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PREDICTION OF FUTURE LAND USE-LAND COVER USING CELLULAR AUTOMATA-MARKOV CHAIN MODEL IN SIND RIVER BASIN OF CENTRAL INDIA

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ABSTRACT

Modelling of Landuse-Landcover (LULC) change using spatiotemporal data is important to know the land use change and environmental monitoring, especially in agricultural fields which allows us to comprehend the potential changes in crop area and for considerate management of land in future. Efforts have been made to evaluate LULC changes from 2005 to 2020 and to predict future land use changes in 2030, 2050 and 2080 using an integrated Cellular Automata-Markov Chain (CA-MC) model in the Sind River Basin in Central India. To evaluate the spatiotemporal change and future simulation, LULC Landsat images of 2005, 2015 and 2020 collected from NRSC Bhuvan were used. A module called Land Change Modeller in TerrSet was selected to study the land use dynamics. The over-all accuracy and the Kappa coefficient were found as 90.5% and 0.83 respectively, when the simulated and actual LULC map for the year 2020 were compared. The study finds that the major areas under Agriculture, forest land and waterbody are likely to convert into urban area in future which could lead to decrease in evapotranspiration and increase in runoff. Measures should be implemented for proper use of cultivable land and forest conversion has to be managed well. The predicted maps can be utilized as input thematic maps in various climatic and environmental models to achieve the goals of sustainable development in the region.

Key words : CA-Markov Chain, LULC, Predictive modelling, Kappa coefficient.

Introduction

Land use-Land Cover (LULC) are two key features that characterize the Earth's surface. Land use refers to how people use the land area which considers the activities and arrangements. Land cover is a physical feature on the facet of the Earth such as soil, water, vegetation, etc. The anthropogenic activities on land have significantly affected the terrestrial ecosystem and environmental change both locally and globally (Ramankutty *et al.*, 2006). In the recent years, the mechanism of LULC has greatly changed (Beroho *et al.*, 2023). The primary cause of this is the accelerated human-mediated processes like deforestation, urbanization and agricultural development (Sun *et al.*, 2021). Because of the land interaction with human and environment, its changes are integral part of the global plan. It is evident that the insufficient knowledge regarding the usage of environmental resources causes the magnitude and dynamics of land use change to become a serious problem in a country like India with a growing population.

LULC changes are sustained globally due to a number of variables, including the alarmingly growing population and the perceived necessity for natural resources like residential and agricultural land (Hyandye and Martz, 2017; Halmy *et al.*, 2015; Khan *et al.*, n.d.). Due to its dynamic nature, the LULC necessitates ongoing evaluation, research, planning, and monitoring using socio-economic and geospatial data to produce comprehensive and precise results (Cunha *et al.*, 2021 and Yifru *et al.*, 2021). The land cover data can be determined by analyzing aerial and satellite imagery. In recent years, less efforts are entailed in identifying LULC classes due to the easy availability of high-resolution remote sensing satellite images and classified data facilitated by authorized organizations (Li *et al.*, 2019; Venter *et al.*, 2022; Tessema *et al.*, 2020). Some of them are Environmental System Research Institute's LULC classified data and MODIS land cover classes from NASA (global), National Remote Sensing Center (NRSC), Bhuvan which maintains the land cover images and statistics of India.

A realistic prediction of land use demand and its simulation in potential future scenarios are essential for maximizing the effectiveness of land use policy and planning (Nourqolipour *et al.*, 2015). Therefore, land change models should be used to simulate a wide range of potential earth system evolution scenarios to aid in the development of strategies and land use evaluation studies (Liu *et al.*, 2017). One of the notable human advancements since the pre-historic era is the use and application of geospatial technologies such as Remote Sensing (RS), Geographical Information System (GIS) and Global Positioning System (GPS) (Hussain *et al.*, 2022; Revuelta-Acosta *et al.*, 2022). RS is an effective tool for regularly tracking and quantifying LULC changes in the environment and for analyzing geomorphological data to determine how landforms have changed over time (Alshari and Gawali, 2021; Seyam *et al.*, 2023). Use of machine learning image classifiers in RS has increased because of availability of free satellite data. For mapping and modeling land cover, both the supervised and unsupervised techniques of machine learning are becoming steadily more common (Wang *et al.*, 2022). Over the past 20 years, a number of models pertaining to LULC have been developed to study future land use scenarios at various scales and various regions, plus to assess and simulate the impact of changes in land usage on the Earth system (Aburas *et al.*, 2017; Gollnow *et al.*, 2018; Firozjaei *et al.*, 2019).

Spatial models are widely used, where the primary feature that sets spatial models apart from non-spatial models (based on econometric applications and economic theories of development (Aburas *et al.*, 2019) is their capacity to clearly illustrate changes in land use on a map (Yang *et al.*, 2020). The cellular automata may be characterized as a physical system model where time and space are considered discrete and interactions are local (Tsompanas *et al.*, 2021). The traditional CA are insufficient to create a realistic simulation because the models structure solely considers the spatial data (Jokar Arsanjani *et al.*, 2013). In fact, the CA is a limited model for implementing the factors that drive land use change, which makes it challenging to manage (Mohammady *et al.*, 2014). Considering this, the combined modelling methodologies are to be suited well for simulating LULC processes (Karimi *et al.*, 2018). So, the integration of a traditional CA model with a spatio-temporal model like Markov Chain (MC) is done for better results and to overcome the above constraints (Gharaibeh *et al.*, 2020). The MC approach tracks the temporal evolution on the basis of transition matrices.

The decrease in areas of cultivated land and waterbodies with increase in urban land is now a critical problem and shortcoming in recent times. In this study, the loss and gain of each land class and future amount of change prediction is understood. The combined CA-MC model hasn't been applied in the land-use simulations in the Sind basin, which makes its use to forecast future land use conditions. This study was therefore an aim to assess the spatial and temporal changes in 2005-2015-2020; to simulate and validate for 2020 LULC; as well as to predict the LULC for 2030, 2050 and 2080 based on CA-MC model.

