MULTI-TEMPORAL URBAN LAND-USE CHANGE DETECTION AND PREDICTION USING CNN-BASED CA-MARKOV MODEL FROM GAOFEN SATELLITE IMAGES

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ABSTRACT:

The intelligent interpretation of land-use change has become a research frontier. Reasonably and effectively utilizing limited land resources and making scientific predictions to promote sustainable utilization of land resources is significant for establishing a resource-saving and environmentally friendly society. Remote sensing technology can efficiently complete multi-temporal and dynamic land-use change detection, especially using high-spatial resolution remote sensing images. However, the existing land-use change and prediction have not been combined. In addition, land-use change detection mainly relies on shallow feature design, resulting in low prediction accuracy and weak generalization performance. To solve the above problems, we proposed a CNN-based CA Markov model using multi-temporal GaoFen satellite remote sensing images for the change detection and prediction of land cover. Taking the city of Panzhihua in China as an example, the study constructed training sample data that includes a multi-temporal remote sensing training dataset from 2006, 2010, 2015, and 2021 using GaoFen satellite remote sensing images. Meanwhile, a multi-temporal CNN land-use detection model was constructed to generate a land-use transfer matrix by training the dataset. Furthermore, the comprehensive driving factors were selected, including terrain factors (height and slope) and social factors (economic and population density). Then, the CA-Markov model was constructed to predict the land-use development trend in Panzhihua City after ten years. Compared with the traditional methods, experimental results demonstrate that the proposed model can improve the model's automatic interpretation ability and prediction accuracy with an increase of 24.6% in the FoM index and 4.37% in the Kappa coefficient.

1. INTRODUCTION

The utilization and change of land are related to the sustainable development of society and economy and the earth's natural resources and ecological environment. Due to the rapid growth of the social economy, the continuous expansion of population size, and the acceleration of urbanization and industrialization, various resources have been severely scarce (Foley et al., 2005). Although the utilization rate of land by humans has steadily increased, unfortunately, it has also been accompanied by a series of problems caused by unreasonable land resource utilization. For example, some issues can occur, such as global warming, reduction of biological species, vegetation destruction, severe desertification, deterioration of the ecological environment, and impact on food security (Rhind and Hudson, 2023).

The study of land use change has become a core field. Emerging technologies such as geographic information systems have entered an extensive stage of land use change research (Yuan et al., 2022). In the study of land use change, remote sensing mainly completes the classification and dynamic monitoring of land use change, while geographic information systems quickly extract spatial information about land use change and conduct scientific processing. The combination of the two can ultimately obtain the spatial differences and corresponding driving factors of land in the same region at different periods and provide scientific suggestions for the rational use of land in the future, achieving the goal of attaining energy-saving land use, environmentally friendly society, and sustainable development of resources.

Traditional methods mainly use remote sensing images with shallow features, such as spectral information, geometric elements, color, and texture. Machine learning algorithms have been widely used in automated land use classification mappings, such as Support Vector machines, Fandom Forest, and Decision Trees (Yuan et al., 2021). However, these methods rely on manually designed parameters and have limited classification accuracy due to their weak feature construction ability. Due to its efficient feature extraction ability, deep learning methods have been widely applied in object detection (Yuan et al., 2021), image retrieval, and medical image segmentation and have achieved fruitful research results. In recent years, the deep learning method has been applied to land-use multi-classification, which extracts robust, advanced, and deep abstract features by a convolutional neural network (CNN) to achieve accurate multi-categories feature classification (Yuan et al., 2022). For example, Marcos et al. Memon et al. (2021) used the Transfer learning strategy to improve the robustness of features. Alam et al. (2018) used hyperspectral images to combine the conditional random field (CRF) model and CNN to classify objects and obtain better results.

Some methods attempt to explore a variety of CNN with complex structures and a strong ability for feature extraction, such as U-Net (Oktay et al., 2018), Link Net (Zhou et al., 2018), and PSPNet (Zhao et al., 2017), in remote sensing images. For example, Yao et al. (2019) constructed a feature extraction module, CoordConv, focusing on spatial features to improve spatial information. Yuan et al. (2021) used superpixel segmentation, combined with PSPNet's excellent contextual scene parsing ability, and obtained excellent classification results. Zhu et al. (2019) constructed deep neural networks using convolutional kernels of different sizes and classified remote sensing scenes, improving classification accuracy. CNN can capture more deep abstract features to express separate parcels. However, these methods perform poorly in extracting irregular parcels by stacking convolution and pooling layers and have low spectral anti-interference for complex areas. Therefore, it is challenging to classify multiple types of land objects in high aggregation and complex scenes.

