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Review Article

Application of soft computing techniques in coastal study – A review

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Abstract

Coastal zone is the triple interface of air, water and land and it is so dynamic in nature which requires expeditious management for its protection. Impulsive change in shoreline and submergence of low lying areas due to sea level rise are the solemn issues that need to be addressed. Indian coastline of about 7516 km is under threat due to global warming and related human interventions. Remote sensing data products provide synoptic and repetitive view of the earth in various spatial, spectral, temporal and radiometric resolutions. Hence, it can be used in monitoring coastal areas on a temporal scale. Critical Erosion hotspots have to be given proper protection measures to avoid further damages. Satellite images serve in delineating shoreline and extracting the hotspots to plan the mitigation works. Coastal inundation maps can be created using remote sensing and geospatial technologies by assuming different sea level rises. Those maps can serve as a base for planning management activities. Soft computing techniques like Fuzzy Logic, Artificial Neural Network, Genetic Algorithm and Support Vector Machine are upcoming soft computing algorithms that find its application in classification, regression, pattern recognition, etc., across multi-disciplinary sciences. They can be used in classifying remote sensing images which in turn can be used for studying the coastal vulnerability. The present paper reviews the works carried out for coastal study using conventional remote sensing techniques and the pertinency of soft computing techniques for the same.

Keywords: Artificial neural network; Coastal inundation; Remote sensing; Shoreline; Soft computing; Support vector machine.

1. Introduction

Coast is ever-changing in nature and is one of the significant environmental, biological and ecological zones of India. It is the intersection of three landforms namely land, water and air, extending between 200 m bathymetric contour to 200 m elevation contour [13]. It gains attention due to its multiple uses like tourism, productivity, trade and commerce etc., Shoreline is considered as the incomparable part of the earth surface and is recommended to be one of the 27 features acknowledged by International Geographic Data Committee (IGDC). Coastal zones face both natural and man-made hazards namely Sea Level Rise, shoreline change, tropical cyclones, storm surge, salt water intrusion and coastal inundation. The above endangerments lead to severe socio-economic losses.

Remote Sensing (RS) is a multi-disciplinary science and which can be effectively used in the coastal studies because of its repetitive and synoptic coverage. Sensors mounted at different heights provide data in various spatial, spectral, radiometric and temporal resolutions. The temporal characteristic of the sensor helps in change detection studies. Hence, shoreline mapping which depends on a temporal scale to find out the erosion and accretion hotspots can be carried out with RS images. Classification of RS images aids in converting a raw data into a meaningful set of information. It can be of two types namely supervised or unsupervised classification. Conventional methods of supervised classification include Parallelopiped, Minimum distance to mean and Maximum likelihood classifiers. Soft classifiers are also being developed namely Fuzzy Logic (FL), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Neural Network (ANN), Support Vector Machine (SVM), Self-Organizing Maps (SOM) etc., One of the above classification strategies can be used in preparing coastal inundation maps

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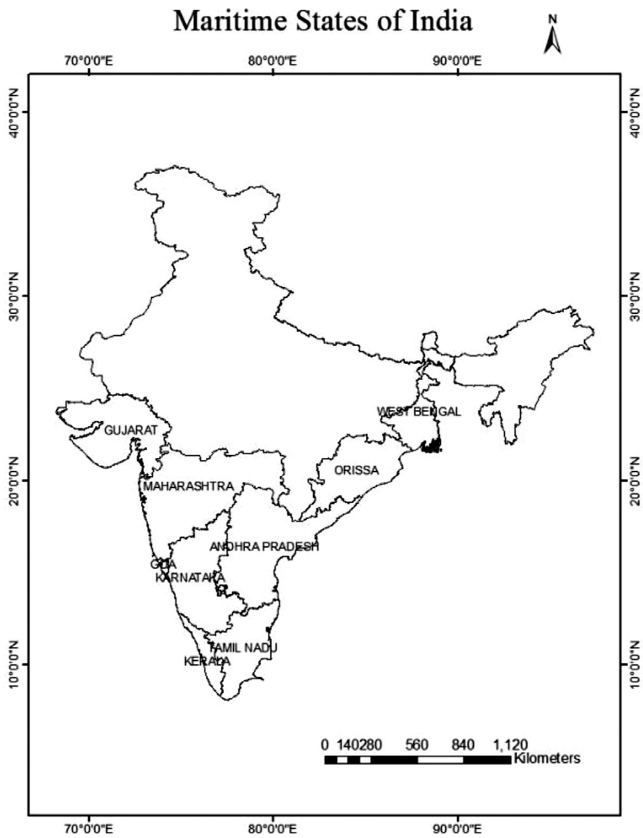

