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Urban Growth Prediction Using Satellite Imageries with Applications of Machine Learning Algorithm in Pokhara Metropolitan City

Sandesh Sapkota[1], Niraj KC[1], Umesh Bhurtyal[1]

[1]*Department of Geomatics Engineering, IOE, Pashchimanchal Campus, Tribhuvan University, Nepal*

Corresponding author. sandeshsapkota.cr07@gmail.com

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Abstract

Accurate land use and land cover (LULC) classification is essential for sustainable resource management and understanding landscape changes due to climate variations. High-quality datasets and robust classification methods are necessary for effective LULC classification. This study evaluates the LULC pattern of Pokhara Metropolitan City using Landsat 5, 7, and 8 satellite imagery over 30 years (1991-2021) through supervised classification techniques, employing random forest (RF) and support vector machine (SVM) algorithms to compare their accuracy. The study further utilizes the artificial neural network (ANN) model in the MOLUSCE plugin in QGIS to predict future LULC patterns for 2031 and 2050. Results indicate a significant urbanization trend, with agricultural land decreasing from 54.74% in 1991 to 32.02% in 2021, while built-up areas and forest cover increased from 2.93% to 10.96% and from 38.87% to 53.56%, respectively. Future predictions show continued trends, with agricultural land decreasing to 26.62% and built-up areas increasing to 12.08% by 2031. The findings provide crucial spatial information for urban planners, meteorologists, and policymakers to develop local and regional strategies for sustainable development.

***Keywords*: LULC; RF; SVM; Landsat; Urbanization; PMC**

1. Introduction

Urbanization, accumulating population and activities at a particular location, brings various economic, social, and political benefits through shared functions. This urban transformation is driven by increased built-up environments and socioeconomic activities, leveraging shared facilities in space and time. However, urbanization also presents significant challenges for sustainable urban development, particularly in developing countries where guidelines and policies may be insufficient due to continuous transitions. Land Use and Land Cover (LULC) represents the transformations or modifications of land by humans to exploit resources and locations for various activities, making urban growth a key indicator of economic development.

LULC change is inevitable in urban areas due to economic development, natural resource exploitation, and rapid population growth. Monitoring these changes is crucial for understanding urban growth patterns and informing sustainable management strategies. Previous studies have highlighted the importance of LULC studies in providing information about the transition from rural to urban areas, thus aiding in managing and modifying natural environments. Spatial distribution, which depicts the arrangement of characteristics or phenomena on the Earth's surface, plays a vital role in LULC studies. This distribution can be obtained by summarizing raw data or performing sophisticated data analyses, including investigating various land use categories and their influencing factors. In this context, the spatial distribution of land use types in Pokhara Metropolitan City (PMC) is analyzed to understand urban growth patterns.

Due to the perpetual variations in driving factors, urban growth tends to be uneven, altering land uses and affecting LULC transformations. Therefore, studying land use changes and their driving factors is essential in understanding urban growth patterns (Adams et al., 2018). These driving factors can be grouped into three major categories: physical, socioeconomic, and environmental processes. Physical sub-systems refer to the physical settings of the land, including natural and man-made factors. Socioeconomic sub-systems are controlled by factors such as proximity, density, and economic activities. Environmental sub-systems act as the lungs of the urban system and require considerable attention (Rimal et al. 2011).

Although urbanization drives modernization, economic growth, and development, it raises concerns about its impact on human health, livelihoods, and the environment. Expanding cities face significant issues related to employment, food security, water supply, shelter, and sanitation (Verburg et al., 2015). LULC changes typically involve the transformation of forests and vegetation into densely populated areas, leading to natural resource loss and ecological imbalance (Seto et al., 2012). Change can be positive or negative, Positive change means increase in vegetation, negative change means increase in built-up areas. Obviously increase in built-up area will contribute to greenhouse emissions, but increase in vegetation will have positive impact on greenhouse emissions (Castanheira & Freire, 2013). Changes in Earth's cover affect the global carbon cycle, particularly the amount of carbon dioxide (CO_2) in the atmosphere, influencing global warming due to its role as a warming gas (Watson et al., 2000). Study observed that in eastern Amazonia, higher carbon emissions compared to the western part are linked to greater moisture stress, warming, and deforestation, especially in the dry season (Gatti et al., 2021).

