Artificial Neural Network - Cellular Automata (ANN–CA) Modelling for Spatio-Temporal LULC Dynamics in Semi-Arid Akole Tehsil, Maharashtra

Vinit Dhaigude[1] Prasad Balasaheb Wale[1*] Thota Sivasankar[2] Swakangkha Ghosh[3] and Sangeeta Sarmah[4]

[1]Geographic Information Systems (GIS), NIIT University, Neemrana (Rajasthan), India, 301705
[2]School of Computer Science, UPES, Bidholi, Dehradun, Uttarakhand, India – 248007
[3]Institute of Geology, Chinese Academy of Geosciences, Beijing, China
[4]Assam State Disaster Management Authority, Guwahati, India
prasad.wale20@st.niituniversity.in

Abstract. This study investigates Land Use Land Cover (LULC) dynamics in ecologically sensitive Akole tehsil of Ahmednagar district over the past two decades (2001–2021) and predicts future scenarios for 2031 and 2041. Multi-temporal Landsat imagery (Landsat-5 and Landsat-8) acquired in February was classified using Maximum Likelihood Classifier (MLC) into five major classes: Water body, Built-up area, Vegetation, Agriculture, and Barren land. Change detection analysis revealed a substantial expansion of Agricultural land and Built-up area, accompanied by a decline in Barren land, with fluctuating Vegetation and Water body extents. Transition probabilities were quantified using an Artificial Neural Network–Multilayer Perceptron (ANN-MLPNN), while Cellular Automata (CA) modeling was employed for spatial prediction of future LULC. The simulation results indicate continued Agricultural expansion (468.53 km² in 2021 to 604.17 km² in 2041) and Vegetation growth (160.53 km² in 2021 to 283.46 km² in 2041), whereas Barren land and Water bodies are projected to shrink significantly. These findings reveal significant anthropogenic dominance over land cover alterations, where Agricultural expansion and Vegetation fluctuations are projected to drive future LULC changes, potentially threatening the biological richness of the Kalsubai–Harishchandragad Wildlife Sanctuary.

Keywords: Land Use Land Cover (LULC), Landsat, Artificial Neural Network (ANN), Cellular Automata (CA)

1 Introduction

Land use and land cover (LULC) are frequently considered as same terminologies, however they differ conceptually. Land cover linked to the physical entities of the Earth's surface, such as forests, water and topographical structures, whereas land use refers to the human induced utilization of these physical features [1]. Accurate mapping and monitoring of LULC dynamics are crucial for long term infrastructure planning and

S. Mantena (ed.), *Proceedings of the Conference on Social and Sustainable Innovation in Technology & Engineering (SASI-ITE 2025)*, Advances in Intelligent Systems Research 199,
https://doi.org/10.2991/978-94-6463-940-7_11

climate change adaptation to address growing population and urbanization [2,3]. Rapid anthropogenic development along with climate change impacts have already altered ~40% of land cover at global scale [4,5,6]. Numerous studies have identified LULC transformation as a critical driver of ecological change, influencing natural habitats at local, regional, and global scales [4,7]. In India, rapid and unplanned LULC changes, influenced by population growth and infrastructure expansion creates serious environmental challenges [8]. Akole tehsil, located in the ecologically sensitive Western Ghats nurtures the Kalsubai Harishchandragad Wildlife Sanctuary (KHWS), which supports several threatened and endangered floral and faunal species. However, natural vegetation is increasingly being converted to agricultural land under the combined influence of migration and population pressure, leading to landscape degradation [9].

Remote Sensing (RS) data acquired by satellites play a crucial role in near real-time, cost-effective, continuous, and reliable mapping and monitoring of natural resources as well as anthropogenic activities [10,5]. RS has also been widely adopted for detecting, mapping, and simulating LULC transformations [1]. The Landsat satellite constellation, with nearly five decades of illuminations, provides a valuable long-term archive that supports assessments of historic to present LULC changes at national to regional scales [11]. In comparison, the Moderate Resolution Imaging Spectroradiometer (MODIS) dataset facilitates large-scale, daily observations [12]. Sentinel-2A and Sentinel-2B launched by European Space Agency in 2015 and 2017 are preferable choice for high resolution (10 m) LULC analysis however they lack historical archives [13,14]. Therefore, Landsat constellations often ger preference for long term spatio temporal LULC explorations [4,6,15].