Materials and Methods

Study area

The Sind River Basin lies between 77°10′ 19′′ to 79°07′ 32′′ E longitude and 24°01′ 04′′ to 26°47′ 01" N latitude. The Sind River is one of the longest rivers of the Central India which joins the Yamuna River on its right bank of length 470 km (Fig. 1). The geographical area of the river basin is 28,975 km^2. The precipitation variability ranges between 800 to 1000 mm experiencing dry tropical climate (Narsimlu *et al.*, 2018). The majority of the study area exists in the state of Madhya Pradesh while some part lies in Utter Pradesh, India. The mean daily minimum temperature in the study area goes up to 3°C and maximum up to 48°C (Kumar *et al.*, 2021). The relative humidity generally exceeds 83%, and the wind velocity is higher during the pre-monsoon season than the post-monsoon (Kumar *et al.*, 2021). The study area has denudational hills, pediment (granite), Deccan plateau, alluvial plains, intermountain valley, mesa and ridges (Narsimlu *et al.*, 2018). A major part of the river basin has low productivity with subsistence agriculture and has excessive runoff (Narsimlu *et al.*, 2018).

Data Acquisition and maps preparation

The LULC maps of 2005, 2015 and 2020 of scale 1:2,50,000 scale were acquired from the National Remote Sensing Center (NRSC), Bhuvan. The basin shape file was extracted from SRTM 90 m DEM which was taken from the United States Geological Survey (USGS)

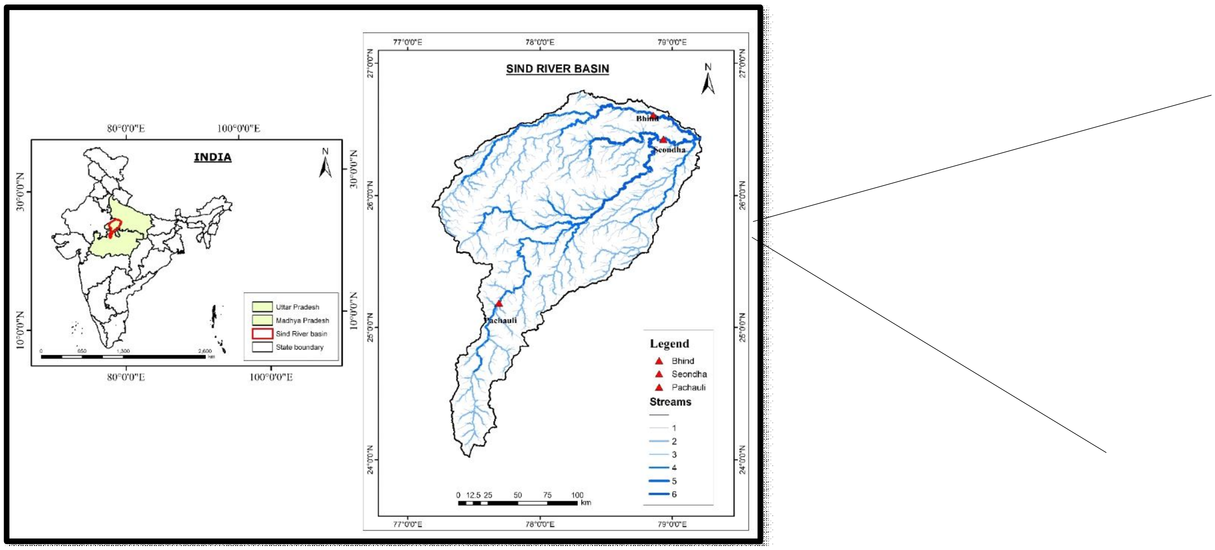


Fig. 1 : Location of the study area.

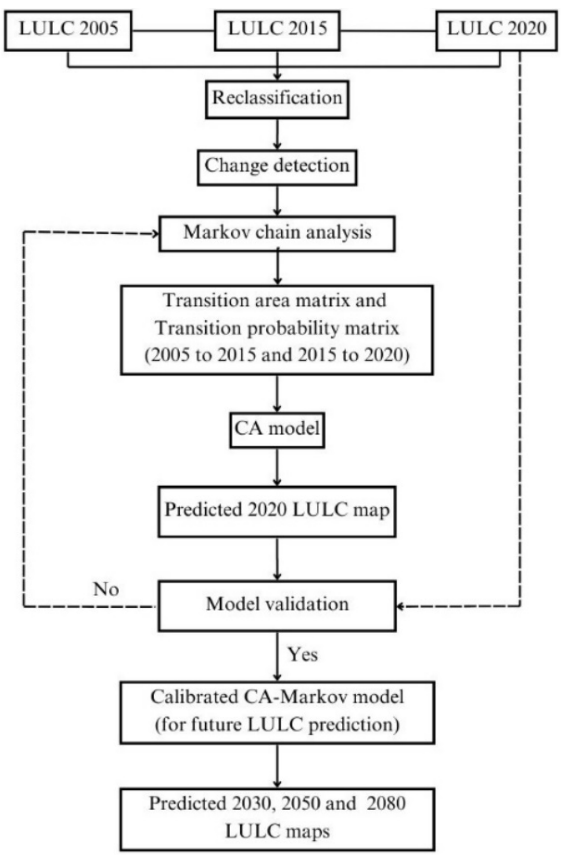


Fig. 2 : Methodological flowchart applied in this study.

website (https://earthexplorer.usgs.gov/) accessed on 15 April, 2014. The 2005, 2015 and 2020 maps were integrated into ArcMap 10.2.2 to prepare the maps for LULC analysis.

The original LULC map of Sind basin has 12 classes, namely built-up, *kharif* crop, *rabi* crop, *zaid* crop, double/ triple crop, current fallow, plantation, deciduous forest, scrub forest, wasteland, waterbodies max and waterbodies min. They were reclassified in TerrSet software using the RECLASS module which was developed by Clark Labs. Five classes were made by considering *kharif* crop, *rabi* crop, *zaid* crop and double/ triple crop as one entity called 'Agriculture'; current fallow and wasteland as 'Barren land'; plantation, deciduous forest and scrub forest as 'Forest'; min and max waterbodies as 'Waterbody' and the 'built-up land'. So, the final LULC categories are Agriculture, Built-up, Forest, Barren land and Water body for the year's 2005, 2015 and 2020.

