Dean&Francis

ISSN 2959-6157

# Urban Expansion Simulation and Prediction Based on Night-Time Light and Land Use and Land Cover Change Data - Taking Tokyo Metropolis as an Example

**Kun Hai**

School of Computer Science and Technology, China University of Petroleum (East China), Qingdao 266580, China
musecakeintj@gmail.com

**Abstract:**

Urban expansion can indirectly reflect the economic development level and social resource environment of a region while night-time light data is closely bound up with human economic activities. Taking urbanized regions with a high population density as a research area demonstrates a clear correlation between night-time light data and urban expansion. Based on the night-time light and land use/land cover (LULC) change data of Tokyo Metropolis in 2020 and 2022, Land Change Modeler (LCM) model is utilized to assess the LULC situation of Tokyo Metropolis in 2024, which is then compared with the observed data through accuracy assessment method to examine the relationship connecting night-time light data with urban expansion. It can not only explain the driving mechanisms behind past urban expansion but also predict future expansion scenarios. The research suggests that the LCM model exhibits high precision and can be employed for the simulation and prediction of future urban expansion in Tokyo Metropolis which provides crucial references for Tokyo's urban planning and development trajectory.

**Keywords:** Night-time Light Data; Land Use/Land Cover; Urban Expansion; LCM Model; Tokyo Metropolis.

## 1. Introduction

Land use/land cover (LULC) change exerts a significant influence on regional and global environmental evolution, representing the most prominent change phenomenon in the history of global environmental change and the past of the way that human has induced alterations to the surrounding environment, thereby establishing itself as a focal area in global change research [1]. Simultaneously, LULC is the most prominent anthropogenic driver of environmental change across all spatial and temporal scales that covers a wide range of central issues in today's human society including climate change, biodiversity loss, and the contamination of water, soil and air [2]. Night-time light data can effectively represent factors

ISSN 2959-6157

related to human activities, such as population, economic conditions, and the level of urbanization development. Additionally, it reveals the intensity of human activities and the level of urbanization development, serving as a new and effective data source for monitoring the process of urbanization development [3]. Therefore, it is feasible to utilize the relationship between LULC data and night-time light data to map urban expansion as well as formulate effective urban planning strategies. Imhoff et al. discovered that the DMSP/OLS data can use the critical point at which the interior of polygons begins to fragment as the frequency of detection increases as the threshold for extracting urban area. Sutton employed the empirical threshold method to extract the built-up area and established a population density model accordingly. Henderson et al. combined the higher-precision TM images with DMSP/OLS data to obtain a more accurate urban area [4]. Currently, the commonly used night-time light data are sourced from two night-time light satellites, DMSP/OLS and NPP/VIIRS. The quality of NPP-VIIRS is superior to that of DMSP/OLS as it mitigates the saturation effect issue present in DMSP/OLS [5]. For studies conducted after 2013, NPP/VIIRS night-time light data is the preferable option. The findings identify Land Change Modeler (LCM) in the IDRISI Selva software as an effective tool for simulating land changes. This model integrates the Cellular Automata (CA)-Markov chain with the neural network Multi-Layer Perceptron (MLP) intelligent algorithm, enabling it to productively predict future scenarios of LULC change. In this study, after preprocessing the annual NPP-VIIRS night-time light and LULC data via the use of ArcGIS software for the years 2020 and 2022, LCM algorithm in the IDRISI Selva was employed in order to forecast the urban expansion situation of Tokyo Metropolis in 2024 on the basis of the real data for the years 2020 and 2022, and the output was validated against the actual situation.

# 2. Background

## 2.1 An Overview of the LCM Model

The LCM model integrated into the IDRISI Selva primarily employs the coupled method of Multi-Layer Perceptron Neural Network-Cellular Automaton-Markov Chain (MLPNN-CA-MC) to analyze the historical changes in LULC in the watershed and predict its future evolution trends based on the relative transfer potential map. It can evaluate the land use changes between two different periods, identify the content of the changes, visualize the change situation, and present the results through various maps and charts [6]. The LCM leverages historical land-cover maps and explanatory variable maps to identify drivers of change, simulate potential land use transitions, and generate predictive maps of future land cover [7].

