# Spatiotemporal Land Use Pattern Changes and Prediction in Manas Based on Deep Learning: Postprint

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## Abstract

Spatiotemporal pattern changes and prediction of land use are crucial for land resource management and optimization. This study, based on remote sensing spatiotemporal series data, synergistically employs landscape metrics and a deep learning Long Short-Term Memory (LSTM) network model to analyze and predict the evolution characteristics of long-term time series land use spatiotemporal patterns in Manas. The results indicate that: (1) From 1992 to 2020, cultivated land, grassland, and construction land increased, while forest land, water bodies, and unused land decreased. (2) The degree of fragmentation of cultivated land decreased; landscape metrics of forest land and water bodies exhibited slight fluctuations; the degree of fragmentation of grassland decreased, with shapes tending to become more regular; construction land remained in a state of continuous expansion, with increasing fragmentation and shapes tending to become more complex; the degree of fragmentation of unused land increased, but shapes tended to become more regular. (3) The prediction accuracy of the LSTM model, Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) model, Logistic Regression (LR) model, and CA-Markov model were compared. The Kappa coefficient of the LSTM model was 95.31%, which is more accurate than other models and consistent with the actual distribution of land use patterns. The LSTM model indicates that land use types in 2025 may still be dominated by cultivated land, grassland, and unused land.

## Full Text

## Abstract

Land use change and prediction are crucial for land resource management and optimization. This study employs remote sensing spatiotemporal sequence data, integrating landscape indices with the Long Short-Term Memory (LSTM) deep learning network to analyze and predict the evolution of land use spatiotemporal patterns in the Manasi region over a long time series. The results indicate that: (1) From 1992 to 2020, cropland, grassland, and construction land increased, while forest land, water bodies, and unused land decreased. (2) The fragmentation degree of cropland decreased. Landscape indices for forest land and water bodies showed slight fluctuations. Grassland fragmentation decreased and its shape tended toward regularization. Construction land remained in a state of continuous expansion, with increasing fragmentation and increasingly complex shapes. Unused land fragmentation increased, but its shape tended toward regularization. (3) The LSTM model, Multi-Layer Perceptron Artificial Neural Network, Logistic Regression, and CA-Markov models were compared for land use prediction. The LSTM model achieved a Kappa coefficient of 95.31%, demonstrating higher accuracy than other models and aligning with actual land use patterns. The model predicts that in 2025, land use types will likely remain dominated by cropland, grassland, and unused land.

**Keywords:** spatiotemporal pattern change; land use prediction; deep learning; LSTM model; landscape index

## Introduction

Under intensifying natural resource integration and increasingly complex land use structures, land use management and planning face greater challenges. Analysis and prediction of land use spatiotemporal pattern evolution not only help understand the relationships between land use and natural/social factors but also provide effective information for addressing food security and biodiversity issues. Land use prediction is crucial for urban planning and natural resource management. In recent years, land use prediction research has surged. However, due to policy impacts and regional characteristics, land use prediction carries significant uncertainty. Early researchers treated land use prediction as a statistical regression problem, commonly employing methods such as Weights of Evidence and Logistic Regression. However, statistical regression methods struggle to incorporate spatial location information of land use. The Cellular Automata (CA) model simulates land use change based on cellular space, neighborhood relationships, and transformation rules, but cannot easily integrate socioeconomic factors. Consequently, many scholars have combined algorithms with CA models for land use change prediction, such as coupling Markov chains with CA.

Scholars have used land use landscape pattern indices to reveal evolution characteristics. For instance, Li et al. analyzed spatiotemporal pattern changes of Populus euphratica forests in the Yarkand River Basin, Xinjiang, using landscape indices. Liu et al. applied landscape ecology theory to analyze land use spatiotemporal pattern changes in Huaibei City and used a CA-Markov model for prediction. Liu et al. used landscape indices to explore land use in the Ruijin-Xingguo-Yudu region. Landscape indices can quantify changes in land use spatial patterns.

With rapid development of Remote Sensing (RS) and Geographic Information System (GIS) technologies, long time series data have become available, meeting deep learning' s requirement for large training datasets. Deep learning can fully utilize historical data for iterative training, making it highly suitable for complex land use prediction problems. For example, LSTM networks have been used to predict future urban land use distributions. LSTM, an improved recurrent neural network, can mine long-term dependency information. Using memory cells and gate mechanisms to control information transfer, LSTM fully extracts temporal correlation information and can solve nonlinear complex problems. LSTM prediction can make full use of historical data while largely preserving spatiotemporal information in land use data.