Simulation of LULC using CA-Markov Chain model

The Land Change Modeler (LCM) is embedded in TerrSet Geospatial Monitoring and Modeling System. It relies on classified historical satellite imagery to forecast LULC for a specified year. The LCM computes a relative number of transitions after estimating the degree of land cover change that occurred between earlier and later LULC. Changes in the LULC assessment like losses and gains for each class are provided by the module (Leta *et al*., 2021a). The analysis, prediction and validation of the simulated LULC change is possible using the LCM model. Recent patterns, historical land use data and projected future changes serve as base information for future scenarios. The LCM is an empirically driven stepwise process from Change Analysis, Transition Potential Modelling to Change Prediction. The 'change analysis' section analyzes the past landcover change, 'transition potential' section simulates the possibility of land changes and the 'change prediction' section predicts the future direction of change.

CA-Markov Chain analysis is a stochastic process which considers the past state to predict the future changes over time. It is widely used for ecological processes. This spatial model is normally used in enhancing the simulation capability of landcover (Aburas *et al.*, 2016). The CA-MC model is a combination of Cellular Automata & Markov Chain to predict the land use pattern and their characteristics over time (Nouri *et al.*, 2014). The transition probability matrix and transition area matrix are generated by the model. The probability of a particular land use class changing relatively to other classes is represented in probability transition matrix. The pixel number that is expected to change for every LULC class over the time frame given is contained in transition area matrix. Based on transition probability matrix, it predicts the spatial structure of various LULC categories (Li *et al.*, 2015; Wang *et al.*, 2012). The Markov matrix model relies on Bayes equation (Eq (1)) to predict the changes in the LULC. It compares the initial (T_1) and second (T_2) land cover to assess the changes.

$$S_{(t,\, t+1)} = P_{ij} \times S_{(t)} \tag{1}$$

where, $S_{(t)}$ is the system status at time t; $S_{(t+1)}$ is the system status at time of t+1; P_{ij} is the transition probability matrix

$$\left|p_{ij}\right| = \begin{vmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,N} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,N} \\ \cdots & \cdots & \cdots & \cdots \\ p_{N,1} & p_{N,2} & \cdots & p_{N,N} \end{vmatrix} \tag{2}$$

where, ($0 \leq P_{ij} \leq$), P = transition probability; P_{ij} = probability of converting from current state i to another state j in next time; P_N = state probability of any time. The probability transition varies from 0 to 1, where 0 denotes low transition and 1 denotes high (Kumar *et al.*, 2014).

The following are the steps applied using CA-MC model in TerrSet for simulating LULC (Beroho *et al.*, 2023) shown in Fig. 2:

1. The year 2005, 2015 and 2020 LULC maps were selected;
2. To the 2005 and 2015 maps, Markov transition estimator was employed to get the transition probability matrix to switch from a particular LULC class to the another in 2020;
3. The calculated transition probability data and 2015 map acts as the groundwork for simulating 2020 LULC map;
4. The actual 2020 map is considered as a reference, to decide the accuracy of simulated 2020 map for model validation;
5. The future LULC of 2030, 2050 and 2080 are simulated using the calibrated and validated CA-Markov model.

Validation of simulated map

Validation is a crucial step to evaluate the quality of simulated LULC map with the reference map. Validation was done in VALIDATE module using the classified 2020 LULC map as a reference against the simulated 2020 LULC, based on Kappa coefficient. Nevertheless, the expressiveness of the original Kappa coefficient is limited since it does not categorize between location and quantification error (Leta *et al.*, 2021b). This could be resolved by using Kappa Index of Agreement (KIA) variations which include the following: Kappa for location ($K_{location}$), Kappa for standard ($K_{standard}$), Kappa for stratum-level location ($K_{locationStrata}$) and Kappa for no information (K_{no}). $K_{location}$ computes the spatial accuracy in overall map, based on certain location of LULC map (Pontius and Malanson, 2005). $K_{standard}$ is the ratio of inaccurate class category by chance to correct assignments. $K_{locationStrata}$ is a measure of spatial accuracy inside pre-identified strata, which shows how effectively the grid cells are positioned within the strata and K_{no} indicates the overall agreement between the reference and predicted map (Leta *et al.*, 2021b). The level of Kappa agreement values and permissible range of map comparison are shown in Table 1.

Table 1 : Level of kappa agreement values and comparison values.

S. no.	Value range	Strength of Agreement
1	< 0	Poor
2	0.01-0.4	Slight
3	0.41-0.6	Moderate
4	0.61-0.8	Substantial
5	0.81-1.0	Almost Perfect

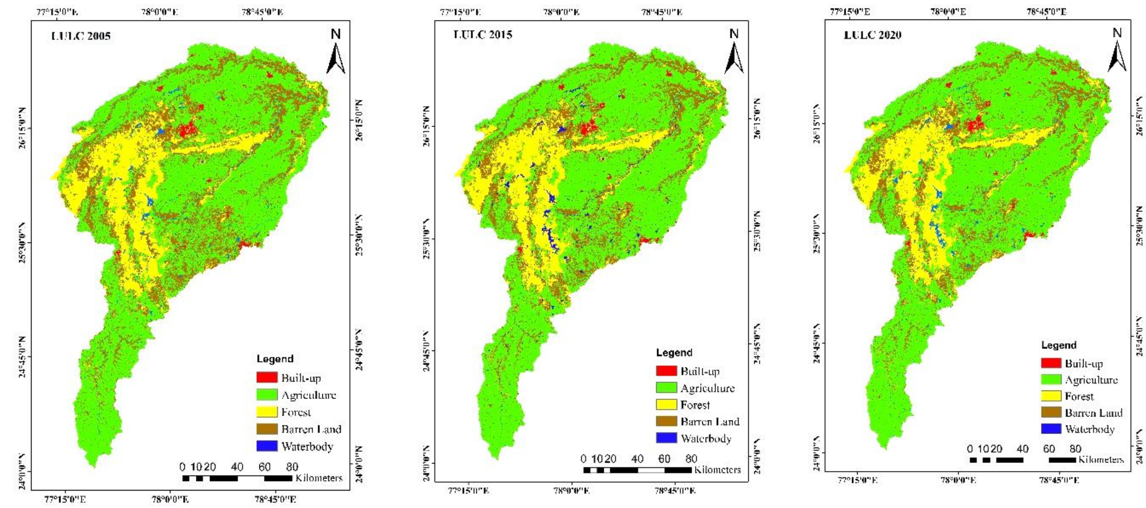
Leta *et al.* (2021c)

Results and Discussion

Land use/Land cover change analysis

The above method produced LULC classified maps of 2005, 2015 and 2020 shown in Fig. 3. The change analysis was performed by evaluation of gains, losses and net change in different classes using change analysis tab in LCM. The evaluation of spatio-temporal change between different classes from 2005 to 2015 was analyzed in Fig. 3 and Table 2. Agriculture is the primary dominant land cover class in the overall distribution followed by forest cover.

