projected in the Everest ellip-

soid with a RMS error of less than 1.0 pixel. The nearest neighbour method was used for resampling satellite data. FCCs were generated in blue, green and red filters, and based on interpretation keys such as tone and texture, ground points were identified. Training sets for various

classes have been collected by displaying the multi-spectral image onto a colour monitor. Care was taken to cover the variation while identifying different features for training the computer. The MLC was applied on all the scenes by using PCIWORKS Ver 7.0 software. Parameters for the classification are in-built algorithms of the PCIWORKS software. Detailed description is available in the PCIWORKS on-line manual. Six classes, viz. water bodies, vegetation, barren land, mangroves, urban land and sandy beaches were identified in all the scenes used in the study.

The MLC has been used to classify satellite images of three years by training set pixels. This led to change detection analysis in the coastal zone of Goa (Figure 3). Table 2 shows an average accuracy of 85.69, 77.66 and 88.43% for the images of 1990, 2001 and 2003 respectively, and the corresponding kappa coefficients are 0.89, 0.84 and 0.86 respectively. A classification is not complete until its accuracy is assessed. Error matrices compare on a category-by-category basis between the reference data and classified data. Accuracy estimates were prepared from the error matrix. The precision of the classification was estimated by applying the kappa coefficient ($K = \text{observed accuracy} - \text{chance agreement} / 1 - \text{chance agreement}$), an analytical way to evaluate total accuracy of the classification⁹. The efficiency and accuracy of MLC have been verified by random selection. The classified images were checked visually by displaying both the classified image and satellite image in the colour monitor. Limited field checks were also carried out to validate the classified images.

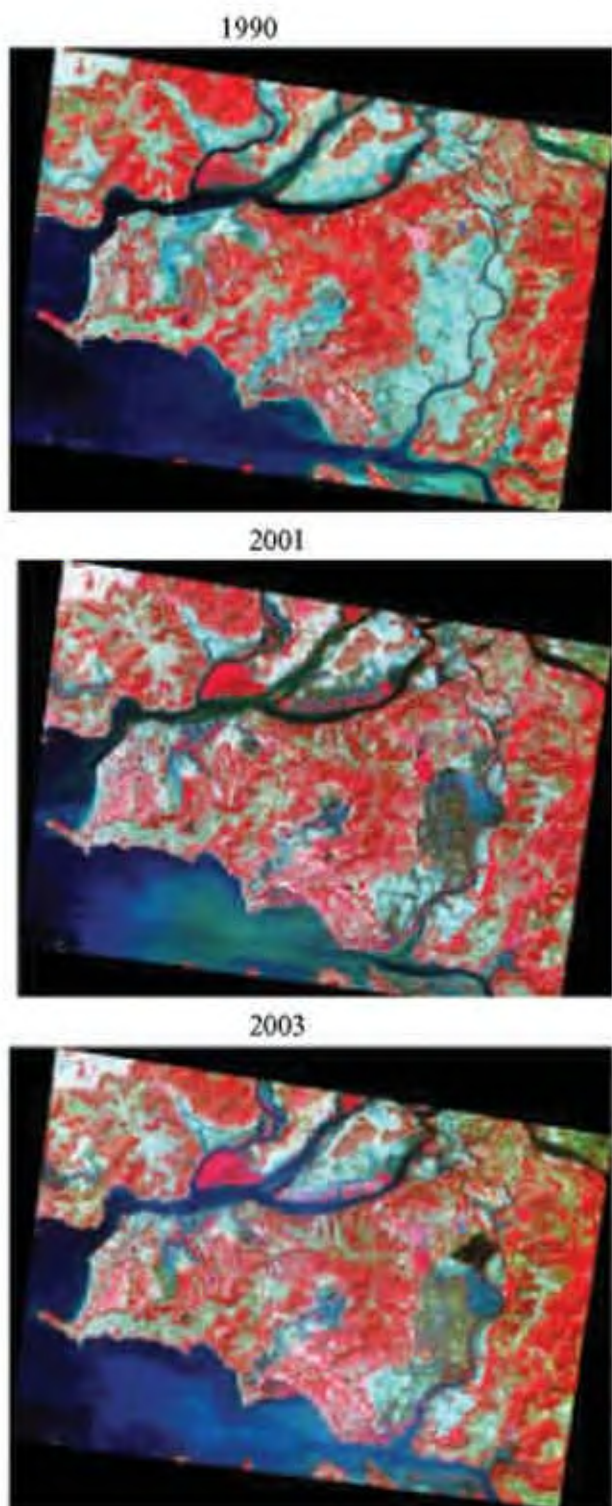


Figure 2. False colour composite of the study area.