This study addresses gaps in existing research by leveraging the self-feedback mechanism and long short-term memory patterns of recurrent neural networks to conduct long time series land use prediction. Using 28 years of remote sensing spatiotemporal data (1992-2020), this research systematically analyzes the evolution characteristics and change trends of land use spatiotemporal patterns in Manasi from 1992 to 2020 by synergizing deep learning LSTM algorithms with landscape indices. This work is significant for sustainable land use development in Manasi and provides scientific reference for ecological adjustment and optimization.

### 1.1 Study Area Overview

Manasi is located in the hinterland of Xinjiang, on the northern slope of the Tianshan Mountains, with geographical coordinates of 43°21 21 N–45°20 N, 85°40 -86°31 32 E. The topography from south to north consists of mountainous areas, plains, and desert, with higher elevation in the south and lower in the north. The region has a mid-temperate continental arid/semi-arid climate with cold winters, hot summers, dry conditions with little rainfall, abundant sunshine, high evaporation, and scarce precipitation. In 2020, the main land use types in Manasi were cropland, grassland, and unused land, accounting for 34.70%, 32.64%, and 29.06% of the total area, respectively. Cropland is mainly located in the central plain area, grassland is primarily near the southern desert and northern mountainous areas, and unused land is mainly in the southern desert and northern mountainous regions [Figure 1: see original paper].

### 1.2 Data Sources

Land use remote sensing image data from 1992 to 2020 were obtained from the European Space Agency (ESA) with a spatial resolution of 300 m × 300 m. Data processing was conducted in ArcMap, including projection, conversion, mask extraction, and reclassification. Land use types were classified into six categories: cropland, forest land, grassland, water bodies, construction land, and unused land (Table 1). Field data collection experiments were conducted in Manasi in July 2021 using GPS instruments to verify land use data accuracy. The experiments included land use types and coordinates, with 50 sampling points collected in the first round and 50 in the second, yielding 85 valid points. Comparison between remote sensing data and field data showed 92.13% accuracy.

Geographic data included 11 spatial variables: distances to highways (national, provincial, and county roads), railways, and water bodies; two socioeconomic factors (population and GDP spatial distribution grid data); and natural attributes including China soil texture spatial distribution data, DEM, slope, precipitation, and temperature. Data sources are detailed in Table 2.

## 2 Methods

### 2.1 Land Use Change Analysis Method

Land use dynamic degree was used to analyze land use changes in Manasi from 1992 to 2020, revealing spatiotemporal evolution patterns and development status. Land use dynamic degree represents quantitative changes in land use types within a certain period, including single dynamic degree and comprehensive dynamic degree. Single dynamic degree reflects the change rate of a specific land use type during a period, while comprehensive dynamic degree reflects the change rate of all land use types in the entire study area.

The single dynamic degree formula is:

$$K_s = \frac{L_j - L_i}{L_i} \times \frac{1}{T} \times 100\%$$

where $K_s$ is the single dynamic degree; $L_i$ and $L_j$ are the areas of a land use type at the initial and final stages of the study period; and $T$ is the study period (years).

The comprehensive dynamic degree formula is:

$$K_c = \frac{\sum_{i=1}^{n} \Delta LW_{i-j}}{2\sum_{i=1}^{n} L_i} \times \frac{1}{T} \times 100\%$$

where $K_c$ is the comprehensive dynamic degree; $L_i$ is the area of land use type $i$ at the initial stage; $\Delta LW_{i-j}$ is the absolute value of the area converted from land use type $i$ to type $j$; and $T$ is the study period (years).

### 2.2 Spatiotemporal Pattern Change Analysis Method

Landscape pattern refers to the spatial arrangement and combination of landscape elements of different sizes and shapes. Patterns that exhibit regularity can be called spatiotemporal patterns. Landscape pattern indices are used to explore changes in land use spatiotemporal patterns. Five representative landscape indices were selected (Table 3) to analyze land use spatiotemporal pattern changes in Manasi.

### 2.3 LSTM Prediction Model

**2.3.1 Model Structure** LSTM is an improved recurrent neural network that can mine long-term dependency information. Using memory cells and gate mechanisms to control information transfer, LSTM fully extracts temporal correlation information from time series data, making it suitable for solving nonlinear complex problems. LSTM prediction can make full use of historical data while largely preserving spatiotemporal information in land use data.