Global urbanization and population growth exert pressure on environmental systems but also offer development opportunities (Kim & Kirschbaum, 2015). Detecting, classifying, and characterizing urban growth patterns are crucial for managing urbanization pressures effectively. Remote sensing and GIS techniques provide powerful tools for such analyses. Post-classification comparison (PCC) is a common approach where land cover classifications are compared to detect changes at different times. These technologies offer detailed information on urban LULC changes, including land use types, urban development intensity, and environmental impacts.

Machine learning offers significant advantages in LULC change analysis, enhancing precision and efficiency. Machine learning algorithms, such as Random Forest (RF) and Support Vector Machine (SVM), can process large volumes of satellite and aerial imagery data, enabling the detection of subtle land cover changes over time. These algorithms accurately classify land cover types and handle diverse datasets, improving the robustness of LULC mapping. They can identify patterns and trends that may not be immediately apparent to human capability, providing deeper insights into the drivers and consequences of land cover changes. This predictive capability is crucial for forecasting future changes and informing sustainable land management and urban planning policies.

This study aimed to evaluate the LULC pattern of Pokhara Metropolitan City based on Landsat 5, 7, and 8 satellite imagery over 30 years from 1991 to 2021. Supervised classification techniques using RF and SVM have been employed, comparing their accuracy to determine the more effective method. An artificial neural network (ANN) model in the MOLUSCE plugin in QGIS will also be applied for future LULC predictions for 2031 and 2050. The findings of this study provided valuable insights for urban planners, meteorologists, and policymakers to formulate local and regional strategies for sustainable development.

2. Materials and Method

2.1 Data Acquisition

To evaluate land use and land cover (LULC) changes, this study focused on creating spatiotemporal LULC maps from satellite images using Google Earth Engine (GEE). Landsat satellite data products from 1991, 2001, 2011, and 2021 were utilized due to their detailed 30-meter resolution. Cloud-free images captured during the post-monsoon period (October–February) were selected to avoid cloud interference. These datasets were acquired from the United States Geological Survey (USGS) web portal. Additionally, digital elevation data from the Shuttle Radar Topography Mission (SRTM) and road map from the open street map were incorporated to enhance the spatial analysis. The use of GEE allowed for efficient processing and analysis of large datasets, facilitating an in-depth examination of LULC changes over the selected periods.

2.2 Feature Selection and Training Data Preparation

Following preprocessing, feature extraction was performed to improve the differentiation of land cover types. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) were evaluated from the composite images. These indices emphasize specific vegetation characteristics, aiding in the distinction between different land cover classes during classification. In Google Earth Engine, points representing various land cover classes were manually delineated to prepare the training data. A total of 750 ground truth samples were collected, including 200 samples each for forest and agricultural land, 150 samples for built-up areas, 100 samples for water bodies, and 100 samples for barren land. These samples were split into training and testing datasets using a 70:30 ratio via random sampling technique, resulting in 490 samples for training and 210 samples for testing. The training dataset was used to develop the classification model, while the testing dataset was reserved for assessing the model's accuracy. The extracted features from the composite image were used to build a comprehensive training dataset, which was crucial for effectively training the classification models by providing representative examples of each land cover class.

2.3 Image Classification

The classification process utilized two machine learning algorithms: Random Forest (RF) and Support Vector Machine (SVM). The RF classifier was selected for its robustness and ability to manage large datasets with multiple features, making it ideal for complex land cover classifications. The SVM classifier was also employed due to its effectiveness in high-dimensional spaces and flexibility in distinguishing between classes. Both classifiers were trained using the prepared training dataset, producing two separate classified images representing the Land Use/Land Cover (LULC) map. These LULC types included agriculture, barren land, built-up areas, forests, and water bodies. Image classification is a highly effective method for processing satellite imagery, enabling the detection, identification, and classification of different features based on their actual classes on the ground.