Table 2. Results of maximum likelihood classifier			
Year	Average accuracy (%)	Overall accuracy (%)	Kappa coefficient
1990	85.69	90.93	0.89
2001	77.66	88.03	0.84
2003	88.43	88.69	0.86

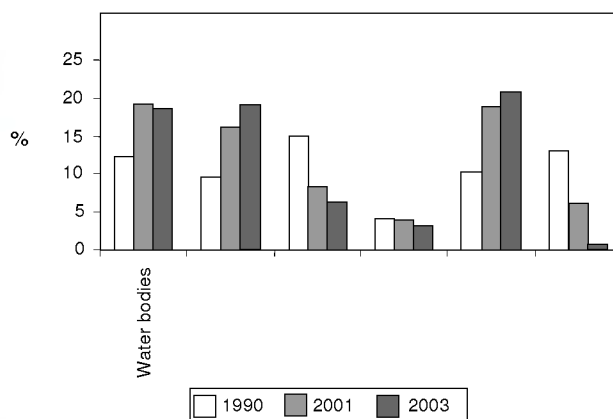


Figure 3. Change detection analysis.

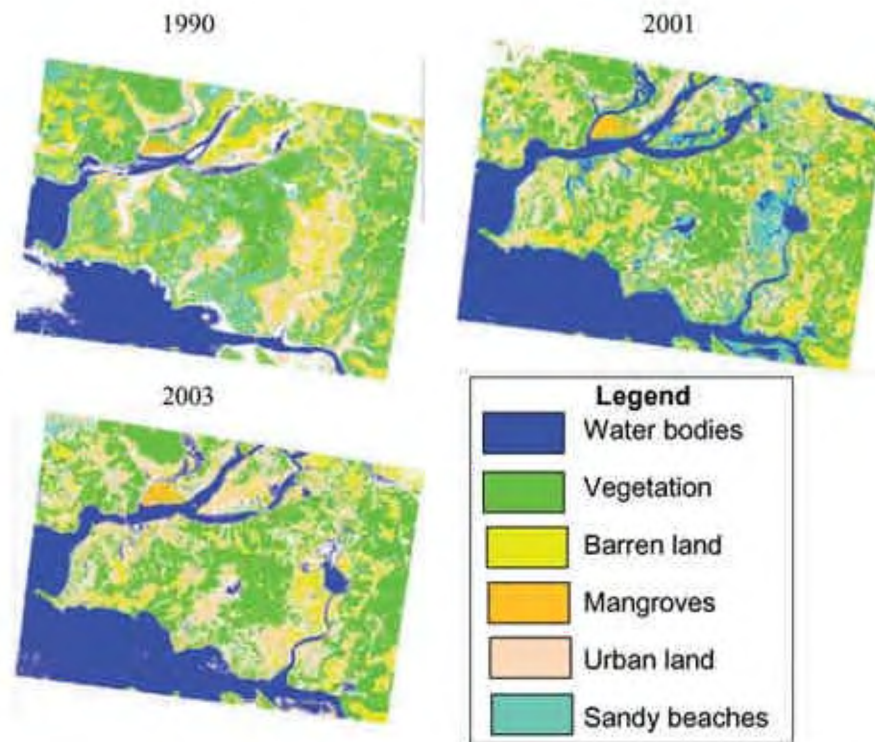


Figure 4. Features classified by maximum likelihood classifier.

Table 3. Classes separated by maximum likelihood classifier

Class	Pixel			Percentage		
	1990 SPOT	2001 IRS-1C	2003 IRS-1D	1990 SPOT	2001 IRS-1C	2003 IRS-1D
Water bodies	109433	120526	112355	12.29	19.25	18.38
Vegetation	85124	101506	116824	9.56	16.22	19.11
Barren land	133607	52251	38408	15.01	8.35	6.28
Mangroves	36692	118125	18830	4.12	3.88	3.08
Urban land	91065	38082	126005	10.23	18.87	20.62
Sandy beaches	116816	171190	3143	13.12	6.08	0.51
Unclassified	317363	171190	611226	35.65	27.35	32.01

The classified results have been validated in the field with the help of interpretation keys such as tone, texture and shape. Field validation confirmed the output of the MLC.

