Evaluating implementation of Coastal Zone Regulation notification in India using remote sensing change detection techniques, aided with machine learning algorithms.

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Abstract

Marine or coastal wetlands that host a diverse variety of flora and fauna are unique and fragile as they are subjected to changing coastlines and undergo dynamic spatial shifts with respect to tidal movements. In India, the Coastal Regulation Zone (CRZ) notification aims at the conservation of coastal regions, under the Environment (Protection) Act, 1986, and regulates developmental and construction activities within the CRZ regions of marine wetlands, in addition to the coastal belt. Remote sensing techniques can be of great use in understanding if the implementation of the CRZ has helped to regulate the proliferation of settlements in the wetland system. In this study, remote sensing techniques along with machine learning classifiers have been used for detecting and quantifying the recent settlements that have been built in the zones regulated by the CRZ of the Vembanad wetland of Kerala. Three standard change detection pre-processing techniques were used over Linear Imaging Self-Scanning Sensor (LISS) IV imagery which was followed by classification using machine learning algorithms: Support Vector Machine (SVM), random forest, and Artificial Neural Network (ANN) to identify the built-up erected in the CRZ region between 2012 and 2018. Comparing the performance of these classifiers, the random forest model was found to have the highest overall accuracy of 96%. It was found that the total area of new built-up that were constructed between 2012 and 2018 in the CRZ regions of 48 villages, that span across Ernakulam, Kottayam and Alappuzha districts of Kerala is 149 hectares. This usage of change detection techniques aided by machine learning algorithms over high-resolution LISS IV imagery would help to evaluate the effectiveness of the CRZ notification over other marine wetlands in India.

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1. Abstract

Marine or coastal wetlands that host a diverse variety of flora and fauna are unique and fragile as they are subjected to changing coastlines and undergo dynamic spatial shifts with respect to tidal movements. In India, the Coastal Regulation Zone (CRZ) notification aims at the conservation of coastal regions, under the Environment (Protection) Act, 1986, and regulates developmental and construction activities within the CRZ regions of marine wetlands, in addition to the coastal belt. Remote sensing techniques can be of great use in understanding if the implementation of the CRZ has helped to regulate the proliferation of settlements in the wetland system. In this study, remote sensing techniques along with machine learning classifiers have been used for detecting and quantifying the recent settlements that have been built in the zones regulated by the CRZ of the Vembanad wetland of Kerala. Three standard change detection pre-processing techniques were used over Linear Imaging Self-Scanning Sensor (LISS) IV imagery which was followed by classification using machine learning algorithms: Support Vector Machine (SVM), random forest and Artificial Neural Network (ANN) to identify the built-up erected in the CRZ region between 2012 and 2018. Comparing the performance of these classifiers, the random forest model was found to have the highest overall accuracy of 96%. It was found that the total area of new built-up that were constructed between 2012 and 2018 in the CRZ regions of 48 villages, that span across Ernakulam, Kottayam and Alappuzha districts of Kerala is 149 hectares. This usage of change detection techniques aided by machine learning algorithms over high-resolution LISS IV imagery, would help to evaluate the effectiveness of the CRZ notification over other marine wetlands in India.

***Keywords**:* Coastal Regulation Zone, Vembanad, Built up change detection, Machine learning, LISS IV, Artificial Neural Networks

1. Introduction

Wetlands are one of the most productive ecosystems on the earth and they serve several important ecological functions (Bassi et at., 2014). They are the kidneys of a landscape as they play an essential role in the hydrological cycle: cleansing polluted water, maintaining streamflow, and recharging groundwater aquifers (Mitsch and Gosselink, 2015). India has about 757,060 wetlands covering 15.3 million hectares, or nearly 4.7% of the total geographic area of the country (SAC, 2011) out of which 37 wetlands with a total span of 1,067,939 hectares are designated as Ramsar Sites or Wetlands of International Importance (Ramsar, 2020). The wetlands function as multi-use water service providers for irrigation, groundwater recharge, drinking water, domestic needs and play a significant role in the economy of the country as they support fisheries, agriculture, and tourism. They also help in nutrient transformation, carbon sequestration, sediment retention, and floral/faunal refugee habitat. Eight out of these 37 Ramsar recognized wetlands are marine/coastal wetlands which host diverse and unique varieties of marine and coastal biota such as seagrass, corals, shellfish, seaweeds, sponges, and molluscs and provide breeding grounds for several fishes, as well as for certain resident and migratory birds. Impromptu anthropogenic activities of agricultural reclamation, urban development or urban sprawl, industrial advancements and tourism have been resulting in the gradual degradation and shrinking of these wetlands. Additionally, further degradation of these wetlands is happening due to by-products of developmental activities such as global warming, industrial pollution, untreated sewage disposal, agricultural runoffs, and overexploitation of natural resources (Venkataraman, 2008).

The Ministry of Environment and Forests (MoEF, Govt. of India), to protect the coastal environment and to ensure livelihood security to the fisher and other local communities living in the coastal areas, promulgated the Coastal Regulation Zone (CRZ) notification in 1991, under the Environment (Protection) Act 1986. As per the notification, CRZ is a certain swath of land measured landward side from the High Tide Line (HTL) for tidal influenced water bodies connected to the sea which includes estuaries, rivers, creeks, backwaters, lagoons, and ponds, most of which can be discerned as marine or coastal wetlands. The act restricts industrial and other development activities in the CRZ to reduce anthropogenic effects over the coastal and marine ecosystems. The implementation of the law is imperilled by frequent amendments, poor governance, rapid economic reforms, lack of scientific forecast and undue favours to coastal infrastructure (Panigrahi and Mohanti, 2012). The latest amendments to the CRZ were in 2011 and 2018. As opposed to the 1991 notification, that declares 200m on landward side from the HTL as No Development Zone (NDZ), the CRZ boundary had been reduced to 100 meters landward from the HTL for tidal influenced water bodies and 50 meters landward from the HTL for the islands in coastal backwaters, as per the 2011 notification. This has been further reduced to 20 meters as NDZ for all islands close to the mainland coast and all backwater islands and 50 meters or the width of the creek, whichever is less as the CRZ limits on land along tidal influenced water bodies (CRZ 2018). Approximately 34% of the Indian coastline (2246.49 km) has been eroded primarily due to anthropogenic factors between the period 1990 and 2016 (Kankara, 2018). A survey conducted in 1998 on the effectiveness of CRZ notification has reported that more than 400 violations have occurred across various states in India, between June and September of 1998 (Nandakumar and Muralikrishna, 1998). In addition to this, the Coastal Zone Management Authority of Orissa has reported almost 63 violations, between 2000 and 2012 (CZMA, 2020). So, understanding the implementation of CRZ notification and its efficacy, in wetland ecosystems is vital for implementing further policies for the conservation of wetlands.