2.4 Accuracy Assessment

For the accuracy assessment, 70% of the ground truth point dataset extracted from satellite imageries was used to train the Random Forest (RF) and Support Vector Machine (SVM) models. This involved specifying the desired number of decision trees, maximum tree depth, and other hyperparameters for the image classification. The remaining 30% of the dataset was used to test the developed models. Confusion matrices were generated for both RF and SVM classifications, and accuracy metrics such as Overall Accuracy and the Kappa Coefficient were calculated. These metrics provided a quantitative measure of the classification performance, helping to validate the effectiveness of the classifiers and the overall methodology. The RF method demonstrated a higher accuracy compared to the SVM model; hence, the RF technique was further used for change detection, validation, and forecasting purposes.

2.5 Forecasting

Utilizing the QGIS tool and the MOLUSCE plugin, this study employs Artificial Neural Networks (ANN) to predict future land use scenarios based on current patterns. ANNs, integrated into QGIS, offer advanced methods for modeling and predicting land use changes by analyzing complex spatial data. By inputting multiple raster layers representing land use at different time points and various explanatory variables, the neural network learns patterns to provide accurate predictions. With the ability to handle large datasets and complex relationships, ANNs enhance understanding land use dynamics. The forecasted land use maps provide valuable insights into future urban growth and environmental changes.

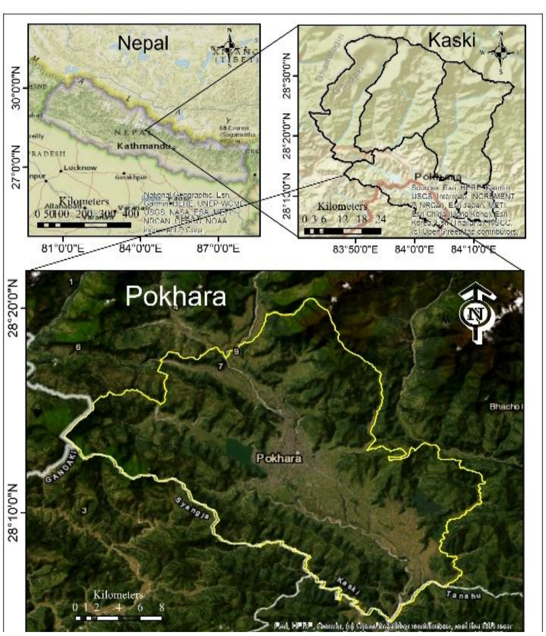

Figure 1: Locational Map of Study Area

2.6 Study Area

Located within Nepal's Gandaki Province, Pokhara Metropolitan City (PMC) is a focal point reflecting the nation's urbanization trends. Covering 464.94 square kilometers, PMC holds the distinction of being the largest metropolitan area by administrative boundary, boasting a varied terrain from 505 to 2650 meters above sea level. Renowned for its picturesque setting amidst the Annapurna Himalayan Range, PMC entices visitors with its array of natural attractions, including lakes, caves, and numerous cultural sites. PMC, home to 513,504 residents across 140,459 households, experiences significant urban growth driven by its status as the regional hub of the western region and its reputation as Nepal's second most visited tourist destination after Kathmandu and recently declared as the tourism capital of Nepal. This rapid urbanization and the city's dynamic land use transformations position PMC as ideal research setting for applying machine learning algorithms to analyze and predict urban development patterns.

