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Urbanization and Its Impact on Land Use and Land Cover in Dhangadi Sub-Metropolitan City: Comprehensive Analysis and Forecasting

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Abstract

Urbanization, a global phenomenon characterized by the growth and expansion of urban areas, presents significant challenges and opportunities for sustainable development. This study investigates the spatial impact of urbanization on land use and land cover (LULC) in Dhangadhi Sub-metropolitan City (DSMC) from 2002 to 2022 and forecasts urban sprawl for 2032 using CA-Markov chain analysis. The CA-Markov model simulates future land use changes based on historical data. Landsat images from 2002, 2012, and 2022 were analyzed using the Maximum Likelihood algorithm, classifying the landscape into agricultural land, barren land, forest land, built-up area, and water bodies. Weighted overlay and suitability analyses considered physical, accessibility, social, economic, and environmental factors to create a suitability map for future urban development. The LULC analysis showed significant changes: agricultural land decreased from 58.35% in 2002 to 26.31% in 2022, while the built-up area expanded from 6.03% to 33.48%. Accuracy assessments confirmed the reliability of the classification results, with high user and producer accuracies and kappa values. The results indicated significant urban expansion into peri-urban and rural areas, driven by population growth, economic activities, and inadequate urban planning. Ecological consequences include biodiversity loss, habitat fragmentation, and climate changes, while social impacts involve community structure and service access, and economic impacts affect land value and infrastructure costs. The forecast for 2032 suggests continued urban expansion, emphasizing the need for sustainable urban planning. Recommended strategies include green belt development, zoning regulations, promoting public transportation, protecting agricultural land, preserving natural habitats, and involving local communities in planning. These findings offer valuable insights for policymakers and urban planners in DSMC to manage growth sustainably and mitigate the adverse effects of urban sprawl.

***Keywords*:** Land Use Change; Urban Growth; Urban Sprawl; Sustainable Urban Planning; Environmental Impact; Forecasting

1. Introduction

Urbanization, characterized by the rapid expansion and growth of urban areas due to population growth, internal migration, and economic development, has profound implications for infrastructure, resource management, and environmental sustainability globally and in Nepal. In Nepal, this process is often accompanied by unplanned developmental activities, leading to significant infrastructure and resource management challenges. Typically, urbanization in Nepal spreads radially around well-facilitated cities or linearly along highways, resulting in a dispersed expansion pattern known as urban sprawl [1].

Urban sprawl, the uncontrolled and unplanned expansion of urban areas into peri-urban and rural regions, leads to significant land use and cover changes (LULC). This phenomenon critically impacts the affected regions' environment, agriculture, transportation, infrastructure, and socio-economic dynamics. Adverse effects of urban sprawl include habitat fragmentation, biodiversity loss, increased greenhouse gas emissions, and declining agricultural productivity. Therefore, effective urban planning, economic development, and resource management are essential for mitigating these adverse effects and promoting sustainable development [2][3].

Dhangadhi Sub-Metropolitan City (DSMC) is one of the fastest-urbanizing cities in Nepal. According to preliminary data from the National Census 2021, DSMC has a total population of 204,788, with 32,249 households and 46,670 family populations. Rapid urbanization in Dhangadhi has led to the fragmentation of arable land for residential purposes, significantly impacting its residents' environment, infrastructure, and quality of life. The uncontrolled expansion has resulted in various ecological and socio-economic challenges, necessitating comprehensive urban planning and land-use management [4].

Despite significant urbanization in Dhangadhi, there is a lack of studies analyzing the spatial impact of urban sprawl using advanced modeling techniques such as CA-Markov chain analysis. Previous research often focused on descriptive analysis or used less sophisticated models, which do not adequately capture the complex dynamics of urban growth and land use changes. This study aims to fill this research gap by employing the CA-Markov model, which combines cellular automata and Markov chain models to simulate future land use changes based on historical data, providing a robust framework for understanding and predicting urban sprawl dynamics [5][6].

2. Objectives

The primary objective of this study is to investigate the LULC changes in DSMC from 2002 to 2022 and forecast urban sprawl for 2032. Secondary objectives include:

- **a.** Analyzing Landsat images from 2002, 2012, and 2022 using pixel-based supervised classification with the Maximum Likelihood algorithm.
- **b.** Conducting weighted overlay and suitability analyses considering physical, accessibility, social, economic, and environmental factors to create a comprehensive suitability map for future urban development.
- **c.** Assessing the ecological, social, and economic impacts of urban sprawl in DSMC.
- **d.** Providing policy recommendations for sustainable urban planning and land-use management in DSMC.

