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RESEARCH ARTICLE

Short-term predictions of land use fragmentation in Panchnoi River Basin, Assam, India using artificial neural networks

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Abstract - Land use and land cover monitoring, management and prediction are critical aspects of overseeing specific Earth's surface segments or river basins. These changes often influence man and environment relationships. Escalating population pressure and demand for land resources induce substantial alterations which are predominantly driven by human activities. The 'Panchnoi' river basin exemplifies similar changes. This study evaluates the rate of land use fragmentation and land cover changes utilizing satellite imagery and GIS. Different key metrics, such as the number of patches (NP) and mean patch size (MPS), reveal insights into land fragmentation patterns. The impact is evident in the rising NP and declining MPS, indicating significant fragmentation in the Panchnoi River Basin between 2008 and 2019 across multiple land-use and land-cover categories. Anticipating future changes, a Land Use and Land Cover Prediction Map for 2026, generated using MOLUSCE Plugins (specifically, ANN-Multi Layer Perception) within QGIS Version 2.8.2, aims to predict shifts and discern the evolution in land use patterns from 2008 to 2019 and into 2026. The ANN-Multi Layer Perception is a quick way of projecting future transitions of land use and land cover of the Panchnoi River basin. As the forest and grassland areas are declining rapidly, such type of prediction will help policymakers for effective management of ecosystems of the river basin. The grassland area is projected to experience the most significant reduction, decrease from 6421.860 hectares in 2008 to just 0.0224 hectares by 2026 over a span of 18 years. The study not only focuses on land use fragmentation in the Panchnoi River basin but also predicts the changing trend of land use using the Artificial Neural Network (CA-ANN) technique.

Keywords: Land use Fragmentation, number of patches, mean patch size, MOLUSCE, QGIS

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1. INTRODUCTION

The rapid urbanization and population growth have triggered the phenomenon of land use fragmentation in most part of the world. It is a division of land into continuous isolated and smaller parcels. Escalating demand for land resources results in increased land conversion and spatial isolation. These in turn disturb the natural connectivity of ecosystems and upset the fragile man and environment relationship. Land use fragmentation compromises biodiversity conservation efforts and also leads to vulnerable species extinction. The changing landscape patterns as well as reduced niche size have a direct effect on the ecosystem. Besides ecosystems, land use fragmentation also affects the society and economy. Fragmentation poses a significant threat to efficient land utilisation over time, contributing to declining agricultural productivity and risking food security. Additionally, it aggravates socioeconomic inequalities, disproportionately affecting vulnerable communities by restricting their access to financial resources, limiting mobility, and undermining livelihoods. Consequently, the imperative arises for region-specific policies that foster a harmonious balance between progressive ecological practices and socioeconomic land use, all while addressing the evolving needs of human society. It creates challenges and policy issues to solve environmental and social problems arising from the phenomena.

Fragmentation is a distinguished feature in agricultural landscapes across the globe with many ecological consequences (Wei et al., 2020). It is worth mentioning that ecosystem degradation is primarily attributed to fragmentation as it diminishes the capacity of habitats to provide essential ecosystem services (Bryan Brown et al., 2020). The tropical region is marked by the complex interaction of various factors that shape spatial patterns through changes in land use and land cover. In the United States land use changes have exerted an influence on the Lyme disease spirochete Borrelia burgdorferi sensu stricto (Diuk-Wasser et al., 2021). The ongoing global environmental changes and the modification of land use and land cover (LULC) has emerged as a persistent issue requiring immediate attention (Talukdar et al., 2021). This study is an attempt to understand the pattern of changes caused by land use fragmentation in the locality of the Panchnoi River basin based on GIS-based methods. Many researchers (Houet et al., 2010; Sivrikaya et al., 2007; Vitousek, 1994; Bradley & Mustard, 2005; Geist & Lambin, 2001; Turner 2001; Saikia et al. 2013; Singh et al., 2017; Areendran et al., 2020 and Kamaraj & Rangarajan, 2022) have shown a keen interest in exploring these areas due to the adverse ecological effects associated with land-use change (Hunsaker et al., 1994).

Similar studies on land use predictions are reported from different parts of India and the world, including Pearl River Delta, China (Jiao et al., 2019), Dhaka, Bangladesh (Kafy et al., 2021), China (Muhammad et al., 2022), Sundarbans deltaic region (Ahmed et al., 2023), Pakhal Lake area, Telangana (Amgoth et al., 2023), Mand catchment area (Baghel et al., 2024), and many other. Jiao et al. 2019 in their study assessed the changing nature of future land use and land cover under intense human disturbances of economic development in Pearl River Delta of China. Kafy et al. (2021) in their study on Dhaka Metropolitan Development Plan found that rapid increase of urban area is reducing ecosystem services and thus a future prediction of LULC will be helpful in planned urban infrastructure development. Muhammad et al. (2022) has used the integrated CA-ANN (Cellular Automata-Artificial Neural Network) methodology within the MOLUSCE plugin of QGIS was used for spatiotemporal change analysis and future land use and land cover (LULC) simulation of Linyi, China. They further emphasize on physical and socio-economic factors on landscape changes. Ahmed et al. (2023) in their investigation on sundarban deltaic region, predicts that by 2050, the mangrove forest area in the Sundarbans will decrease, while waterbodies will increase. Amgoth et al. (2023) also employed The Cellular Automata–Artificial Neural Network (CA-ANN) technique to predict LULC changes. Baghel et al. (2024) in their study predicts future land use scenarios in the Pakhal Lake area of India.