3. Results and Discussion

3.1 LULC Classification Map

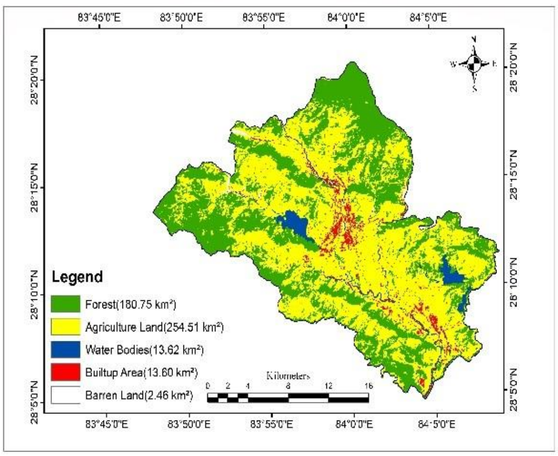

Figure 2: LULC map of 1991

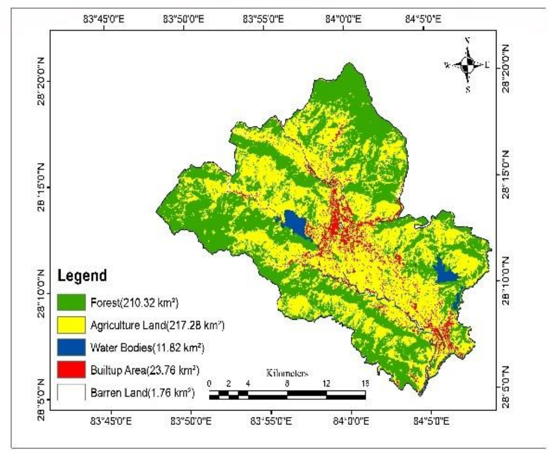

Figure 3: LULC map of 2001

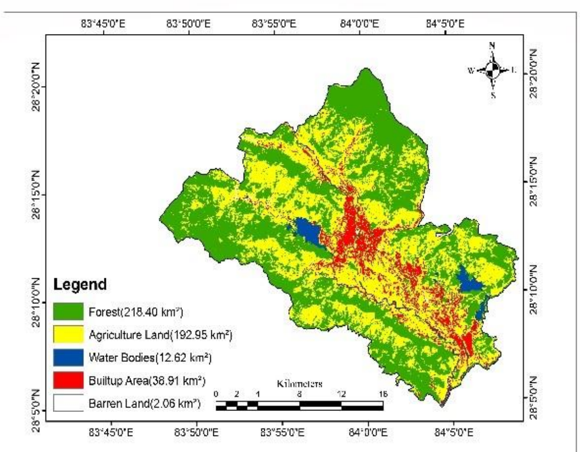

Figure 4: LULC map of 2011

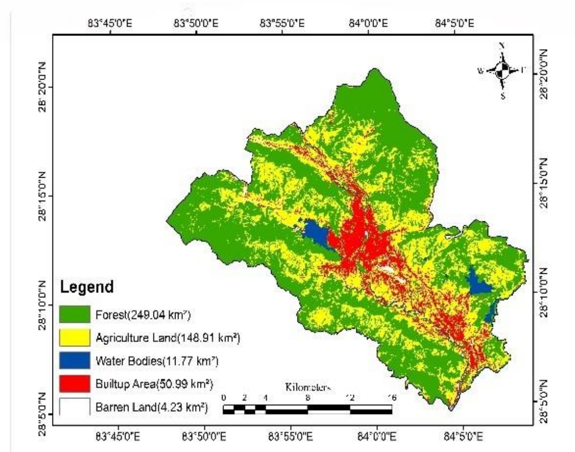

Figure 5: LULC map of 2021

The LULC map for the different study years 1991, 2001, 2011 and 2021 were prepared, shown in Figures 1, 2, 3 and 4, respectively. From these figures, I found that during the study period between 1991 and 2021, there was a rapid loss in agricultural land, and built-up areas and forests are gaining. It shows that the agricultural land of the plain regions is converted into built-up areas. In contrast, the agriculture and grassland of remote areas are converted into forest areas due to the migration of people from the rural area towards the nearest plain city areas.

Table 1 shows that agricultural land has significantly declined from 254.51 sq km to 148.91 sq km, while forest areas have grown from 180.75 sq km to 249.04 sq km. Built-up Areas have expanded from 13.62 sq km to 50.99 sq km, reflecting urban development. Barren Land has increased from 2.46 sq km to 4.23 sq km, and Water Bodies have seen slight fluctuations, decreasing from 13.60 sq km to 11.77 sq km.