By achieving these objectives, this study aims to provide valuable insights for policymakers and urban planners in managing urban growth sustainably and mitigating the adverse effects of urban sprawl. Addressing urban sprawl in Dhangadhi requires a holistic approach involving green belt development, zoning regulations, public transportation promotion, agricultural land protection, preservation of natural habitats, and active involvement of local communities in the planning process [7][8].

3. Materials and Method

3.1 Study Area

Dhangadhi Sub-Metropolitan City, located in the Kailali District of Nepal's Sudurpaschim Province, is an important case study for urban sprawl analysis due to its rapid growth and significant transformation. Initially established as Dhangadhi Municipality in 1976 (2033 B.S.), the municipality was elevated to Sub-Metropolitan City status on September 17, 2015 (2072/06/01 B.S.) [9]. Geographically, Dhangadhi is positioned at 28.6852°N latitude and 80.6216°E longitude, with an elevation of approximately 109 meters above sea level. It is situated around 750 kilometers west of Kathmandu, the capital of Nepal, highlighting its strategic location within the country [10][11], as shown in Figure 1.

Dhangadhi, which covers an area of 261.75 square kilometers, is characterized by flat terrain, influencing its urban development pattern. Kailari Rural Municipality borders the city to the east, the Mohana River to the west, Godawari and Gauriganga Municipalities to the north, and India to the south [12]. The flat geographical features and strategic location along major transportation routes have facilitated linear urban expansion, contributing significantly to urban sprawl [13].

According to the 2021 Census, Dhangadhi Sub-Metropolitan City has a population of 198,792 residents [14]. The city is organized into 19 wards, each displaying unique demographic and socio-economic characteristics. This division into wards reflects the city's diverse needs and development challenges, which has evolved from an agrarian-based economy to a more complex urban economy driven by commerce, services, and significant migration from rural areas [15][16].

Dhangadhi experiences a subtropical climate with hot summers, mild winters, and substantial rainfall during the monsoon season, affecting local agriculture and urban planning [17]. The Mohana River and its tributaries are crucial for the city’s water supply and irrigation systems, playing a vital role in supporting both urban and agricultural needs [18]. The river systems also influence land use patterns and the city's expansion dynamics [19].

The city’s location along major highways has facilitated linear urban growth, which has resulted in urban sprawl. This sprawl has led to various challenges, including habitat fragmentation, loss of agricultural land, and increased pressure on infrastructure and resources [20]. Factors such as population growth, economic development, and insufficient urban planning have driven the expansion of built-up areas into peri-urban and rural regions [21].

This study employs advanced modeling techniques, specifically the CA-Markov chain analysis, to assess these trends and provide valuable insights into future urban development and planning [22]. By examining land use and land cover (LULC) changes over time, the study aims to understand urban sprawl dynamics better and inform sustainable development strategies for Dhangadhi Sub-Metropolitan City [23].