LULC dynamics can be quantified using either Supervised or Unsupervised classification techniques [16,17]. Unsupervised approaches (K-Means) are more automated, time efficient, and remain independent from training but subjected to manual LULC labelling [18]. Supervised classification algorithms such as Maximum Likelihood Classification (MLC), Random Forest (RF), and Support Vector Machine (SVM) need manual training, hyperparameter optimization but typically provides higher accuracy [19]. Comprehensive illustrations of these Supervised and Unsupervised algorithms including their technical advancements and limitations have been studied by [20,21,5]. Potential future LULC scenarios could be produced by leveraging probabilistic models driven by past LULC patterns and integrating several geo physical variables [5,7]. Several Simulation models including Evolutionary, SLEUTH, Cellular Automata (CA), Markov Chain Models (MCM), and Artificial Neural Network–Multilayer Perceptron Neural Networks (ANN/MLPNN) have been applied for LULC predictions at various scale [5,22]. These MCM calculates transition probabilities to project the likelihood of future LULC scenarios [23,24]. Meanwhile, CA based simulations are widely incorporated and preferred for future LULC prediction through the MOLUSCE plugin in QGIS. MOLUSCE supports multiple methods, including Weights of Evidence (WoE), Logistic Regression (LR), ANN, and Multi-Criteria Evaluation (MCE), offering researchers flexibility in scenario-based modelling [8,25,26].

Recently, researchers utilized RS datasets to analyse the population, LULC, and land hazard suitability dynamics of Akole. [27] analyzed the spatio temporal distribution of tribal populations, noting their concentration in forested and hilly regions. LULC changes have been extensively mapped using RS and GIS. [9] demonstrated agricultural expansion into barren land using LISS III and Landsat 8 data, whereas [28] applied hybrid classification and NDVI to show degradation from urbanization and migration. [29] used AHP for land suitability analysis, finding only 5% land highly suitable for plantations. Similarly, [30] identified landslide susceptible villages in the Kalsubai region, linking hazards to rainfall and steep slopes. However, most studies emphasize present conditions, with limited focus on long term LULC prediction. The present study addresses this gap by analyzing Landsat based LULC patterns (2001–2021) and projecting future changes using Cellular Automata (CA) for 2031 and 2041, offering insights into sustainable land management.

2 Study Area

Akole is situated in the western hilly region (Sahyadri) of Ahmednagar district [27]. Geographically, it spans between 19º13′ N to 19º45′ N latitudes and 73º35′ E to 74º15′ E longitudes (Fig. 1). The elevation ranges between 362 m and 1514 m MSL, with the highest peak of the Western Ghats, Kalsubai (1646 m), located within the area [29]. The region witnesses an average temperature of ~ 29°C and annual rainfall of ~ 543.5 mm throughout year [28]. This dynamic geo-physical setting and climatic regime sustain abundant forest cover in the area and serve as the origin of several rivers, including the Pravara, Mula, and Aadhala, (Fig. 1) ultimately contribute sustaining the floral and faunal diversity of KHWS. However, recent population growth, migration towards urban centers, and construction of new dams for agricultural water supply have significantly transformed the LULC pattern of Akole.