The changes between 2005 and 2015 were evaluated by gain and loss of each LULC class as shown in Fig. 4. The green band indicates the gain per class in km^2 while



(a) (b) (c)

Fig. 3 : Classified LULC maps of a) 2005, b) 2015 and c) 2020.

Table 2 : Temporal distribution of the land use/land cover in km^2.

Class	2005		2015		2020	
	Area km^2	**%**	**Area km^2**	**%**	**Area km^2**	**%**
Built-up	484.60	1.73	493.43	1.76	509.63	1.82
Agriculture	13127.2	46.94	15334.33	54.82	17555.92	62.77
Forest	9148.21	32.71	6902.41	24.68	4781.32	17.1
Barren land	4787.01	17.12	4773.67	17.06	4637.16	16.58
Waterbody	420.68	1.5	463.78	1.65	484.32	1.73
Total	27967.70	100	27967.62	100	27968.35	100

the purple band shows the loss per class from the year 2005 to 2015. The agriculture land has the highest amount of area gain, while the barren land has the highest amount of area loss.

The built-up has gained 210.5 km^2 and lost 153.8 km^2 with a net gain of 56.6% between 2005 and 2015. Agriculture has the highest amount of gain 2309.2 km^2 and lost 1489.6 km^2 with net gain of 819.6 km^2. Forest has gained 685.2 km^2 and lost 743.9 km^2 with a net loss of 58.7 km^2. Barren land has the gain of 1635.7 km^2 and the highest loss of 2496.2 km^2 with a net loss of 860.5 km^2. Waterbody has the gain of 167.5 km^2, while the loss of 101.8 km^2 with a net gain of 65.7 km^2.

Transition probability matrix (TPM)

The probability of each LULC class to switch to other class is assessed by the TPM (Leta *et al.*, 2021). It calculates the predicted changes in future LULC maps (Pontius and Malanson, 2005). The TPM generates the likelihood of each land use class to alter into other class depending on the suitable transition area. Table 3 shows the transition probability matrix created by the CA-MC model between 2005-2015. The model performed a cross-tabulation of the spatiotemporal LULC change evaluation between the first and later LULC maps which determines the amount of change occurred between land cover maps. In Table 3, the bolded values in TPM which are diagonal, states the probability of each class that remains unchanged from the former to the later land cover class. While, the off-diagonal values reveal the possibility of change from one class to another. The probability of switching from Agriculture to built-up and barren land is 0.17% and from Agriculture to waterbody is 0.19%.

The results of the TPM are given as an input data to the CA-MC model to simulate the map of 2020. This simulated 2020 map is validated with the actual 2020 LULC map.

Validation of the model

The model has to be validated, to evaluate its accuracy. Validation is important to assess the standard of the simulated map with the actual land cover map. A validation module in the LCM has measured the agreement of two land cover maps. To validate the predicted map, a comparison between the simulated and the actual LULC 2020 map was done. The 2020 actual

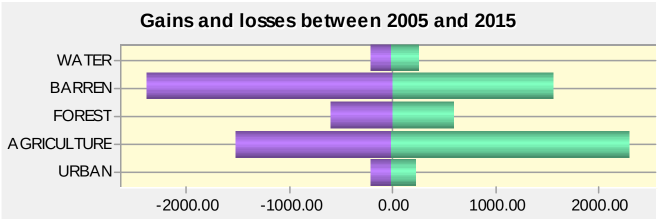


Fig. 4 : Gains and losses area (km^2) of LULC between 2005-2015.

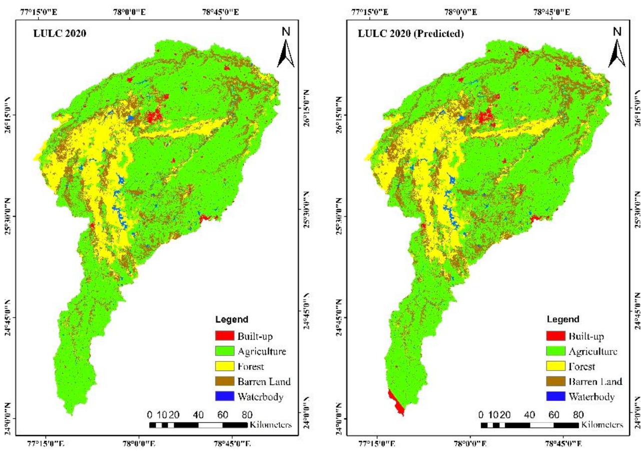


Fig. 5 : Observed and simulated LULC maps of 2020.

Table 3 : Transition probability matrix between 2005 to 2015.

	Built-up	Agriculture	Forest	Barren land	Waterbody
Built-up	**0.7487**	0.1749	0.0201	0.0534	0.0029
Agriculture	0.0053	**0.9491**	0.0046	0.0374	0.0036
Forest	0.0021	0.0166	**0.9343**	0.0431	0.004
Barren land	0.0051	0.1722	0.0361	**0.7743**	0.0123
Waterbody	0.0037	0.1931	0.0316	0.0708	**0.7008**

and simulated LULC maps are shown in Fig. 5. The confusion matrix is generated by the model which compares the classes in the actual map and the simulated map. From the analysis, the simulated map showed reasonably similar results as the reference or actual 2020 LULC map.