Monitoring new built up or expansion of existing built up over time in a vast area would require onerous resources to be achieved using ground truthing techniques. Also, as the ground techniques would take longer time span (months - years) to complete such mapping, its infeasible to obtain the required information for a given point of time due to the dynamicity of changes in built-up. Remote sensing techniques are advantageous in such cases as the satellite images provide a snapshot of the entire region at one point of time. Also, the availability of high-resolution satellite images and machine learning aided image processing would speed up mapping the new built up with minimum financial resources. High-resolution satellite imagery and advanced classification techniques are used for identifying major changes even in minor scale in vast landscapes (Pham et al., 2011; Tong et al., 2010; Liu and Lathrop, 2010; Jain et al., 2014; Kumar et al., 2017). In this study satellite imagery from LISS (Linear Imaging Self Scanning Sensor) IV sensor of Resource Sat-2 platform has been used for quantifying the built up that was constructed after the year 2012 in the region regulated by the CRZ notification of 2011 (MoEF, 2011) within a part of the Vembanad wetland system in Kerala which is an important Ramsar site (a wetland of global importance) on the Southwestern side of Peninsular India. The construction activities violating the CRZ is rampant here with a plethora of court cases going on against the violation of CRZ. The recent demolition of a huge residential complex, built in violation of CRZ as per the decision of the Supreme Court of India has attained even academic and international attention (Singh, 2020; Chugh, 2020; Bindu, et. Al. 2021). Though

CZMA has been formed and some institutional mechanisms are set up at government level for the implementation or enforcement of the legal instrument, there are no proper techniques yet available for monitoring the CRZ. This study aims at bridging this gap using remote sensing and machine learning aided change detection techniques. Though the aim of this study is specific to the Vembanad wetland, the methods adapted in this study can be expanded to other CRZ applicable wetlands to understand the implementation of the CRZ in those regions.

2. Study Area and Field Survey

The Vembanad wetland system spans across 96 kilometres in a North - South direction, covering an area of about 151,250 hectares, occupying 4% of the total area of Kerala state, India (Ramsar, 2002, Nair and Babu, 2016). It falls under three revenue districts, Ernakulam, Kottayam, and Alappuzha of Kerala. The revenue districts are further divided to Taluks and revenue villages (Figure 1). It supports almost 117 species of fishes (ATREE, 2019) and is an important wintering site for several migratory birds. The Thanneermukkom Bund (TMB), a saltwater barrage built midway, to enhance the paddy farming divides the lake and halts the saline water from entering to its southern half. The rich biodiversity of this wetland system alongside geographical significance has led to its recognition as a wetland of international importance by the Ramsar Convention (Ramsar, 2002). According to various studies, due to increase in anthropogenic pollution related to industrial discharge, environmental conditions of the estuary are in steady decline (Priju and Narayana, 2007; Selvam 2012, Rajan e. al. 2008) with the wellbeing of the people and habitat needs of other life forms being severely compromised. The wetland has shrunk to ~37% of its original area due to land reclamation, mainly for paddy cultivation between 1834 & 1984 (James, 2011). Study that examined the shrinkage of the estuary between 1920 to 1980 portrayed a reduction in water depth from 6.7m to 4.4m (Gopalan et al., 1983). The estuary has shrunk by 7% with a loss of 12.28 sq. km surface area between 1973 and 2015 (Nair and Babu, 2016) and a further reduction of average depth from 4.5m to 2.9m in the period between 1980 and 2016 (Asha et al., 2016). Between 1991 and 2016, the mangroves in the Ernakulam district have decreased primarily due to the developmental activities around the Kochi port (Shaji et al., 2017). Also, being a global destination for backwater tourism, the increase in the number of tourist resorts and houseboats has resulted in several ecological issues, mainly due to waste disposal and oil pollution (Hatha et al., 2008; Safoora Beevi and Devadas, 2014).

According to the CRZ notification 2011, the Vembanad Wetland system is categorized as a Critical Vulnerable Coastal Area (CVCA) under which special consideration is given to protect its critical coastal environment. The CRZ notification restricts construction of new built up in the CRZ region close to the estuary, with certain exceptions (MoEF, 2011). Even after the implementation of the regulation, the degradation of the wetland has continued due to various developmental activities (Sreejith, 2013; Asha et al., 2016; Sruthy et al., 2017). Also, since 2011, an increase in new residential complexes and settlements that violate the notification, was noticed (Sudhi 2016) which has raised questions regarding the effectiveness of the CRZ implementation. To understand how the notification has brought changes to the wetland, a survey was conducted by us between 29th May 2019 to 2nd June 2019 where 200 buildings constructed between 2012 and 2018 in the CRZ region were identified using Google Earth and 185 of those buildings were verified on the field. Through this survey, it was found that residential as well as commercial buildings have been built in this time period, over the CRZ region. To quantify all such encroachments (to the CRZ), in the Vembanad wetland system, the detection and mapping of the built up using remote sensing was essential.