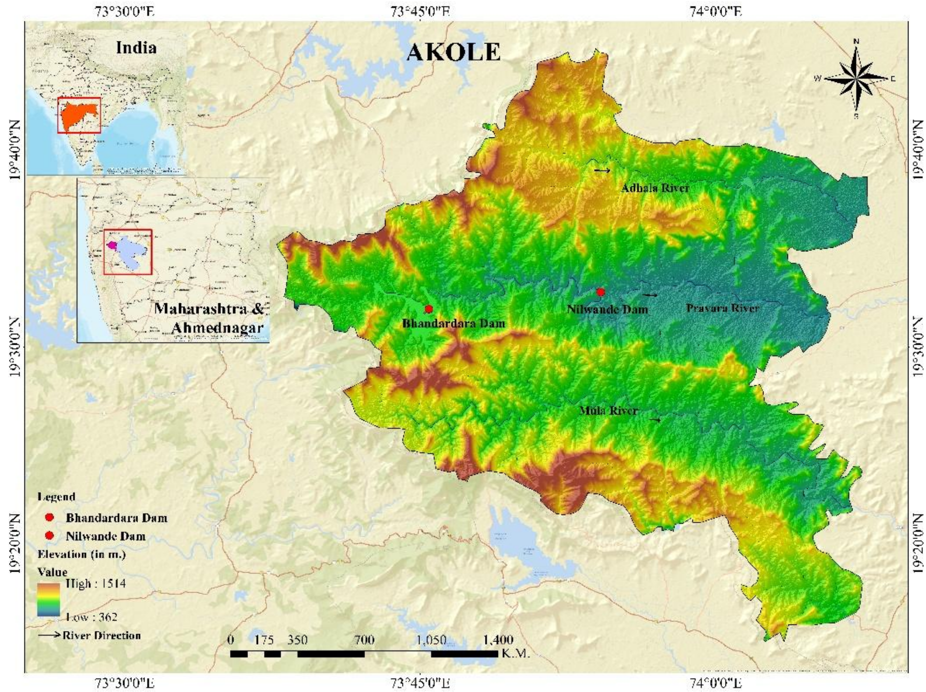

Fig. 1. Geographical location of Akole tehsil in Ahmednagar district, showing the SRTM DEM based elevation insights overlaid with major rivers, their flow directions, and key dams.

3 Methodology

This study examines LULC dynamics in Akole tehsil using Landsat-5 (2001, 2011) and Landsat-8 (2021) imagery acquired in February. LULC maps were generated through MLC and analyzed for changes over two decades. Transition probabilities were estimated using an ANN-MLPNN, while future LULC trends were simulated through CA. The adopted workflow for mapping, monitoring, and prediction is outlined in Fig. 2 and detailed in the following subsections.

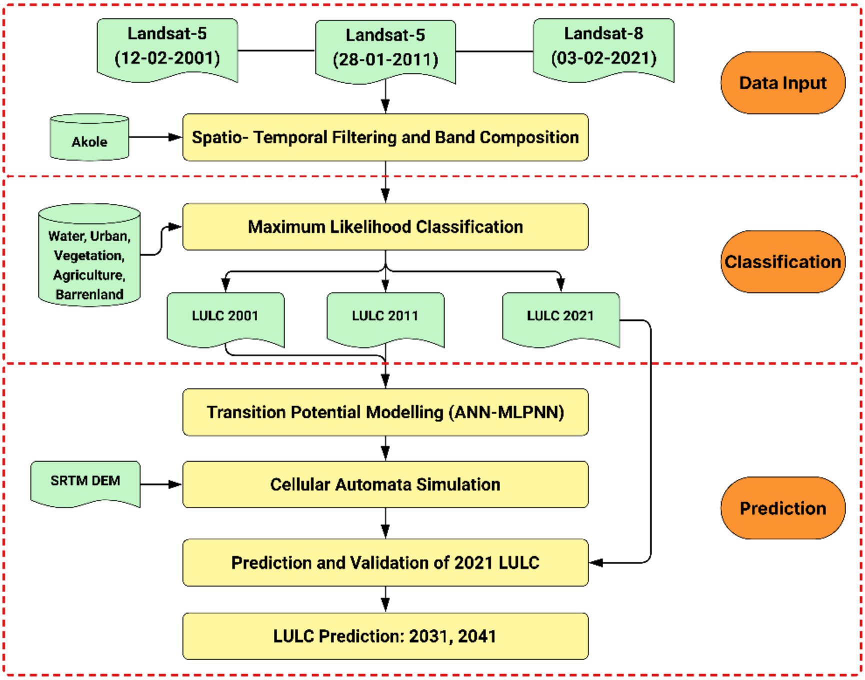

Fig. 2. Workflow adopted for LULC mapping, change analysis, and prediction in Akole tehsil, including Landsat data pre-processing, MLC based classification, ANN-MLPNN transition probability estimation, and CA-based future simulation.

3.1 Dataset:

Landsat 5, launched in March 1984, operated for nearly 29 years and earned a Guinness World Record as the longest-serving Earth observation satellite before its decommissioning in 2013. In this study, Landsat 5 Thematic Mapper (TM) images for 2001 and 2011 and Landsat-8 image for 2021 years were acquired from the USGS. Landsat-5 provides 30 m data with 16 days revisit cycle illuminates earth surface in 7 various spectral bands [32]. Landsat 8, launched in 2013 by USGS, NASA equipped with Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) provide optical and thermal infrared imagery with 11 spectral bands [31]. A Landsat 8 OLI/TIRS image acquired on 03 February 2021, with the same spatial and temporal resolution, was used in this study. The details of the images utilized for the analysis are summarized in Table 1.

Table 1. Details of Landsat satellite images (2001–2021) used for LULC mapping in Akole tehsil.