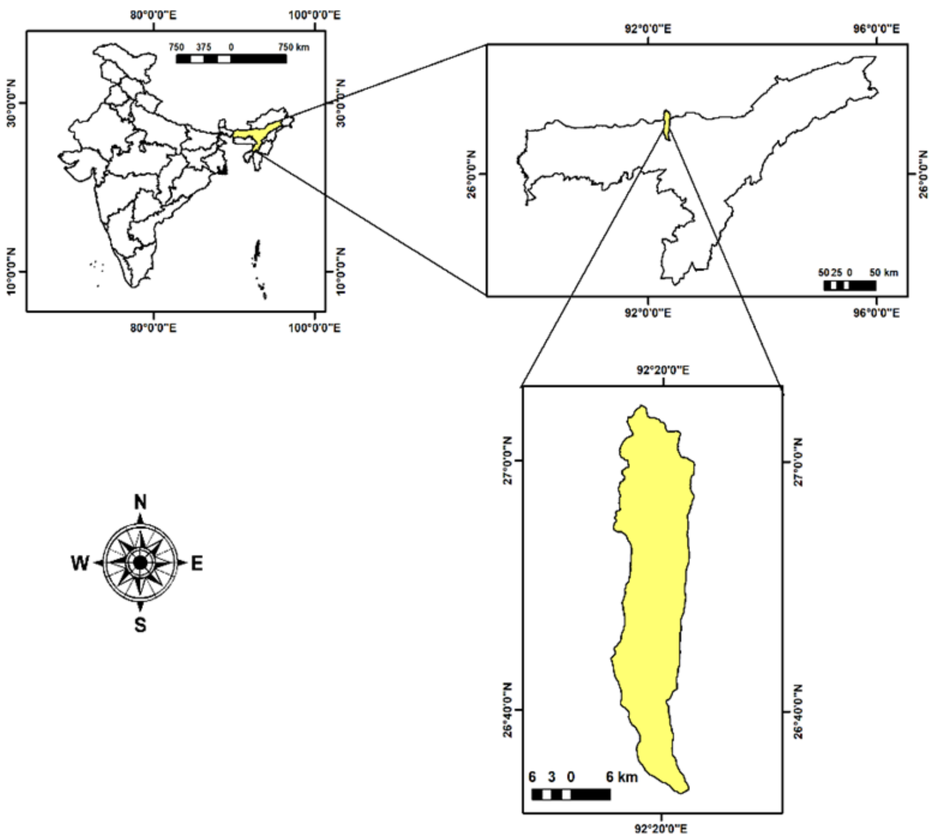

Figure 1 Location of the study area

2. MATERIALS AND METHODS

2.1 Study Area

The study area is one of the right-bank tributaries of the Brahmaputra River (Figure 1). The river basin experiences unique geology and topography. The Panchnoi River basin has a total basin area of 545.84 sq. km (Jaiswal et al., 2014). The river forms the boundary between Darrang and Udalguri in the west and Sonitpur in the east and was once a tributary of the Dhansiri river and flows from north to south. The river originates from the southwestern part of Kameng district of Arunachal Pradesh and enters Assam after travelling 15 km from its origin from the elevation of 450 meters with a steep gradient in its initial length. The lower part of the basin experiences frequent floods of varying intensities due to the backwater force of the mighty river Brahmaputra during monsoon. The total population of the river basin in 2001 was 1,36,604 persons (Meiyappan et al., 2016) and in 2011 it is 1,61,195. These data are extracted for the river basin from the district census handbook of Assam, India. For the year 2020, it was estimated from the Socioeconomic Data and Application Center's Gridded Population of the World (GPW), version 4 as 2,13,323 persons (Warszawski et al., 2017). The region witnessed an increase of 76,719 numbers of inhabitants within a gap of 19 years. This high increase in population is the local driver of land use change within the basin. The study area is endowed with faunal resources. The notable fauna of the study area are leopards, wolves, elephants, wild cats and monkeys. The region is also blessed with avifaunal diversity. Notable bird species including Greater Adjutant Stork, Hornbill, and whistling teals are found here.

2.2 Methodology

The Landsat 5 satellite imagery of the year 2008 and Landsat 8 OLI imagery of 2019 is used to understand the changing pattern of land use and land cover within the river basin. These images were obtained from the GLCF website and served as vital descriptions of the landscape during specific years. A geographic information system (GIS) environment is used to analyse these images following supervised classification procedures. Both sets of imagery offered a spatial resolution of 30 meters which allows for a detailed examination of the study area as well as the wider surrounding region. The larger context of land use and land cover changes that occurred within the basin is obtained by these imageries. The population data is extracted from the District census handbook released by the Census of India for the year 2001, 2011 and NASA Socioeconomic Data and Applications Center (SEDAC) Gridded Population of the World (GPW), v4.