The extent of this study was limited to the Northern half of the estuary as CRZ around inland water bodies are applicable only to regions that have a tidal influence, which is decided upon the salinity levels of the water body during the driest period of the year. And as the TMB (figure 1) regulates the southward entry of saline water, the CRZ regulations are not applicable to these regions south of the TMB (MoEF, 2011). The study area stretches for 46 km in the North-South direction covering a total area of 4620 ha which was selected based on the extent of CRZ area in the CZMP (NCESS, 2018) and the extent of available LISS-IV satellite imagery.

As per the 2011 notification CRZ refers to all CRZ I, II and III zones, but in this study “CRZ region” refers to the CRZ II and the NDZ of CRZ III, where the construction of new built up was restricted as per the notification. The width of this CRZ region is narrow and ranges between 50 to 100 meters as shown in figure 3. The detailed information on CRZ, the restrictions and exceptions are described in (MoEF, 2011) while a summary about the zones are provided in supplementary table 1.

3. Materials and Method

3.1 Materials

In accordance with the CRZ Notification of 2011, the National Centre for Earth Science Studies has published the CRZ maps with a scale of 1:25,000 in the Coastal Zone Management Plans which delineate the HTL, the CRZ boundary (a line that runs parallel to the HTL on the landward side) and the four different regions of CRZ (NCESS, 2018). CRZ regions along the Vembanad estuary other than that on the coast of Arabian sea were georeferenced and digitized from the Coastal Zone Management Plan of Kerala. To identify the newly constructed built up in the narrow swath of the CRZ region which may be smaller than 10m by 10m, satellite images with at least 5m spatial resolution were essential. Linear Imaging Self-Scanning Sensor-4(LISS IV) has been proven useful in such cases for urban change detection (Gupta and Jain, 2005; Kiran, 2014; Basawaraja et al., 2011; Kumar et al., 2017; Jain et al., 2014) as well as land use land cover mapping (Verma et al., 2016; Reng et al, 2018) and up to level 3 land cover maps can be prepared using its data product (Gupta and Jain, 2005). LISS-4 is one of the sensors in the ResourceSat-2 satellite which operates on three different spectral ranges: green (0.52-0.59µm), red (0.62-0.68µm), and near-infrared (0.77-0.86µm), capturing images at 10-bit quantization with a spatial resolution of less than 5.8 meters. LISS-4 images were obtained from the National Remote Sensing Centre, India for the dates 8th February 2012 and 24th February 2018 an interval of 6 years after CRZ 2011 came into effect.

Ground truth information was collected by a combination of field survey and Google Earth identification. Google Earth has been used in various studies for analysing the changes and mapping specific features in many studies (Abbas et al., 2010; Vikrant et al., 2015; Chinnasamy et al., 2021) as well as for preparation of land cover maps (Hu et al., 2013, Malavizhi et al., 2016). It serves as an alternate approach for ground truthing due to the high-resolution imageries available over different time periods and have been used as ground truth data (Jan et al., 2009; Gordon et al., 2011; Dorais et al., 2011). The Google Earth platform was used to visualize the CRZ region at two different time periods and identify the built-up changes in the CRZ region. About 185 buildings constructed after 2012 in the CRZ region were identified using Google Earth and were further verified through field surveys.

3.2 Methodology

3.2.1 Preprocessing

Radiometric corrections that convert the Digital Number (DN) values in the data to Top of Atmospheric Reflectance (TOA) were performed on the satellite imagery to normalize the images that were obtained at different solar illumination angles. Regions covering vegetation and water bodies as per the 2018 imagery were masked in both the imagery (2012 and 2018) using Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI; McFeeters, 1996) thresholding. As the aim of the study is focused on areas that have changed to built-up, this masking would reduce the number of pixels used in further analysis and would not affect the objectives of the study. The threshold values for NDVI and NDWI masks were decided by collecting the NDVI and NDWI values of pure vegetation and pure water pixels respectively and finding the minimum values (0.65 for NDVI and 0.2 for NDWI). As the threshold for this masking process was chosen carefully to exclude pixels that are purely water bodies or vegetation, the masking did leave some vegetation and waterbody pixels behind.

With the advancement of digital image processing techniques, various change detection techniques have been used in different studies for analysing general as well as specific land cover changes (Lu et al., 2004). Each technique has its own pros and cons and the performance of one technique over the other is always debatable (Lu et al., 2004). In this study we have chosen three different change detection methods: image ratio/ band ratio, Principal Component Analysis (PCA), and spectral–temporal combined analysis; as a pre-processing step, the results of which were used for classification using machine learning classifiers to extract the pixels which denote the changes to built-up.

3.2.1.1 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) (Wold et al., 1987) has been used in several change detection studies where the principal components derived from temporal stack of imagery is used to detect changes in vegetation (Fung and LeDrew, 1987); land cover change (Maldonado et al., 2010); urban land use changes (Deng, 2008).In this study the PCA is used as a pre-processing step on the stack of two masked images of 2012 and 2018 transforming the six-band temporal stack to six principal component layers which was further used for classification. In the False Colour Composite (FCC) images formed by using principal components 2, 3 and 4, the newly constructed buildings showed a bright cyan colour which was helpful in sample collection in complements to Google Earth (figure 2).

3.2.1.2 Image ratio / Band Ratio (BR)

Image ratio or band ratio involves dividing the pixel value from images of two different time periods. Each spectral band in the 2012 imagery was divided by its corresponding spectral band in the 2018 imagery to obtain the band ratio image. The resulting band ratio image thus consists of three bands which were used for the classification. As the spectral reflectance at the same locations of two different time periods are divided by each other, this technique reduces impacts caused by sun angle, shadow, and topography (Rosen, 2005).

