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Climatic influence on solar saltpans with specific reference to Thoothukudi district

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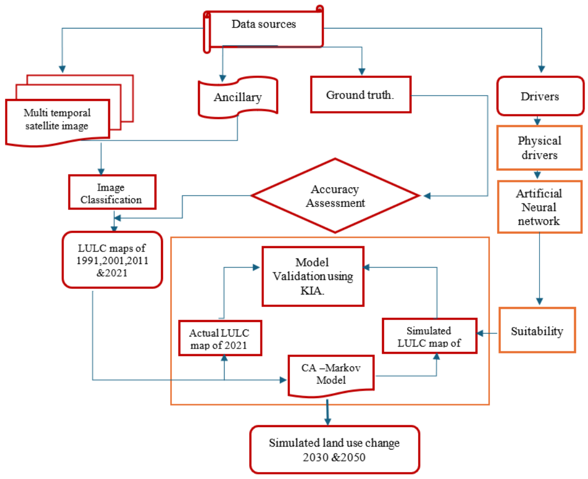
Graphical abstract



Abstract

Eco-sensitive Coastal Solar Saltpan (CSS), also known as Saltpan, provides many essential ecological and societal functions. However, changes in coastal saltpan land use resulted in the loss of salt production activities and impacted the socio-economic status of salt workers along the coast of Tamil Nadu. Therefore, it is imperative to ascertain the origins and ramifications of land-use modification within this ecosystem. The change detection results were examined on the parameters of the proportion of land cover classes and change trajectories with particular emphasis on Saltpan.This study used Artificial Neural Network (ANN) models and Cellular Automata - Markov Chain (CA-MC) models to predict the changes in 2030 and 2050. The study shows that the overall Saltpan increased from 1990 to 2021. Results also reveal that saltpan magnitude varies spatial and temporally in coastal taluks. An increasing trend of Saltpan was observed in Vilathikulam, a gradual increase in Ottapidarm, Srivaikuntam &Thiruchendur, and a decreasing trend in Thoothukkudi. The scenario projected for 2030 and 2050 indicated a decline in agriculture and coastal saltpans, while urban land usage increased. Detailed predictive models of the saltpan dynamics base on coastal land-use change can be highly advantageous in developing management strategies for sustainable coastal ecosystems.

Keyword:Cellular Automata (CA)-Markov chain (MC), Artificial Neural Network (ANN), Coastal Salt Pond, Coastal ecosystems, land use prediction.

1. Introduction

Man-made coastal wetland such as Saltpan provides ecological service by supporting thousands of species of migratory birds (Pandian *et al.* 2013). The CSS, which also has thick mangroves, acts as a buffer line that protects from floods during monsoon and coastal erosion. CSS is used to produce salt for several purposes, such as table salt for cooking, and is also used in several industries as raw material. Saltpan also provides livelihood opportunities to the salt workers and the salt industry. Salt production entirely depends on the CSS. Hence, there is an urgent need to identify and assess the distribution of salt production at global scales, regional and local scales.The British Geological Survey (2018) and the United States Geological Survey (2019) indicate that China, the United States, India, Germany, and Canada are some of the world's leading salt-producing countries. India is the third-largest salt-producing country in the world (Ministry of Mines 2018) and the primary salt-producing states are Gujarat, Tamil Nadu, and Rajasthan, and the rest of the states are Maharashtra, Karnataka, Andhra Pradesh, Odisha, and Goa, which together account for 96.31% of total salt production in the country. Tamil Nadu was the second-largest producer of salt. In Tamil Nadu, the total saltpan area allotted for salt production was about 8.06 lakhs acres, and around 80,000 salt workers are involved in salt production. Thoothukudi, Ramanathapuram, Nagapattinam, Villupuram, and Kancheepuram are the primary salt-producing districts in Tamil Nadu. Much of the state's salt production comes from the coastal area of the Thoothukudi district. Hence, in this research Thoothukudi coastal stretch is considered the study area. The coastal saltpan land use has been under particular stress with the loss of Saltpan due to a labour shortage during peak season from February to October. Saltpan gets polluted because it is located near chemical industries, linked with urban growth and industrialization. John Prince *et al.* 2009 studies in Thoothukudi taluk showed that 10.07% of saltpan area decreased between 1969-2003 due to urban growth. A separate study showed that 5.04 % of the saltpan area was lost between 2001-2006 (Jhon Prince *et al.*, 2011). Loss of Saltpan in this region will negatively impact salt workers' socio-economic status. Thoothukudi has the highest number of salt workers in the state, with more than 55,000 workers from Kayalpatnam to Vembar hamlets located along the coast of Thoothukudi district. Thus, effective monitoring of Saltpan is urgently required. Therefore, Remote sensing technology is used to understand the magnitude and rate of changes in Saltpan in the study area.The Remote Sensing and Geographic Information System (GIS) made it possible to study the changes in LULC with better accuracy (Verburg *et al.* 2004). Land-use models are essential to studying land-use changes (Lambin 1997). Several models are available to perform LULC change prediction, including CLUE-S (Verburg & Overmars 2009), Cellular Automata (CA), Markov Chain model (Bose and Chowdhury 2020), Cellular Automata-Markov chain (CA-MC) model, Multi-Layer Perception Markov Chain (Mishra and Rai 2016), Artificial Neural Network (Sliva *et al.* 2020), statistical, cellular and hybrid models, Logistic Regression (Wang *et al.* 2019), System dynamic and machine learning algorithm (Yubo *et al.* 2020).