## 2.2 Data Resource

This study is conducted against the backdrop of Tokyo Metropolis, Japan. The night-time light data is sourced from the official website of VIIRS Nighttime Light and the data collected by VIIRS can be utilized to generate monthly and annual scientific-grade global radiance maps that encompass information on human settlements and their electric light sources. The administrative division data of Tokyo Metropolis, Japan is obtained from the official website of GADM, which is a high-precision global administrative division database that contains data on administrative boundaries at multiple levels, including national, provincial, municipal, and district boundaries for all countries and regions across the globe. Correspondingly, the LULC data derive from the official website of Japan's Earth Observation Research Center (EORC), adopted in GeoTiff format covering the entire territory of Japan with a spatial resolution of 100 meters.

# 3. Methods

## 3.1 Data Preprocessing

### 3.1.1 Night-time Light Data Preprocessing

The NPP-VIIRS night-time light data features extremely high resolution and is free from the issue of pixel saturation. In comparison with the DMSP-OLS night-time light data, it is more suitable for conducting economic research at a finer spatial scale within the administrative divisions of the Tokyo metropolitan economic zone. However, the NPP-VIIRS night-time light data does not exclude high-brightness pixels caused by fires, gas combustion, reflected light and auroras, nor does it eliminate the background noise generated by low-radiation detection. Moreover, a substantial number of glows are produced in the surrounding area [8, 9]. Upon completion of the denoising procedure for the NPP-VIIRS data, stable night-time light data reflecting human economic activities in the Tokyo metropolitan economic zone are derived. Subsequently, within the ArcToolbox window of the ArcGIS spatial analysis software, the Project Raster tool is applied to convert the projection coordinates of all layers of the annual NPP-VIIRS night-time light raster data for the years 2020 and 2022 into the same coordinate system, namely GCS_WGS_1984. Following this, the NPP-VIIRS night-time light data for the Tokyo metropolitan economic zone in 2020 and 2022 are extracted based on the data before cropped through the Extract by Mask tool by designating the vector of Tokyo's administrative boundary as the mask.

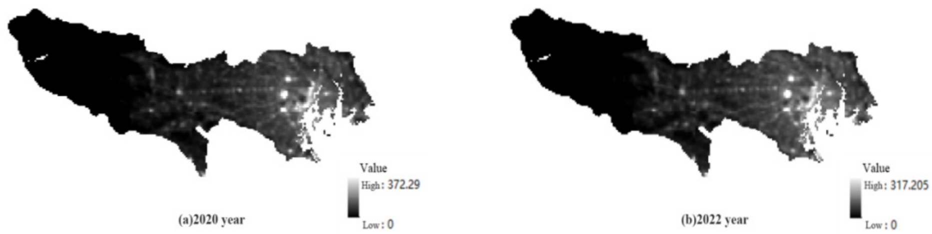



**Fig. 1 NPP-VIIRS night-time light maps of the Tokyo metropolitan economic zone in 2020 and 2022.**

A comparison between Fig. 1 reveals that in 2022, the lighting intensity in peripheral areas such as Adachi Ward, Edogawa Ward, Ota Ward, and Itabashi Ward was fuller and more balanced than that in 2020. It is likely that due to the scarcity of land resources and the high cost of living in the urban central area, some of the population and small and medium-sized commercial activities have been squeezed out to the peripheral areas. Therefore, these areas have gained drivers of development as well as the intensified lighting. The lighting in the central area shows a steady westward transition trend. This might be because the functional strength and attractiveness of the western sub-city centers, for example, Shinjuku and Shibuya are surpassing or complementing those of the traditional core areas, emerging as new growth poles of urban vitality.