Data	Periods	Spatial Resolution	Temporal Resolution	Path and Raw	Bands
Landsat 5[TM]	12-02-2001 & 28-01-2011	30 m	16 days	147-46 147-47	Band: 1-5
Landsat 8 [OLI and TIRS]	03-02-2021				Band: 2-6

3.2 Maximum Likelihood Classification (MLC)

In the present study, the MLC technique was accessed through ERDAS Imagine software to produce LULC maps of Akole for 2001, 2011 and 2021 year. Study area was classified into five major LULC classes including Water body, Built up, Natural Vegetation, Agriculture, and Barren land. MLC is one of the most widely used Supervised classification algorithms, designed on probabilistic measurements to assign classes to pixels for LULC mapping and monitoring. This probability is calculated by leveraging statistical measures including the mean and covariance of the class pixel values as a normal distribution in the multispectral feature space [19]. The method considers that the distribution of pixel values within each class follows a multivariate Gaussian distribution [33]. A detailed illustration of MLC's mathematical foundation and implementation is studied by [17].

3.3 Cellular Automata Model

The CA simulation method was utilised in this study to model future LULC scenario of Akole using the MOLUSCE plugin in QGIS 3.4. MOLUSCE is dedicated plugin introduced to simulate LULC transitions and future prediction driven by historical LULC changes and incorporating spatial variables linked to these dynamics [5]. In this study, the February 2001 and 2011 LULC maps of Akole assigned as an initial and final time maps to understand the historic LULC shift, with DEM serving as an additional spatial variable. During the Transition Potential Modelling phase, the ANN-MLPNN method was implemented with the following parameters optimization. Neighborhood 1 px, Learning Rate 0.10, Maximum Iterations 300 and Hidden Layers 5 were assigned. Careful selection of these parameters is essential to achieve accurate results. However, the optimal settings of these parameters may vary depending on the study area and the spatial variables considered [7,8,24]

4 Results and Discussion

In the present study, LULC maps prepared using the MLC for two decades were analyzed to provide socio-economic insights of Akole. The analysis highlights significant LULC transitions between 2001 and 2011, as shown in Fig. 3 (I and II) and summarized in Table 2. The most notable increase was observed in Agricultural land, which expanded by 136.8 sq. km (from 230.53 to 367.33 sq. km), reflecting a strong shift toward cultivation. Barren land, though still dominant, showed a sharp decline of 229.6 sq. km (from 1095.64 to 866.07 sq. km) indicating large scale conversion into anthropogenic activities.

Table 2. Actual (2001–2021) and predicted (2021–2041) LULC class areas (in Sq. KM) for Akole tehsil derived from Landsat imagery and CA–ANN simulations.

Data	Actual (Sq. KM)			Predicted (Sq. KM)		
Class	**2001**	**2011**	**2021**	**2021**	**2031**	**2041**
Water Body	14.29	34.39	38.6	31.02	26.9	23.89
Built-up Area	1.51	8.97	19.28	4.84	2.89	1.81
Vegetation	142.27	207.48	160.53	232.8	258.71	283.46
Agriculture	230.53	367.33	468.53	468.54	545.02	604.17
Barren Land	1095.64	866.07	797.3	747.02	650.72	570.92

Natural Vegetation also increased substantially by 65.21 sq. km, possibly due to reforestation, conservation measures and precipitation increase. Water bodies expanded by 20.1 sq. km, due to the construction of Nilwande dam for agriculture water supply. Although relatively small in extent, the Built-up area grew markedly from 1.51 to 8.97 sq. km, highlighting a clear trend of urban expansion. The class-wise LULC change is illustrated in Fig. 4 (I: 2001-2011 transition, II: 2011-2021 transition)

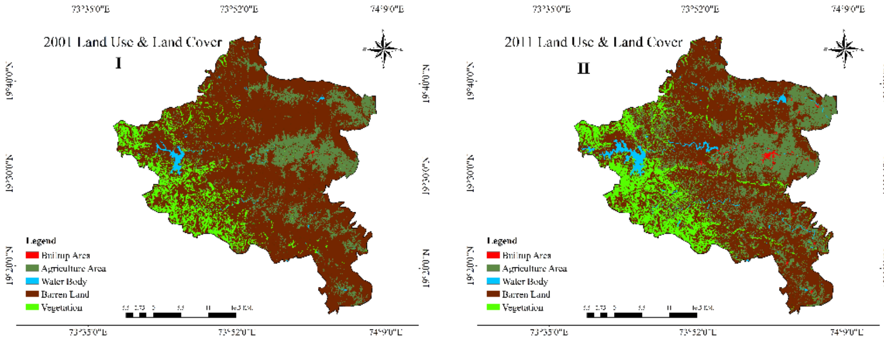

Fig. 3. Supervised LULC classification maps of Akole tehsil for the years 2001-2011 prepared using MLC.