3.2.1.3 Spectral Temporal Combined Analysis or Temporal Composite

Spectral Temporal Combined Analysis (STCA) involves the stacking of different temporal bands which are then used as independent variables to classify the different types of changes using training data. In this study, we used STCA by stacking the 2018 imagery over the 2012 imagery to form a spatial-temporal stack comprising of six bands and further, each band in the stack was standardized with respect to the mean and standard deviation values of that band. Another such standardized stack was created, where in addition to the primary bands, the NDVI for each year's image was added, resulting in a stack of eight bands. This was done to understand if the inclusion of NDVI will improve the classification results.

3.3 Classification

For classifying pixels that indicate new built-up that appeared between 2012 and 2018 (target pixels), samples of both target pixels and background pixels (i.e., pixels from regions that remained the same or went through some other land cover changes) were required. Some of the target samples were collected using Google Earth and verified by ground truthing during the field visit, while the rest of the target samples were collected using the FCC of PCA and were cross verified using Google Earth. To include all possible combinations of land cover changes or non-changes other than those that are a part of target pixels into the background sample, four level-1 land cover types, vegetation, water, barren, and built-up area were assumed, and unchanged samples were collected for each land cover type. For the changed samples, pixels were collected for water to barren, vegetation to barren, barren to water, vegetation to water and barren to vegetation. All these changed and unchanged samples were then combined to form the background samples. The target and background samples were divided into training (60%), validation (20%) and testing samples (20%) for the purpose of training and validating the classifiers. The training set had 2632 target pixels and 2407 background pixels while the validation samples consisted of 803 target pixels and 878 validation pixels.

Initially to compare the efficiency of four different change detection pre-processing techniques (PCA, BR, STCA, STCA-NDVI), a common machine learning algorithm was used to classify the four different datasets produced by these techniques. The classifier chosen was SVM with Gaussian RBF (Radial Basis Function) kernel (Scholkopf et al., 1997) and was implemented on Google Earth Engine platform. The classifier was trained using the training samples and was validated using the set aside validation samples for each of the four pre-processed datasets. Further grid search was done by repeated training and validation for each case to find the optimum cost and gamma values which are the hyperparameters of the RBF-SVM classifier. The cost (C) is the regularization constant, or penalty parameter of the classifier and gamma (ɣ) is the kernel width that defies the shape of the gaussian kernel. The optimum cost and gamma values that were obtained through grid search for each of the four cases along with their validation accuracy are listed in table 1. The four SVM models which were trained over PCA, BR, STCA and STCA+NDVI pre-processed layers and were further tuned to optimum hyperparameter values were then evaluated using the testing samples. The number of target and background samples in the testing dataset were almost similar in number to those present in the validation dataset. In order to compare the performance between the four approaches, assessment metrics, overall testing accuracy (OA), recall, precision, and f1- score were evaluated for each case, which are listed in table 2.Based on the testing accuracy of the four pre-processed datasets (table 2), the dataset that gave the best validation accuracy was selected and two additional classifiers (random forest, and ANN) were used with the aim of improving the performance of classification. For the random forest models, tuning was done two of the hyperparameters- number of decision trees to create per class and maximum number of variables (dataset bands in this case) are considered for splitting a node of decision tree. The Neural Network model was implemented using Colaboratory (https://research.google.com/colaboratory), a machine learning research tool by Google that provides computational resources. The network architecture of the back propagation neural network model used in this study consisted of an input layer, two hidden layers and an output layer. The neuron in the input layer was equal to the number of layers in the selected pre-processed dataset. There were 64 and 32 neurons in the first and second hidden layers respectively. Each neuron in hidden layers was activated by ReLU (Rectified Linear Unit) (Dahl et al., 2013) activation function and were passed on for batch normalization before getting connected to their following layers. A 20% dropout was implemented on the hidden layer neurons to reduce overfitting. The output layer consisted of two neurons representing the target and background classes which were activated by SoftMax function. The training of this network was driven by stochastic gradient descent along with Adam optimization algorithm with initial learning rate fixed to 0.0005 (Kingma et al., 2014). The network was trained and validated over 200 epochs with a step size of 15, using categorical cross entropy as the loss function. For both random forest and the ANN the training, testing validation samples were same as the ones used for the SVM model. Results Comparing the classification results of SVM over the four pre-processed datasets, it was found the PCA pre-processed dataset furnished better testing accuracy and F1-score compared to the other approaches (table 2). As, the principal components formed over the temporal stack of imagery were able to capture the targeted changes better, the PCA pre-processed dataset was further used to compare between the SVM, random forest and ANN classifiers. The random forest classifier produced maximum validation accuracy (95.18%) was achieved when the number of decision trees were fixed to 32 and the number of principal components required to split a node was set to three. The comparison of the evaluation metrics using the testing samples between the SVM, random forest and ANN models using the testing samples are shown in table 3. Although the ANN model had the best recall value which specifies that it detects the new built up better than the other models, its lower precision value indicates that the model overpredicts some background pixels as target when compared to other models. The SVM however performed with a good balance in such a case, where it had the highest precision which was also equal to its recall. The random forest classifier showed better recall when compared to precision and outperformed the other classifiers in terms of overall accuracy. The detection of buildings at three different locations by all the three classifiers are shown in figure 3. Visualizing the results for all the three models, it was inferred that though random forest was able to classify the targets precisely, it fails to classify some of the target pixels captured by the ANN model. While in the case of SVM, the model overpredicts target pixels. However, as the classification of principal components using the random forest model produced better overall accuracy and recall than the other models, the trained random forest model was used to classify the PCA dataset over the entire extent covered by the CRZ region. The target pixels falling in the CRZ region were clipped and the area of the targets within the region is quantified as per each village. As the area covered by the CRZ region differs from village to village, the percentage of new built-up area within the CRZ region, for each village was also calculated (Table 4, Figure 4).