The Cellular Automata - Markov Chain (CA-MC) model is one of the most commonly used methods for modelling the spatiotemporal change in LULC (Sang *et al.*, 2011). Markov chain models have difficulty simulating the spatial pattern of land use/land cover change (Ye and Bai 2008). However, spatial differences in land use can be predicted using CA models with strong spatial computing (Sang *et al.*, 2011). Thus, combining Markov chain models with cellular automata may make it possible to forecast changes in land usage (Kafy *et al.*, 2021). which models both temporal change and spatial distribution of land-uses, respectivelyHowever, the potential strength of the driving elements, such as socioeconomic and physical data, must be considered when modelling LULC change (Mas *et al.* 2014). In considering this, the integration of the CA-MC model with other models helped improve its prediction capability (Saputra and Lee 2019). Among many methodologies, Artificial Neural Network is an effective approach that introduces a better understating of the land change process and driving factor of land-use change (Grima *et al.* 2022). In this study, Remote Sensing and Geographic Information System technologies were used to study saltpan changes from a series of Landsat data from 1990 to 2021. This study aimed to produce a likely scenario of LULC change in the Thoothukudi coast for 2030 and 2050. A computer simulation model of LULC change in the basin was used to accomplish the purpose. The primary component of the model is the CA-MC model, which was parameterized using Remote sensing and GIS analysis.

2. Materials and methods

2.1. Study area

The research region, also referred to as the "salt bowl of south India," spans a sizable 163 km of coastline, running from Vembar to Kayalpatnam along the coast of Thoothukudi district. Figure 1 shows the Thoothukudi district coast with a buffer distance of 10 km; considering that SEP ecosystems are mainly distributed in the intertidal zone, the study area was limited to a buffer zone along the coastal line. It covers five coastal taluks, namely Vilathikulam, Ottapidaram Thoothukudi, Srivaikuntam, and Thiruchendur, which are major salt-producing areas of Tamil Nadu. The favourable climate and topographical condition make salt production possible along the coastal stretch of the study area as it comes under the rain shadow of the southwest monsoon, and the northeast monsoon is comparatively weak in this region. The salt industry is one of the oldest industries in the country and the main backbone of the economic development of this district.

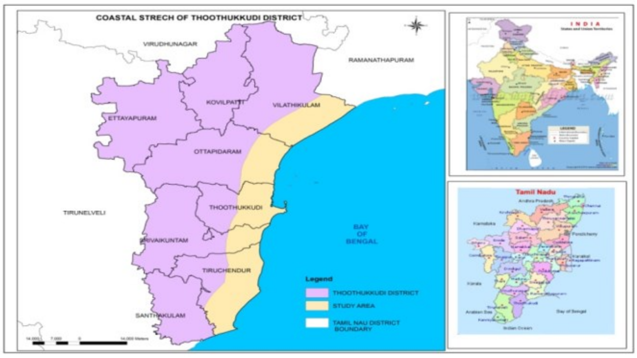


Figure 1. Map showing the study area with boundaries of the coastal taluk of Thoothukudi, Tamil Nadu, India

2.2. Datasets

For this research, time-series satellite images were selected, namely: t_1(1990), t_2(2000), t_3(2010), and t_4(2021); as shown in Table 1, Land cover mapping of the study area was performed based on Landsat satellite images obtained from the US Geological Survey platform with a spatial resolution of 30m, to detect changes of land use with special reference to Saltpan in the coastal stretch of Thoothukudi district. The Landsat images were selected such that they have the same resolution & help to solve the resolution problem and since these images do not contain clouds. The baseline time of 1990 was selected because resource-based industries such as textile, salt, and food started to develop from 1990 onwards (Khare *et al.* 2015). Furthermore, a digital elevation model (DEM), soil map, geology, and geomorphology map are derived from Remote sensing data. The overall methodology is presented in Figure 2.

Table 1. General characteristics of Landsat Images.

Year	Path-row	Acquisition date	Sensor	Spatial resolution (m)
1990	143-54	12/5/1990	TM	30
2000	143-54	12/8/2000	TM	30
2010	143-54	23/10/2010	TM	30
2021	143-54	16/4/2021	OLI	30

2.3. Land use/land cover mapping

Land use/ land cover (LU/LC) mapping was done using two data sets with different time series information covering thirty years. The LU/LC was classified based on the first-level classification scheme. LU/LC was classified using visual image interpretation, and these classes were Built-up, Agriculture, Forest, Wasteland.