Class wise LULC transitions across two decades illustrated in Fig. 4 where Section (I) illustrates changes between 2001 and 2011, while section (II) highlights the transitions during 2011 to 2021. During the first decade, the most prominent transitions involved conversion of 170 sq. km of Barren land into Agricultural land, 85 sq. km of Barren land into Vegetation, and 17 sq. km of Barren land into Water bodies, the latter largely influenced by dam construction.

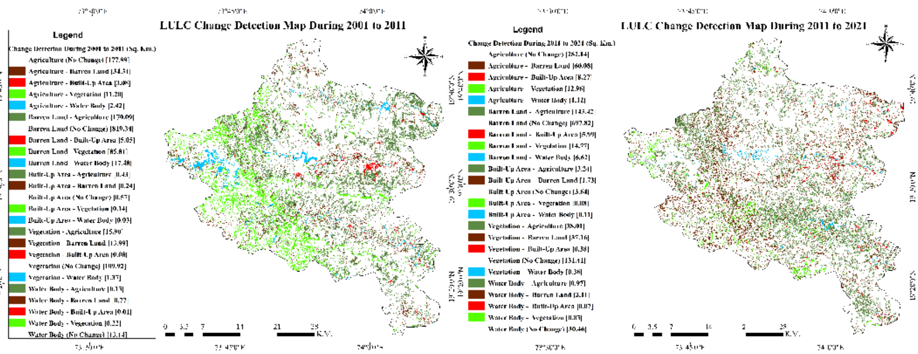

Fig. 4. Class-wise LULC transitions in Akole tehsil across two decades: (I) transitions between 2001–2011 and (II) transitions between 2011–2021.

These conversions emphasize the large-scale reduction of Barren land and its transformation into cultivated land. In the subsequent decade (2011–2021), similar trends continued, though with some additional dynamics. About 143 sq. km of Barren land transitioned into Agriculture, 14 sq. km into Vegetation, and 6.6 sq. km into Water bodies. Notably, new conversion pathways emerged, including 38 sq. km of Vegetation turning into Agriculture indicate intensified agricultural practices. Across both decades, the dominant trajectory remained the conversion of Barren land into Agricultural land, underscoring the strong pressure for cultivation and expansion of farmland. However, the second decade also reflects a more complex pattern, with bidirectional shifts involving Vegetation, suggesting both land degradation and agricultural encroachment.

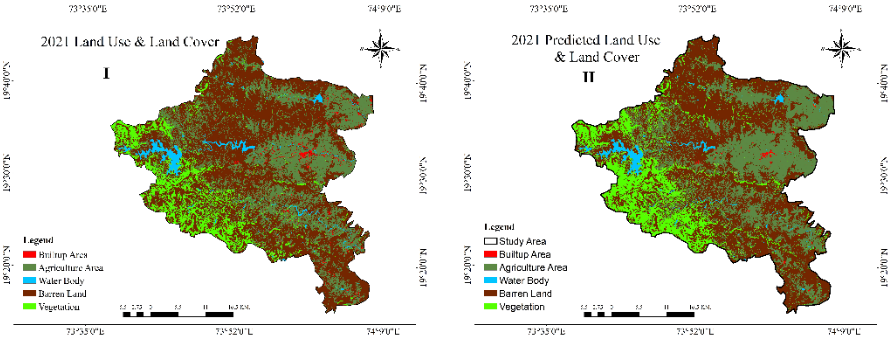

Fig. 5. Comparison of actual and predicted LULC classification for 2021: (I) actual LULC map and (II) predicted LULC map.

Comparison between the actual and predicted LULC classification for 2021 illustrated in Fig. 5, where section (I) shows the actual LULC and section (II) displays the predicted LULC map. The class wise area statistics are provided in Table 2, allowing a detailed assessment of prediction performance. The accuracy assessment indicates an overall correctness of 75.6%, with a Kappa index of 0.92 confirming a strong agreement between the classified and predicted data. Furthermore, the correlation analysis between the predicted and actual class areas yielded a high correlation coefficient of 0.989, suggesting excellent consistency between observed and modeled results. Notably, the highest difference between the two maps was observed in the Vegetation class, with an actual area of 160.53 km² compared to a predicted area of 232.8 km².