4. Discussion

The different preprocessing and classification algorithms used in this study has been used in many change-detection studies, and the performance of the algorithm has differed from one to another (Lu et al., 2004). Studies have shown that PCA combined with other classifiers such as ANN provides better performance than training the classifiers directly over the combined temporal imageries (Deng, 2008; Liu and Lathrop, 2010). One the contrary, Zong et al., (2013) compared the STCA technique with the PCA technique for land cover change detection and found that found that STCA using ANN gave better results as compared to PCA technique. Similarly, Seto and Liu, (2003) showed that spatial temporal analysis using the ARTMAP ANN classifier produced better results compared to Bayesian maximum likelihood classifier. Tong et al., (2010) also used back propagation neural networks but in addition to a genetic algorithm evolved model over STCA for urban sprawl analysis in Shanghai. In the case of detecting the land use changes related to built-up or settlements, spectral temporal analysis or PCA has been used alone or in combination with a classifier in most of the studies pertaining to urban land use changes (Liu and Lathrop, 2010; Pagot and Pesaresi, 2008; Seto and Liu, 2003; Huang et al., 2010; Tong et al., 2010). Like the pre-processing algorithms, the use and preference of the classifiers for change detection also differs with respect to the studies. Cao et al., (2014) has used multiresolution set evolution with SVM for automatic change detection by combining both pixel-based and object-based changes. SVM was also found to outperform binomial logistic regression (Huang et al., 2010) and ANN (Nemmour and Chibani, 2006) in spectral temporal analysis for land cover change monitoring. Random forest has also been used in various land cover mapping and land cover change analysis studies (e.g., Noi and Kappas, 2018; Galiano et al, 2012; Eisavi et al., 2015) and is known for its capability to determine the importance of variables. Different variations of neural networks have also been used in such cases for detecting the changes in land cover (Liu and Lathrop, 2010; Tong et al., 2010; Zong et al., 2013; Seto and Liu, 2003).

In the current study, we selected three different preprocessing and classification techniques for our study purpose and were able to obtain maximum accuracy with the combination of PCA pre-processed dataset and random forest classifier. The CRZ region in our study area has a width less than or equal to 100m and mapping the new built up in the narrow width of the CRZ is quite challenging, as it demands very high-resolution imagery for capturing the features. This can be understood from figure 3, where the buildings are barely distinguishable in the LISS IV image. However, the random forest was able to capture these features quite accurately with an overall testing accuracy of 95.8%. The total area of target pixels in CRZ region was quantified as 149.31 hectares using the random forest model, which in turn is the total area of built up that appeared after 2012 in the CRZ region. Table 4 summarizes the area of the CRZ region occupied by targets and the percentage of area covered by targets within the CRZ region, for each village. All the villages in which the percentage of target area is more than 5% belong to Kanayannur and Kochi taluks, which form the Kochi corporation. Thiruvankulam village shows a highest percentage (12%) of targets occupying the CRZ region, which is attributed to the expansion of the Bharat Petroleum Corporation Limited (BPCL) installation in the region. The next highest proportion of targets in CRZ region is observed in the three villages of Edakochi, Rameswaram and Poonithura, which contains the major portion of CRZ region areas of Kochi taluk and the percentage of CRZ region occupied by target pixels in these villages are between 7% to 8%. Most of the villages in Alappuzha district have very less percentage of area occupied by targets ranging between 0% to 4%. It is obvious that the target areas within the CRZ region are greater in the urban areas (around Kochi and Ernakulam in the north) compared to rural towards the south of the study region. As the percentage gradually decreases from the north~~ern part~~ to the south~~ern~~ (figure 4), it should be considered that with the expansion of urban centres, the intrusion of new built-up in the CRZ might begin to increase in the southern villages in the future. Partly in agreement with our results various studies have shown substantial increase in built up with reduction in barren land and mangroves in regions that intersect with the current study region (Prasad and Ramesh, 2019; Sundar and Deka 2021; Shaji et al., 2017). Between 2013 and 2017, a 41% increase in built up areas have been estimated in six districts of Kerala which includes the three districts covered in the current study (Ernakulam, Alappuzha, and Kottayam) (Sundar and Deka, 2021).

During the field visit done by the authors as a part of sample collection, a stark difference was noted in the cleanliness of the water bodies around the buildings in rural areas compared to those in the urbanized locations. Areas where people’s livelihood is dependent on the water body for fishing and clam collection, had negligible waste dumping compared to the urban areas where the people’s livelihood is no longer dependent on the wetland. For example, during the field visit it was noted that Thevara-Perandoor canal in Kochi was so much polluted that it appears as a sewage canal. This was also implied in the Kerala High Court order on 6th November 2019 that the Thevara-Perandoor canal had turned into a "rancid, putrid, sewage canal", dumping waste and draining sewage in the canal was made liable for prosecution and punishment, under relevant sections of Kerala Panchayat Raj Act 1994, Kerala Irrigation and Water Conservation (Amendment) Act 2018 (The News Minute, 2019). The CRZ also surrounds this canal as it is connected to the Vembanad estuary and eight buildings were identified in the CRZ, surrounding this canal during the field visit and these were built between 2012 and 2018. Also, in the CRZ region surrounding the channel, a total built-up of 1.1 ha was detected by the random forest model.

4.1 Limitations

Though the CRZ notification of 2011 is focused on violations with respect to the specific type of newly constructed buildings and similar structures, in this study we have mapped the general built-up instead of specific structures, as identifying such structures requires very high-resolution satellite imagery which was beyond the limits of this study. It should be noted that the result in table 4 provides the overall area captured by new built-up but not the specific area occupied by new buildings alone, i.e., this result also includes new roads and other built-up features. Hence, further processing and manual editing would be required to extract the buildings, or such similar structures mentioned in the CRZ notification from all the detected built-up. Even with extraction of interested structures, not all structures would be under violation of the notification, as some of them might fall under the exceptions denoted by the CRZ notification such as facilities for receipt and storage of petroleum products (hence the BCPL facility extension that was detected in Thiruvankulam village), desalination plants, weather radars stations, etc. Even with the above limitations it must be noted that the output will cover the intended new built-up features. Secondly, though some of the training/validation/testing samples were collected and verified on ground, most samples were collected directly using google earth temporal imageries and were not verified on ground. This might decrease the accuracy of the models to some extent when tested with new sets of samples acquired directly from the study area through field survey. With respect to the algorithms used in classification section, though the performance of all the three classifiers over the PCA dataset was tested, the performance of ANN and random forest classifier over the STCA and band ratio output dataset was not tested as the PCA dataset displayed higher accuracy with SVM classifier compared to the STCA and band ratio output dataset. Also tuning for hyperparameters of the neural network model such as number of neurons in each hidden layer, dropout percentage, number of hidden layers was not performed.