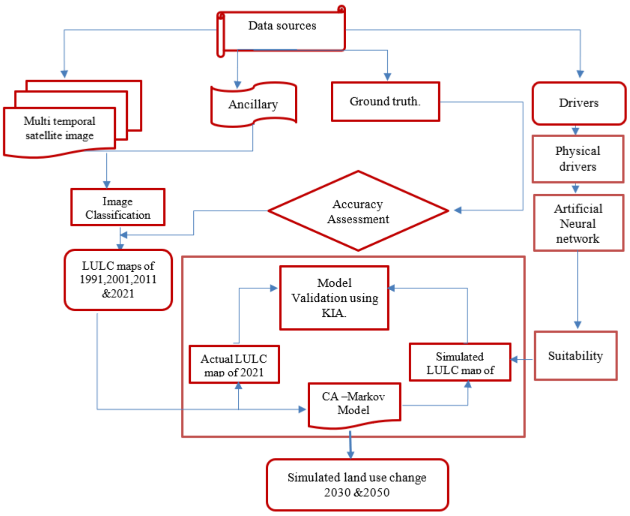


Figure 2. Flow chart for future land use prediction

2.3.1. Validation of Classified LU/LC maps

Prior to change detection and future prediction, assessment of classification accuracy is important to test the accuracy of imagery. To assess the accuracy of land use, a confusion matrix was adopted to measure the agreement between the classification result and the validation samples (Congalton & Green 1999). Equation (Eq. (1)-(4)) based on the confusion matrix was used to determine the accuracy of user's accuracy, producers' accuracy, total accuracy, and Kappa coefficient (Foody1992).

$$\frac{\sum_{i=1}^{r} D_{ii}}{N} \tag{1}$$

$$A = \frac{\sum D_{ij}}{x_{i+}} \tag{2}$$

$$PA = \frac{\sum D_{ij}}{x_{i+}} \tag{3}$$

$$Kappa = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i+} * x_{+i}\right)}{N^2 - \sum_{i=}^{r}\left(x_{i+} * x_{+i}\right)} \tag{4}$$

Where x is the number of pixels in row i and column i; the marginal totals of row I are x_{i+} and x_{+i} and column i, respectively; and N represents all of the pixels (observations); and the number of correctly categorized pixels D_{ii}, D_{ij} is the quantity of pixels in row i that are accurate, D_{ij} is the number of correctly categorized pixels in column j, the integer r is denotes the matrix's row count . The user's accuracy represents the likelihood that a classified feature matches the ground situation. The producer's accuracy shows the proportion of object types that were correctly classified. The Kappa coefficient indicates how much the classification differs from a random classification. The overall accuracy shows the percentage of correctly identified points falling within the agreement of accuracy assessment (Monserud and Leemans 1992) presented in Table 2. The performance of the accuracy assessment was carried out with ArcGIS 10.5.

Table 2. Agreement of accuracy assessment

S.No	Kappa values	Agreement
1.	<0.4	Poor or very poor agreement
2.	0.4 to 0.55	Fair agreement
3.	0.5 to 0.7	Good agreement
4.	0.7 to 0.85	Very good
5.	> 0.8	Excellent agreement

2.3.2. Quantification of changes

Quantification of changes included three steps (i) the area, trend, and spatial characteristics of SPL change were obtained by analysis of the classified results using GIS, and the changes were evaluated in the following three time period: Initial Period (from 1990 to 2000), Second Period (from 2000 to 2010), Third Period (from 2010 to 2021) and Fourth Period (from 1990 to 2019). A detailed change analysis matrix helps identify the process of change within the land use (Manonmani & Vidhya 2017). Thus, the transition matrix was employed to interpret categorical change information, which included conversions from Saltpan (earlier date) to other classes (later date) and conversions to Saltpan (later date) from other classes (earlier date).

2.4. Land use/land cover model

This section explains each model, CA-MC, and ANN, separately.The flowchart is then used to apply an evaluation of the updated model's process and capabilities.

2.4.1. Markov Chain model and CA-Markov

A stochastic process called a Markov Chain (MC) indicates the likelihood that a given state (first time period) changes into another state (second time period). MC is a suitable technique for modelling land use change because it can express the temporal changes from one time to another providing a foundation for future change prediction. To determine the likelihood of a transition between the two lines period, at least two distinct maps for the same region for two times steps are required. In this study, maps of the research region from 2000 and 2010 were used by the researchers . TerrSet was used to build the transition matrix. The land-use changes were calculated using the following formula, which was derived from Bayes' theorem of conditional probability. (Sang *et al.* 2011):

$$S(t+1) = P_{ij} \times S(t) \tag{5}$$

Where S(t) represents the system's at time t, the state of the system at time (t+1) is represented by S(t+1) , and the matrix of transition probability in a state is denoted by P_{ij}

$$P_{ij} = \begin{pmatrix} P_{11} & P_{12} & P_{1n} \\ P_{21} & P_{22} & P_{2n} \\ P_{n1} & P_{n2} & P_{nn} \end{pmatrix} \quad (6)$$

$$P_{ij} = \left(0 \le P_{ij} < 1 \, and \sum_{j=1}^{N} P_{ij} = 1, (i, j = 1, 2, \ldots n \right)$$

Where i,j represents the land use type for the first and second time period, and N is the total number of land use kinds.However, this MC model cannot produce changes in spatial dimension and does not account for the influence of the neighbouring cells (Ye and Bai 2008). As a result, the Markov Chain model has been combined with Cellular Automata model. The CA model combined with powerful spatial computing can be used to predict the spatial variation within land-use change. It has been proved that integrating a Markov chain model and CA effectively predicts land use/ land cover changes (Behera *et al.*, 2012).Cellular Automata (CA) is a spatial modelling tool that has been widely applied in land use simulation .CA's appeal stem for the capacity to the model closeness, which is regarded a crucial spatial element that reflects the dynamic of land use change.CA considers that region is more likely to a convert land use a category if its neighbors are in that category.CA divides the region in to a grid cell. Each cell is equivalent to a pixel on an area map. Cellular state is one of the land use categories. The cell's state in the following phase is determined by a set of transition rules that consider in the both the cell's current condition and the current condition of the surrounding cells (the neighborhood). The neighbourhood types know as Von Neumann and Moore are the most frequently used in CA (Memarain *et al.*, 2012). The transition rules that are employed in this study to forecast future changes in land use are created using a Moore neighbourhood filter that is 5 by 5.