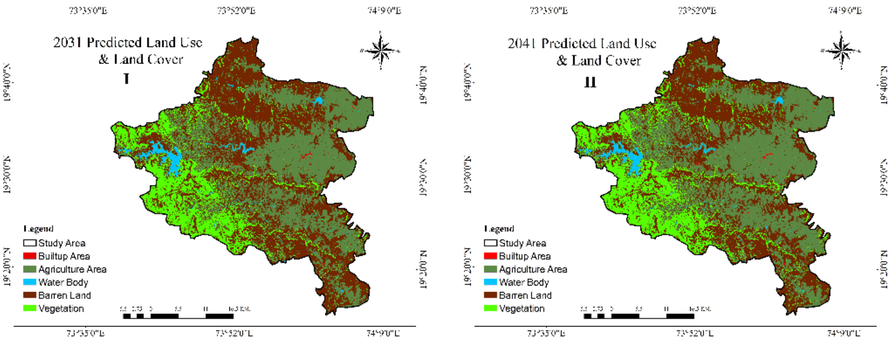

Fig. 6. Predicted LULC maps for future scenarios: (I) 2031 and (II) 2041, showing projected spatial distribution of different land use/land cover classes.

Predicted LULC scenarios for 2031 (I) and 2041 (II) demonstrated in Fig. 6, while the corresponding class-wise area statistics are presented in Table 2. The results indicate notable shifts in LULC over the two decades. The Built-up area is projected to decrease slightly from 26.9 km² in 2031 to 23.89 km² in 2041, while Water bodies are also expected to shrink from 2.89 km² to 1.81 km². In contrast, Vegetation cover shows a significant increase, expanding from 258.71 km² in 2031 to 283.46 km² in 2041. Similarly, Agricultural land is projected to rise from 545.02 km² to 604.17 km², reflecting a strong upward trend. However, the Barren land category demonstrates a decline, reducing from 650.72 km² in 2031 to 570.92 km² in 2041.

5 Conclusion

The Spatio-temporal analysis of Akole tehsil highlights significant LULC transitions over the past two decades, with agriculture emerging as the dominant land use class. Future simulations indicate sustained agricultural expansion and vegetation recovery, alongside a considerable decline in barren land and water resources. The integration of MLC with ANN–CA modelling proved highly effective in capturing both temporal dynamics and spatial patterns of land system transformations. Validation against the 2021 LULC map demonstrated strong predictive accuracy, underscoring the robustness of the modelling framework. Overall, the study advances methodological applications of ANN–CA in regional LULC prediction and provides a scientifically grounded decision-support framework for sustainable land management, agricultural intensification, and water resource conservation in semi-arid landscapes such as Ahmednagar district.

6 References

1. Alam, A., Bhat, M. S., & Maheen, M. (2019). Using Landsat satellite data for assessing the land use and land cover change in Kashmir valley. *GeoJournal*, *85*(6), 1529–1543. https://doi.org/10.1007/s10708-019-10037-x
2. Hussain, S., Qin, S., Nasim, W., Bukhari, M. A., Mubeen, M., Fahad, S., Raza, A., Abdo, H. G., Tariq, A., Mousa, B. G., Mumtaz, F., & Aslam, M. (2022). Monitoring the Dynamic Changes in Vegetation Cover Using Spatio-Temporal Remote Sensing Data from 1984 to 2020. *Atmosphere*, *13*(10), 1609. https://doi.org/10.3390/atmos13101609
3. Phan, T. N., Kuch, V., & Lehnert, L. W. (2020). Land Cover Classification using Google Earth Engine and Random Forest Classifier—The Role of Image Composition. *Remote Sensing*, *12*(15), 2411. https://doi.org/10.3390/rs12152411
4. Chowdhury, M., Hasan, M. E., & Abdullah-Al-Mamun, M. (2018). Land use/land cover change assessment of Halda watershed using remote sensing and GIS. *The Egyptian Journal of Remote Sensing and Space Science*, *23*(1), 63–75. https://doi.org/10.1016/j.ejrs.2018.11.003
5. Talukdar, S., Singha, P., Mahato, S., Shahfahad, N., Pal, S., Liou, Y., & Rahman, A. (2020). Land-Use Land-Cover Classification by Machine Learning Classifiers for Satellite Observations—A review. *Remote Sensing*, *12*(7), 1135. https://doi.org/10.3390/rs12071135
6. Vinayak, B., Lee, H. S., & Gedem, S. (2021). Prediction of land use and land cover changes in Mumbai City, India, using remote sensing data and a multilayer Perceptron Neural Network-Based Markov Chain model. *Sustainability*, *13*(2), 471. https://doi.org/10.3390/su13020471
7. Kafy, A.-. A., Naim, M. N. H., Subramanyam, G., Faisal, A., Ahmed, N. U., Rakib, A. 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. https://doi.org/10.1016/j.envc.2021.100084