#### 3.1.2 Land Use/Land Cover (LULC) Data Preprocessing

LULC results from the complex interactions among social, ecological and geophysical processes. Thus, it is imperative to predict future LULC Change based on current trends, enabling planners to acquire the necessary technical information for formulating intervention strategies and mitigating the intensification of relevant LULC issues [10]. The Extract by Mask tool in the ArcGIS spatial analysis software is employed to extract the LULC data of Tokyo Metropolis for the years 2020, 2022, and 2024. Afterwards, the Project Raster tool is utilized to convert the projection coordinates of the data into GCS_WGS_1984, ensuring that it is in the same coordinate system as the night-time light data with the NEAREST resampling technique applied. Ultimately, the original LULC types are reclassified utilizing the Reclassify tool in ArcGIS and eight Level-I LULC types areas are obtained, specifically Waterbody, Built-up, Cropland, Grassland, Forest, Bare, Construction, and Reef. Following this, the classified Level-I LULC type data for three years are exported as text files in ASCII format via the Raster to ASCII tool, facilitating further operations in the IDRISI Selva software.

### 3.2 Simulation and Prediction

#### 3.2.1 Identify Driving Factors

Factor analysis is a tool employed for dimensionality reduction. Its objective is to identify latent variables (i.e., common factors) that drive the observable variables which drive the observable variables. Potential factors are correlated to observable variables through factor loadings, and the values of these factor loadings indicate the direction and strength of this relationship [11]. The static factor layer generally refers to the light intensity in a specific base year, representing the "background" or "stock" of economic development while the dynamic factor layer refers to the changes in night-time light data between two periods, representing the "trend" or "increment" of economic development. Firstly, the NPP-VIIRS night-time light data for the Tokyo metropolitan economic zone in 2020 and 2022 are resampled to obtain two raster datasets, Raster2020 and Raster2022 for the years 2020 and 2022 respectively. Subsequently, these raster datasets are standardized to the range [0, 1] by means of Raster Calculator, thereby guaranteeing the comparability of the data and the accuracy of the calculation results. To apply the Raster Calculator tool to create static and dynamic factor layers for night-time light (NTL), the specific formulas are as follows:

Static Factor Layer:

$$"NTL\_STASTIC" = \frac{"Raster2020" - Min}{Max - Min} \tag{1}$$

The dynamic factor layer pertains to lighting changes, which are primarily expressed in two ways: absolute change and relative change. Their respective formulas are as follows:

Absolute Change:

$$"NTL\_ABS" = "Raster2022" - "Raster2020" \tag{2}$$

Relative Change:

ISSN 2959-6157

$$"NTL\_REL" = Con("Raster2020" > 0, ("Raster2022" - "Raster2020") / "Raster2020", 0) \tag{3}$$

In Equation (1), Max represents the maximum gray value of the Raster2020 raster data, and Min represents the minimum gray value. The obtained NTL_STASTIC, NTL_ABS and NTL_REL data are also exported into text files in ASCII format through the Raster to ASCII tool.

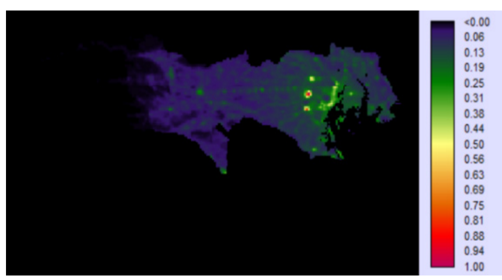
#### 3.2.2 Dynamic Prediction of LUCC Based on the LCM Model

The CA-Markov model integrates the advantageous features of both the CA model and the Markov model. This model combines the ability of cellular automata to handle spatial changes in complex systems with the characteristics of Markov chains in predicting land quantity changes, thus achieving dynamic evolution prediction of land use types in both temporal and spatial dimensions [12]. MLP is a fully connected neural network defined by input layer, hidden layer, and output layer. In deep learning, it is employed to tackle tasks where both the input and output are continuous numerical values. On the other hand, the LCM model conducts predictions based on the built-in modules of neural networks and the CA-Markov model.