Fig. 1. Maritime states of India.

that will help in planning the mitigation measures. The principle of traditional classification methods is Experimental Risk Minimization (ERM) where it can obtain good result when huge training data is available. On the other hand, soft methods work on Structural Risk Minimization (SRM) wherein with minimal training data, one can achieve good results [14].

The present paper is organized in six sections as follows: Section 1. Introduction; Section 2. Shoreline mapping – conventional method; Section 3. Coastal inundation – conventional method; Section 4. Soft computing techniques in wind turbine study; Section 5. Soft computing in classification; Sub-Section 5.1 ANN in classification; Sub- Section 5.2. SVM in classification; Section 6. Discussion and concluding remarks.

2. Shoreline mapping – conventional method

The occurrence of shoreline change may be due to natural or anthropogenic processes. The natural processes includes the effects of waves, currents, tides and winds while the latter includes sand mining, offshore dredging or building of coastal structures. Shoreline changes draw more attention since they are the most important environmental indicants that directly impact on the economic development and coastal land management. The nine maritime states of India are Gujarat, Maharashtra, Goa, Karnataka, Kerala, TamilNadu, Andhra Pradesh, Orissa and West Bengal as shown in Fig. 1.

Various studies have been carried out in all the above mentioned states by many researchers. Murali et al. [49] have studied the coastline of Paradip in the state of Orissa from 1998–2005. Paradip region is located at the mouth of Mahanadi river and hence the change in coastline due to the seasonality of the river had been well understood. Natesan et al. [52] have done an extensive study on the most vulnerable coast of TamilNadu by using geospatial technologies and Digital Shoreline Analysis System (DSAS) for the period of 1978–2014. For ease of analysis, TamilNadu coast had been divided into four zones, each stretch covering the coastal areas of Bay of Bengal, Palk Strait, Gulf of Mannar and Indian Ocean. Natesan et al. [53] and Chandrasekar and Mujabar [48] have also done the study on Vedaranyam coast and Kanyakumari coast of TamilNadu respectively and concluded that proper nourishment had to be given alongside the shoreline to prevent accretion and erosion.

Research work by Rao et al. [65] on the narrow Kerala coast had identified the actuating factors, processes and frequency of dynamic changes in coastline stretches. It has been found that shoreline change is maximum in the stretch underlain by soft sediments and also at the intersection of lineaments. Karnataka coast has one major port and ten minor ports and is one of the most indented areas with a number of river mouths, bays, spits, sand dunes, lagoons, creeks, cliffs and long beaches. This clearly unveil the problems associated with this coast. A numerous researchers have studied this coast either as a complete stretch or by considering a particular river mouth. ChenthamilSelvan et al. [11] and Hedge et al. [28] have analyzed the entire stretch covering three coastal districts namely Dakshina Kannada, Udupi and Uttar Kannada for the years 1973–2006 and 1991–2014 respectively by utilizing DSAS. Dakshin Kannada coast has two crucial river mouths namely Netravathi–Gurpur river mouth (with breakwater) and Mulky–Pavanje river mouth (without breakwater). Thus this stretch of Karnataka coast is ideal in studying the effect of breakwater on coastal erosion. Shetty et al. [74] have worked on the shoreline change along Mangalore coast having the above said river mouths for the period of (2005–2013) without employing DSAS. In addition to the studies on shoreline change over past years, there are also researchers working to predict the position of shoreline from historical data [43]. For the entire coast of India, long-term shoreline change for a period of 38 years from 1972–2010 has been done by Institute of Ocean Management, Anna University, Chennai and the database had been created and presented in the public domain.

A numerous studies have reported in the recent past stating the significance of satellite images in studying the retrieval of shoreline after the damage had happened. Katchal island in Andaman and Nicobar where the erosion is more prevalent has been studied for aftermath of 2004 Tsunami [82].