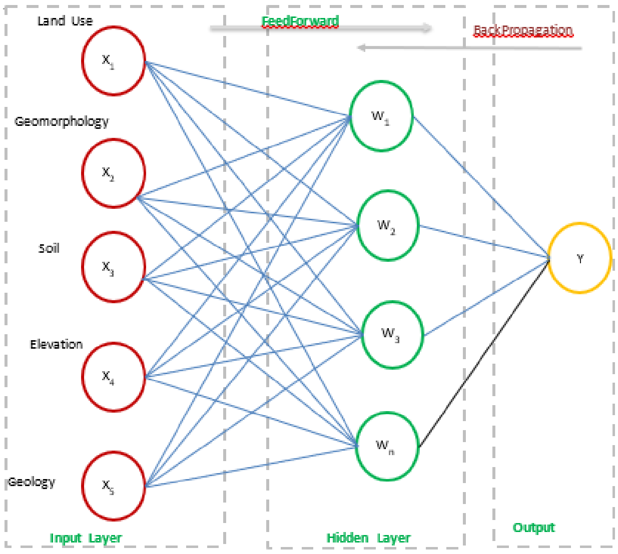


Figure 3. Artificial Neural Network Architecture

In addition, CA-MC has an open structure that allows for the incorporating of wide range of external socio-economic and environmental elements that influence the land-use changes processes; In other words,CA transition rules can be developed in a variety ways to account for these aspects. The combination of CA and MC strengths the prediction, but is it not adequate. Consequently, this model has been combined with ANN.

2.4.2. Artificial Neural Network

ANNs, or artificial neural network, are machine learning technique to model complex patterns and behaviour. ANN has a remarkable ability to simulate the possible transformation of LULC. This study develop the ANN Multi-layer Perception (MLP) model with three-layer, including the input, hidden, and output layers, constructed to create a potential transition map (Pijanowskiet al 2002) based on historical data and driving factors. The architecture of the ANN used in this work is given in Figure 3. ANN MLP machine learning is a kind of supervised algorithm that is used for learning non-linear function by different factors presented in Figure 4 for showing the future land use transformation and Saltpan. The training process is known as back propagation, which is an extensively utilized algorithm. The number of iterations for optimal accuracy was chosen through a trial-and-error process. In the present study, ANN MLP has been used to create a potential transition map.Land-use change 2021 is simulated by integrating the potential maps generated by the ANN the transition matrix of the MC model, and the transition rules of the CA, our approach of ANN-CA-MC modelling considers both spatial and temporal dynamics of the land use as well as incorporates the impact of the driving

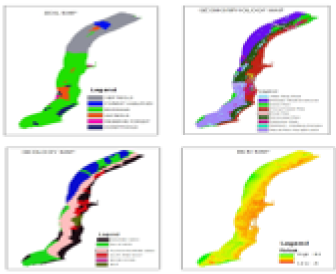


Figure 4. Driving factors connected with the simulation of land use and land cover of change with special reference to saltpan

2.5. Validation of MLP-CA-MC model output

Model validation is an essential step in the modelling process. There are several methods used to evaluate prediction method and one of the methods commonly used is Kappa statistics (Pontius and Schneider 2001) such as (i) For no information, use Kappa (Kno), (ii) For location ,use Kappa (Klocation), (iii) For quantity, use Kappa (Kquantity) and (iv) For standard,use Kappa (Kstandard). When Kno, Klocation, and Kquantity all have values of 1, the simulation's output is deemed ideal. The validation process was executed to measure the existing agreement and disagreement between the actual LULC map (T4 satellite driven) and simulated (T4) LULC map of 2021 to ensure the reliability and acceptance of the MLP-CA –MC model in predicting the future changes in 2030 and 2050.

3. Results and discussion

3.1. Accuracy assessment

The accuracy assessment in this study aims to evaluate whether land-use dynamics are correctly detected through the proposed approach. Referenced data for 2010 and 2021 were collected 2010 and using high-resolution imagery via Google Earth, a frequently used source for ground truth data in remote sensing studies (Swades Lal and Ziaul 2017). For the year 2000, validation used ETM Plus. For the year 1990, the historical data for validation were collected from published papers. The overall accuracy of land use classified images was shown to be,in that order, 90%,93%,95%, and 95% . While kappa coefficients of these outputs were 0.88,0.92,0.92 and 0.96 respectively.The distribution of various land use/ land cover (LU/LC) classes of coastal stretch of Thoothukudi district in 1990, 2000, 2010, and 2021 are shown in Figure 5.