Table 1: Area under each LULC class

Year / Class	1991	2001	2011	2021
	Area (sq km)	**Area (sq km)**	**Area (sq km)**	**Area (sq km)**
Agriculture Land	254.51	217.28	192.95	148.91
Barren Land	2.46	1.76	2.06	4.23
Built-up Area	13.62	23.76	38.91	50.99
Forest	180.75	210.32	218.40	249.04
Water Bodies	13.60	11.82	12.62	11.77
Grand Total	**464.94**	**464.94**	**464.94**	**464.94**

3.2 Accuracy Assessment

Table 2: Accuracy Assessment of Classification

Year	A (%)	AL	BL	BA	F	WB	OA (%)	KC
1991	UA	88	68	73	84	85	83	0.80
	PA	85	65	70	90	89		
2001	UA	73	77	80	81	87	81	0.77
	PA	77	81	75	82	86		
2011	UA	79	73	76	89	87	83	0.79
	PA	84	69	72	83	92		
2021	UA	89	82	83	88	88	85	0.82
	PA	88	83	82	92	86		

Table 2 provides accuracy assessment results for land cover classification over four different years: 1991, 2001, 2011, and 2021. The metrics include accuracy(A), i.e. User's Accuracy (UA) and Producer's Accuracy (PA) for each land cover class Agriculture Land (AL), Barren Land (BL), Built-up Area (BA), Forest (F), and Water Bodies (WB), along with Overall Accuracy (OA) and the Kappa Coefficient (KC).

1991, the OA was 83%, and the KC was 0.80. Agriculture Land had a UA of 88% and a PA of 85%, while Forest had the highest PA at 90%. By 2001, OA slightly decreased to 81% and KC to 0.77, with Built-up Areas achieving the highest UA at 80% and forests the highest PA at 82%.

In 2011, the OA improved to 83% with a KC of 0.79. Forest had a high UA of 89% and PA of 83%, indicating reliable classification for this class. By 2021, the OA had increased to 85% and KC to 0.82. Agriculture Land had a high UA of 89%, and forest maintained a high PA of 92%, reflecting the continued accuracy improvements in land cover classification over time.

3.3 Forecasting

An Artificial Neural Network (ANN) based Land Change Modeler(LCM) was adopted to predict the future spatial pattern of LULC. LULC of 2001 and 2011 were utilized to simulate the LULC of the year 2021. In this process, transition potentials were computed by executing the ANN technique with a percentage of correctness of 81.02, an accuracy rate of 80.14%, and a kappa coefficient of 0.78. The spatial variables SRTM digital elevation model and distance from the road were used in this study. The above figures, Figure 6 and Figure 7, represent the predicted LULC map of Pokhara Metropolitan City for the years 2031 and 2050, respectively. They also follow the previous trend of decreasing agricultural land and increasing built-up areas and forests. The urban and suburban areas will rapidly increase in the plain areas, whereas forest areas will increase in the remote and sloppy regions.