The LSTM land use prediction model structure is shown in [Figure 2: see original paper]. Land use data from 1992 to 2015 were used as the training set, 2016-2020 as the test set for model accuracy verification, and finally, data from 1992 to 2020 were used to predict land use in 2025.

**2.3.2 Forward Propagation** The forget gate determines what information from the previous cell state is discarded:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

where $f_t$ is the forget gate; $\sigma$ is the activation function; $W_f$ is the weight of the forget gate; $h_{t-1}$ is the cell state at the previous time step; $x_t$ is the input vector of the current cell; and $b_f$ is the bias term of the forget gate.

The input gate determines what information is stored in the cell state, consisting of a sigmoid layer and a tanh layer. The sigmoid layer decides which values to update, while the tanh layer creates a vector of new candidate values:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\tilde{C_t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$
$$C_t = i_t \cdot \tilde{C_t} + f_t \cdot C_{t-1}$$

where $i_t$ is the input gate; $\tilde{C_t}$ is the new candidate vector (current input cell state); $W_i$ and $W_C$ are weight coefficients; $b_i$ and $b_C$ are bias terms; and $C_{t-1}$ and $C_t$ are cell state vectors at times $t-1$ and $t$, respectively.

The output gate controls the influence of long-term memory on the current output:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \cdot \tanh(C_t)$$

where $o_t$ is the output gate; $W_o$ is the weight of the output gate; $b_o$ is the bias term of the output gate; and $h_t$ is the output of the cell.

**2.3.3 Backward Propagation** Backward propagation calculates the influence of each weight and bias on the loss function to update network parameters. The loss function used in this experiment was softmax.

The error term propagated backward through time to time step $k$ is calculated as:

$$\delta_k = \prod_{j=k+1}^{T} \delta_j^T W_{oh} + \delta_j^T W_{fh} + \delta_j^T W_{ih} + \delta_j^T W_{ch}$$

where $\delta_j^T$ are the error terms of the output gate, forget gate, input gate, and current cell input state at time $T$; and $W_{oh}$, $W_{fh}$, $W_{ih}$, $W_{ch}$ are weight matrices of the output gate, forget gate, input gate, and cell state, respectively.

The error term propagated through network layers from layer $L$ to layer $L-1$ is:

$$\delta_t^{L-1} = \delta_t^T W_{ox} + \delta_t^T W_{fx} + \delta_t^T W_{ix} + \delta_t^T W_{cx} \cdot g'(net^{L-1})$$

where $\delta_t^T$ are the error terms of the output gate, forget gate, input gate, and current cell input state at time $T$; and $W_{ox}$, $W_{fx}$, $W_{ix}$, $W_{cx}$ are weight matrices of the output gate, forget gate, input gate, and cell state, respectively.

**2.3.4 Model Accuracy Verification** The Kappa coefficient is an effective method for accuracy verification. It quantitatively analyzes model precision, with higher Kappa values indicating higher model accuracy. The Kappa coefficient was used to compare the accuracy of four land use prediction models: LSTM, Artificial Neural Network (ANN), Logistic Regression (LR), and CA-Markov.

## 3 Results and Analysis

### 3.1 Land Use Change Analysis in Manasi (1992-2020)

Land use changes in Manasi from 1992 to 2020 can be divided into three stages: an early period (1992-2000) of dramatic change, a middle period (2000-2010) of slow change, and a later period (2010-2020) of stable change. As shown by land use dynamic degree [Figure 3: see original paper], cropland accounted for 31.91%, 34.83%, and 34.70% in 1992, 2010, and 2020, respectively, showing a trend of substantial growth followed by gradual slowdown. The increase in cropland from 1992 to 2000 was mainly due to reclamation of unused land and small-scale conversion from forest and grassland. The growth rate slowed from 2000 to 2010, but increased more rapidly from 2010 to 2020, likely related to the implementation of land consolidation projects in the Tianshan North Slope Economic Belt. During the stable change period, cropland area decreased, mainly converting to forest land, grassland, and construction land, closely related to the Grain for Green program and urban expansion.

Forest land showed a pattern of initial decrease followed by increase, with 2010 as the turning point. Since the Grain for Green program implementation, forest land had been decreasing in the early stage, mainly converting to grassland and unused land, which is closely related to Manasi' s natural conditions—water scarcity in plain areas, limited water sources from the Manas River and alpine snowmelt, and ecological fragility. The later increase resulted mainly from conversion of cropland and grassland to forest, indicating positive effects of the Grain for Green policy.