The same category of covered land in high-resolution images often has different scales, spectra, and texture information. Thus, it is difficult for CNN networks to use a single-scale feature to represent complex land. To address this problem, researchers used multi-scale semantic features to express complex land blocks on the surface and built a land classification network with a larger receptive field to improve accuracy. For instance, Yang et al. (2018) combined the multi-scale dilated convolution module, ASPP, with the Dense-Net (Huang et al., 2017) network to propose a DenseAPP network that can extract richer multi-scale features, better extracting multi-class parcels of different scales. Aihicre et al. (2021) extracted the basic features of land parcels by a pre-trained network and used an attention mechanism to suppress the semantic unrelated background information to classification.

Although the above methods obtained advanced performance in some datasets, they cannot complete the prediction effectively of land use in the future. To solve these problems, we proposed a CNN-based CA Markov model using multi-temporal GaoFen satellite remote sensing images for the change detection and prediction of land cover.

2. METHOD

2.1 Model formulation

Figure 1 presents the overall method framework. High spatial resolution images are visually interpreted to obtain land-use maps and prediction, and training label samples are produced with 512×512 pixels. Training sample data includes a multi-temporal remote sensing training dataset from 2006, 2010, 2015, and 2021. These data are transmitted to the DeeplabV3+ deep neural network for training. We introduce a spatial-channel attention mechanism into the network to enhance feature expression ability. Ultimately, the land-use classification map can be predicted.

DeepLabv3+ adopts an end-to-end training method. The network consists of an encoder and a decoder. The encoder uses the Xeption Convolutional neural network as the backbone network. The feature map extracted from the backbone network is divided into two parts. One part extracts high-level semantic information by parallel dilated convolutions at different rates in the ASPP module and then reduces the number of channels by convolution1×1. The other part is concatenated and fused with high-level features. Then, convolution 3×3 is used to restore spatial information, and the target boundary is refined by bilinear upsampling. Finally, a segmentation result can be obtained with the same resolution as the original image. In addition, the channel-spatial attention mechanism is introduced into each encoder stage to enhance contextual representation. The structure of the DeepLabv3+ network is shown in Figure 1.

Multiple factors influence land use. Thus, several essential driving factors are constructed for land use, including social and topographic factors. These influence factors are input into the CA Markov model for prediction. The Markov model is suitable for the dynamic prediction of land use change. This method obtains the interconversion status and ratio of the same class in a specific year, which predicts the spatiotemporal change. Markov model first receives the transfer probability matrix of the interconversion of land-use types between the beginning and end years to reveal the transfer rate. The mathematical formula is defined in equation (1), where n expresses the number of different land types and $P_{i,j}$ represents the probability that land use category i changes to j during the beginning and end years. The matrix $P_{i,j}$ elements should conform to the conditions defined in equation (2). Based on the Markov model, the state probability vector $P(n)$ of the object studied by the system at any time can be determined by its initial state probability vector $P(n-1)$ and transition probability matrix $P_{i,j}$, as defined in equation (3).

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \tag{1}$$

$$\sum_{j=1}^{n} P_{ij} = 1 \quad \text{(i, j=1,2,3, ……, n)} \tag{2}$$

$$P(n) = P(n-1) P_{ij} \tag{3}$$

3. STUDY MATERIAL DESCRIPTION

Panzhihua, the object of this study, is a municipality directly under the Sichuan province in China, also known as Dukou City. It is located in the southwest of China, at the intersection of the Yalong River and Jinsha River. It is adjacent to Yuannan province. Topographically, the north is the Great Snow Mountain, the west is the Hengduan Mountains, and the east is the Daliang Mountains. The whole terrain is high in the northwest and low in the southeast. In addition, Panzhihua is an important channel and transportation hub between Sichuan Province and South Asia, Southeast Asia, and coastal ports, known as the "Southern Silk Road." Panzhihua is the only city in China named after flowers and was built in a dry and hot valley. It is a typical mountain city with undulating terrain and complex geological conditions, as shown in Figure 2.