In the IDRISI Selva tool, the data in text format of LULC and night-light driving factors are converted into RST format files for visualization.

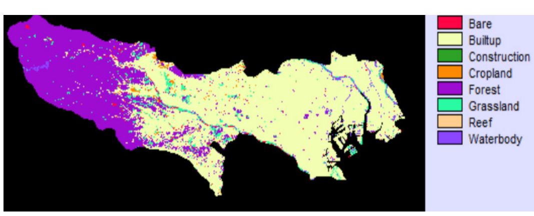

**(a)NTL_ABS**


**(b) NTL_REL**

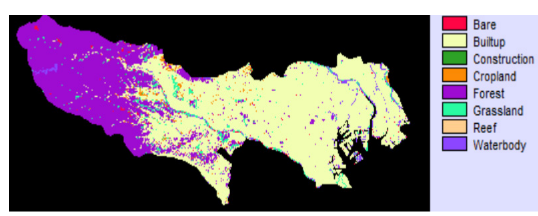



**(c) NTL_STATIC**

**Fig. 2 Visualization of driving factors of night-time light in the Tokyo metropolitan economic zone.**




**(a)2020year**




**(b)2022year**

**Fig. 3 Level I LULC classification maps of Tokyo Metropolis for the years 2020 and 2022.**

The absolute change factor graph in Fig. 2 (a), which reflects the overall change in reaction, suggests that the pixel values in the central and eastern regions of Tokyo Metropolis range from 0.03 to 0.05. There are a few sporadic red dots in the city center while the western region generally maintains a value of 0.00, indicating that Tokyo Metropolis is in a stage of slow economic growth or land development, with stable socioeconomic activities. Fig. 2 (b), the image of relative change can reflect the speed of the change intensity. The pixel values in the central and eastern regions are mostly around 0.24, and a few scattered areas are between 0.40 and 0.56. Located in the mountainous regions, Odomachi town and Hinohara village in the western area maintain pixel values ranging from 0.00 to 0.09, pointing to a slow pace of economic and land development. The overall night-time light intensity in Tokyo Metropolis shows a moderate, widespread, and robust growth trend, with an average annual growth rate of approximately 15%-24%, which reflects an “inclusive” growth model. The relatively balanced distribution of economic momentum indirectly implies that the urban expansion of Tokyo Metropolis occurs concurrently along with the enhancement of the economic intensity in the existing built-up areas as well. Fig. 2 (c) demonstrates the night-time economic activities in Tokyo where the well-lit areas represent the economic core zones and high-density built-up areas, whereas the poorly-lit areas represent regions with relatively weak economic activities.

A comparison between Fig. 3 (a) and (b) reveals that the land use types of Waterbody and Cropland have increased significantly, while those of Grassland and Bare have decreased correspondingly. Meanwhile, the types of Reef and Construction have remained largely unchanged, and Forest and Built-up have been increasing slowly. This indicates that Tokyo Metropolis, as a typical example entering the stage of “smart growth” or a “regenerative city”, is actively striving to strike a balance between economic development and ecological conservation. It aims to achieve sustainable development by enhancing internal efficiency and optimizing the spatial structure.

After ensuring that all raster data have exactly the same number of rows, columns, geographical extent, and pixel size, open the LCM tool and import the LULC data for the years 2020 and 2022 in Fig. 3 into the LCM Project Parameters tab to automatically calculate the change amount and transition matrix. Thereafter, navigate to the Transition Potentials tab and set the status values for all transitions from non-urban types to urban types as ‘Yes’, while setting the others as ‘No’, which will serve as the conversion sources. Subsequent to the completion of inserting three driving factors into the Driving Factors tab, select the MLP Neural Network model from the Model menu. Once the operation is executed, the software will train the neural network and automatically generate a comprehensive suitability image, which encompasses the overall probability of all types of non-urban land transforming into urban land. Upon entering the Change Prediction tab, set the expected year to 2024. After loading the generated suitability image, run the module. Consequently, a multi-class predicted LULC data of Tokyo Metropolis in 2024 will be acquired.