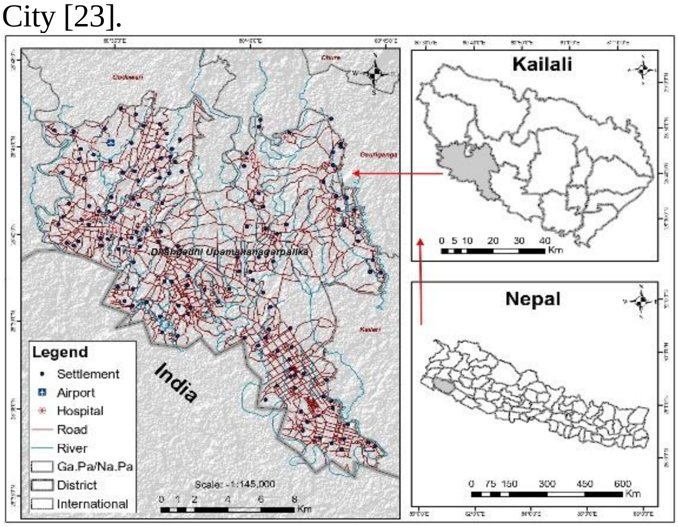

Figure 1: Study Area

2.2 Datasets Used

The principal dataset for this study consisted of satellite imagery, including Landsat 5 images from 2002 and 2012, and Landsat 8 images from 2022. The Digital Elevation Model (DEM) was sourced from the United States Geological Survey (USGS) for topographical information. Administrative boundary shapefiles, which delineate the geographical limits of the study area, were provided by the Survey Department of Nepal. In addition, various secondary data sources were utilized: information from the Dhangadhi Sub-Metropolitan City authorities offered local insights. In contrast, statistical data were drawn from the Central Bureau of Statistics, and road network data were obtained from the Department of Roads.

Table 1: Datasets Used

S.N.	Data	Description
1	Landsat 5 TMC2L1	Pixel size:30m Date: 4/16/2002 and 12/05/2012
2	Landsat 8 OLI/TIRS	Pixel size:30m Date: 11/28/202
3	Aster DEM	
4	DoS	Administrativeboundary
5	SRN data	SRN GIS shapefiles
6	LULC map, suitability classes	LULC for 2002, 2012 & 2022

A comprehensive overview of these crucial datasets is summarized in Table 1.

2.3 Data Processing and Analysis

The data processing and analysis methodology comprised several crucial steps to assess land use and land cover changes accurately. Initially, Landsat imagery from 2002, 2012, and 2022 was processed and classified using advanced software tools, specifically ERDAS IMAGINE and ArcGIS. These tools enabled a detailed examination of land use patterns and detection of changes over the two-decade period. To ensure the reliability of the results, accuracy assessments were conducted for the land use and land cover maps generated for each of the years in question. This process involved comparing the classified maps with reference data to evaluate their accuracy and precision.

Additionally, modeled land use and land cover maps were created for the forecast year 2032. These predictive maps were developed using advanced modeling techniques to simulate future land use changes based on historical data and observed trends.

Urban landscape analysis tools generated urban footprint maps, illustrating urban areas' spatial extent and distribution. This analysis provides valuable insights into the patterns of urban sprawl and its impact on the surrounding landscape.

Therefore, the methodology involved a comprehensive data processing and analysis approach, ensuring robust results and meaningful insights into urban dynamics.

2.4 Image Classification, Validation, and Change Assessment

2.4.1 Image Classification

The study employed Landsat 5 TM and Landsat 8 OLI/TIRS satellite imagery for the years 2002, 2012, and 2022 to assess land use and land cover changes. The Landsat imagery was chosen for its historical consistency and ability to provide high-resolution data essential for temporal analysis of land use patterns [24][25].

2.4.1.1 Supervised Classification

The supervised pixel-based classification was utilized to categorize the imagery into five distinct land cover classes: water bodies, built-up areas, agricultural land, barren land, and forest land. This process involved the following steps:

- ***a. Training Sample Selection:*** Training samples were manually defined for each land cover class. These samples were selected based on visual interpretation and high-resolution imagery from Google Earth, ensuring that they accurately represent the spectral characteristics of each class [26][27].
- ***b. Classification:*** The training samples were used to classify the Landsat images using the Maximum Likelihood Classification (MLC) algorithm. MLC assigns each pixel to the class for which it has the highest probability based on the statistical distribution of training samples [28].
- ***c. Post-Classification Refinement***: Manual editing was conducted to correct misclassified pixels and refine the classification. This step involved adjusting the boundaries between classes and ensuring that the classification accurately reflected the land cover types [29].

2.4.2. Validation

Validation is crucial for assessing the accuracy of the classification results. The following methods were employed:

a. **Error Matrix Construction**: An error matrix (confusion matrix) was created by comparing the classified image to ground truth data. This matrix compares the number of correctly classified pixels to those that were incorrectly classified, providing a basis for calculating accuracy metrics [30]. The error matrix is defined as:

$$E = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix}$$

where TP is True Positive, FP is False Positive, FN is False Negative, and TN is True Negative.

b. **Accuracy Metrics Calculation:** Accuracy metrics were calculated from the error matrix.

c. **Ground Truthing**: Field surveys and high-resolution imagery were used to collect ground truth data. This data served as the reference for validating the classified images. When field data were unavailable, secondary sources and expert knowledge were used to approximate the class types [31[[32].