Furthermore, the model's efficacy and reliability in producing future LULC maps that are closest to reality are determined by different Kappa indicators. The $K_{standard}$, K_{no}, $K_{location}$ and $K_{locationStrata}$ are 0.9308, 0.9499, 0.9445 and 0.9445, respectively (Fig. 6). The degree of agreement between two maps increases with the values of these indices approaching 100%. All the indices are greater than 80% which justifies that the CA-MC simulated model was well structured and the accuracy was satisfactorily accurate for the simulated map of 2020 (Hamad *et al*., 2018). Based on the observed and simulated results of the LULC 2020, in the class of Agriculture and barren land there was a slight difference of 1.84% and 1.56%, respectively as shown in Fig. 7. However, this dissimilarity has not affected the validation as the over-all accuracy of the model was 90.5% and the over-all Kappa-coefficient was 0.83. The forest land, built-up and waterbody has not shown much variation.

Prediction of future LULC

Use of CA-Markov to analyze future LULC from past LULC is important for land use planning and forest management (Behera *et al*., 2012; Yirsaw *et al*., 2017). The simulated future LULC maps of 2030, 2050 and 2080 of Sind River Basin are shown in Fig. 8 and the areal distribution and percentage are tabulated in Table 4. From 2005 to 2080, the built-up rose tremendously from 484.6 km^2 to 995.4 km^2. The reason could be the increase in population, infrastructure development, industrialization, urbanization, highway expansion, etc. expected to happen in the region. Agricultural land significantly increased from 46.94% in 2005 to 62.7% in 2020, but found in a decreasing trend from 60.69% in 2030 to 60.06% in 2080. This was mainly due to expansion in urban land and deforestation in the future predictions. A similar trend of decrease in crop land and forests due to expansion in urban area through CA Markov modelling was reported by Mitsova *et al*. (2011). Similarly, a continuous increase was observed in waterbody from 420.6 km^2 in 2005 to 484.3 km^2 in 2020, but found decreasing after 2020 in the future years. This decrease in waterbody might be due to horizontal spread of built-up occupying dried lakes, ponds and barren land. Most of the barren land, forest land and agriculture land are found on a decreasing trend in future due to expansion of urban area. Fig. 9 shows the graphical illustration of the area covered by five LULC classes for the past years (2005, 2015, 2020), simulated 2020 LULC and future predicted years (2030, 2050 and 2080).

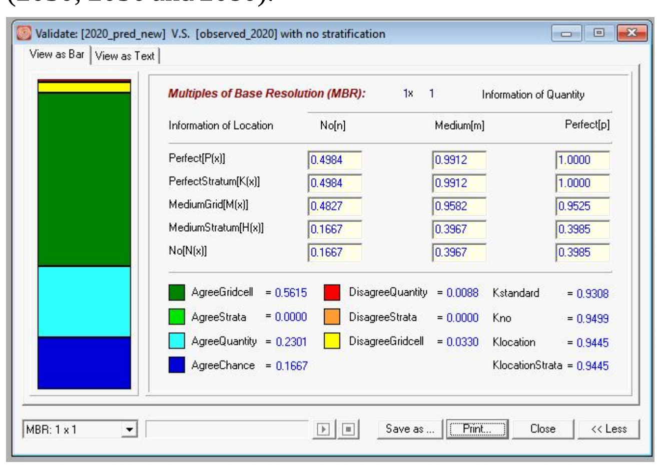


Fig. 6 : Validation of the CA-Markov model.

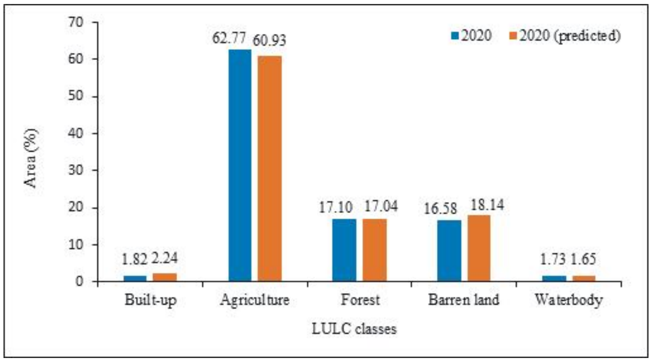


Fig. 7 : Observed and simulated LULC of 2020.

in rural and urban population, the stress on agricultural land and river water for irrigation and domestic purpose is severe. Therefore, thorough environmental evaluation and assessment is required to prevent risks in the future stages. The changes in LULC are closely linked to resource management, environmental health and sustainability. Predicting and monitoring the Land use and Land cover changes is essential for ecosystem health like loss and fragmentation of habitat can result from urban development and deforestation. This alarms the need to protect ecosystem services and biodiversity. With

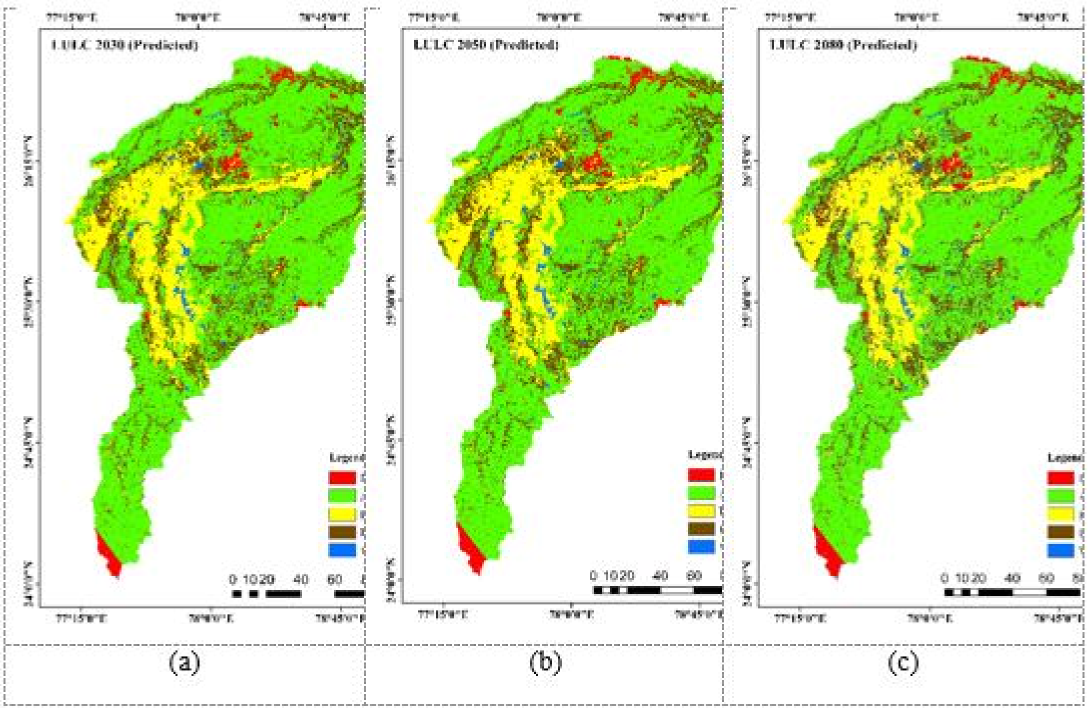


Fig. 8 : Simulated a) 2030, b) 2050 and c) 2080 LULC maps.