The impact of coastal structures such as sea wall, groins and breakwater on shoreline change has been studied in the Puducherry region [71].

The summary of data used in the above studies is presented in this section. Survey of India (SOI) toposheets,

Table 1
Study on Shoreline Mapping.

Researchers' Name	Year	Study area
Rao et al.	2007	Kerala Coast
Maiti et al.	2008	Balasore, Orissa and Midnapur, West Bengal
Murali et al.	2009	Paradip Coast, Orissa
Chandrasekar and Mujabar	2011	Kanyakumari Coast
Natesan et al.	2013	Vedaranyam Coast
ChenthamilSelvan et al.	2014	Karnataka Coast
Natesan et al.	2015	TamilNadu Coast
Hedge et al.	2015	Karnataka Coast
Shetty et al.	2015	Mangalore Coast, Karnataka
Yunus et al.	2016	Katchal island, Andaman
Selvan et al.	2016	Puducherry

Indian Remote Sensing (IRS) – Linear Imaging Self Scanner – III (LISS III) data product, Shuttle Radar Topographic Mission's (SRTM) Digital Elevation Model (DEM) and/or LandSat data products have been used. The general methodology followed is geometric correction of the satellite images, delineating the shoreline as vector maps using ArcGIS software and analyzing it with or without employing DSAS. Table 1 shows the works done by various researchers related to shoreline mapping.

3. Coastal inundation – conventional method

Sea Level Rise (SLR) is the one of consequences of global warming. This, in turn, causes the inundation of coastal low lying areas that bring on potential habitat and economic losses. Hence, it is primary to quantify the perils associated with the SLR to guide decision makers in future coastal infrastructure development. Land Use/ Land Cover (LU/LC) of the coastal area and its dynamics have to be considered in prior to contemplating the SLR owing to inundation losses. Coastal LU/LC undergoes change due to the dynamic nature of their surrounding environment.

Change detection studies are becoming important in the coastal areas. A review about all the types of change detection techniques for various LU/LC had been done in detail [41]. Image differencing, Change Vector Analysis (CVA), Gramm Schmidt (GS) transformation, Principal Component Analysis (PCA), Spectral mixture model, Li Strahler reflectance model and Tasselled Cap (TC) Transformation are some of the techniques on change detection. CVA method had been applied in monitoring changes in marine environments [45]. CVA method along with Transformed Normalized Difference Vegetation Index (TNDVI) have been used to study the recovery potential of Tsunami affected area along the Andaman sea coast of Thailand [67]. The change of spatial use of the coastal area can be estimated by calculating the exposure value which is the sum of Land Use Intensity (LUI) and Shoreline Use Intensity (SUI). LUI can be calculated by using the ratio of various LU/LC types. Similarly SUI can be calculated by using the ratio of various types of shoreline [34].

Table 2
Study on Coastal inundation.

Researchers' Name	Year	Remarks
Michalek et al.	1993	CVA in Marine region
Lu et al.	2004	Studied various change detection techniques for LU/LC
Marfai et al.	2008	Estimated inundation due to SLR
Dwarakish et al.	2009	Studied CVI of the Coast
Huang et al.	2010	LUI and SUI to study coastal change detection
Romer et al.	2012	CVA and TNDVI to study Andaman coast
Nayak et al.	2013	Estimated inundation due to SLR
Murali et al.	2014	Implication of SLR
Murali et al.	2015	Implication of SLR
Atif et al.	2016	Flood extent using MODIS
Belur et al.	2016	CVI of Karnataka Coast
Haldar et al.	2016	Study on aftermath of cyclone
Dhakate et al.	2016	Saline water intrusion

Murali [50] and Murali and Kumar [51] have examined the implications of SLR on LU/LC classes of coastal zones of Orissa and Cochin respectively. Effect had been studied on the major LU/LC classes like Agriculture, Built-up, Water body etc., by preparing inundation maps. They are useful in assessing the extent of SLR and potential impact on inundation. LU/LC map generated with conventional maximum likelihood classifier is merged with Digital Elevation Model for quantifying inundation. They considered the SLR of 1 m and 2 m to calculate the habitat loss. Dwarakish et al. [20] had done an extensive study along the Udupi coast of Karnataka, by calculating Coastal Vulnerability Index (CVI) along the coast and by preparing LU/LC map and inundation map of the study area. Nayak et al. [54] have divided the whole Indian coast into four regions namely coasts along Mumbai, Kochi, Chennai and Visakhapatnam and estimated that 34.906 sq. km. of Indian coast had been inundated due to SLR. Similar study had been done by Marfai and King [43] over Semarang city, Indonesia using IKONOS data. This study gained significance because there are about 17,500 islands covering 88,000 km of coastline in the Indonesian region.