5. Conclusion

This study is one among the very few studies that has used remote sensing for understanding the increase in built-up in the CRZ (e.g., Chinnasamy et al., 2020) and the only study that has used change detection methods along with machine learning algorithms to map these built-up regions to understand the implementation of the CRZ notification over a Ramsar wetland, in India. Monitoring anthropogenic activities at the proximity of water bodies is crucial in understanding its impacts over vulnerable wetland systems. This will aid in drawing necessary policies for the conservation of the system and in protecting the lives and livelihoods of its many dependents. In this study, the built up that appeared in the CRZ-II and NDZ zones (CRZ region) after February 2012 and before February 2018 was mapped with 96% accuracy. The construction of many of these built ups might violate the norms laid out in the CRZ Notification of 2011. This study emphasizes on the significance of using remote sensing techniques backed with on ground corroboration, along with machine learning algorithms, in monitoring the changes on land after the implementation of the regulation and the new cloud processing platforms that helped process the data more rapidly. Though the satellite imagery that was used in this study did not have a high spectral resolution, satisfactory results were obtained with the advantage of machine learning algorithms. The results of this study which includes the locations of the new built-up identified by the model, can further be used for collecting background information about the identified buildings to understand the gap between the regulations of the 2011 notification and its implementation. The techniques used here can be extended to other wetlands systems in India, to understand the true impacts of the CRZ notifications that have been issued in the past.

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8. Conflicts of interest

The authors declare no conflicts of interest.

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10. Figures and captions

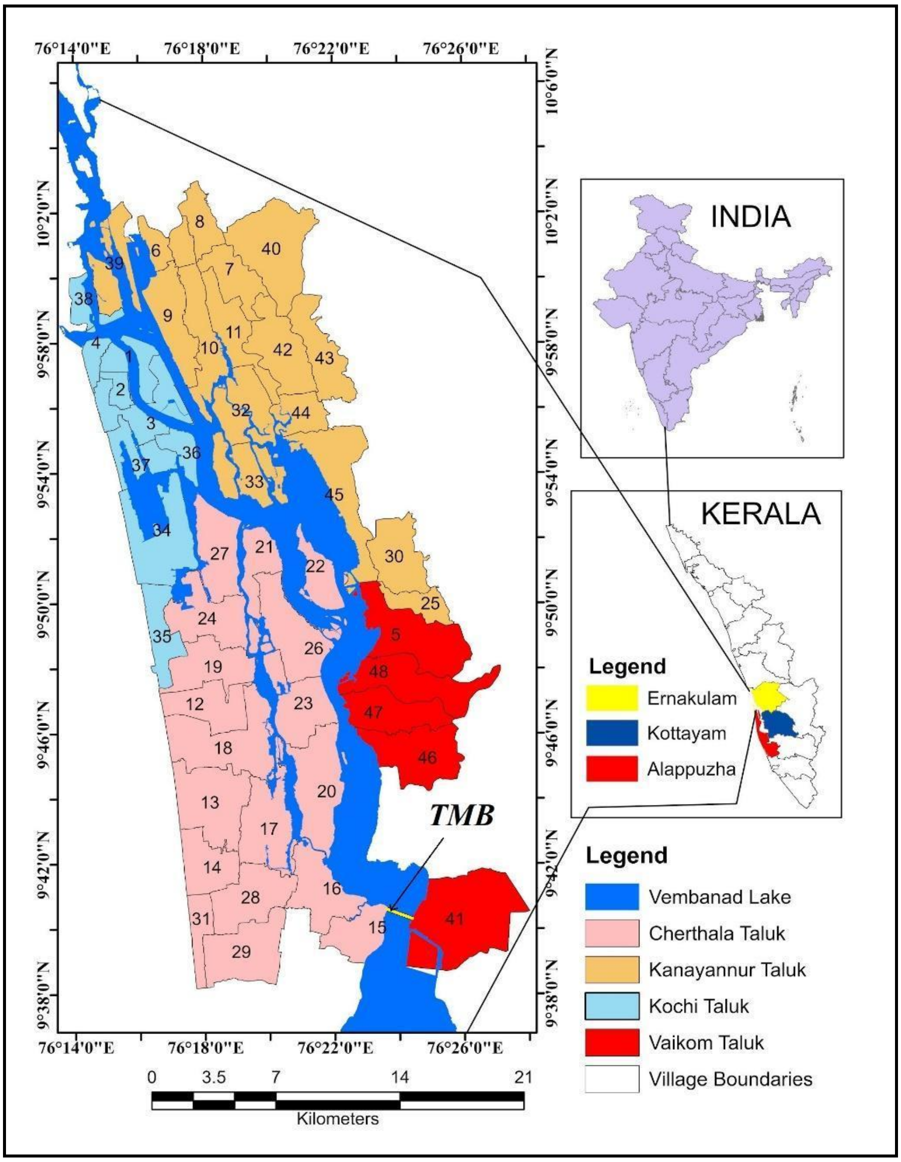

Figure. 1. Study area map showing part of Vembanad estuary, villages considered in this study area that contains the CRZ region and the Thanneermukkom Bund (TMB). Village boundaries source (NCESS, 2018).