This paper uses the Gaofen satellite remote sensing images of Panzhihua in 2006, 2010, 2015, and 2021 as the pre-processing and supervision classification dataset and combines them with relevant data to obtain impact factors. Data processing included radiometric calibration, atmospheric correction, image cropping, image mosaic, and band selection.

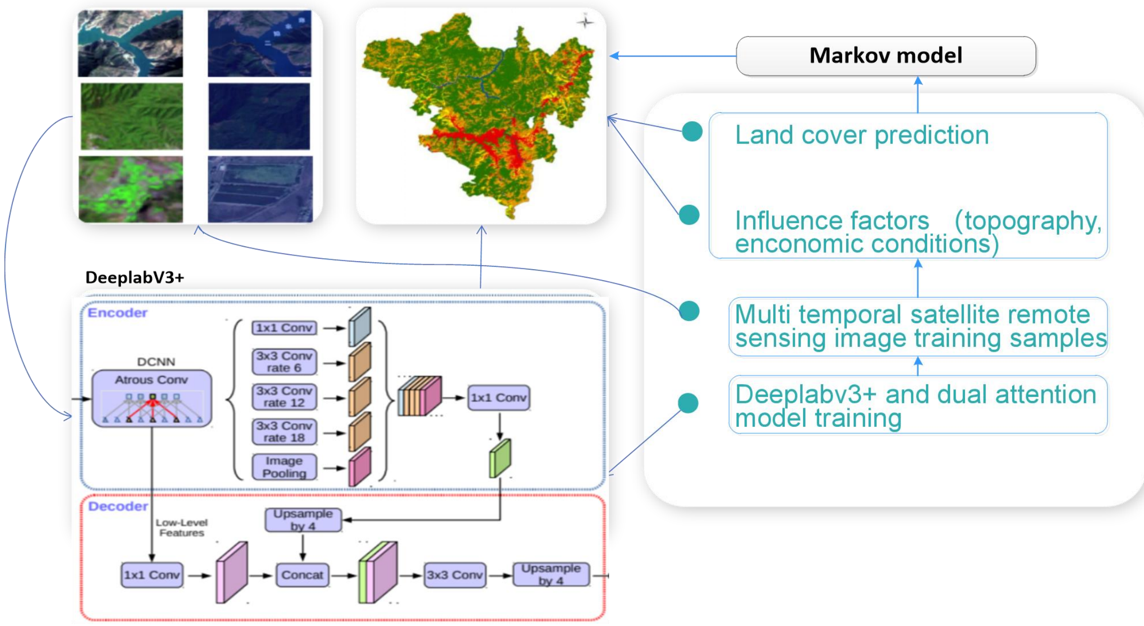


Figure 1. Method framework for the land-use classification and prediction.

Panzhihua City is known as the "Sunshine Flower City" and the "Holy Land of Health Care." Due to its warm climate and historical memory of Third Line Construction, it is suitable for tourism, health care, and high yield of fruits and vegetables. However, the economic development of Panzhihua City is relatively slow due to the significant terrain elevation difference, the difficulty in developing and utilizing the unused land, the severe water pollution caused by mining, the excessive consumption of resources, and the inconvenient transportation and other factors. With the transformation of cities from industrialization to tourism and health, it is necessary to achieve the conversion of land types by adjusting the internal utilization structure and investing a large amount of energy and financial resources.

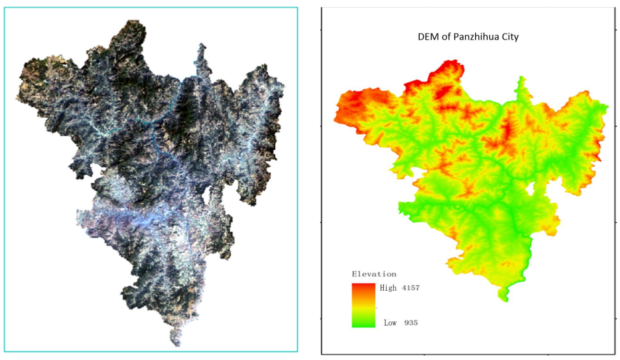


Figure 2. Study area overview

4. EXPERIMENTAL RESULTS AND DISCUSSION

In the operating configuration of the experimental machine, Intel (R) Core (TM) i9-10900X is used, and the graphics card is NVIDIA GeForce RTX 3090 has a running memory of 64GB. The deep learning framework used in the experiment is Pytorch. After several experiments, the initial Learning rate is set to 0.0005; Set the batch size to 16; Set the number of training iterations to 100; The optimizer uses the Adam algorithm.