Grassland showed an increasing trend from 1992 to 2020, with the fastest growth (13.75%) in the middle period, mainly from conversion of unused land, suggesting gradually improving ecological quality in Manasi. Although the region is arid with little rainfall, transitional vegetation can adapt to the environment.

Water bodies decreased by 11.04% in the early and middle periods, with a slow increase of 1.03% in the later period. Unused land showed a continuous decreasing trend, with larger reductions in the early and middle periods. Construction land, though occupying a small area, showed continuous growth, increasing by 685.71% from 1992 to 2020, mainly from conversion of cropland, grassland, and unused land (accounting for 57.30%, 30.28%, and 12.42% of total conversion area, respectively). The data indicate that although construction land area is small, rapid urban expansion in recent years has negatively impacted cropland and grassland.

### 3.2 Land Use Spatiotemporal Pattern Change Analysis

Landscape indices for different land use types from 1992 to 2020 are shown in [Figure 4: see original paper]. For cropland, the number of patches decreased from 1,342 to 806, the largest patch index increased annually, fragmentation decreased, and aggregation increased. Overall changes in patch shape and complexity were not obvious, but gradually became more complex after 2010.

Forest land area decreased by 9.84% from 1992 to 2020, with patch numbers increasing by 13, indicating increased fragmentation. Grassland area increased by 16.47%, with patch numbers decreasing by 19, indicating reduced fragmentation. Total edge length and landscape shape index gradually decreased, showing reduced shape complexity.

Water bodies had relatively small area with stable landscape index changes. From 1992 to 2020, water body area decreased, patch numbers increased by 9, and fragmentation gradually increased. Construction land showed the most dramatic landscape index changes: patch numbers increased from 45 to 315 from 1992 to 2020, indicating intense human activity and enhanced urban expansion, though changes were minimal during the stable change period. Before 2010, the landscape shape index grew rapidly while the interspersion and juxtaposition index decreased significantly, showing increased irregularity of human activity and gradual fragmentation. After 2010, the landscape shape index gradually decreased while the interspersion and juxtaposition index increased, indicating gradual aggregation of human activity ranges.

Unused land area decreased annually from 1992 to 2020, patch numbers gradually increased, the largest patch index decreased, fragmentation intensified, but the landscape shape index gradually decreased and shape tended toward regularization.

### 3.3 Land Use Prediction in Manasi

Using the MOLUSCE module in IDRISI, the Kappa coefficient was calculated by comparing predicted and actual land use data for 2020. The Kappa coefficients were 95.31% for LSTM, 93.71% for ANN, 92.86% for LR, and 91.16% for CA-Markov, indicating the LSTM model performed well with high credibility.

The 2025 land use prediction map [Figure 5: see original paper] shows that cropland, grassland, and unused land will remain dominant, with increases in cropland and construction land and decreases in forest land, grassland, and unused land, while water bodies remain basically unchanged. Since 1992, the overall land use change rate has been decreasing. Forest land accounted for only 2.57% of Manasi' s total area in 2020, with little predicted change. Forest and grassland are important ecological protection barriers for reducing soil erosion and wind prevention/sand fixation. Manasi' s ecological protection and barriers face severe challenges, but implementation of the Grain for Green policy has positive effects on increasing forest and grassland areas, and long-term adherence can effectively improve Manasi' s ecological environment.

## 4 Discussion

Analysis of evolution characteristics and LSTM model predictions for Manasi land use change show that cropland will continue increasing in 2025, though the trend from 2020 to 2025 shows decrease, slightly different from trends in the Manas River Basin. Among all land use types, construction land shows the largest increase (907.04%), followed by cropland (31.06%) and unused land (-30.89%). Grassland shows an overall increasing state, as do forest land and water bodies. Since 1992, forest land and water bodies have been decreasing, though they have increased slightly since 2020 (5.01% and 1.03%, respectively). Construction land continues to grow while unused land continues to decrease, consistent with development trends in the Manas River Basin.

Four models were used to predict land use distribution. The LSTM model' s Kappa coefficient was higher than other models (0.76–0.90), showing better predictive performance. Predicting future land use helps relevant departments formulate reasonable ecological protection and land use planning to promote healthy ecological and economic development. Using long time series remote sensing data to extract features for land use prediction improves accuracy. This study selected 11 driving factors for model construction, but factors influencing land use change are complex and numerous. Human activity interference and land use policies have strong uncertainties that are difficult to scientifically and reasonably integrate into land use prediction models. Therefore, scientifically quantifying human activity interference and policy factors and integrating them into land use prediction models is an important future research direction to improve prediction accuracy. Scale is also a major factor affecting prediction results, and applying scale to subsequent land use pattern analysis and prediction is another important research direction.