2.4.3 Change Assessment

Change detection between the years 2002 and 2022 was performed to identify and quantify land cover changes. The methodology involved:

- **e.** Overlay Analysis: Land cover maps for 2002 and 2022 were overlaid to detect changes. This involved creating a change detection matrix to quantify transitions between land cover types [33].
- **f.** Change Detection Equation: The amount of change between the two-time points was calculated using:

$$\text{Change} = \frac{\text{Number of Changed Pixels}}{\text{Total Number of Pixels}}$$

- **g.** Urban Footprint Analysis: Urban footprint maps were generated to visualize and analyze the extent of urban sprawl and land cover transformations over time. This analysis helped identify patterns of expansion and its impact on the landscape [34][35]

3. Results and Discussion

This section presents a detailed analysis of the Land Use and Land Cover (LULC) changes observed in Dhangadhi Sub-Metropolitan City (DSMC) across three key time periods: 2002, 2012, and 2022 — using Landsat imagery. The analysis covers the classification and validation of LULC maps, discusses significant changes in land cover, and models future urban expansion for 2032. The discussion integrates findings with existing literature and cites relevant studies to contextualize the results.

3.1 LULC Map 2002

The LULC map for 2002 (Figure 3) reveals the spatial distribution of land cover types within DSMC. In 2002, Agricultural Land was the predominant land cover, encompassing 152.74 km², or 58.35% of the total area. Forest Land covered 80.20 km² (30.64%), while Built-Up Areas occupied 15.79 km² (6.03%). Barren Land and Water Bodies were the least prevalent, covering 7.06 km² (2.70%) and 5.96 km² (2.28%), respectively.

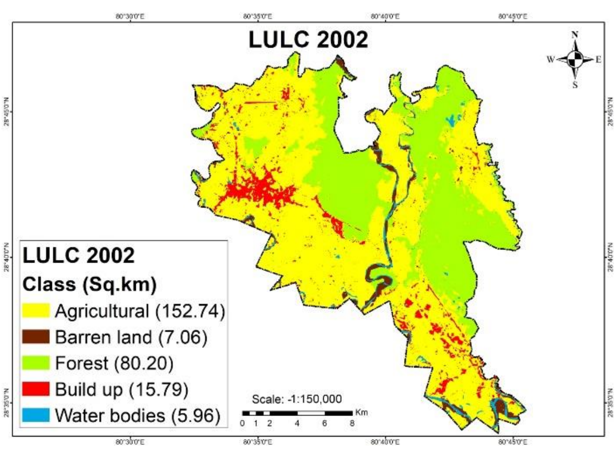

Figure 3: LULC Map 2002

These findings reflect a landscape primarily dominated by agricultural and forested areas, with minimal urban development. This aligns with studies in similar regions where agricultural lands often constitute a significant portion of land use in the early stages of urbanization [36][37]. The accuracy assessment showed an overall accuracy of 86.32% and a Kappa coefficient of 0.82, suggesting the high reliability of the classification results. These values are comparable to those reported in other studies using Landsat data for LULC classification [38][39].

3.2 LULC Map 2012

The 2012 LULC map (Figure 4) indicates notable changes from 2002. Agricultural Land decreased to 106.49 km² (40.68%), while Forest Land increased to 90.84 km² (34.70%). Built-up areas expanded to 47.98 km² (18.33%), reflecting significant urban growth. Barren Land increased to 11.21 km² (4.28%), and Water Bodies slightly decreased to 5.24 km² (2.00%). This shift illustrates the ongoing urban expansion and conversion of agricultural land into built-up areas, consistent with trends observed in rapidly urbanizing areas worldwide [40][41]. The stability in Water Bodies and the increase in Barren Land can be attributed to natural and anthropogenic changes in the landscape. The accuracy of the 2012 map also demonstrated high reliability, with an overall accuracy of 86.32% and a Kappa coefficient of 0.82, comparable to the results from previous years [42][43].