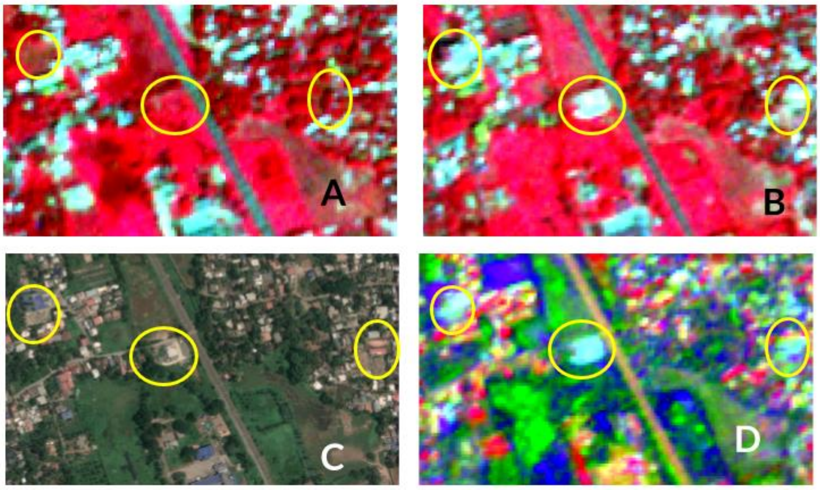

Fig. 2. Comparison of February 2012 and February 2018 LISS IV imagery (A, B respectively) with yellow circles indicating new buildings that were constructed between the two periods at Thripunithura in Kochi. Image D is False colour composite (FCC) of Principal Component Analysis (PCA) pre-processed dataset with PC 2,3,4 used for red, green, and blue bands. **A**- LISS IV False Colour Composite of February 2012, **B**- LISS IV FCC of February 2018, **C**- Google Earth, Maxar Tech. April 2019 imagery, **D**- False colour composite (FCC) of Principal Components 2, 3, 4.

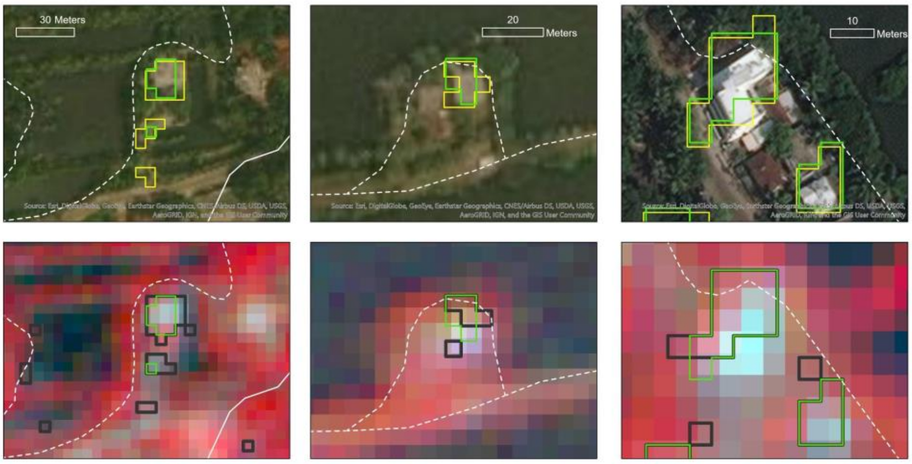

Fig. 3. Target pixels that indicate new built-up classified by Artificial Neural Network (ANN), random forest and Support Vector Machine classifiers shown with yellow, green, and black lines respectively. The area between the dashed white line (High Tide Line) and the solid white line (CRZ boundary) is the CRZ region. Top image: ESRI World imagery, Bottom image: LISS-IV imagery of February 2018.

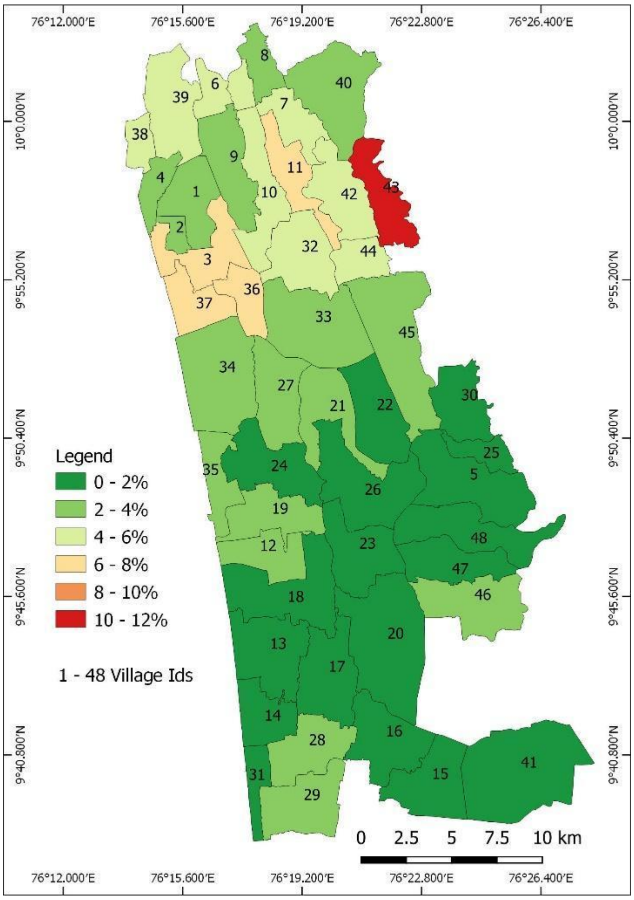

Fig. 4. Percentage of built-up appeared between 2012 and 2018 within the CRZ region computed using the PCA – random forest model. (Village Id shown on the map are listed in table 4)

11. Tables

Table 1. Validation results for Support Vector Machine (SVM) classification over output from Principal Component Analysis (PCA), Band Ratio (BR), Spectral Temporal Combined Analysis (STCA) and STCA with Normalized Difference Vegetation Index (NDVI) using the validation samples. C and ɣ are the optimum cost and kernel width values chosen for each of the SVM-RBF model using grid search.