8. Pandey, S., & Kumari, N. (2022). Prediction and monitoring of LULC shift using cellular automata-artificial neural network in Jumar watershed of Ranchi District, Jharkhand. *Environmental Monitoring and Assessment*, *195*(1). https://doi.org/10.1007/s10661-022-10623-6
9. Surindar, W., & Aankush, A. (2015). Land Use / Land Cover Mapping using Remote Sensing Data in Pravara River Basin, Akole, Maharashtra, India. *In Int. Res. J. Environment Sci. International Science Congress Association* (Vol. 4, Issue 9). www.isca.me
10. Wale, P. B., Sivasankar, T., Mishra, V. N., & Sanyal, R. (2022). Flood inundation mapping from synthetic aperture radar and optical data using support vector machine. In *Elsevier eBooks* (pp. 203–217). https://doi.org/10.1016/b978-0-12-823457-0.00017-3
11. Prăvălie, R., Sîrodoev, I., Nita, I., Patriche, C., Dumitraşcu, M., Roşca, B., Tişcovschi, A., Bandoc, G., Săvulescu, I., Mănoiu, V., & Birsan, M. (2022). NDVI-based ecological dynamics of forest vegetation and its relationship to climate change in Romania during 1987–2018. *Ecological Indicators*, *136*, 108629. https://doi.org/10.1016/j.ecolind.2022.108629
12. Huang, C., Chen, Y., & Wu, J. (2013). Mapping spatio-temporal flood inundation dynamics at large river basin scale using time-series flow data and MODIS imagery. *International Journal of Applied Earth Observation and Geoinformation*, *26*, 350–362. https://doi.org/10.1016/j.jag.2013.09.002
13. Cîmpianu, C. I., Mihu-Pintilie, A., Stoleriu, C. C., Urzică, A., & Huţanu, E. (2021). Managing Flood Hazard in a Complex Cross-Border Region Using Sentinel-1 SAR and Sentinel-2 Optical Data: A Case Study from Prut River Basin (NE Romania). *Remote Sensing*, *13*(23), 4934. https://doi.org/10.3390/rs13234934
14. Rehman, A. U., Zhang, L., Sajjad, M. M., & Raziq, A. (2024). Multi-Temporal Sentinel-1 and Sentinel-2 data for orchards discrimination in Khairpur District, Pakistan using spectral separability analysis and machine learning classification. *Remote Sensing*, *16*(4), 686. https://doi.org/10.3390/rs16040686
15. Ahmad, F., Hassan, Z. U., Farooq, S., & Shah, J. A. (2015). Assessment of Land Use/Land Cover change in Hirpora Wildlife Sanctuary, Kashmir. *Asian Journal of Earth Sciences*, *8*(3), 64–73. https://doi.org/10.3923/ajes.2015.64.73
16. Li, X. C., Liu, L. L., & Huang, L. K. (2020). COMPARISON OF SEVERAL REMOTE SENSING IMAGE CLASSIFICATION METHODS BASED ON ENVI. *the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences/International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-3/W10, 605–611. https://doi.org/10.5194/isprs-archives-xlii-3-w10-605-2020
17. Shivakumar, B. R., & Rajashekararadhya, S. V. (2018). Investigation on land cover mapping Capability of maximum likelihood Classifier: A case study on North Canara, India. *Procedia Computer Science*, *143*, 579–586. https://doi.org/10.1016/j.procs.2018.10.434
18. Borah, S. B., Sivasankar, T., Ramya, M. N. S., & Raju, P. L. N. (2018). Flood inundation mapping and monitoring in Kaziranga National Park, Assam using Sentinel-1 SAR data. *Environmental Monitoring and Assessment*, *190*(9). https://doi.org/10.1007/s10661-018-6893-y
19. P. S. Sisodia, V. Tiwari and A. Kumar, "Analysis of Supervised Maximum Likelihood Classification for remote sensing image," *International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2014)*, Jaipur, India, 2014, pp. 1-4, doi: 10.1109/ICRAIE.2014.6909319.
20. Feng, Q., Liu, J., & Gong, J. (2015). UAV remote sensing for urban vegetation mapping using random forest and texture analysis. *Remote Sensing*, *7*(1), 1074–1094. https://doi.org/10.3390/rs70101074