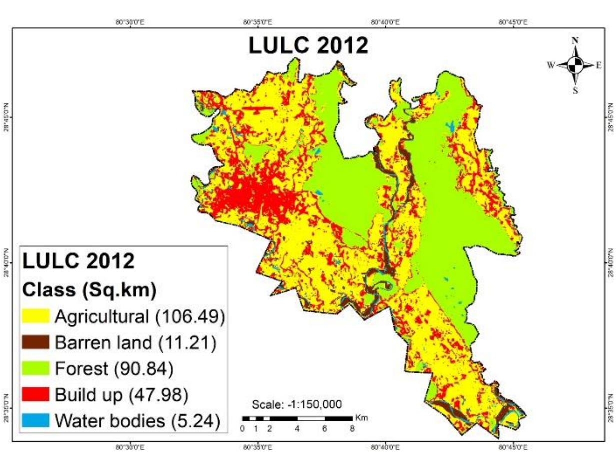

Figure 4: LULC Map 2012

3.3 LULC Map 2022

The 2022 LULC map, as shown in Figure 5, shows further transformation in land cover. Forest Land remains the largest category, covering 88.90 km² (33.97%). Built-up areas saw significant growth to 87.62 km² (33.48%). Agricultural Land decreased to 68.88 km² (26.31%). Barren Land and Water Bodies changed to 8.66 km² (3.31%) and 7.69 km² (2.94%), respectively.

The increase in Built-Up Areas and decrease in Agricultural Land reflect ongoing urbanization and land conversion, which are consistent with patterns observed in other urbanizing regions [44][45]. Despite

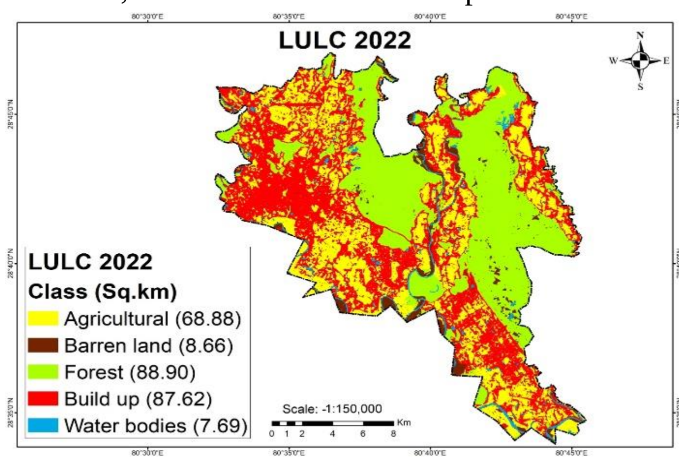

Figure 5: LULC Map 2022

urban expansion, Forest Land and Water Bodies stability suggests that conservation efforts or natural barriers may have mitigated further changes. The 2022 map's accuracy, with an overall score of 86.32% and a Kappa coefficient of 0.82, affirms the robustness of the classification process [46][47].

3.4 Urban Sprawl Modeling for 2032

The projection of urban sprawl for 2032 was conducted using the Land Change Modeler (LCM) within the Terr Set Geospatial Monitoring and Modeling Software. The Cellular Automata-Markov (CA-Markov) model was employed to predict future land cover changes based on historical data from 2012 and 2022. The CA-Markov model utilizes parameters such as DEM, slope, proximity to roads and rivers, aspect, and suitability maps to forecast land cover transitions [48][49].

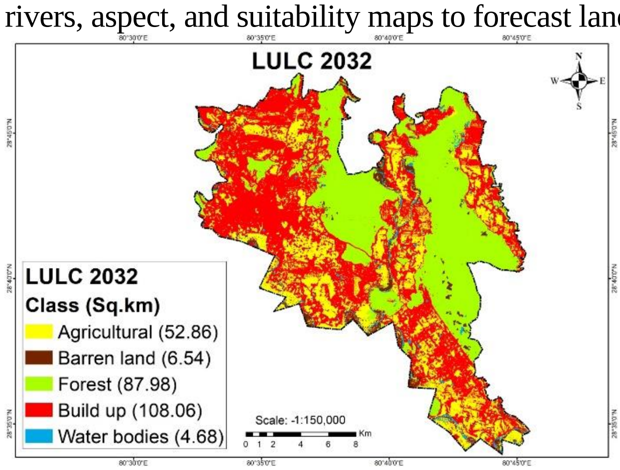

Figure 6: Urban Sprawl for 2032

The modeling results, shown in Figure 6, indicate a continued expansion of Built-Up Areas and potential reductions in Agricultural Land and Forest Land. This prediction aligns with other studies forecasting urban growth trends based on historical data and land change modeling [50][51]. The use of CA-Markov for land cover prediction is well-documented in the literature and provides a reliable framework for anticipating future urban sprawl [52][53].