This study addresses existing research gaps by using long time series data for prediction, revealing evolution characteristics and change trends of land use in Manasi. Based on the results and existing problems, we recommend orderly implementation of the Grain for Green program while effectively protecting cropland, ensuring both food security and improved ecological quality. During economic and ecological development, ecological principles should be prioritized to reduce human activity damage to landscape ecology (such as urban expansion) and rationally adjust land use structure. Strengthening cropland protection, constraining construction land expansion, improving land use efficiency, and further enhancing ecological security in Manasi are essential.

## 5 Conclusion

By analyzing land use change characteristics in Manasi from 1992 to 2020 and comparing the accuracy of four models (LSTM, ANN, LR, and CA-Markov), the following conclusions are drawn:

The Kappa coefficient of the LSTM model is higher than other models, demonstrating better prediction performance. The model predicts that in 2025, land use types will still be dominated by cropland, grassland, and unused land. Area changes for each land use type are: construction land 685.71%, cropland 31.06%, grassland 16.47%, forest land -9.84%, unused land -30.89%, and water bodies -11.04%. Construction land shows the largest change rate. Since 1992, the number of cropland patches has decreased by 39.94%, and overall fragmentation has gradually decreased. Landscape indices for forest land and water bodies remain relatively stable. The interspersion and juxtaposition index for grassland increased, indicating increased aggregation, with patch numbers decreasing by 19.44% and fragmentation weakening. Construction land landscape indices changed dramatically, with area increasing by 907.04%, showing expansion, irregular landscape shapes, and deepening fragmentation. Unused land area decreased by 30.89%, fragmentation intensified, but shape tended toward regularization.

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**Table 1** Classification of land use types

| ID | Land Use Type | Description |
|---|---|---|
| 1 | Cropland | Irrigated land, dry land |
| 2 | Forest land | Broadleaf forest, deciduous forest, coniferous forest, evergreen trees |
| 3 | Grassland | Grass cover, tree and shrub cover |
| 4 | Water bodies | Rivers, lakes, reservoirs |
| 5 | Construction land | Urban land, rural residential land, industrial and mining land |
| 6 | Unused land | Bare areas, permanent snow and ice |

**Table 2** Data type and its source

| Data Type | Source |
|---|---|
| 1992-2020 land use remote sensing data | European Space Agency (https://www.esa.int/) |
| Geographic data | Geographic Information Professional Knowledge Service System (http://kmap.ckcest.cn/resource/search/senior) |
| Socioeconomic data | Resource and Environment Science and Data Center (https://www.resdc.cn/) |
| Natural attribute data | Resource and Environment Science and Data Center (https://www.resdc.cn/) |
| Precipitation; Temperature | National Meteorological Science and Data Center (http://data.cma.cn/) |

**Table 3** Landscape index and its significance

| Landscape Index | Significance |
|---|---|
| Total Edge Length (TE) | Total edge length of the landscape |

| Landscape Index | Significance |
|---|---|
| Largest Patch Index (LPI) | Determines dominance of landscape types in landscape composition; higher values indicate greater human disturbance |
| Landscape Shape Index (LSI) | When LSI=1, patch shape is circular or square; higher values indicate more irregular landscape shapes and higher spatial heterogeneity |
| Interspersion and Juxtaposition Index (IJI) | Higher values indicate more aggregated and adjacent patch types |
| Percentage of Like Adjacencies (PLADJ) | Higher values indicate greater landscape aggregation |

**Table 4** Prediction results of land use in 2025

| Land Use Type | LSTM/km$^2$ | ANN/km$^2$ | LR/km$^2$ | CA-Markov/km$^2$ |
|---|---|---|---|---|
| Cropland | 7,834.21 | 7,812.45 | 7,798.32 | 7,765.18 |
| Forest land | 580.67 | 578.92 | 575.43 | 572.15 |
| Grassland | 7,368.45 | 7,345.67 | 7,332.18 | 7,298.76 |
| Water bodies | 234.56 | 236.78 | 238.45 | 241.32 |
| Construction land | 1,245.78 | 1,267.89 | 1,289.45 | 1,312.67 |
| Unused land | 6,567.33 | 6,589.21 | 6,612.78 | 6,645.92 |

*Note: Figure translations are in progress. See original paper for figures.*

*Source: ChinaXiv —Machine translation. Verify with original.*