Table 1 Data sources

Sensor	No. of Bands	Bands used for analysis	Path-Row	Acquired on
TM Landsat 5	7	4, 3,2	136-41	17 November, 2008
TM Landsat 5	7	4, 3,2	136-42	17 November, 2008
OLI-TIRS Landsat 8	11	5, 4, 3	136-41	16 January, 2019
OLI-TIRS Landsat 8	11	5, 4. 3	136-42	16 January, 2019

Extensive field surveys were also conducted (Peak monsoon months and non-monsoon months) to ensure the accuracy of the land use classification procedure. This helps in validating and confirming the correctness of the obtained results from the GIS analysis. Additionally, the kappa coefficient was calculated in QGIS as a measure of classification accuracy. This statistical value provided an objective assessment of the agreement between the classified results and the actual ground truth data. To assess the accuracy of a classified image, it is essential to have both an interpreted map and a reference map or reference points. The relationships between these two sets of data are frequently articulated through an error matrix and the kappa coefficient. The kappa coefficient is considered to be a multivariate measure of agreement between rows and columns of the error matrix.

$$Khat = (\text{Obs} - \text{exp})/(1 - \text{Exp}) \qquad (1)$$

Here, Obs= Observed correct, it represents accuracy reported in error matrix and Exp= Extended correct, it represents correct classification (Cohen 1960). In corresponding, the landscape fragmentation was assessed using FRAGSTATS 4.2 (McGarigal et al., 2012) software. It is a computer-based software tool that manages land use and land cover patterns. It investigates the diversity of the land, including the classification of a landscape mosaic and the exploration of a landscape gradient. Several indices are used by the application, including the Number of Patches (NP), Percentage of Landscape (PLAND), Mean Patch Size (MPS), and Edge Density (ED).NP measures the count of different patches, PLAND indicates the proportion of the landscape occupied by a specific land cover, MPS calculates the average size of patches, and ED quantifies the amount of edge present in a given area. Moreover, FRAGSTATS uses the term Component Area (CA) to measure the size of specific land cover classes, such as forests, wetlands, or grasslands, within the landscape. This CA measurement is widely used in landscape ecology to evaluate landscape composition.

Furthermore, as part of this comprehensive study, a LULC prediction map has been created using the MOLUSCE plugin in QGIS. The reasons for selecting MOLUSCE over other software are its integration with QGIS, advanced modelling techniques, flexibility, and community support for open-source software. This forward-looking map provided an intriguing glimpse into the anticipated state of land use and land cover within the basin for the year 2026, based on the existing trends and patterns identified through the analysis.

1. **Inputs:** The model uses four spatial variables (elevation, distance from rivers, distance from roads, and slope) to integrate and analyze the pattern of the transition matrix.
2. **Evaluation correlation:** The study uses joint information uncertainty, Crammer's coefficient, and Pearson's correlation to analyze changes in various land types and LULC between 2008 and 2019.
3. **Area change**: The change detection of the area is calculated in hectares.
4. **Transitional potential modelling**: For 2026, ANN Multi-layer perception (MLP) was used to predict land use. The QGIS Molusce plugin used (MLP) method based on the input LULC data. The main reason for selecting this algorithm is to deal with uncertain input data (Kamaraj et al., 2023). The kappa coefficient is measured while validating real and predicted land use maps. The rationale behind selecting these specific periods for the study is that short-term predictions inform policy decisions and land management.
5. **ANN-CA:** A continuous index, ranging from 0 to 1, is used to describe the terrain. This index is determined based on terrain usability using Artificial Neural Networks (ANN) with fuzzy logic. The key elements of the ANN model are the interactions between linked neurons and the modification of weight connections (Bhattacharya *et al.*, 2020). When projecting the LULC map for the year 2026, the following parameters were finally determined: neighbourhood - 1, iterations - 1000, hidden layer - 10 numbers, momentum value - 0.05, and learning rate - 0.1.
6. **Validation:** Several spatial variable combinations were done and finally the four combined variables (elevation, distance from rivers, distance from roads, and slope) gave a fair result. By taking reference map 2019 and simulated map 2026 an overall kappa value of 0.93 is achieved with 95.16 % correctness (Figure 4).

Several other data are collected manually from government and non-government sources including educational institutions. Survey of India topographical maps of 1: 50,000 scale are also used for mapping and accordingly analyzed. Apart from these secondary data and information are also collected from different e-journals and e-books at individual and official credits and government reports.