4.1 Driving force factors analysis

Figure 3 presents the land use mapping using the proposed method from 2006 to 2021. The built-up land of Panzhihua City is mainly located in the east, west, and Miyi County in the administrative division. It is built along the river in a zonal distribution, which is a standard linear zonal city. Secondly, the area of construction land and forest land in Panzhihua City is increasing, the area of unused land is decreasing, the river is roughly unchanged, and the farmland is scattered, mainly distributed along the river.

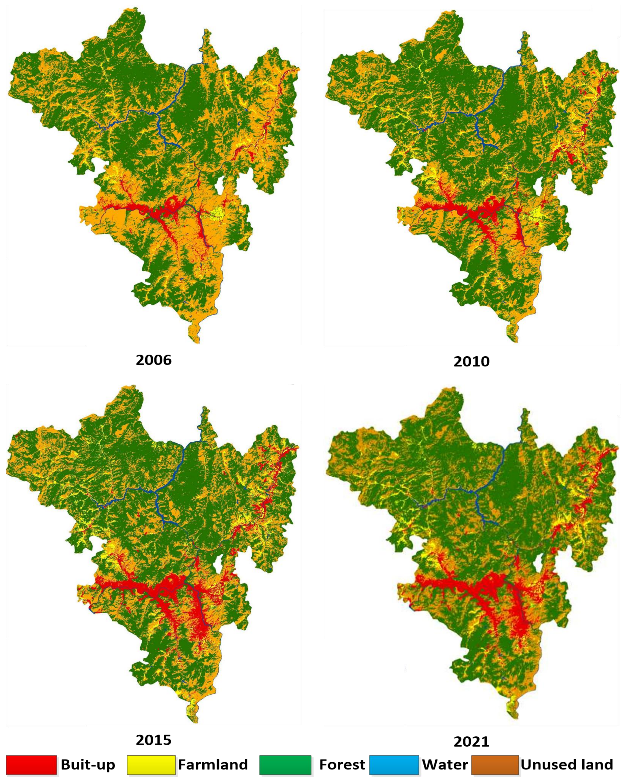


Figure 3. Land use mapping from 2006 to 2021.

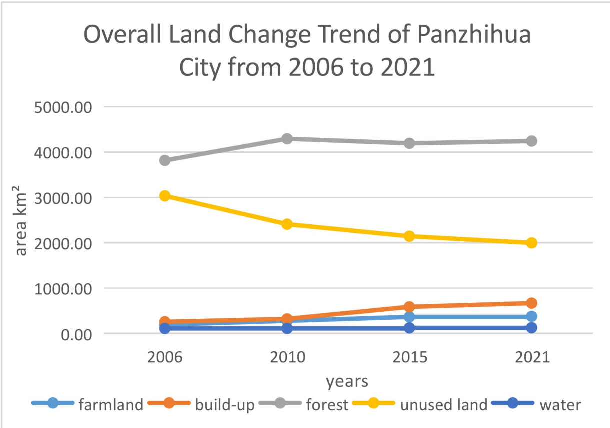


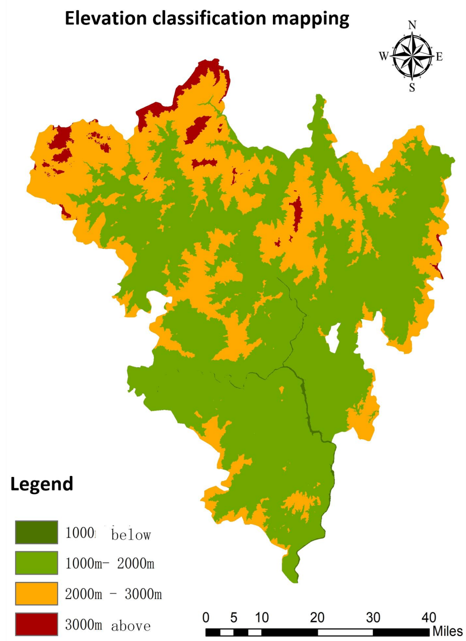
Figure 4. Land use change from 2006 to 2021.