### 3.3 Accuracy Verification

The Kappa coefficient is employed to evaluate the degree of consistency between simulation results and observational data. This indicator is extensively utilized in the research domains of the prediction accuracy of LULC change and the interpretation accuracy of remote sensing images [9]. In IDRISI Selve, click on the CROSSTAB tab and input the predicted and actual LULC data of Tokyo Metropolis in 2024, in that case, the Kappa coefficient will be printed. The final verification result indicates that Kappa is approximately equal to 0.986.

## 4. Conclusion

The development of the Tokyo Metropolitan Area model commenced in the early 1950s during the post-war reconstruction phase, which has primarily gone through three historical periods, each characterized by distinct development features. Eventually, it has evolved into the current regional spatial structure of “multiple cores and multiple rings” and a highly complementary urban functional layout. To a certain extent, night-time light data can also serve as a quantitative method for the urbanization process, which is crucial for scientifically measuring the current development stage of the Tokyo Metropolitan Area. The overall Kappa coefficient between the measured map and the simulated map in the study area in 2024 is 0.986, indicating that the LCM model has a relatively high accuracy and can be employed for the simulation and prediction of future urban expansion in Tokyo Metropolis. The LULC change prediction model based on NPP/VIIRS night-time light data provides a solid scientific basis and forward-looking perspective for Tokyo Metropolis to understand urban development patterns and optimize its territorial spatial planning. This method holds significant practical value for achieving intelligent urban growth and sustainable management of land resources.

## References

[1] Nina Xiong, et al. “Land use and Land cover changes and prediction based on Multi-Scenario Simulation: A case study of Qishan County, China.” Remote Sensing 14.16 (2022): 4041.

[2] Kumar, K. Sundara, P. Udaya Bhaskar, and K. Padmakumari. “Application of land change modeler for prediction of future land use land cover: a case study of Vijayawada City.” Int. J. Adv. Technol. Eng. Sci 3.1 (2015): 773-783.

[3] Yueru Zhang, and Liwen Wang. “Analysis of the expansion of the built-up area in Shenyang City based on NPP/VIIRS night-time light data.” Green Science and Technology 25, no. 20 (2023): 224 - 228.

[4] Heting Bai, et al. “Research on urban expansion in Chongqing based on night-time light data.” Remote Sensing Technology and Application 34, no. 01 (2019): 216-224.

[5] Yuan Ding, et al. “Monitoring the distribution and variations of city size based on night-time light remote sensing: a case study in the Yangtze River Delta of China.” Remote Sensing

ISSN 2959-6157

14.14 (2022): 3403.
[6] Leta, Megersa Kebede, Tamene Adugna Demissie, and Jens Tränckner. “Modeling and prediction of land use land cover change dynamics based on land change modeler (Lcm) in nashe watershed, upper blue nile basin, Ethiopia.” Sustainability 13.7 (2021): 3740.
[7] Qacami, Meryem, et al. “Land-cover/land-use change dynamics modeling based on land change modeler.” The Annals of Regional Science 70.1 (2023): 237-258.
[8] Xi Cheng, and William D. Nordhaus. “VIIRS nighttime lights in the estimation of cross-sectional and time-series GDP.” Remote Sensing 11.9 (2019): 1057.
[9] Weizhe Du, et al. “Research on Urban Expansion Patterns in Gansu Province Based on Time-Series Nighttime Light Data.” Remote Sensing Technology and Application 39.3 (2024): 659-668.
[10] Estacio, Ian, et al. “A statistical model of land use/cover change integrating logistic and linear models: An application to agricultural abandonment.” International Journal of Applied Earth Observation and Geoinformation 120 (2023): 103339.
[11] Pape, Markus. Model Identification in Bayesian Analysis of Static and Dynamic Factor Models. Diss. 2015.
[12] Kai Li, and Beiying Zhang. “Simulation and Prediction of Land Use on the Loess Plateau Based on CA-Markov Model.” Hubei Agricultural Sciences 61.16(2022): 64-69.