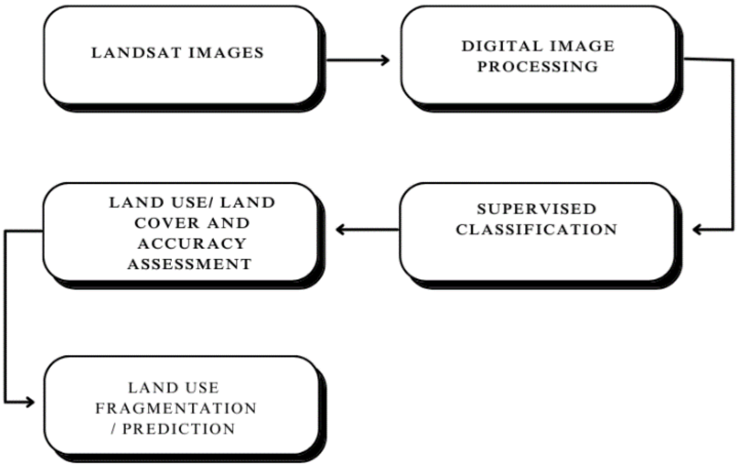

Figure 2 Methodology

3. Results and Discussion

3.1 Accuracy Assessment

In the study, it is observed that the overall Kappa Coefficient value is 0.63 for the year 2008 and 0.69 for the year 2019. This implies that the classification process achieved an agreement that avoided 63% and 69% of the errors that would occur if the classification were done randomly (Congalton, 1991).

3.2 Fragmentation

The area under dense forest, mixed vegetation and grassland areas under LULC classes have decreased, with grassland showing the most significant reduction (Table 2). The grassland area decreased significantly from 6,421.860 hectares in 2008 to 772.177 hectares in 2019 which is 87.975% followed by mixed vegetation (39.745%) and dense forest (36.218%). These changes suggest a shift in land use, possibly due to urbanization (increase in settlement and bare soil), agricultural expansion (increase in agricultural fields), and changes in natural features (decrease in forest and vegetation, increase in water and sandbars) which are evident from the classified LULC map of the study area.

Table 2 Per cent change of LULC, 2008 to 2019

Class_Name	Area in hectares (2008)	Area in hectares (2019)	Per cent Change
Dense forest	15758.600	15139.800	-3.926
Settlement	3890.120	5299.070	36.218
Mixed vegetation	11085.700	6679.650	-39.745
Grassland	6421.860	772.177	-87.975
Sandbars	1004.880	1579.080	57.141
Water	625.301	799.024	27.7823
Agricultural field	8002.370	15615.700	95.138
Bare soil	13.798	918.753	6558.547
Total	46803	46803	

Table 3 **Landscape Matrices of Panchnoi River Basin, 2008**

TYPE	CA	PLAND	NP	ED	MPS
Dense forest	15762.31	33.6767	1939	19.8704	8.1291
Settlement	3934.17	8.4055	10903	79.9267	0.3608
Mixed vegetation	11026.01	23.5574	5716	95.4065	1.929
Grassland	6463.575	13.8096	7918	92.5722	0.8163
Sandbars	1006.965	2.1514	1464	12.2523	0.6878
Water	623.34	1.3318	479	6.6381	1.3013
Agricultural field	7973.618	17.0359	2821	46.7721	2.8265
Bare soil	14.85	0.0317	172	0.449	0.0863

Table 4 Landscape Matrices of Panchnoi River Basin, 2019

TYPE	CA	PLAND	NP	ED	MPS
Dense forest	15130.22	20.3974	4489	17.7194	3.3705
Settlement	5316.84	7.1677	11266	56.1592	0.4719
Mixed vegetation	6674.468	8.998	7002	42.9746	0.9532
Grassland	788.8275	1.0634	3080	7.8756	0.2561
Sandbars	1588.568	2.1416	4652	16.357	0.3415
Water	803.0475	1.0826	1619	7.2026	0.496
Agricultural field	15555.31	20.9704	3156	43.2229	4.9288
Bare Soil	946.53	1.276	7199	15.604	0.1315

Abbreviations: CA (Class Area), PLAND (Percentage of Landscape), NP (Number of Patches), ED (Edge Density), MPS (Mean Patch Size)

The analysis of landscape metrics for the Panchnoi River basin over the period from 2008 to 2019 reveals significant changes in land use and land cover, indicating the impact of human activities on the environment. The dense forest area decreased from 15,762.31 hectares to 15,130.22 hectares, with the number of patches (NP) increasing and mean patch size (MPS) decreasing, highlighting fragmentation. Similarly, mixed vegetation and grassland areas saw substantial reductions, with mixed vegetation experiencing a drop from 11,026.01 hectares to 6,674.468 hectares and grassland plummeting from 6,463.575 hectares to 788.8275 hectares. Both categories also showed increased NP and decreased MPS, further indicating fragmentation.

On the other hand, settlement areas increased from 3,934.17 hectares to 5,316.84 hectares, with a slight rise in NP and an increase in MPS, suggesting urban expansion and densification. Agricultural fields nearly doubled in area from 7,973.618 hectares to 15,555.31 hectares, with increased NP and MPS, reflecting significant agricultural expansion. The dramatic rise in bare soil from 14.85 hectares to 946.53 hectares, with a substantial increase in NP and edge density (ED), points to intensified land disturbance and soil exposure. Water bodies and sandbars also saw increases in area, with water expanding from 623.34 hectares to 803.0475 hectares and sandbars from 1,006.965 hectares to 1,588.568 hectares. Both categories exhibited increased NP and decreased MPS, indicating more fragmented and dispersed patches. Overall, the landscape has become more fragmented, with increased NP and decreased MPS across most land use categories. This pattern signifies heightened human influence and activities such as deforestation, urbanization, and agricultural expansion, profoundly impacting the Panchnoi River basin's land use dynamics and environmental health.