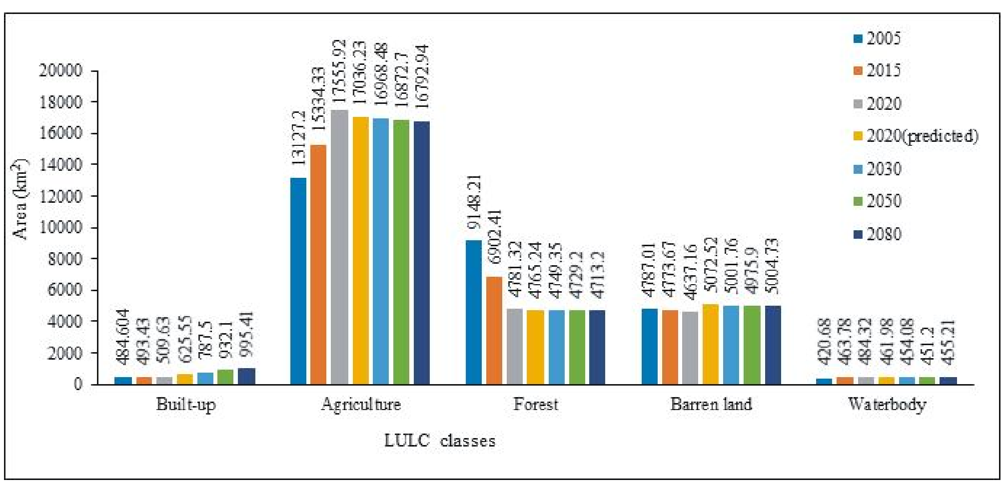


Fig. 9 : LULC classes by area.

Surface and sub-surface water resources, soil fertility, climate variability, agricultural productivity influences the LULC changes directly or indirectly. With the increase the change in land cover, the changes in urbanization and vegetation affects greenhouse gas emissions and local microclimate. This alters the hydrological cycle by

Table 4 : Areal coverage of LULC in 2030, 2050 and 2080 in Sind River basin.

Class	2030		2050		2080	
	Area km^2	%	Area km^2	%	Area km^2	%
Built-up	787.5	2.82	932.1	3.33	995.41	3.56
Agriculture	16968.48	60.69	16872.7	60.34	16792.94	60.06
Forest	4749.35	16.99	4729.2	16.91	4713.2	16.86
Barren land	5001.76	17.89	4975.9	17.80	5004.73	17.90
Waterbody	454.08	1.62	451.2	1.61	455.21	1.63
Total	27961.17	100	27961.1	100	27961.49	100

affecting the ground water recharge and runoff in the basin and also degrades soil health, influences soil erosion and land productivity.

The present study for the prediction of LULC changes in the future found that the model is reliable and effective. Even so, employment of socio-economic variables like climate variability, technological growth, political economy, etc are suggested for further studies. Larger regions can be effectively simulated using CA-MC model (Yang *et al*., 2019), as this work has done. However, it is sensitive in simulating smaller areas (Berling-Wolff and Wu, 2004; Yang *et al*., 2019).

Conclusion

The intention of the current study was to understand how the LULC patterns have changed historically and predictably between 2005 and 2080 in Sind River Basin in Central part of India with a focus on agriculture and water. It is feasible to forecast future land use by using several land change models and accounting for the socioeconomic and ecological elements that affect land use change. An integrated approach including GIS and CA-Markov Chain model was used to comprehend the spatio-temporal LULC dynamics and future LULC change prediction. For the purpose of change analysis, the historical LULC maps of 2005, 2015 and 2020 were used. Then, the future prediction was performed proficiently for 2030, 2050 and 2080 by validating 2020 with proper assessment using Kappa index statistics. The predicted result of 2030 showed sturdy increase of 162.0 km^2 in built-up while a decrease of 70.75 km^2 in agriculture land and a little decline of 8 km^2 in waterbody between 2020 and 2030. Further, the result for predicted 2050 showed an increase of 422.5 km^2 in built-up area where as a decrease of 163.5 km^2 in agriculture land and a slight decrease of 10.7 km^2 in waterbody between 2020 and 2050. Moreover, 2080 showed an increase of 485.8 km^2 in built-up area where in a huge decrease of 243.26 km^2 in agriculture land and a slight decline of 6.7 km^2 in waterbody between 2020 and 2080. The analysis between 2020 and 2080 indicated that there is tremendous decline in agricultural land and water resources, which alarms the crop land loss. The profitability and productivity of the agricultural crops are needed to be improved while conserving the resources. Implementing strategies to protect and conserve cultivated land and waterbodies is crucial to achieve a sustainable equilibrium between natural resources and human activities. The conservation strategies include adapting efficient agricultural practices, maintaining waterways, improving public policies and concentrating on rehabilitation and conservation of degraded lands. The outcomes from the study can be utilized by policy makers for sustainable land use planning and management. They can serve as input layers as well in various hydrological climate models to assess the impact of climate change on water resources.

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Author contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Rooha Blessy and C.K.Saxena. The first draft of the manuscript was written by Rooha Blessy and Rooha Blessy, C.K. Saxena, K.V. Ramana Rao, R.K. Singh, Karan Singh, Manoj Kumar commented on previous versions of manuscript. All authors read and approved the final manuscript.

Conflict of interest

The authors have no competing interests to declare that are relevant to the content of this article.

References

Aburas, M.M., Ahamad M.S.S. and Omar N.Q. (2019). Spatio-temporal simulation and prediction of land-use change using conventional and machine learning models: a review. *Environ Monit Assess*, **191**, 205. doi: 10.1007/s10661-019-7330-6

Aburas, M.M., Ho Y.M., Ramli M.F. and Ash'aari Z.H. (2016). The simulation and prediction of spatio-temporal urban growth trends using cellular automata models: A review.