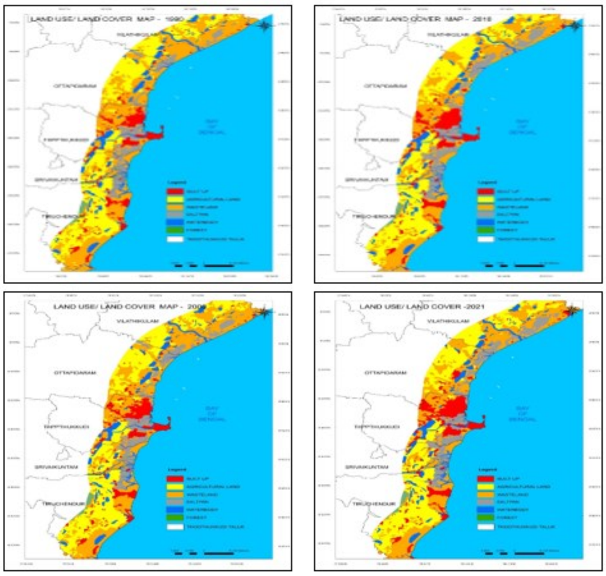


Figure 5. Land use/land cover (LU/LC) classification of the study area (a) LU/LC in 1990 (b) LU/LC in 2000 (c) LU/LC in 2010 and (d) LU/LC in 2021

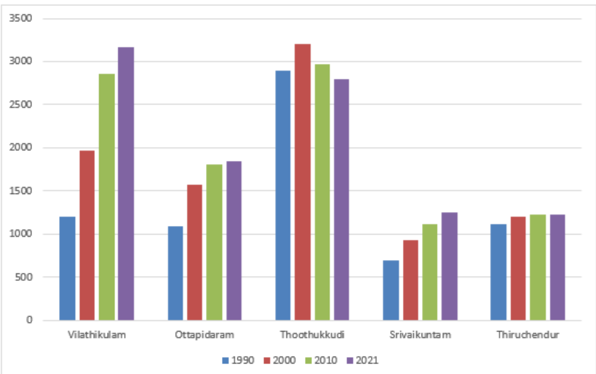


Figure 6. Trend of saltpan in costal taluk of Thoothukudi district

The major land use/land cover at the first level was classified, namely Agriculture, wasteland, built-up, Saltpan, water body, and forest. The built-up area significantly increased over 30 years from 6.07 % in 1991 to 11.77% in 2020, followed by Saltpan. Wasteland increased by 147.25 ha and 452 ha between 1990-2000 and 2000-2010 respectively. In comparison, observed a decrease of 279 ha from 2010-2021. The waterbody and forest land cover area remained unchanged in all four years because it required a temporal seasonal satellite image.

3.2. Change of Saltpan land

The extent of the saltpan trend is presented in Figure 6. Results indicate that the extent of saltpan land increased by 1870.42 ha between 1990 and 2000, 1108.51 ha between 2000 and 2010, and a gradual increase of 300.52 ha between 2010 and 2021 as presented in Figure 6

The five coastal taluks are numbered as 1 (Vilathikulam),2 (Ottapidaram)3.(Thoothukkudi), 4 (Srivaikunam) & 5 (Thiruchendur). To understand how saltpan land has changed over a period of 30 years, the study area was analysed using the area statistics 1990-2021 respectively. The result shows that saltpan land almost changes were found between 1990-2000,2000-2019, and fewer changes were found between 2010-2019. It is observed that between 1990-2021, Saltpan gained 3894.28 ha of area and at the same time lost 677.71 ha area. The specific location of saltpan loss and gain between 1990-2021 is shown in Figure7.

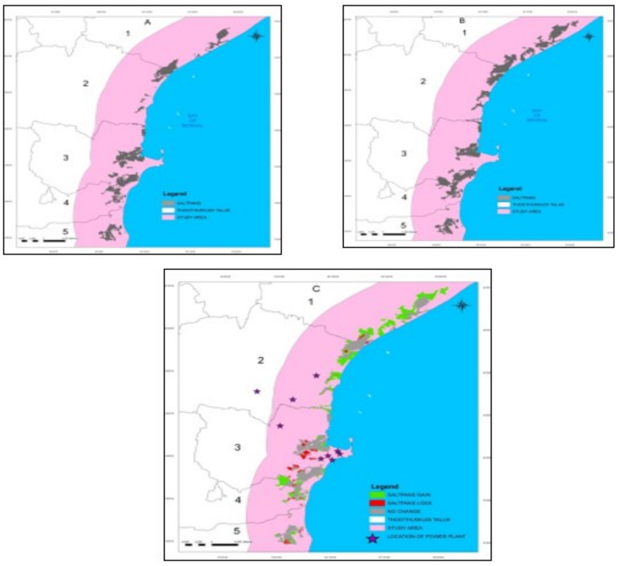


Figure 7. Saltpans cover changes between 1990-2020 (A) Saltpan land in 1990 (B) Saltpans cover in 2021 and (C) Loss and gain of saltpans between 1990-2021.