21. Mehmood, M., Shahzad, A., Zafar, B., Shabbir, A., & Ali, N. (2022). Remote Sensing Image Classification: A Comprehensive review and Applications. *Mathematical Problems in Engineering*, *2022*, 1–24. https://doi.org/10.1155/2022/5880959
22. Abdelkarim, A. (2023). Monitoring and forecasting of land use/land cover (LULC) in Al-Hassa Oasis, Saudi Arabia based on the integration of the Cellular Automata (CA) and the Cellular Automata-Markov Model (CA-Markov). *Geology Ecology and Landscapes*, 1–32. https://doi.org/10.1080/24749508.2022.2163741
23. Antomi, Y., Angraina, D., Arif, D. A., & Fitriawan, D. (2024). Exploring the Effects of Land use Land Cover (LULC) Change on Menhir in 2053: Utilizing the Cellular Automata-Artificial Neural Network (CA-ANN) Algorithm: A Case Study of Menhir Tourist Site in Nagari Maek, *Indonesia. International Journal of Geoinformatics*, 20(11), 54–73. https://doi.org/10.52939/ijg.v20i11.3685
24. Ghalehteimouri, K. J., Shamsoddini, A., Mousavi, M. N., Ros, F. B. C., & Khedmatzadeh, A. (2021). Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model based scenarios (2019–2049) Zarriné-Rūd River Basin in Iran. *Environmental Challenges*, *6*, 100399. https://doi.org/10.1016/j.envc.2021.100399
25. Jain, M. (2024). Future land use and land cover simulations with cellular automata-based artificial neural network: A case study over Delhi megacity (India). *Heliyon*, *10*(14), e34662. https://doi.org/10.1016/j.heliyon.2024.e34662
26. Sajan, B., Mishra, V. N., Kanga, S., Meraj, G., Singh, S. K., & Kumar, P. (2022). Cellular Automata-Based Artificial Neural Network Model for assessing past, Present, and Future Land Use/Land Cover dynamics. *Agronomy*, *12*(11), 2772. https://doi.org/10.3390/agronomy12112772
27. Deshmukh, S. (2019). MONITORING SPATIAL VARIATION IN TRIBAL POPULATION AT TAHSILS OF AHMEDNAGAR DISTRICT, MAHARASHTRA USING GIS TECHNIQUE. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-5/W3*, 21–25. https://doi.org/10.5194/isprs-archives-xlii-5-w3-21-2019
28. Gadekar, D., Deepak Janardhan, G., Mhaske A Hybrid Land Cover Classification of Landsat-7 & 8 (OLI) ETM+ Data for Resourceful Vegetation Mapping-Akole Thasil Dist-Ahmednagar, M.S, India. *American International Journal of Research in Humanities, Arts and Social Sciences* AIJRHASS, 15–872. http://www.iasir.net
29. Zolekar, R., & Bhagat, V. (2018). Multi-Criteria land suitability analysis for plantation in Upper Mula and Pravara Basin: Remote Sensing and GIS approach. *Journal of Geographical Studies*, *2*(1), 12–21. https://doi.org/10.21523/gcj5.18020102
30. Gawali, P. B., Aher, S. P., Lakshmi, B. V., Gaikwad, R. D., Deendayalan, K., Hanamgond, P. T., Babu, J. L. V. M., Arote, S. A., & Bairage, S. I. (2017). Identification of Landslide Susceptible Villages around Kalsubai Region, Western Ghats of Maharashtra Using Geospatial Techniques. *Journal of the Geological Society of India*, *90*(3), 301–311. https://doi.org/10.1007/s12594-017-0718-4
31. Ullah, W., Ahmad, K., Ullah, S., Tahir, A. A., Javed, M. F., Nazir, A., Abbasi, A. M., Aziz, M., & Mohamed, A. (2023). Analysis of the relationship among land surface temperature (LST), land use land cover (LULC), and normalized difference vegetation index (NDVI) with topographic elements in the lower Himalayan region. *Heliyon*, *9*(2), e13322. https://doi.org/10.1016/j.heliyon.2023.e13322
32. Duarte, E., Barrera, J. A., Dube, F., Casco, F., Hernández, A. J., & Zagal, E. (2020). Monitoring approach for tropical coniferous forest degradation using remote sensing and field data. *Remote Sensing*, *12*(16), 2531. https://doi.org/10.3390/rs12162531

33. Ahmad, A., & Quegan, S. (2012). Analysis of maximum likelihood classification on multi-spectral data. *Applied mathematical sciences*, *6*(129), 6425-6436