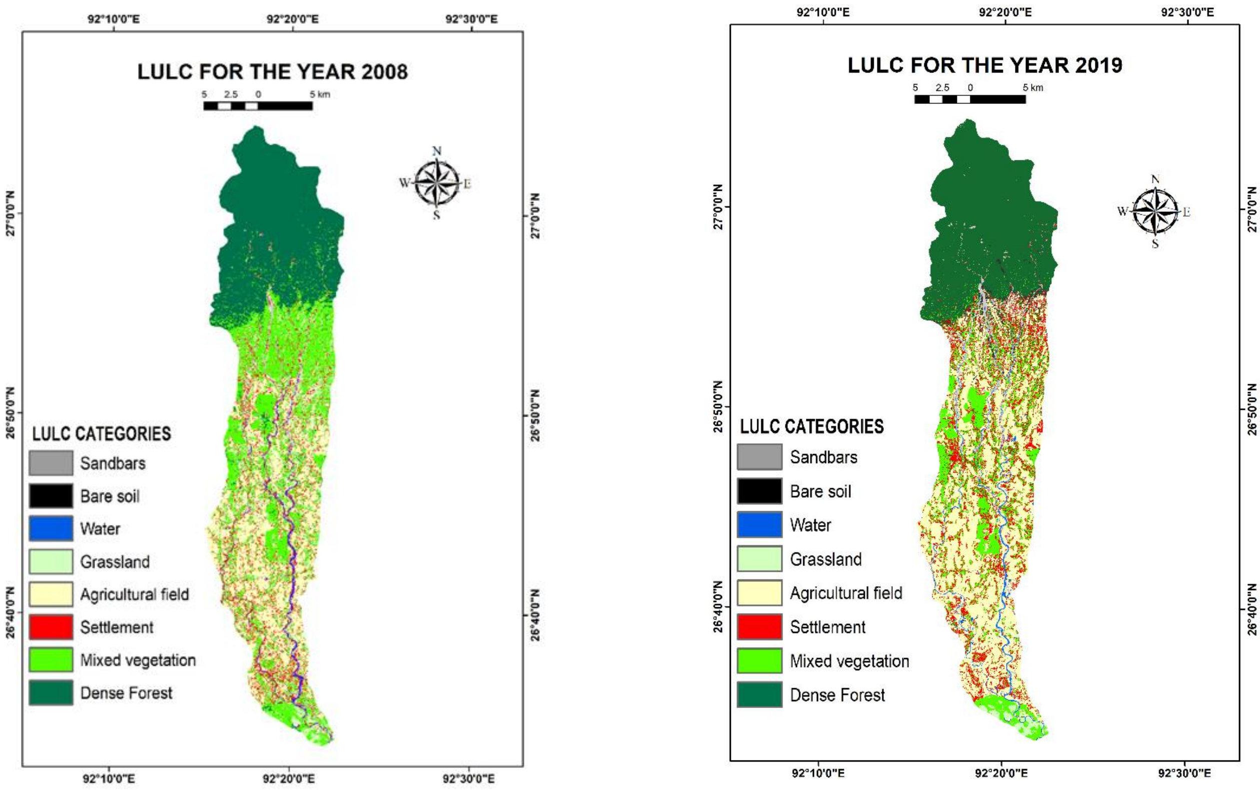

Figure 3 LULC Maps for the year 2008 and 2019

3.3 LULC Prediction

The LULC prediction is computed using various geographical factors, including elevation, rivers, roads, and slope, with the QGIS MOLUSCE plugin. The advantage of using open-source GIS tools is that they are cost-effective, innovative, and offer rapid development and interoperability. The plugin reclassifies the LULC maps from 2008 and 2019 for analysis and creates a transition matrix and an area change map to help users understand land use changes over these years. The plugin makes use of artificial neural networks (ANN), which can handle large and complex raster data to estimate LULC transitions for 2026 based on current patterns and dynamics. The predicted map indicates a decline in dense forest, mixed vegetation and grassland land use classes (Table 5). Notably, the grassland area is predicted to be most affected, decreasing from 6421.860 hectares in the year 2008 to just 0.0224 hectares in 2026, highlighting significant environmental changes over the 18 years. The overall kappa value of 0.93 is observed for the predicted year 2026. The reason for selecting 2026 for short-term predictions is that it produces higher accuracy values for the study area.