Flood extent maps have been produced for Punjab province of Pakistan using Moderate Resolution Imaging Spectroradiometer (MODIS). In-situ data coupled with remote sensed data have been used to develop flood damage indexAtif, Mahboob, and Waheed [3]. Coastal Vulnerability Index (CVI) has been assessed for 298 km of Karnataka coast by dividing it into eight Taluks namely Karwar, Ankola, Kumta, Honnavar, Bhatkal, Kundapura, Udupi and Mangaluru. It had been reported that 68.65 km of the coast is under very high vulnerable category [4]. The repercussion of a cyclone event on the rice crop has been studied using Remote Sensing over the region of Odisha. Aforementioned study has been done using Synthetic Aperture Radar (SAR) data where backscattered radiation is recorded [25]. Saline water intrusion pathways has been found with the help of land forms and lineaments extracted from LISS III and SRTM [16]. Table 2 shows the works done by various researchers related to coastal inundation.

4. Soft computing techniques in wind turbine study

Coastal and offshore area serve as a potential region for the construction of wind farms to produce electricity. The wind speed over the offshore region is higher when compared to land and so fewer offshore wind turbines cab be able to produce more energy. Wind energy from a turbine encounters problem such as curtailment in the wind speed due to wake effect by other turbines. Wake effect is caused when a turbine is placed within the area of turbulence caused by another turbine or the area behind another turbine. This in turn triggered the reduction in wind speed leading to lessened power production. So as to increase the efficiency of wind farm, evaluating the parameters that influence on the wake effect, is one of the important research areas. One of the soft computing techniques, employed to study the various aspects of wind turbines and wake effect is, an Adaptive Neuro-Fuzzy Inference System (ANFIS). The prediction capacity of ANFIS has also been studied in the estimation of wind speed distribution. The output has been validated against most commonly used two parameter Weibull distribution. It is seen that ANFIS is preferable for assessing Weibull parameters for wind energy applications [60]. Similar research work has been done by Shamshirband [72] by using Extreme Learning Machine (ELM) and its efficiency had been compared with Support Vector Machine (SVM), Artificial Neural Network (ANN) and Genetic Programming (GP) for estimating the Weibull parameters (shape and scale parameter). A new class of Diffuser Augmented Wind Turbine (DAWT) is in use wherein the diffuser draws more wind towards low pressure regions and thus increases the energy production. Nikolić [56] have studied the effect of diffuser on the performance of rotor through estimating power output, torque output and rotational speed of the rotor using ANFIS and Simulink. Support Vector Regression (SVR) has also been used for envisaging wind turbine reaction torque [73]. Some more researchers have also contributed to the above area of research [61,55,73]. An attempt has been made by Pai et al. [57] to estimate the wind and wave parameters using SAR imagery. A numerous studies are made on wave and tidal forecasting that aid in proficient coastal management [24,64].

5. Soft computing techniques in remote sensing classification

Soft computing techniques can be used capably for Remote sensing image classification. In conventional classification technique, training and testing are done based on one pixel – one class method. So there arises a conflict in classifying mixed pixels, which most often end up in misclassification. Fuzzy Logic (FL) which takes into account of the belongingness of an element to a particular class through membership functions had been used for this purpose as an alternative method. [75,6]. Zadeh proposed the concept of fuzzy logic that dates back to 1960′s. Crispy sets, where an abrupt boundary exist were replaced by fuzzy sets where a tolerance is given to the boundary based on the degree of belongingness. The outcome of fuzzy classification depends on the predefined fuzzy rules. Genetic Algorithm (GA) which depicts the natural evolution can be used for optimizing the fuzzy rules which in turn provides good classification result [81]. Particle Swarm Optimization (PSO), one of the effective data mining technique was proposed by Eberhart and Kennedy. It had also been used in framing classification rules for remote sensing images [76].