The MLC has clearly separated features such as water body, vegetation, urban land, barren land and sand beaches (Figure 4) in all the scenes. The FCCs clearly show the movement of sediment plume from the Zuari river, which may probably be due to dredging in the Mormugao port.

The changes are evident on the urban land, barren land, sandy beaches and mangroves over the period 1990–2003 (Table 3). The areas of vegetation and urban land increased from 9.56 to 19.11% and 10.23 to 20.62% respectively. This urbanization is due to tourism and associated activities. Barren land decreased from 15.01 to 6.28%; as a

result of the increase in urban land and vegetation. Sandy beach cover reduced from 13.12 (in 1990) to 0.51% (2003) due to coastal erosion and mushrooming of resorts, coastal shacks and construction along the coastal zone. In this study, a comparison was done of the November and January data. Season and climate are the same for the region during these months. Hence, errors due to changes in vegetation are almost negligible, as they belong to the same season. All these scenes pertain to a peak in tourism, when the beaches are covered by man-made huts. Hence, changes in the sandy beaches are to be studied in detail for other scenes also. A minute reduction in mangrove vegetation is noticed from 4.12 to 3.08%. Degradation of mangrove cover was noticed by the concerned authorities, and to mitigate this, plantation of new man-

groves has been already initiated. The overall rise in water bodies is attributed to climatic conditions of the area and improved watershed management programmes.

The present study was undertaken to detect changes in the coastal zone of Goa using remote sensing and digital image classification techniques. After mapping the coastal land-use and land-cover features of the study area for three different years, changes that took place over that region for a period of 13 years have been detected. There are significant changes in urban land, barren land, vegetation and mangrove covers. This exercise reveals that the coastal zone of Goa has undergone extensive development in the last decade. In such a situation, the change detection study will be of use to the decision makers.

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Seasonal evaluation of hydro-geochemical parameters using correlation and regression analysis

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Correlations and multiple linear regressions were used to develop models relating well water chemical quality parameters to a set of independent chemical variables in post- and pre-monsoon seasons in the upper Gunjanaeru River basin, Cuddapah district, Andhra Pradesh, South India. The correlation between the specific electrical conductance (SEC) and other parameters except potassium (K^+) is significantly positive, whereas $Ca^{2+} + Mg^{2+}/Na^+ + K^+$ is significantly negative for both post- and pre-monsoon seasons. In predicting SEC for both post- and pre-monsoon, the independent variables, viz. HCO_3^- , SO_4^{2-} and Cl^- in the model had a significant effect (from 't' test for partial regression coefficient at the 5% level of probability). The multiple R^2 values 0.982 and 0.997 indicate that 98.2 and 99.7% of variability in the observed SEC could be ascribed to the combined effect of Na^+ , Cl^- , $Ca^{2+} + Mg^{2+}$, HCO_3^- , and SO_4^{2-} for post- and pre-monsoon seasons, respectively. Out of the 98.2% variability in SEC due to the combined effect of Na^+ , $Ca^{2+} + Mg^{2+}$, HCO_3^- , SO_4^{2-} and Cl^- ; 44.8% is due to HCO_3^- , 44.4% is due to Cl^- , 9% is due to SO_4^{2-} and 2% each is due to Na^+ and $Ca^{2+} + Mg^{2+}$ for post-monsoon season. Whereas in the pre-monsoon season, 99.7% variability in SEC is due to the combined effect of Na^+ , $Ca^{2+} + Mg^{2+}$, HCO_3^- , SO_4^{2-} and Cl^- ; 38.8% is due to Cl^- , 36.9% is due to HCO_3^- , 12% is due to Na^+ , 7% is due to SO_4^{2-} and 3% is due to $Ca^{2+} + Mg^{2+}$. This shows that HCO_3^- , Cl^- , SO_4^{2-} and Cl^- , HCO_3^- , Na^+ , SO_4^{2-} are the most significant independent variables in predicting SEC for post- and pre-monsoon seasons respectively.

Keywords: Correlation, groundwater quality, hydro-geochemistry, regression models.

MAN has demonstrated control of some of undesirable chemical constituents in water before it enters the ground. But once the water has entered the soil mantle, man's control over the chemical quality of the percolating water is significantly reduced¹. The quality of well water should be better in an area where the soil and aquifer permeability is greater than in an area which is less permeable, assuming that the chemical constituents of the recharge water and evapo-transpiration effects in the two areas are similar. Multivariate analyses are especially useful because the relative importance of the combinations of chemical vari-

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