As illustrated in Figure 4, the land use types of Panzhihua City mainly include built-up land, farmland, forest, water, and unused land. In the past decade, forest and unused land in the region have dominated the area accounting for the most significant proportion, reaching 51.52% in 2006. The proportion of water and farmland is relatively small. By 2010, the forest area had significantly increased, accounting for 57.98%. The unused land area has decreased but still accounts for 32.53%. The water area remains unchanged, accounting for 1.47%. Farmland and built-up land have increased, accounting for 3.73% and 4.30%, respectively. By 2015, the unused land area decreased, accounting for 28.93%. Built-up land and farmland increased slightly, accounting for 4.91% and 7.90%, respectively. The forest and water area remains unchanged, accounting for 56.62% and 1.64%, respectively. By 2021, the unused land area will still decrease, accounting for 26.95%. The built-up land area has slightly increased, accounting for 9.00%. The area of forest has increased, accounting for 57.30%. The water and farmland areas remain unchanged, accounting for 1.68% and 5.06%, respectively.

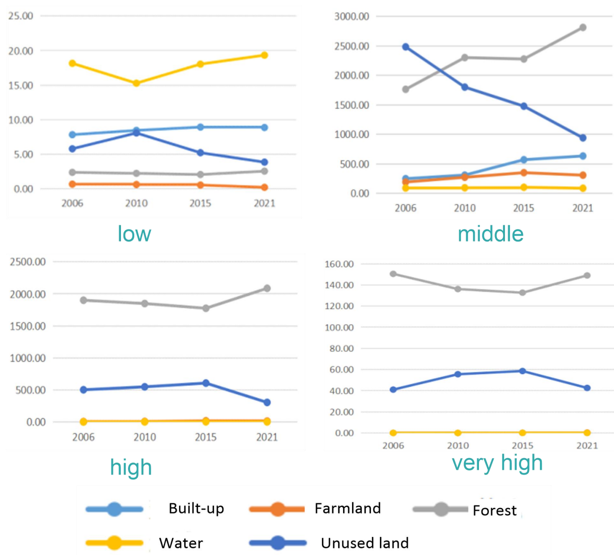
As illustrated in Figure 5, the five types of land have undergone significant changes over the past decade and mostly occurred in areas below an altitude of 2000m, with significant changes in the areas of built-up land, farmland, forest, and unused land. In areas with elevations above 2000m, the changes are relatively small and almost negligible in farmland, water, and built-up land. It can be observed that the lower the elevation, the greater the change in land use area, while the higher the elevation, the smaller the change in land use area.

Panzhihua is a typical mountainous city with an urban height of about 1200m. Low-elevation areas are conducive to developing farmland and built-up land, while high-elevation areas restrict urban land development, and various regions are suitable for lower elevations. These areas change rapidly, especially the planning, development, and adjustment of construction land, which are mainly carried out in the low-elevation areas. The lower the elevation, the more intense the land type changes.

The size of the slope generally affects the changes in land use quantity and layout of different land types. Areas with smaller slopes are more suitable for developing built-up land and farmland land, while areas with more extensive slopes are less conducive to selecting them. Therefore, there is a greater demand for places with smaller slopes in various regions. Based on the situation of Panzhihua City and the slope range of 0~77.89 °, the slope is divided into five grades, as shown in Figure 5 (a).



(a)



(b)

Figure 5. Land use changes with variations of elevation. (a) is the elevation classification map; (b) is land-use area change curves in different elevation levels.

As illustrated in Figure 6, unused land decreases with the increase of years, while forest land, farmland, and built-up land increase. In 2021, built-up land reached 21.98% of the gentle slope area, ranking second. The medium slope land category is also mainly composed of forest and unused land, with a total proportion of over 89%. The proportion of farmland and built-up land increases with the increase of years, and the water changes are insignificant. Steep slope land mainly comprises forest and unused land, accounting for over 95%. Farmland has shown a slight upward trend since 2010, while other land types have not changed significantly.