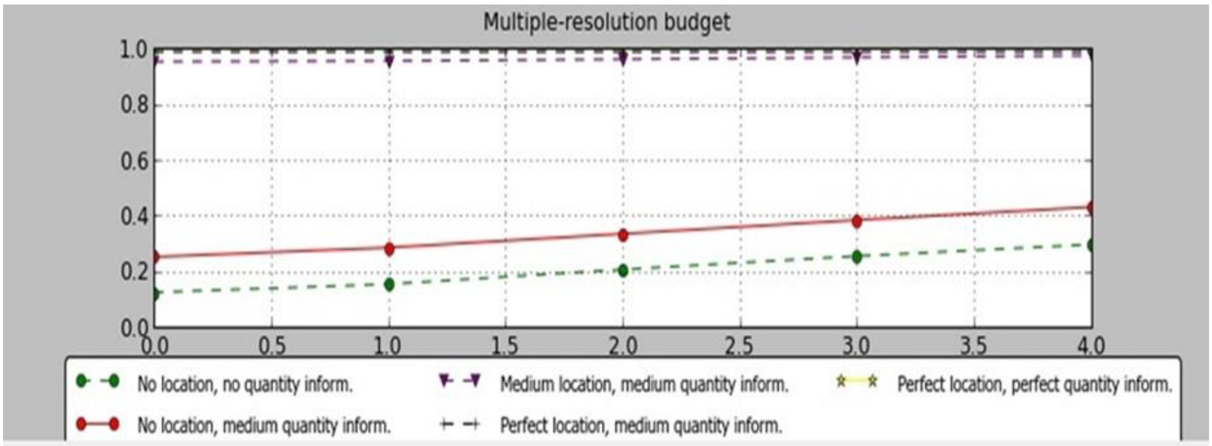

Figure 4 Validation Graph between Observed and Predicted 2026 LULC Map

Table 5. Per cent Change for the Predicted Year 2026 from the Base Year 2008

Class_Name	Area in hectares (2008)	Area in hectares (2019)	Area in hectares (2026 Predicted)	Per cent Change from the Year 2008
Sandbars	1004.880	1579.080	1595.9	58.814
Dense Forest	15758.600	15139.800	15091	-4.236
Settlement	3890.120	5299.070	5444.1	39.946
Agricultural Field	8002.370	15615.700	16069	100.803
Bare Soil	13.798	918.753	932.36	6657.162
Mixed Vegetation	11085.700	6679.650	6105	-44.929
Grassland	6421.860	772.177	0.0224	-99.999
Water	625.301	799.024	796.54	27.385

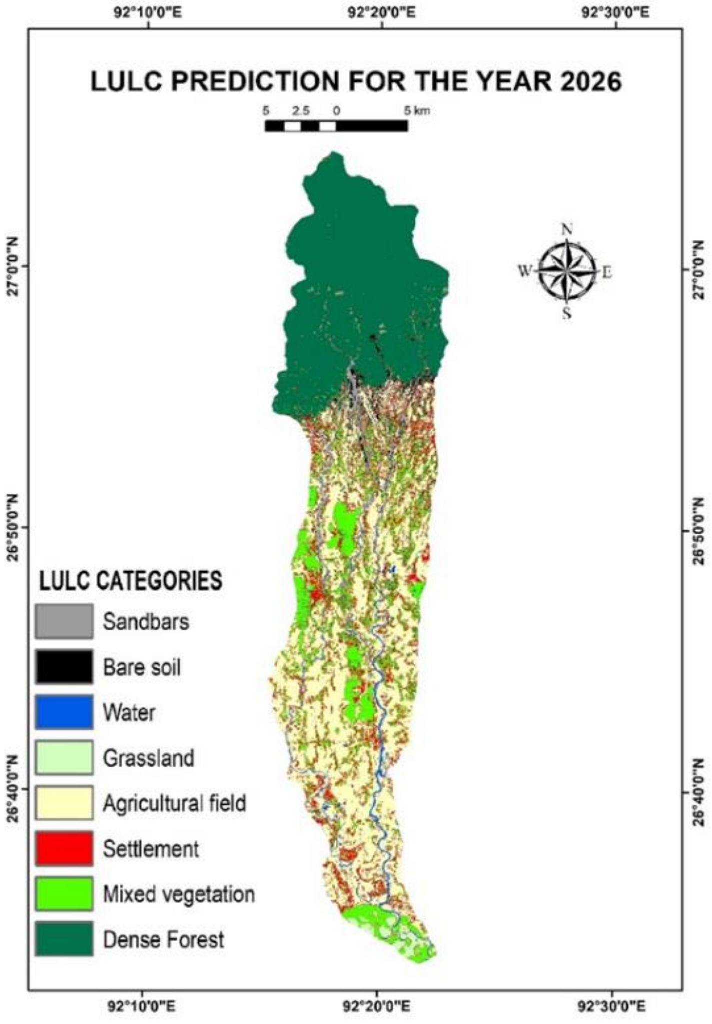

Figure 5. LULC Prediction for 2026

The predicted LULC changes for 2026 reflect a significant human impact on the landscape. Urban and agricultural expansions are prominent, often at the expense of natural habitats such as forests, mixed vegetation, and grasslands. These changes underscore the need for sustainable land management practices to balance development with environmental conservation. The dramatic shifts, especially the near-complete loss of grasslands and the massive increase in bare soil highlight urgent areas for policy intervention and ecological restoration efforts.