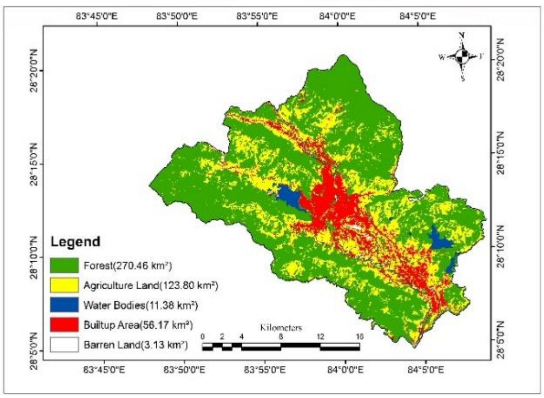

Figure 6: Predicted LULC map of 2031

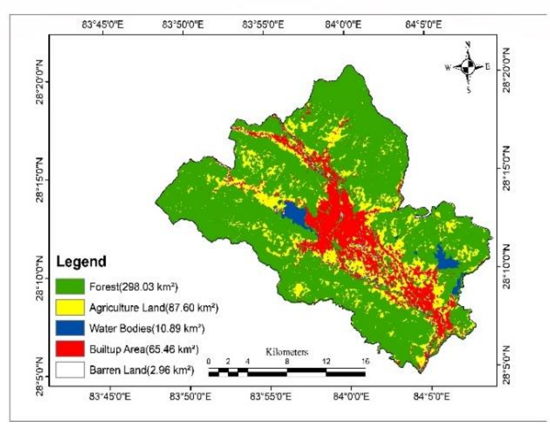

Figure 7: Predicted LULC map of 2050

For the verification of the built-up area, a population density map of PMC was generated using the 2021 census data and Land Use Land Cover (LULC) map of 2021, as shown in Figure 8. The population density map revealed high population densities in various wards, specifically wards 1-10 and 12, with slightly lower densities in wards 11, 14, 15, and 17. Both maps feature a circle highlighting the same geographical area, which shows high population density in the density map and significant urbanization in the LULC map. This correlation suggests that areas with high population density are also highly urbanized. By analyzing both maps and the defined locations, the classification of the built-up area is verified.

Table 3: Predicted LULC of Pokhara Metropolitan City (PMC) for the years 2031 and 2050

Year / Class	2031	2050
	Area (sq km)	**Area (sq km)**
Agriculture Land	123.80	87.60
Barren Land	3.13	2.96
Built-up Area	56.17	65.46
Forest	270.46	298.03
Water Bodies	11.38	10.89
Grand Total	**464.94**	**464.94**

3.4 Verification of Urban Growth in PMC

For the verification of the built-up area, a population density map of PMC was generated using the

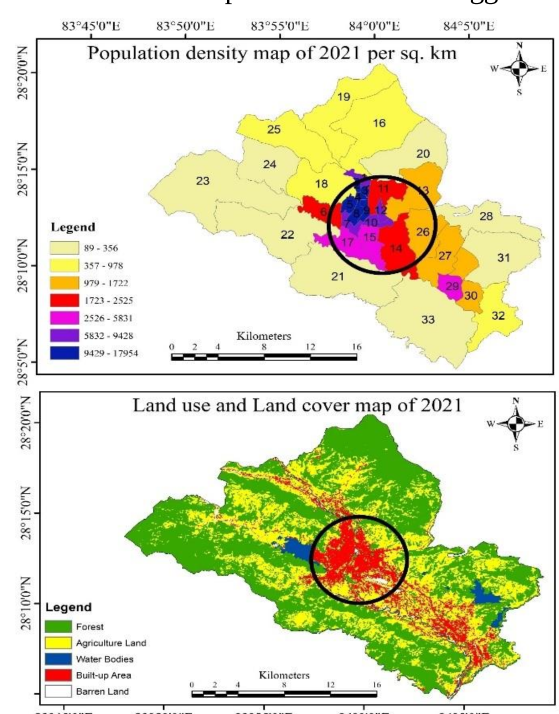

Figure 8: Population Density map vs LULC map of 2021

2021 census data and the Land Use Land Cover (LULC) map of 2021, as shown in Figure 8. The population density map revealed high population densities in wards 1-10 and 12, with slightly lower densities in wards 11, 14, 15, and 17, whereas other wards have relatively less population density. Both maps feature a circle highlighting the same geographical area, which shows high population density in the density map and significant urbanization in the LULC map. This correlation suggests that areas with high population density are also highly urbanized. By analyzing both maps and the defined locations, the classification of the built-up area is verified.