Artificial Neural Network (ANN) mimics the human brain through a number of elements, similar to neurons which are interconnected to do processing. This processing depend on weighted connections, that are similar to synapses in the human brain. Neural network has to be trained to establish a relation between the input and output given during training. A good data set is required to draw better classification accuracy.

Machine learning examines the study and building of algorithms that can efficiently learn from and make predictions on data. SVM is one such powerful tool to classify the data into two categories, which implies that SVM is a binary classifier. The principle is to optimize the decision boundary that would maximize the margin around it. Margin is the region around each training sample through which decision boundary cannot pass. There exists two problems in classification. (i) When a problem is easy to classify and the boundary function is complicated more than it needs to be, the boundary is likely overfit. (ii) When a problem is hard and the classifier is not powerful enough, the boundary becomes underfit. SVMs are excellent examples of supervised learning that tries to maximize the generalization by maximizing the margin. It also support non-linear separation using advanced kernels, by which SVMs try to avoid over-fitting and under-fitting [80]. Multi- class SVM is achievable by concatenating multiple binary classifiers. In this paper, ANN and SVM are chosen to review their applications in the classification of remote sensing data and coastal study.

5.1. Ann in remote sensing data classification

Each of the pixel in the remote sensing images have its own characteristic value. The spatial organization of these pixels will be used for LU/LC classification [23]. The variation of the above mentioned characteristic values of the pixel give rise to the concept of texture. Several studies had been carried out based on texture based image classification by applying several parameters [27]. These techniques had been applied to Landsat images and an accuracy upto 80% had been obtained.

ANN research had experienced three periods of extensive activity. The first peak in 1940 s, when McCulloch and Pitts [44] proposed the first mathematical neuron model. This was followed by Rosenblatt’s [68] perceptron theory in 1960 s. Since the late 1980 s, there has been a dramatic growth in the level of research activity in the neural network field. The major development was the introduction of back- propagation learning algorithm for the multilayer perceptron. These advantages make ANNs an accepted alternative to traditional statistical methods for improving classification accuracy. Studies carried out by Hilbert and Ostendorf [31], Blaschke [8] and Kavzoglu and Colkesen [38] prove that in the last decade, neural network classifiers have been widely used in the fields of pattern recognition, image interpretation and clustering/categorization. Hepner [29] explains about how neural network can be applied to land cover classification of Thematic Mapper images. The neural network model had several training site examples to 'learn' the association between these sites and the desired land-cover classes. The obtained results were compared with the conventional supervised classification method and it was found that ANN is superior to conventional classification methods. Zhou and Yang [87] studied about developing some guides for parameterizing the multilayer perceptron (MLP) feed-forward back-propagation neural networks. It is found that the internal parameters significantly affect the classification accuracy. Madhubala et al. [42] classified LISS-III satellite images into different classes as agriculture, urban and water body by using pixel based classification and Back propagation technique in neural network Model. Accuracy was found to be increased as the size of the training dataset is increased. Gray scale aerial images can be classified into various types of classes like forest, water, city, agricultural field etc., by using ANN based classification [2]. With the advent of new technology, ANN was combined with various other methods like Fuzzy Logic, Genetic algorithms etc., Foody and Strahler [22] carried out a combination study of neural networks and fuzzy classification and concluded that fuzzy classification techniques are only a partial solution to the mixed pixel problem, as they only enable an appropriate representation of the land cover composition of pixels. Milan et al. [46] studied about the comparison of fuzzy classification and neural network classification with each other and both of them with Minimum distance method. Fuzzy and Neural network showed significant increase in classification accuracy than the conventional method. Xiong et al. [78] used both ANN and Decision Trees (DT) classifiers to extract LU/LC from remote sensing images and compared their accuracies with the statistical Minimum Distance (MD) classifier. Results indicate that ANN has better accuracy than the DT and MD classifiers. This shows that ANN is a more effective method for remote sensing image classification of mountainous areas because of its higher accuracy and superior performance than DT and MD classifiers. Investigating the sensitivity of neural networks with respect to various parameter settings has been the subject in an increasing number of studies, since this knowledge is critical to the design of efficient neural network models for improved performance [36,79].