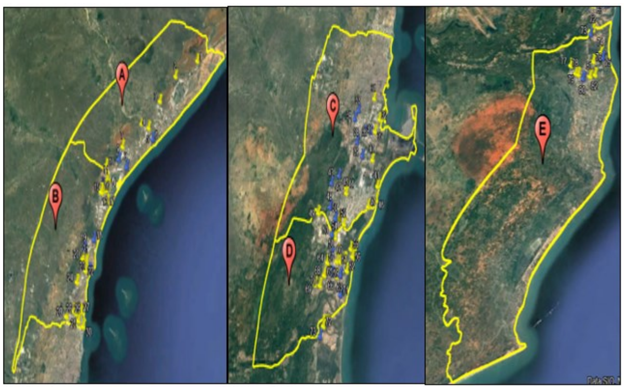


Figure 8. Google Earth image

In this research, the identified saltpan change area from satellite images was verified with Google Earth maps dated 17/1/2005, 28/7/2012, 31/12/2016, 11/8/2018 & 3/3/2019. The location was compared visually with the Google Earth map, and whether they have changed or not changed is shown in Figure 8. Changes of 60 areas were compared and it was observed that satellite images correctly detected 57 areas.

Location of Changed saltpans land area as detected from satellite image (yellow pushpins-saltpans gain and blue pushpins- saltpans loss between 1990-2021) overlaid on a Google earth. The five coastal taluks are numbered as A (Vilathikulam), B (Ottapidaram) C. (Thoothukkudi) , D (Srivaikunam) &E (Thiruchendur). The current study indicates an overall positive change in saltpan land in the coastal stretch during the last three decades as presented in Figure 9.

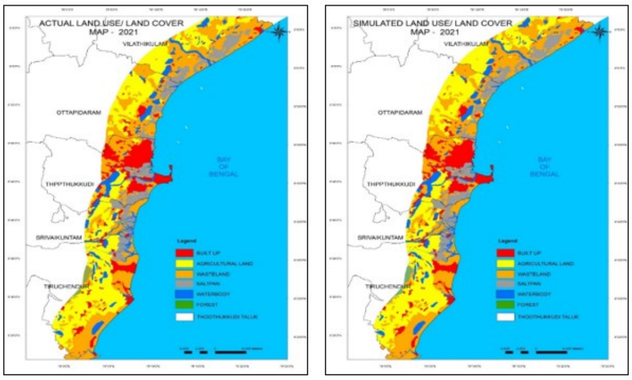


Figure 9. Actual and simulated land use and land cover map of 2021

Table 3. Validation of the land use land cover change (LULCC) prediction based on the actual and simulated 2021 LULC image

LU/LC	Actual area in % (2021)	Simulated area in % (2021)	Difference
Saltpan	11.30	12.21	-0.91
Water Body	8.08	9.52	-1.44
Wasteland	34.20	35.25	-1.05
Agriculture land	33.96	33.58	0.38
Built Up	11.77	9.02	2.75
Forest	0.69	0.80	-0.11
	100.00	100.38	

In contrast, negative changes were found in Thoothukudi taluk. The previous estimation of the Saltpan in the study area differs from other studies due to different data sources, methodology, and boundary selection. In the study area, the saltpan area gained 3894.28 ha and lost 677.71 ha between 1990-2021. The estimation of the areal extent of saltpan land in the year 1990 and 2010 was matched with previous studies (Nagamani 2017). In Thoothukudi coastal district, the saltpan land change rate was high between 1991-2000 compared to 2000-2010 and 2010-2021. An increase in Saltpan area was observed in Vilathikulam, a gradual increase in Ottapidarm, Srivaikuntam & Thiruchendur, and a decreasing trend was observed in Thoothukkudi. Among the coastal taluk, Vilathikulam observed the highest change rate. This shows the least physical disturbance in the last 30 years compared to other taluks due to the availability of salt workers and the absence of chemical industries.Saltpan land change rate decreased in 2010-2021 compared to 2000-2010 in the taluk of Thoothukkudi, Ottapidaram, Srivaikuntam, and Thiruchendur. Thoothukudi taluk of Tuticorin Corporation has thousands of acres of land that are utilised for salt production. Saltpans are found in Mappilaiurani, Thoothukudi municipal, Milavittan, Mulaikadu, Muttayyapuram, and Athimarapatti. At the beginning of 2013, there were frequent power cuts because of which they could not pump water for the pan and this severely affected the production of the industry. In the same period, labour costs increased by almost 36 % and power costs by three times. While total production cost has gone up by nearly 20%, the price of salt has come down by almost Rs 50 per tonne. Thoothukudi is unable to compete with Gujarat as their labour and power cost are cheaper, and they have taken over Thoothukudi's export market.Additionally, Thoothukudi taluk alone lost 148.51 ha and 96.14 ha between 2000-2010 and 2010-2019 respectively due to urban expansion (Industry and parking yard). These results are consistent with other remote sensing studies, such as Jhon *et al.* 2009. Salt quality is affected mainly because of pollution from Thermal power plants located close to Saltpan land. More than 13 power plants emerged after 2000 and among them five are situated in and around Thoothukudi taluk (Khare *et al.* 2015). With Thoothukudi emerging as a power hub for Tamil Nadu, it is evident that saltpan land has decreased Continuous loss of Saltpan would influence the production of salt and will have an impact on the socio-economic status of salt workers. Prakash and Maria 2018 reported that salt workers' socio-economic status is poor, and they face many health-related problems due to their heavy work (Arockia Amuthan 2011). Proper measures must be taken to protect the saltpan ecosystem, and measures should be taken to improve the socio-economic status of salt workers