3.5 Urban Area Growth

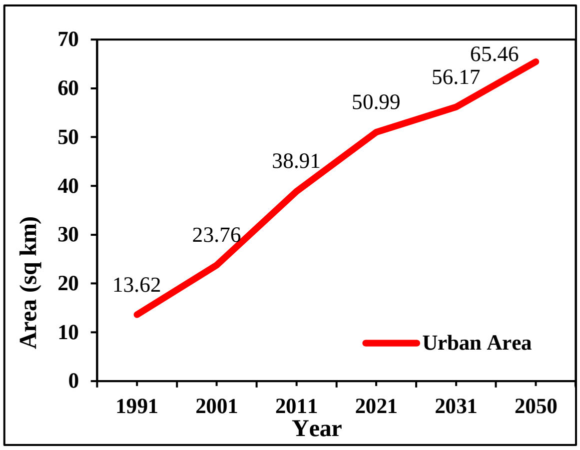

Figure 9: Urban Area growth trend of PMC

The above result illustrates the urban growth in PMC over several decades, highlighting a consistent and significant increase in urban areas from 1991 to 2050. In Figure 9, the red line indicates the trend of urban area in PMC, which shows the urban area in 1991 was 13.62 sq km. By 2001, it had nearly doubled to 23.76 sq km. This growth trend continued, with the urban area expanding to 38.91 sq km in 2011 and 50.99 sq km in 2021. Projections for future growth show the urban area reaching 56.17 sq km by 2030 and further expanding to 65.46 sq km by 2050. This result indicates a rapid urban expansion in PMC.

3.6 Discussion

The study aimed to predict the future LULC map of Pokhara Metropolitan City and analyze the trends in changing LULC classes using Landsat 5,7 and 8 satellite imageries and Google Earth Engine (GEE). The findings reveal that agricultural land is rapidly decreasing and has been converted into built-up areas and forests. The plain areas are highly urbanized and also bear high population density. Future projections also show a similar result following the trend where the built-up area had become four times in 2021 and will be five times by 2050 compared to 1991. study (Rimal et al., 2013) used remote sensing and GIS tools to reveal significant LULC changes in Pokhara between 1999 and 2009, with urban areas increasing by 47% and agricultural land decreasing by 34%. This study concurs with these findings, illustrating similar urban expansion trends in peri-urban regions. The spatial orientation of built-up spaces shows that development is primarily concentrated along major highways, and urbanization has largely expanded towards the southeast, northeast, and northwest along the Siddharth Highway, Prithvi Highway, and Baglung Highway, respectively (Raju Rai et al., 2020). This study also reflects the same scenario in places like Birauta, Lekhnath, Malepatan, and Hemja, which have high urban growth rates. The study (Muzzini & Aparicio, 2013) on urban growth and development in Nepal highlights the rapid pace of urbanization driven by rural-to-urban migration and economic opportunities. Governance issues such as inadequate urban management and regulatory frameworks further complicate these challenges. Rapid urbanization—coupled with a lack of proper planning and high rural-urban migration—is the key driver of the LULC changes (Wang et al., 2020). This study also found out the key factor for LULC change is the rural-urban migration, where the agricultural land has an impact from both scenarios. This is because most agricultural land in rural areas has been abandoned and converted into forest, whereas the agricultural land of urban regions is transformed into built-up areas. The successful practice of community forestry in Nepal after 2001 also provides aid in increasing the forest area.

4. Conclusions

In conclusion, this study has provided comprehensive insights into the spatiotemporal patterns of urbanization in Pokhara Metropolitan City over 30 years from 1991 to 2021. Using Landsat images and machine learning algorithms such as Random Forest (RF) and Support Vector Machine (SVM), I accurately classified land cover types and assessed changes in urban sprawl. By employing an Artificial Neural Network (ANN) model, I projected future urban growth trends up to 2050, highlighting the continued reduction of agricultural land and expansion of urban and forest areas which is the outcome of rural-urban migration.

This research comprehensively explores advanced technologies such as satellite imagery, machine learning, and GIS techniques in predicting urban growth and land use change dynamics. Analyzing historical patterns and trends in Pokhara Metropolitan City provides critical insights for urban planners and policymakers, empowering them to anticipate and respond to future development scenarios effectively. Through an enhanced understanding of spatial-temporal characteristics, the thesis facilitates informed decision-making in land use management, allocation, and infrastructure planning, optimizing resource utilization and promoting sustainable urban development.