ANN is suitable for problems when a large diversity in the dataset exist. It can also be used for segmentation and classification purposes effectively [70]. ANN had been used in image classification and high accuracy had been obtained [66]. Some of the classical statistical classification methods were compared with ANN to prove its superiority [7,59,83]. The use of artificial neural networks is, however, challenged by the difficulty of network design and parameterization. Many factors affect the performance of ANN that include network topology, training algorithm and parameters setting, and network architecture [39,86,87]. Table 3 shows the works done by various researchers related to ANN in Remote Sensing.

5.2. Svm in remote sensing data classification

Image classification and pattern recognition have become important in many fields of engineering and medicine. Many researchers are working towards development of algorithms so as to improve the accuracy in classifying and recognizing the patterns of image. SVM is a supervised and non- parametric machine learning algorithm and it was invented as a linear binary classifier by Vapnik and Chervonenkis in 1963. Most of the real world data is non-linear in nature. So, in 1992 some of the researchers recommended non-linear classifiers by applying the kernel trick to study the real world data by maximizing the margin between hyperplanes [9]. SVM classifier can optimally locate hyperplanes with minimal training data. Widely used soft margin based SVM was proposed by Cortes and Vapnik in 1993 and published in 1995 [12]. SVM based classification had been known well to reach the right balance between accuracy attained on a given minimal amount of training data and the capacity to generalize unseen data [47]. SVM had been used to classify various type of data such as heart data, diabetes data, satellite data and shuttle data [19].

Some of the softwares that are being used to execute the SVM algorithm are listed out in this section. SVM ^{light}, SVM ^{struct}, mySVM, JmySVM, LIBSVM (Library for Support Vector Machines), looms, BSVM, SVMTorch, Weka, SVM in R, M-SVM (Multi – class SVM), Gist, MATLAB SVM Toolbox, SmartLab, Gini-SVM, GPDT, HeroSvm, SVMsequel, LSVM (Lagrangian support Vector Machine), ASVM (Active Support Vector Machine), PSVM (Proximal Support Vector Machine), etc.

The application of remote sensing data in various fields is evolving day by day. The high spectral capacity of the sensors had given rise to multispectral and hyperspectral imagery. The usefulness of those images lies in, how well the data is converted into information. Image classification is the process of data mining technique that involves extracting interesting patterns representing knowledge from the satellite data products.

Hyperspectral data having a large number of narrow bandwidths helps us in detail study about the earth features. SVM had been applied in classifying AVIRIS (Airborne Visible Infra-red Imaging Spectrometer) data as it do not suffer from the limitations of data dimensionality and limited samples. Kernels in the SVM algorithm can make use of the high dimensionality of hyperspectral data to transform original input space to higher dimensional feature space [85]. A broad study had been done on the kernels in SVM that will be suitable for image classification. It had been seen that Radial Basis Function (RBF) outperformed polynomial kernel in the same context [37]. To avoid the confusion in selection of kernels,

Table 3
Study on ANN in Remote Sensing.

Researchers' Name	Year	Remarks
McCulloch and Pitts	1943	First Neuron model was proposed
Haralick et al.	1973	Texture based Image classification
Hepner	1990	Application of ANN to LU/LC classification
Milan et al.	1990	Comparison of Fuzzy classification and ANN classification
Bischof et al.	1990	Comparison of ANN and statistical classification techniques
Schalkoff	1992	ANN for segmentation and classification
Fung and Chan	1994	Pixel based LU/LC classification
Yoshida and Omatu	1994	Analysis of Sensitivity parameters of NN
Schowengerdt	1995	Comparison of ANN and statistical classification techniques
Foody	1996	ANN in combination with Fuzzy technique
Wilkinson	1997	Analysis of Sensitivity parameters of NN
Zhang et al.	2001	Comparison of ANN and statistical classification techniques
Ashish	2002	Classification of Aerial images using ANN
Madhubala et al.	2010	Comparing Pixed based classification and Back propagation technique
Yongzhu Xiong et al.	2010	Comparing ANN and Decision Tree algorithm
Zhou and Yang	2011	Development of MLP

Support Vector Selection and Adaption (SVSA) method had been used. The SVSA method consists of selection of the support vectors that contribute most to the classification accuracy and their adaptation based on the class distributions of the data without using the kernels [40]. Techniques like Transducitve SVM (TSVM) and Contextual SVM had been used to make study on hyperspectral data [62].