3.4 Limitations of the study

Using ANN for predicting land use changes has several advantages, but it also comes with notable limitations. ANN models rely heavily on high-quality, comprehensive data;

incomplete or noisy data can lead to poor predictions. They also depend on historical data, which may not always represent future trends accurately, especially with sudden changes in policies or environmental conditions. Overfitting is a risk, particularly with complex models that capture noise instead of general patterns, leading to poor generalization of new data. ANNs are often criticized for their "black box" nature, making it difficult to interpret how decisions are made and understand the influence of different factors. Training ANNs can be computationally intensive, requiring significant processing power, memory, and sometimes specialized hardware like GPUs. Hyperparameter tuning is crucial but challenging and time-consuming, and poor choices can negatively affect model performance. The model's success heavily depends on the selection and quality of input features, and irrelevant or redundant features can degrade performance. Data imbalance can bias predictions towards more common classes, and ANNs may not account for external changes such as new land use policies or climate change. Evaluating ANN models requires appropriate metrics and validation methods to avoid misleading assessments. Despite these challenges, with careful consideration and appropriate techniques, ANNs can provide valuable insights and accurate predictions.

4. Conclusions

The forests in the study area are under threat from humans along with unprecedented progress and transformation leading to deforestation. While some pristine areas still showcase natural beauty, our study reveals concerning trends such as a decline in forest cover and an increase in alternative land use patterns. These activities significantly contribute to the loss of dense forests, escalating conflicts between humans and elephants in the Sonitpur district (Saikia et al., 2013). The landscape of the Panchnoi River Basin exhibits a notable increase in Non-Forest Patches (NP) and a decrease in Mean Patch Size (MPS) across various land cover types from 2008 to 2019, indicating a high rate of fragmentation.

Preserving the Panchnoi basin and its buffer zones necessitates immediate, detailed investigation and effective solutions to address encroachment issues and prevent further habitat loss and degradation. Our predicted land use map underscores a substantial decrease in forested areas, coupled with significant expansions in settlements, agricultural fields, and other land use categories. Urgent action is imperative to mitigate these trends and ensure the sustainable preservation of the Panchnoi basin's ecological integrity.

By integrating ANN-based land use predictions into policy-making and practical applications, stakeholders can promote sustainable development, protect natural resources, and enhance community resilience. These recommendations and applications ensure that the benefits of advanced predictive models are fully realized, leading to informed decision-making and better land management outcomes.

Author contribution

NK, NB, MJN: Conceptualization. NK: Data collection. NK: Methodology and analysis. NK, NB, MJN: Discussed the results and reviewed the manuscript. All authors have read and agreed to the final version of the manuscript.

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References

Ahmad, H., Abdallah, M., Jose, F., Elzain, H. E., Bhuyan, M. S., Shoemaker, D. J., & Selvam, S. (2023). Evaluation and mapping of predicted future land use changes using hybrid models in a coastal area. *Ecological Informatics*, *78*, 102324. DOI: 10.1016/j.ecoinf.2023.102324

Amgoth, A., Rani, H. P., & Jayakumar, K. V. (2023). Exploring LULC changes in Pakhal Lake area, Telangana, India using QGIS MOLUSCE plugin. *Spatial Information Research*, *31*(4), 429-438.
DOI: 10.1007/s41324-023-00509-1

Areendran, G., Raj, K., Sharma, A., Bora, P. J., Sarmah, A., Sahana, M., & Ranjan, K. (2020). Documenting the land use pattern in the corridor complexes of Kaziranga National Park using high resolution satellite imagery. *Trees, Forests and People*, *2*, 100039.
DOI: 10.1016/j.tfp.2020.100039

Bradley, B. A., & Mustard, J. F. (2005). Identifying land cover variability distinct from land cover change: cheatgrass in the Great Basin. *Remote Sensing of Environment*, *94*(2), 204-213.
DOI: 10.1016/j.rse.2004.08.016

Baghel, S., Kothari, M. K., Tripathi, M. P., Singh, P. K., Bhakar, S. R., Dave, V., & Jain, S. K. (2024). Spatiotemporal LULC change detection and future prediction for the Mand catchment using MOLUSCE tool. *Environmental Earth Sciences*, *83*(2), 66.
DOI: 10.1007/s12665-023-11381-5

Bryan-Brown, D. N., Connolly, R. M., Richards, D. R., Adame, F., Friess, D. A., & Brown, C. J. (2020). Global trends in mangrove forest fragmentation. *Scientific Reports*, *10*(1), 7117.
DOI: 10.1038/s41598-020-63880-1

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and psychological measurement*, *20*(1), 37-46.
DOI: 10.1177/001316446002000104

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote sensing of environment*, *37*(1), 35-46.
DOI: 10.1016/0034-4257(91)90048-B

Geist, H. J., & Lambin, E. F. (2001). What drives tropical deforestation. *LUCC Report series*, *4*, 116. Available at: https://www.researchgate.net/publication/248420451_What_Drives_Tropical_Deforestation (Accessed on 05 July, 2024)

Diuk-Wasser, M. A., VanAcker, M. C., & Fernandez, M. P. (2021). Impact of Land Use Changes and Habitat Fragmentation on the Eco-epidemiology of Tick-Borne Diseases. *Journal of Medical Entomology*, *58*(4), 1546–1564.
DOI: 10.1093/jme/tjaa209

Houet, T., Loveland, T. R., Hubert-Moy, L., Gaucherel, C., Napton, D., Barnes, C. A., & Sayler, K. (2010). Exploring subtle land use and land cover changes: a framework for future landscape studies. *Landscape Ecology*, *25*, 249-266.
DOI: 10.1007/s10980-009-9362-8