4. Limitations

While this study comprehensively analyzes urbanization and its impact on Land Use and Land Cover (LULC) in Dhangadhi Sub-Metropolitan City (DSMC), several limitations must be acknowledged to contextualize the results and guide future research.

4.1 Data Limitations

a. Resolution Constraints: The Landsat imagery used in this study has a spatial resolution of 30 meters, which, while suitable for many land cover classification tasks, may not capture finer details of land use changes. Higher-resolution imagery could potentially provide a more accurate classification of smaller land cover types and urban features [54][55].

b. Temporal Gaps: The study uses Landsat data from three specific years (2002, 2012, and 2022). The lack of intermediate data points limits the ability to analyze more granular changes in land use and land cover between these periods. More frequent observations could provide a clearer picture of urban dynamics and transitions [56].

4.2 Methodological Constraints

a. Classification Accuracy: Despite high overall accuracy and Kappa coefficients for LULC maps, there is inherent uncertainty in classification results. Misclassification can occur due to spectral similarities between different land cover types and the limitations of pixel-based classification methods [57]. While accuracy assessments help mitigate this, they cannot entirely eliminate classification errors.

b. Model Assumptions: The CA-Markov model used for predicting future urban sprawl relies on historical data and certain assumptions about land cover transitions. These models are based on past trends and may not fully account for sudden or unforeseen changes in urban development policies or environmental conditions [58]. Consequently, the predictions for 2032 may not entirely reflect future realities if significant changes in development patterns occur.

4.3 Data Quality and Source

a. Data Source Variability: The study relies on various datasets from different sources, including satellite imagery, DEM data, and administrative shapefiles. Variability in data quality, accuracy, and resolution across these sources can impact the overall analysis [59]. Consistent data quality and source integration are crucial for reliable results.

b. Ground Truth Data: Limited ground truth data may affect the accuracy of the classification results. The study primarily uses satellite data and existing secondary sources for validation. Additional field surveys and more extensive ground truth data could enhance classification accuracy and reliability [60].

4.4 External Factors

a. Socio-Economic Factors: The study focuses on spatial and land cover changes but does not extensively address socio-economic factors driving urbanization. Factors such as economic development, migration patterns, and policy changes significantly influence land use changes and should be considered in future studies [61].

b. Environmental Factors: Changes in climate and natural events (e.g., floods, landslides) can also impact land use patterns. These external environmental factors are not explicitly modeled in this study, which may affect the accuracy of land cover predictions [62].

4.5 Future Research Directions

Future research could address these limitations by incorporating higher-resolution imagery, more frequent temporal observations, and additional socio-economic and environmental data. Exploring alternative modeling approaches and integrating ground-truth validation could further enhance the accuracy and robustness of land cover predictions.

5. Conclusion and Recommendation

This study examined urban sprawl in Dhangadhi Sub-Metropolitan City from 2002 to 2032, revealing significant land use and cover changes. The analysis showed a dramatic increase in built-up areas, which expanded from 15.79 km² in 2002 to 87.62 km² in 2022—an almost six-fold increase. In contrast, agricultural and cultivated land decreased substantially, from 152.74 km² to 68.87 km², with a total of 83.87 km² of agricultural land being converted for other uses over the twenty-year period. Bare and open land remained relatively stable throughout the study period. The rapid and uncontrolled expansion of built-up areas into previously rural and agricultural lands has significantly degraded valuable farmland.

Several challenges were encountered during the study, including the limited resolution of Landsat imagery, which affected the accuracy of land use and land cover (LULC) maps for 2002 and 2022. Additionally, high processing requirements for predictive modeling constrained the analysis. Despite these limitations, the study highlights the critical need for improved urban planning and land management in Dhangadhi.

The observed limited correlation between population growth and urban expansion suggests a need for more strategic urban planning. Existing policies and regulations are insufficient due to a lack of long-term planning and are often influenced by political considerations rather than functional criteria. Local-level institutional capacity for land-use monitoring and enforcement must be significantly enhanced to safeguard agricultural land and promote sustainable development.

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