The complexity of the classifier in working with huge amount of data can be reduced by using Clustering-Based SVM (CB-SVM). CB-SVM utilizes a hierarchical micro-clustering algorithm. It examines the entire data set only once to provide an SVM with high quality samples that carry the statistical summaries of the data such that the summaries maximize the benefit of learning the SVM [80]. This in turn, assists in SVM fast implementations, approximations, selective sampling and SVM for dynamic environments.

Neural Network had been in use for image classification in late 1960 s. Researchers have compared the efficiency of neural network classifiers with other statistical based algorithms [5]. Pal and Mather [58] have compared the promising development of SVM with Neural network classifiers and Maximum likelihood classifier using multispectral Landsat ETM+ and hyperspectral Digital Airborne Imaging Spectrometer (DAIS) data. Studies have also been made to prove the time efficiency of SVM when compared with neural networks (Dixon and Candade [18]). SVM also outperforms traditional classifier like Maximum likelihood classifier (MLC) and Decision Tree Classifier (DTC) [33].

Hierarchical classification approach combined with SVM had been verified to increase the accuracy and also reduces the computational time which is achieved through multilevel wavelet decomposition of each band of hyperspectral image. Pixels of the highest level (lowest resolution) are classified using all support vectors, while pixels at sub-sequent lower levels (higher resolution) are classified using neighborhood SVM classification, that only uses support vectors of classes to which the corresponding neighbors of the higher level belong to [15].

LU/LC analysis is the primary work which is being done by most of the Remote Sensing and GIS analysts. LU/LC of a particular area will be heterogeneous in nature. As SVM is well known as a linear binary classifier, researchers have worked on it to extend to multi-level classification. There are two general approaches: One against One (1A1) and One against All (1AA) approach wherein, both requires multiple implementations of binary classifiers and cascading the outcomes to achieve a single multi-class classification [32]. 1A1 and 1AA approaches were compared by incorporating linear, quadratic, Polynomial and Radial Basis Function kernels [1]. The choice of 1A1 or 1AA becomes a matter of preference as both yield similar results. There also exists Directed Acyclic Graph SVM (DAGSVM) algorithm that combines the outcomes of 1A1 SVMs to get multi-class output [10]. Multi-class SVM with a single classifier is also possible, but with larger optimization problem to arrive at very accurate classification [21]. An improvement had been brought to the cascade SVM by Parallel SVM training algorithm for large scale classification problems that works efficiently [84].

Most often studies are based on a particular type of LU/LC like Agricultural land, wetlands, Urban area, etc., [88]. SVM is a best suitable algorithm for such studies. The mapping of Mangrove fringes had been done to high accuracy by merging Object Oriented Image Analysis (OBIA) and SVM [30]. Remote sensing of tea plantations suffer from the reflectance due to the surrounding orchards and bushes. SVM had been used to map such tea plantations using Modified Normalized Difference Vegetation Index (MNDVI) as a supporting parameter [17]. Sanchez-Hernandez et al. [69] have mapped the coastal salt marsh habitats using Support Vector Data Description (SVDD). It only uses training data from the class of interest and targets to calculate an optimal hyperplane boundary that closes around the target class and separates it from any other possible classes. In the context of study of urban area using remote sensing, there exists some confusion between buildings and roads. SVM has been successfully employed in differentiating the above spectrally similar classes [63]. They

Table 4
Study on SVM in Remote Sensing.

Researchers' Name	Year	Remarks
Vladimir N. Vapnik and Alxey Ya. Chervonenkis	1963	Invention of SVM as linear binary classifier
Boser et al.	1992	Non-linear SVM with Kernel trick
Zhang et al.	2001	Classification of hyperspectral data using SVM
Hsu et al.	2002	Multi- class SVM
Yu et al.	2003	Cluster Based SVM
Foody et al.	2004	Multi- class SVM with single SVM
Pal et al.	2005	Comparison of SVM and NN classifiers
Zhang et al.	2005	Parallel SVM training
Dixon et al.	2007	Time efficiency of SVM
Anthony et al.	2007	Comparison of 1A1 and 1AA techniques of Multi-class SVM
Sanchez-Hernandez et al.	2007	SVM to map Coastal salt marsh habitats
Kavzoglu et al.	2009	Study on suitability of Kernels
Kaya et al.	2009	Support Vector Selection and Adaption method
Plaza et al.	2009	Transductive SVM and Contextual SVM
Demir et al.	2009	Hierarchical classification combined with SVM
Durgesh et al.	2010	SVM based data classification
Hwang et al.	2010	SVM with PCA and DWT
Heumann	2011	SVM with Object Oriented Image Analysis
Yin et al.	2011	SVM for mapping shoreline
Dihkan et al.	2013	SVM with MNDVI to map tea plantations