Hunsaker, C. T., O'Neill, R. V., Jackson, B. L., Timmins, S. P., Levine, D. A., & Norton, D. J. (1994). Sampling to characterize landscape pattern. *Landscape Ecology*, *9*(3), 207-226.
DOI: 10.1007/BF00134748

Jaiswal, M. K., Thakuria, G., Borah, A. C., & Saikia, R. (2014). Evaluation of parametic impact on soil loss of Panchnoi river basin, Northeast India, using revised universal soil loss equation (rusle). *The Clarion-International Multidisciplinary Journal*, *3*(1), 51-60. Available at: https://www.indianjournals.com/ijor.aspx?target=ijor:cla&volume=3&issue=1&article=008 (Accessed on 05 July, 2024)

Jiao, M., Hu, M., & Xia, B. (2019). Spatiotemporal dynamic simulation of land-use and landscape-pattern in the Pearl River Delta, China. *Sustainable Cities and Society*, *49*, 101581.
DOI: 10.1016/j.scs.2019.101581

Kafy, A. A., Naim, M. N. H., Subramanyam, G., 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.
DOI: 10.1016/j.envc.2021.100084

Kamaraj, M., & Rangarajan, S. (2022). Predicting the future land use and land cover changes for Bhavani basin, Tamil Nadu, India, using QGIS MOLUSCE plugin. *Environmental Science and Pollution Research*, *29*(57), 86337-86348.
DOI: 10.1007/s11356-021-17904-6

McGarigal, K., Cushman, S. A., & Ene, E. (2012). FRAGSTATS v4: spatial pattern analysis program for categorical and continuous maps. *Computer software program produced by the authors at the University of Massachusetts, Amherst, 15*. Available at: https://www.umass.edu/landeco/research/fragstats/fragstats.html (Accessed on 05 July, 2024)

Meiyappan, P., Roy, P. S., Soliman, A., Li, T., Mondal, P., Wang, S., and Jain, A. K. (2018). India Village-Level Geospatial Socio-Economic Data Set: 1991, 2001. Palisades, New York: NASA Socioeconomic Data and Applications Center (SEDAC).
DOI: 10.7927/H4CN71ZJ.

Muhammad, R., Zhang, W., Abbas, Z., Guo, F., & Gwiazdzinski, L. (2022). Spatiotemporal change analysis and prediction of future land use and land cover changes using QGIS MOLUSCE plugin and remote sensing big data: a case study of Linyi, China. *Land*, *11*(3), 419.
DOI: 10.3390/land11030419

Saikia, A., Hazarika, R., & Sahariah, D. (2013). Land-use/land-cover change and fragmentation in the Nameri Tiger Reserve, India. *Geografisk Tidsskrift-Danish Journal of Geography*, *113*(1), 1-10.
DOI: 10.1080/00167223.2013.782991

Singh, S., Reddy, C. S., Pasha, S. V., Dutta, K., Saranya, K. R. L., & Satish, K. V. (2017). Modeling the spatial dynamics of deforestation and fragmentation using multi-layer perceptron neural network and landscape fragmentation tool. *Ecological Engineering*, *99*, 543-551.
DOI: 10.1016/j.ecoleng.2016.11.047

Sivrikaya, F., Cakir, G., Kadioğullari, A. İ., Keleş, S., Başkent, E. Z., & Terzioğlu, S. (2007). Evaluating land use/land cover changes and fragmentation in the Camili forest planning unit of northeastern Turkey from 1972 to 2005. *Land Degradation & Development*, *18*(4), 383-396.
DOI: 10.1002/ldr.782

Talukdar, S., Eibek, K. U., Akhter, S., Ziaul, S., Towfiqul Islam, A. R. Md., & Mallick, J. (2021). Modeling fragmentation probability of land-use and land-cover using the bagging, random forest and random subspace in the Teesta River Basin, Bangladesh. *Ecological Indicators*, *126*, 107612.
DOI: 10.1016/j.ecolind.2021.107612

Turner, I. I., & Bill, L. (2001). Land-use and land-cover change: Advances in 1.5 decades of sustained international research. *GAIA-Ecological Perspectives for Science and Society*, *10*(4), 269-272. Available at: https://www.public.asu.edu/~bturner4/TurnerGAIA.pdf (Accessed on 05 July, 2024)

Vitousek, P. M. (1994). Beyond global warming: ecology and global change. *Ecology*, *75*(7), 1861-1876.
DOI: 10.2307/1941591

Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., Zhang, X., Tang, Q., & Ge, Q. (2017). Center for International Earth Science Information Network—CIESIN—Columbia University (2016). Gridded population of the World, Version 4 (GPWv4): Population density. Palisades. NY: NASA Socioeconomic Data and Applications Center (SEDAC). *Atlas of Environmental Risks Facing China Under Climate Change*, 228.
DOI: 10.7927/H4NP22DQ

Wei, L., Luo, Y., Wang, M., Su, S., Pi, J., & Li, G. (2020). Essential fragmentation metrics for agricultural policies: Linking landscape pattern, ecosystem service and land use management in urbanizing China. *Agricultural Systems*, *182*, 102833.
DOI: 10.1016/j.agsy.2020.102833