However, it's important to acknowledge the challenges faced during the research. Further research may incorporate deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which could enhance prediction accuracy by capturing complex patterns in satellite imagery. Comparative studies with other cities could reveal unique and common factors influencing growth, improving the models' generalizability. Moreover, interdisciplinary collaborations across fields like urban planning, environmental science, and sociology will foster more holistic and robust growth models. These advancements will build upon current findings, driving sustainable urbanization efforts in Pokhara.

5. Recommendation

To enhance urban growth forecasting in Pokhara Metropolitan City, it is recommended to use high-resolution satellite imagery and incorporate multi-temporal data for detailed and dynamic analysis. Evaluating the Random Forest algorithm against alternatives like SVM and Neural Networks guarantees precise results. Enhancing rural living standards through upgraded infrastructure, local business support, and community initiatives can deter migration to cities. Employing real-time monitoring and interdisciplinary cooperation will fine-tune urban planning, fostering a more balanced and sustainable development approach in the area.

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References

[1] Adams, R., Murray, A. T., & Band, L. E. (2018). Urbanization impacts on plant phenology: Data mining from remote sensing. Remote Sensing, 10(4), 608

[2] Rimal, B. Urban growth and land use/land cover change of Pokhara sub-metropolitan city, Nepal. J. Theor. Appl. Inf. Technol. 2011, 26, 118–129.

[3] Verburg, P. H., Neumann, K., & Nol, L. (2015). Challenges in using land use and land cover data

for global change studies. https://doi.org/10.1111/j.13652486.2010.02307.x
[4] Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proceedings of the National Academy of Sciences, 109, 16083–16088. https://doi.org/10.1073/pnas.1211658109
[5] Castanheira, E., & Freire, F. (2013). Greenhouse gas assessment of soybean production: Implications of land use change and different cultivation systems. Journal of Cleaner Production, 54, 49–60.
https://doi.org/10.1016/j.jclepro.2013.05.026
[6] Watson, R. T., Noble, I. R., Bolin, B., Ravindranath, N. H., Verardo, D. J., & Dokken, D. J. (2000) Intergovernmental Panel on Climate Change; IPCC Special Report on Land Use, Land-Use Change, and Forestry; Cambridge University Press: Cambridge, UK.
[7] Gatti, L. V., Basso, L. S., Miller, J. B., Gloor, M., Domingues, L. G., Cassol, H. L. G., ... & Peters, W. (2021). Amazonia as a carbon source linked to deforestation and climate change. Nature, 595, 388–393. https://doi.org/10.1038/s41586-021-03629-6
[8] Kim, D.-G., & Kirschbaum, M. U. (2015). The effect of land-use change on the net exchange rates of greenhouse gases: A compilation of estimates. Agriculture, Ecosystems & Environment, 208, 114–126. https://doi.org/10.1016/j.agee.2015.04.026
[9] Rimal, B. (2013). Urbanization and the decline of agricultural land in Pokhara Sub-metropolitan City, Nepal. Journal of Agricultural Science, 5(1), 54. https://doi.org/10.5539/jas.v5n1p54
[10] Raju Rai, Zhang Yili, Basanta Paudel, Narendra Raj Khanal, and Bipin Kumar Acharya. Satellite Image Based Monitoring of Urban Land Use Change and Assessing the Driving Factors in Pokhara and Bharatpur Metropolitan Cities, Gandaki Basin, Nepal. Journal of Resources and Ecology, 11(1):87 – 99, 2020. https://doi.org/10.5814/j.issn.1674-764x.2020.01.009
[11] Muzzini, E., & Aparicio, G. (2013). Urban growth and spatial transition in Nepal: An initial assessment. World Bank Publications.
[12] Wang, S. W., Gebru, B. M., Lamchin, M., Kayastha, R. B., & Lee, W. K. (2020). Land use and land cover change detection and prediction in the Kathmandu district of Nepal using remote sensing and GIS. Sustainability, 12(9), 3925. https://doi.org/10.3390/su12093925