Int. J. Appl. Earth Observ. Geoinform., **52**, 380–389. doi: 10.1016/j.jag.2016.07.007

Aburas, M.M., Ho Y.M., Ramli M.F. and Ash'aari Z.H. (2017). Improving the capability of an integrated CA-Markov model to simulate spatio-temporal urban growth trends using an Analytical Hierarchy Process and Frequency Ratio. *Int. J. Appl. Earth Observ. Geoinform*., **59**, 65–78. doi: 10.1016/j.jag.2017.03.006

Alshari, E.A. and Gawali B.W. (2021). Development of classification system for LULC using remote sensing and GIS. *Global Transitions Proceedings*, **2**, 8–17. doi: 10.1016/j.gltp.2021.01.002

Behera, M.D., Borate S.N., Panda S.N., Behera P.R. and Roy P.S. (2012). Modelling and analyzing the watershed dynamics using Cellular Automata (CA)–Markov model – A geo-information-based approach. *J Earth Syst Sci*., **121**, 1011–1024. doi: 10.1007/s12040-012-0207-5

Berling-Wolff, S. and Wu J. (2004). Modeling urban landscape dynamics: A case study in Phoenix, USA. *Urban Ecosystems* **7**, 215–240. doi: 10.1023/B:UECO.0000044037.23965.45

Beroho, M., Briak H., Cherif E.K., Boulahfa I., Ouallali A., Mrabet R. *et al*. (2023). Future Scenarios of Land Use/Land Cover (LULC) Based on a CA-Markov Simulation Model: Case of a Mediterranean Watershed in Morocco. *Remote Sensing*, **15**, 1162. doi: 10.3390/rs15041162

Cunha, E.R.D., Santos C.A.G., Silva R.M.D., Bacani V.M. and Pott A. (2021). Future scenarios based on a CA-Markov land use and land cover simulation model for a tropical humid basin in the Cerrado/Atlantic forest ecotone of Brazil. *Land Use Policy*, **101**, 105141. doi: 10.1016/j.landusepol.2020.105141

Firozjaei, M.K., Sedighi A., Argany M., Jelokhani-Niaraki M. and Arsanjani J.J. (2019). A geographical direction-based approach for capturing the local variation of urban expansion in the application of CA-Markov model. *Cities*, **93**, 120–135. doi: 10.1016/j.cities.2019.05.001

Gharaibeh, A., Shaamala A., Obeidat R. and Al-Kofahi S. (2020). Improving land-use change modeling by integrating ANN with Cellular Automata-Markov Chain model. *Heliyon*, **6**, e05092. doi: 10.1016/j.heliyon.2020.e05092

Gollnow, F., Göpel J., deBarros Viana Hissa L., Schaldach R. and Lakes T. (2018). Scenarios of land-use change in a deforestation corridor in the Brazilian Amazon: combining two scales of analysis. *Reg Environ Change*, **18**, 143–159. doi: 10.1007/s10113-017-1129-1

Halmy, M.W.A., Gessler P.E., Hicke J.A. and Salem B.B. (2015). Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Applied Geography*, **63**, 101–112. doi: 10.1016/j.apgeog.2015.06.015

Hamad, R., Balzter H. and Kolo K. (2018). Predicting Land Use/Land Cover Changes using a CA-Markov Model under Two Different Scenarios. *Sustainability*, **10**, 3421. doi: 10.3390/su10103421

Hussain, S., Lu L., Mubeen M., Nasim W., Karuppannan S., Fahad S. *et al*. (2022). Spatiotemporal Variation in Land Use Land Cover in the Response to Local Climate Change Using Multispectral Remote Sensing Data. *Land*, **11**, 595. doi: 10.3390/land11050595

Hyandye, C. and Martz L.W. (2017). A Markovian and cellular automata land-use change predictive model of the Usangu Catchment. *Int. J. Remote Sensing*, **38**, 64–81. doi: 10.1080/01431161.2016.1259675

Jokar Arsanjani, J., Helbich M., Kainz W. and Darvishi Boloorani A. (2013). Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. *Int. J. Appl. Earth Observ. Geoinform*., **21**, 265–275. doi: 10.1016/j.jag.2011.12.014

Karimi, H., Jafarnezhad J., Khaledi J. and Ahmadi P. (2018). Monitoring and prediction of land use/land cover changes using CA-Markov model: a case study of Ravansar County in Iran. *Arab J Geosci*., **11**, 592. doi: 10.1007/s12517-018-3940-5

Khan, Z., Saeed A. and Bazai M.H. (n.d.). Land use/land cover change detection and prediction using the CA-Markov model: A case study of Quetta city, Pakistan.

Kumar, A., Kanga S., Taloor A.K., Singh S.K. and Đurin B. (2021). Surface runoff estimation of Sind river basin using integrated SCS-CN and GIS techniques. *HydroResearch*, **4**, 61–74. doi: 10.1016/j.hydres.2021.08.001

Kumar, S., Radhakrishnan N. and Mathew S. (2014). Land use change modelling using a Markov model and remote sensing. *Geomatics, Natural Hazards and Risk*, **5**, 145–156. doi: 10.1080/19475705.2013.795502

Leta, M.K., Demissie T.A. and Tränckner J. (2021a). Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. *Sustainability*, **13**, 3740. doi: 10.3390/su13073740

Leta, M.K., Demissie T.A. and Tränckner J. (2021b). Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. *Sustainability*, **13**, 3740. doi: 10.3390/su13073740

Leta, M.K., Demissie T.A. and Tränckner J. (2021c). Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. *Sustainability*, **13**, 3740. doi: 10.3390/su13073740

Li, S.H., Jin B.X., Wei X.Y., Jiang Y.Y. and Wang J.L. (2015). Using CA-Markov model to model the spatiotemporal change of land use/cover in Fuxian lake for decision support. *ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci.*, **II-4/W2**, 163–168. doi: 10.5194/isprsannals-II-4-W2-163-2015