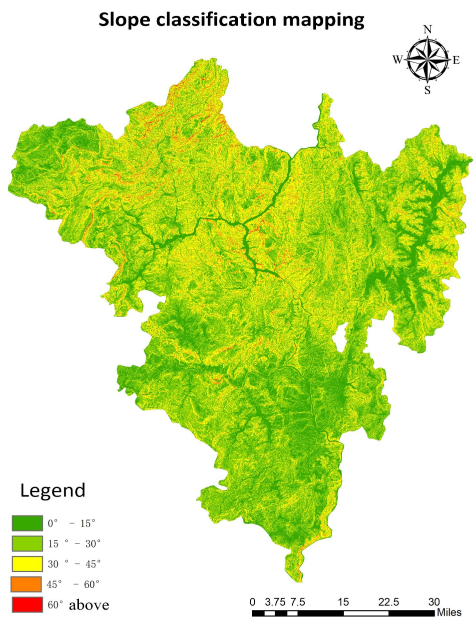


Figure 6. Slope classification map of Panzhihua city.

Social factors cover a wide range, including economy, population, policy, and urbanization. Social factors in mountainous cities like Panzhihua still influence land use change. This study analyzed the land use change in Panzhihua City mainly from the economic and topographic aspects.

As illustrated in Figure 7, the economic growth of Panzhihua City was relatively slow from 2008 to 2009, and the economy of other years from 2006 to 2020 was in a state of continuous change. In the past ten years, the built-up land area has increased with the development and construction of infrastructure and resources in Panzhihua City. Since 2010, the Panzhihua government has started industrial transformation due to its unique climate and geographical factors. Especially in the fruit industry, it has been vigorously promoted, which has promoted economic growth and also increased the area of farmland land.

The total population change of Panzhihua City is relatively small. Figure 7 shows that the change in rural population fluctuates, while the change in urban population gradually increases before 2012 and then decreases until 2020.

4.2 Model prediction accuracy evaluation

Based on the Markov transfer probability matrix from 2010 to 2015, the changing trend of land use types can be predicted in Panzhihua City in 2021. The accuracy verification is carried out by comparing that in 2021. The results are shown in Figure 8. Compare the predicted land use data for 2021 with the actual values for 2021, and calculate the overall accuracy, Kappa coefficient, and FoM accuracy. The overall accuracy is 0.97, the Kappa coefficient is 0.949, and the FoM accuracy value is 0.094. Compared with the traditional methods, experimental results demonstrate that the proposed model can improve the model's automatic interpretation ability and prediction accuracy with an increase of 24.6% in the FoM index and 4.37% in the Kappa coefficient.

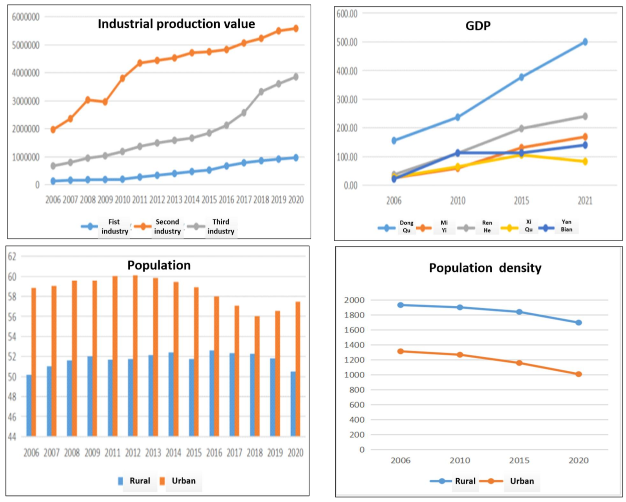


Figure 7. Line chart of changes in social and economic driving forces factors.

Figure 8. Land-use prediction map in 2021 of Panzhihua City.

5. CONCLUSION

This study uses multi-temporal Gaofen satellite remote sensing images to classify the land use of Panzhihua from 2006 to 2021. DeeplabV3+ and channel space attention mechanism have been introduced into the model to improve classification accuracy and automatic interpretation efficiency. This paper expounds on the driving factors of land use change and analyzes and counts the changes, including natural factor data (elevation, slope) and social factor data (economy, population). Finally, the Markov model is used to verify the prediction accuracy and predict the development trend of land use in Panzhihua City. Quantitative analysis and visual expression confirm that the proposed method can improve the accuracy of land use.

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