have also made a mention that Maximum Likelihood classifier fails in such a case, because it considers the mean of training data as representative of each class and not the individual values of training data. Spatial correlation analysis like Principal Component Analysis (PCA), Discrete Wavelet Transform (DWT), Segmentation and Semivariance plays an important role in remote sensing data analysis. SVM had been showed to be effective in studying the images with one or combination of the above spatially correlated images [35]. Coastlines are of many types namely Bedrock coast, Sandy coast, Muddy coast, Mangrove coast and Artificial coast. Different image processing techniques are being applied on each type of shoreline to enhance the same. Adaptive filtering for sandy coast, image sharpening for muddy coast and edge enhancement for bedrock and artificial coast had been effectively used as image enhancement techniques. Enhanced images can then be classified by applying sigmoid kernel in SVM (Hannv et al. [26]). Modification of Normalized difference Water Index (MNDWI) in combination with SVM yields good results in classifying or mapping shoreline [77]. Table 4 shows the works done by various researchers related to SVM in Remote Sensing.

6. Discussion and concluding remarks

- The present review focused on the application of remote sensing techniques for the coastal studies namely shoreline mapping, coastal LU/LC and coastal inundation mapping. Also the application of soft computing techniques for evaluating the wind turbine performance had also been dealt.
- The conventional techniques that had been discussed show the effectiveness of using satellite imagery to study the earth features, in particular, coastal area which requires continuous monitoring.
- The main aim of coastal management planning is to control erosion and flooding. Now a days, microwave radiometers, infrared radiometers, altimeters, ocean color sensors and synthetic aperture radars are used in satellite oceanographic studies.
- However, satellites operating in the optical range like Landsat and Indian Remote Sensing satellites can also be used.
- Conventional image processing techniques are useful to understand the process involved.
- Considering shoreline mapping, which started in the earlier days by manually surveying the beach profile, then developed to the process of digitization using ArcGIS and manually calculating the rate of change. Advancement in software development led to DSAS which can automatically calculate the rate of change of shoreline provided the parameters are properly set.
- Automatic shoreline delineation is also becoming possible due to the algorithmic advancement.
- Considering LU/LC mapping, unsupervised classification technique though not accurate, were in use to study about the earth features at reconnaissance level. Then supervised techniques are developed to improvise the accuracy in mapping the land use and land cover.
- Among the known supervised classification algorithms, Maximum Likelihood Classifier (MLC) gives the better classification accuracy. However, the conventional methods are data intensive.
- Soft computing techniques which find its foot print in computer science application has grown across multi–disciplinary sciences. It take into account of the uncertainty that exist in the real world data. Hence, it can be constructively applied to remote sensing data where huge amount of data is involved.

- Fuzzy Logic reflects the degree of belongingness, Genetic Algorithm reflects the theory of evolution, Particle Swarm Optimization reflects the representation of movement of organisms, Artificial Neural Network mimics the functions of human brain and Support Vector Machine considers the machine learning algorithm.
- ANN and SVM had been widely used in remote sensing field. They had gained a lot of improvement in their configuration.
- The performance of ANN in remote sensing data classification lies mainly on deciding the parameters like number of hidden layers, learning rate of the network, activation function that controls the internal weights of the neurons, momentum coefficient of the neural architecture and number of iterations control.
- However, with an advent of SVM and the concept of kernels for non-linear problems, it occupied higher position in classification algorithm. Selection of kernels play a crucial role in SVM classifier.
- In short, it can be concluded that, high learning capacity with limited amount of available data, adapting itself to newly seen data and kernel tricks on non-linear data make SVM a promising technique for remote sensing data classification.

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