Pre-processed dataset	Number of Bands/Features	Optimum(C)	Optimum (ɣ)	Validation Accuracy
PCA	6	45	0.42	95.36%
BR	3	380	0.53	93.17%
STCA	6	10	1.4	93.58%
STCA+NDVI	8	20	0.4	95.00%

Table 2. Support Vector Machine (SVM) classification test results obtained by testing the trained and validated SVM models over testing samples. Principal Component Analysis (PCA), Band Ratio (BR), Spectral Temporal Combined Analysis (STCA), Normalized Difference Vegetation Index (NDVI)

Pre-processed Dataset on which SVM model was trained	Recall	Precision	F1-Score	Overall Accuracy
PCA	95.67%	95.67%	95.67%	95.48%
BR	93.37%	89.71%	91.50%	91.90%
STCA	95.78%	95.13%	95.45%	95.24%
STCA+NDVI	95.67%	95.45%	95.56%	95.36%

Table 3. Results for testing the Support Vector Machine (SVM), random forest and Artificial Neural Network (ANN) models trained over Principal Component Analysis (PCA) pre-processed dataset. The trained and validated models were tested using the testing samples.

Classifier	Recall	Precision	F1-Score	Overall Accuracy
SVM	95.67%	95.67%	95.67%	95.48%
Random Forest	98.29%	93.90%	96.04%	95.77%
ANN	98.57%	91.51%	94.91%	94.70%

Table 4. Area of new built-up within Coastal Regulation Zone (CRZ) of each village quantified using target pixels identified by random forest classifier that was trained, validated, and tested over Principal Component Analysis (PCA) pre-processed dataset. The village id was assigned to identify the corresponding village in figures 1 and 4. Hectare (ha).

Village Id.	Village Name	Area of target pixels in CRZ (ha)	CRZ Area(ha)	% Of CRZ occupied by target pixels
1	Mattancherry	2.22	60.38	3.68%
2	Thoppumpady	0.75	18.95	3.98%
3	Rameswaram	8.19	107.7	7.61%
4	Fort Kochi	0.80	32.65	2.46%
5	Chempu	0.84	83.84	1.00%
6	Cheranalloor	4.19	78.17	5.36%
7	Edappally South	3.30	67.12	4.92%
8	Edapally North	0.37	17.27	2.16%
9	Ernakulam	3.88	107.39	3.61%
10	Elamkulam	5.53	112.42	4.91%
11	Poonithura	7.27	102.47	7.10%
12	Kuthiyathodu	2.48	90	2.76%
13	Pattanakkad	4.73	239.28	1.98%
14	Kadakkarappally	1.49	88.5	1.69%
15	Thanneermukkom North	0.70	57.42	1.22%
16	Kokkothamangalam	1.40	93.5	1.50%
17	Vayalar East	2.67	181.8	1.47%
18	Thuravoor South	3.14	184.84	1.70%
19	Kodamthuruth	2.66	132.41	2.01%
20	Pallippuram	2.60	142.89	1.82%
21	Arookutty	2.04	95.16	2.15%

22	Perumbalam	0.45	79.35	0.57%
23	Thykkattusserry	1.32	93.62	1.41%
24	Ezhupunna	3.78	196.42	1.92%
25	Keecheri	0.02	19.76	0.10%
26	Panavally	1.36	106.94	1.27%
27	Aroor	4.62	154.9	2.98%
28	Cherthala North	0.18	6.05	3.03%
29	Cherthala South	0.19	5.62	3.35%
30	Amballur	0.41	24.13	1.71%
31	Arthunkal	0.41	21.94	1.88%
32	Maradu	7.20	167.77	4.29%
33	Kumbalam	9.37	235.1	3.98%
34	Kumbalangi	6.96	196.67	3.54%
35	Chellanam	1.16	54.64	2.12%
36	Edakochi	6.28	81.09	7.74%
37	Palluruthi	7.10	103.92	6.83%
38	Puthuvype	1.95	34.82	5.60%
39	Mulavukad	8.88	171.48	5.18%
40	Vazhakkala	1.58	71.55	2.21%
41	Vechoor	0.62	43.24	1.43%
42	Nadama	7.88	170.47	4.62%
43	Thiruvankulam	6.80	58.31	11.66%
44	Thekkumbhagam	1.96	37.4	5.24%
45	Manakkunnam	3.37	145.54	2.32%
46	Naduvila	1.57	43.86	3.59%
47	Vadakkemuri	1.67	134.47	1.24%
48	Kulasekharamangalam	0.93	66.88	1.38%

Supplementary Table 1: Differences between each zone as per CRZ 2011 and 2018

Zones	2011	2018
CRZ I	Eco-sensitive and intertidal zone	1. CRZ I A – Eco-sensitive zone 2. CRZ I B – Inter-tidal zone
CRZ II	Areas which have been developed up to or close to the shore	Areas which have been developed up to or close to the shore
CRZ III	Areas that are relatively undisturbed and do not fall under CRZ I or CRZ II	1. CRZ III A – CRZ III areas, where the population density is more than 2,161 km^2, as per 2011 census 2. CRZ III B – Areas with population density of less than 2,161 km^2, as per 2011 census
CRZ IV	Areas between low tide line (LTL) and 12 nautical miles into the sea/tidal influenced waterbodies	1. CRZ IV A – 12 nautical miles from the LTL towards the sea 2. CRZ IV B – Tidal influenced waterbodies
NDZ (No Development Zone)	Extends up to 200m from high tide line (HTL) landwards in CRZ III area	Extends to 50m from HTL in CRZ III An area and 200m from HTL in CRZ III B area