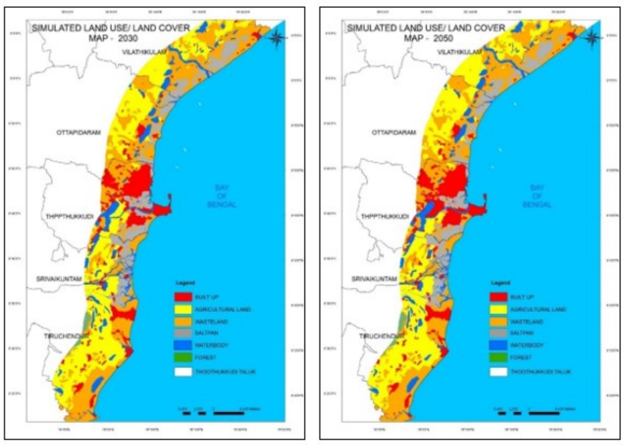


Figure 10. Simulated land use and land cover map of 2030 and 2050

3.3. Validation of Simulated map and future prediction

The LU/LC maps from 2000(T_2) and 2010 (T_3) were first used to simulate the LU/LC patterns in 2024(T_4) as a means of validation for the CA-MC-ANN model. Kappa statistic for quantity and location was derived from the comparison of the 2021 reference map with the simulation map presented in Table 3 and Figure 9. The statistics showed that the K_{no} value is 88 %, the $K_{location\ Strata}$ value is 85 %, and the $K_{standard}$ is 80%. All the kappa index values exceed the satisfactory range (>80%). As a result, there is a good agreement between the simulated and observed LU/LC maps. Figure 10 shows the actual predicted map and simulated map for 2021.

The following Model's successful completion of the training phase in 2020, efforts were made to produce 2030 and 2050 scenarios. As seen in Figure 10, the CA-Markov-ANN model was used to forecast change between 2030 and 2050 for further land cover. The prediction map illustrate the growth of urbanization surrounding Thoothukudi taluk and large cities where the middle southern portion of Thoothukudi district exhibit a decline in Saltpan.There is less agricultural area visible on the map as well. Furthermore, there was no notable alteration in the classification of water bodies and forests.

4. Conclusion

This research aimed to develop a land-use prediction with special reference to Saltpan for the years 2030 and 2050. This was done with the use of an integrated ANN –CA-MC model of the LULC changes on the Thoothukudi coast computer simulation.In SEP areas, where accessibility is challenging and spatial coverage is severely constrained, remote sensing analysis has proven to be a dependable substitute for ground survey approaches.The CA–Markov-ANN model make it possible to track changes in SEP land cover,which is crucial for improving our understanding of SEP conditions over time and directing conservation and restoration efforts . Predicting SEP trends may also result in sustainable ecosystem management in the research area or increase the effectiveness of effort to save this important environment. A decline in the extent of SEP ecosystem and the environmental service they offer is predicted by the ensuing future projection. Therefore, preserving the socio-economic and ecological value is essential. This trend would influence the production of salt and will have an impact on the socio-economic status of salt workers. Socio-economic livelihood would vary in all the five coastal taluks. Hence, in the future socio-economic survey will be conducted on all the coastline districts to know the status of livelihood of salt workers.

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References

Arockia Amuthan V (2011) A study on socio-economic conditions of saltpan workers in Tuticorin district, thesis, Department of Economics, Madras Christian college, university of Madras. Bangalore, vol. 31, pp.1-29

Behera MD, Borate SN, Panda SN, Behera PR, Roy PS (2012) Modelling and analysing the watershed dynamics using cellular automata (CA)–Markov model–a geo-information-based approach Journal of earth system science 121:1011–1024

Bose and Chowdhury 2020, monitoring and modelling of spatiotemporal urban expansion and land use/ land cover change using Markov chain model: a case study in Siliguri Metropolitan area, West Bengal, Indi a, Modelling Earth System and Environment, vol.6, pp 2235-2249

British Geological Survey (2018) World Mineral production 2012-2016, British Geological Survey, Technical report, pp.1-96.

Congalton R.G and Green K 1999 assessing the accuracy of Remotely Sensed Data: Principles and Practices, Lewis Publishers, Boca Raton

Foody, G.M 1992, On the compensation for change agreement in image classification accuracy assessment, Photogrammetry Engineering Remote Sensing S. No58, pp. 1459-1460

Gharaibeh, A., Shaamala, A., Obeidat, R., Al-Kofahi, S., 2020. Improving land-use change modelling by integrating ANN with cellular automata-Markov chain model. Heliyon 6, e05092. DOI: 10.1016/J.HELIYON. 2020.E05092.

Grima R, Furst C, and Moges A 2022, Land use land cover change modelling by integrating artificial neural network with cellular Automata-Markov chain model in Gidabo river basin, main Ethiopian rift, Environmental Challenges, no,6

John Prince. S, Sivasubramanian. P, Chandrasekar. N & Durairaj. KSP (2011) An analysis of land use pattern in the industrial development city using high resolution satellite imagery, Journal of Geographical Sciences, vol.21, no.1, 79-88.

John Prince.S, Sivasubramnain, P Chandrasekar N & Victor Rajamanickem G (2009) Remote sensing and GIS Application in Urban Expansion and Its Impact on Sea Water Intrusion in Thoothukudi, Tamilnadu. Indian Journal of Landscape Systems and Ecological Studies, vol.32, No.2, pp.1-10.