Li, Y., Chang J., Luo L., Wang Y., Guo A., Ma F. *et al*. (2019). Spatiotemporal impacts of land use land cover changes on hydrology from the mechanism perspective using SWAT model with time-varying parameters. *Hydrology Res.*, **50**, 244–261. doi: 10.2166/nh.2018.006

Liu, X., Liang X., Li X., Xu X., Ou J., Chen Y. *et al.* (2017). A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landscape and Urban Planning*, **168**, 94–116. doi: 10.1016/j.landurbplan.2017.09.019

Mitsova, D., Shuster W. and Wang X. (2011). A cellular automata model of land cover change to integrate urban growth with open space conservation. *Landscape and Urban Planning*, **99**, 141–153. doi: 10.1016/j.landurbplan.2010.10.001

Mohammady, S., Delavar M.R. and Pahlavani P. (2014). Urban growth modeling using an artificial neural network a case study of Sanandaj city, Iran. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.,* **XL-2/W3**, 203–208. doi: 10.5194/isprsarchives-XL-2-W3-203-2014

Narsimlu, Narsimlu, B., Gosain A.K. and Chahar B.R. (2018). Hydrological Modeling to Evaluate Future Climate Change Impacts in Sind River Basin, India. *IJESD*, **9**, 56–61. doi: 10.18178/ijesd.2018.9.3.1073.

Nouri, J., Gharagozlou A., Arjmandi R., Faryadi S. and Adl M. (2014). Predicting Urban Land use Changes using a CA–Markov Model. *Arab J Sci Eng*., **39**, 5565–5573. doi: 10.1007/s13369-014-1119-2

Nourqolipour, R., Mohamed Shariff A.R.B., Balasundram S.K., Ahmad N.B., Sood A.M., Buyong T. *et al.* (2015). A GIS-based model to analyze the spatial and temporal development of oil palm land use in Kuala Langat district, Malaysia. *Environ Earth Sci*., **73**, 1687–1700. doi: 10.1007/s12665-014-3521-1

Pontius, G.R. and Malanson J. (2005). Comparison of the structure and accuracy of two land change models. *Int. J. Geographical Information Sci*., **19**, 243–265. doi: 10.1080/13658810410001713434

Ramankutty, N., Graumlich L., Achard F., Alves D., Chhabra A., DeFries R.S. *et al.* (2006). Global Land-Cover Change: Recent Progress, Remaining Challenges. In : *Land-Use and Land-Cover Change*. Lambin, E.F. and Geist H (eds.). (Berlin, Heidelberg: Springer Berlin Heidelberg), 9–39. doi: 10.1007/3-540-32202-7_2

Revuelta-Acosta, J.D., Guerrero-Luis E.S., Terrazas-Rodriguez J.E., Gomez-Rodriguez C. and Alcalá Perea G. (2022). Application of Remote Sensing Tools to Assess the Land Use and Land Cover Change in Coatzacoalcos, Veracruz, Mexico. *Applied Sciences*, **12**, 1882. doi: 10.3390/app12041882

Seyam, M.M.H., Haque M.R. and Rahman M.M. (2023). Identifying the land use land cover (LULC) changes using remote sensing and GIS approach: A case study at Bhaluka in Mymensingh, Bangladesh. *Case Studies in Chemical and Environmental Engineering*, **7**, 100293. doi: 10.1016/j.cscee.2022.100293

Sun, Q., Qi W. and Yu X. (2021). Impacts of land use change on ecosystem services in the intensive agricultural area of North China based on Multi-scenario analysis. *Alexandria Engg. J*., **60**, 1703–1716. doi: 10.1016/j.aej.2020.11.020

Tessema, N., Kebede A. and Yadeta D. (2020). Modeling land use dynamics in the Kesem sub-basin, Awash River basin, Ethiopia. *Cogent Environ. Sci*., **6**, 1782006. doi: 10.1080/23311843.2020.1782006

Tsompanas, M.-A., Fyrigos I.-A., Ntinas V., Adamatzky A. and Sirakoulis G.Ch. (2021). Cellular automata implementation of Oregonator simulating light-sensitive Belousov–Zhabotinsky medium. *Nonlinear Dyn*., **104**, 4103–4115. doi: 10.1007/s11071-021-06521-0

Venter, Z.S., Barton D.N., Chakraborty T., Simensen T. and Singh G. (2022). Global 10 m Land Use Land Cover Datasets: A comparison of Dynamic World, World Cover and Esri Land Cover. *Remote Sensing*, **14**, 4101. doi: 10.3390/rs14164101

Wang, M., Wander M., Mueller S., Martin N. and Dunn J.B. (2022). Evaluation of survey and remote sensing data products used to estimate land use change in the United States: Evolving issues and emerging opportunities. *Environ. Sci. Policy*, **129**, 68–78. doi: 10.1016/j.envsci.2021.12.021

Wang, S.Q., Zheng X.Q. and Zang X.B. (2012). Accuracy assessments of land use change simulation based on Markov-cellular automata model. *Procedia Environ. Sci*., **13**, 1238–1245. doi: 10.1016/j.proenv.2012.01.117

Yang, C., Wu G., Chen J., Li Q., Ding K., Wang G. *et al.* (2019). Simulating and forecasting spatio-temporal characteristic of land-use/cover change with numerical model and remote sensing: a case study in Fuxian Lake Basin, China. *Europ. J. Remote Sensing*, **52**, 374–384. doi: 10.1080/22797254.2019.1611387

Yang, Y., Bao W. and Liu Y. (2020). Scenario simulation of land system change in the Beijing-Tianjin-Hebei region. *Land Use Policy*, **96**, 104677. doi: 10.1016/j.landusepol.2020.104677

Yifru, B.A., Chung I.-M., Kim M.-G. and Chang S.W. (2021). Assessing the Effect of Land/Use Land Cover and Climate Change on Water Yield and Groundwater Recharge in East African Rift Valley using Integrated Model. *J. Hydrol.: Regional Studies,* **37**, 100926. doi: 10.1016/j.ejrh.2021.100926

Yirsaw, E., Wu W., Shi X., Temesgen H. and Bekele B. (2017). Land Use/Land Cover Change Modeling and the Prediction of Subsequent Changes in Ecosystem Service Values in a Coastal Area of China, the Su-Xi-Chang Region. *Sustainability*, **9**, 1204. doi: 10.3390/su9071204.