Kafy, A.-. A., Naim, M.d.N.H., Subramanyam, G., Faisal, A.-A.-, Ahmed, N.U., al Rakib, A., Kona, M.A., Sattar, G.S., 2021. Cellular Automata approach in dynamic modelling of land cover changes using RapidEye images in Dhaka, Bangladesh. Environmental Challenges 4, 100084.

Khare, D, Manuel, M & Sridhar, S 2015, Regulation and development: the emergence

Lambin E.F., 1997: Modelling and monitoring land-cover change processes in tropical regions. Progress in Physical Geography 21: 375–393.

Manonmani.R and Vidhya R (2017) Diagnosis of drivers behind historic change in land use using receiver operating characteristics curve, International Journal of modelling and simulation, vol.38, no.1, pp.1-12.

Mas, J.F., Kolb, M., Paegelow, M., Camacho Olmedo, M.T., Houet, T., 2014. Inductive pattern-based land use/cover change models: a comparison of four software packages. Environ. Model. Softw. 51, 94–111.

Memarian H, Balasundram SK, Talib JB, Sung CTB, Sood AM, Abbaspour K (2012) Validation of CA-Markov for simulation of land use and cover change in the Langat Basin, Malaysia. J Geogr Inf Syst:542–554.

Ministry of mines (2018), Indian minerals yearbook 2017, 56th edition, Nagpur, Bureau of Mines, Government of India

Mishra V N and Rai P.V (2016) A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar)India, Arabian Journal Geosciences, vol 9, no 249, pp1-18

Monserud RA and Leemans R 1992, Comparing a global vegetation maps with the kappa statistics, Ecological modelling ,62, pp 275-293

Nagamani K, Vijayalakshmi M.M, Mohana P & Sriganesh J (2017) Land Use and Land Cover Change in Tuticorin Coast Using Remote Sensing and Geographic

Information System, International Journal of earth and atmospheric science,152- 162.of 'essential' activities in Thoothukudi district, Tamil Nadu, India, Dakshin Foundation,

Omar NQ, Ahamad MSS, Hussin WMAW, Samat N, Ahmad SZB (2014) Markov CA, multi regression, and multiple decision making for modelling historical changes in Kirkuk City, Iraq. J Indian Soc Remote Sens 42(1):165–178.

Pandiyan .J ,Naresh. B & Nagarajan .R 2013 Spatial variations of shorebird community in the saltpans of East coast of Tamil Nadu, Southern India, Journal of scientific transactions in Environment and Technovation , vol.7, no.1,pp. 51 -58

Peter H. Verburg, Paul P. Schot , Martin J. Dijst & A. Veldkamp 2004 Land use change modelling: current practice and research priorities , GeoJournal , vol.61,309-324

Pijanowski, B. C., D. G. Brown, G. Manik, and B. Shellito. 2002a. Using neural nets and GIS to forecast land-use changes: a land transformation model. Computers, Environment and Urban Systems 26(6):553-575.

Pontius RG Jr, Schneider LC (2001) Land-cover change model validation by a roc method for the Ipswich watershed, Massachusetts, USA. Agr Ecosyst Environ 85(1):239–248

Prakash S & Maria N S (2018) A study on the working condition of Salt pan workers in Thoothukudi , International Journal of Science, Engineering and management vol.3,no.4, pp.545-548.

Sang L, Zhang C, Yang J, Zhu D, Yun W (2011) Simulation of land use spatial pattern of towns and villages based on CA–Markov model. Math Comput Model 54:938–943

Saputra, M.H., Lee, H.S., 2019. Prediction of land use and land cover changes for North Sumatra, Indonesia, using an artificial-neural-network-based cellular automaton. Sustainability 2019 11 (11), 3024.

Silva LP , Xavier A .P .C , Silva R.M, Santos C A 2020 Modelling land cover change based on an artificial neural network for a semiarid river basin in north-eastern Brazil, Global Ecology and Conservation , vol.21, pp1-13

Swades Pal and Ziaul 2017 Detection of land use and land cover change and land surface temperature in English Bazar urban centre , The Egyptian Journal of Remote Sensing and Space Sciences , vol.20, pp.125-145

US Geological Survey, Mineral commodity summaries 2019

Verburg, P.H.; Overmars, KP Combining top-down and bottom-up dynamics in land use modelling: Exploring the future of abandoned farmlands in Europe with the Dyna-clue model. Landsc. Ecol. 2009, 24, 1167–1181

Wang.M. Cai L, Xu H and Zhao S (2019) Predicting land-use changes in northern China using logistic regression, cellular automata, and a Markov model, Arabian Journal of Geosciences, vol 12 , no 790

Ye B, Bai Z (2008) Simulating land use/cover changes of Nenjiang County based on CA-Markov model. Computer and Computing Technologies in Agriculture, Volume I. Springer, In, pp 321–329

Yubo Z , Zhuoran.Y, Jiuchun Y , Yuanyuan. Y , Wang Dongyan W , Zhang Yucong .Z, Fengqin Y , Lingxue Y , Liping. C and Shuwen Z (2020) A Novel model integrating deep learning for land use/ land cover change reconstruction: A case study of Zhenlai Country, Northeast China, Remote Sensing, vol.12 no3314, pp 1-22.