Predicting the Metro Scenario-based Spatiotemporal Evolution of Land Use Using CA-Kalman Filter Model: a Case Study of Nanjing City, China

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Predicting the metro scenario-based spatiotemporal evolution of land use using CA-Kalman filter model: A case study of Nanjing City, China

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Abstract

The expansion of metro system can bring varying degrees of impact to the surrounding environment. To study this complex system problem, this paper discusses the temporal and spatial impact by metro system from the perspective of land use change simulation and scenario analysis. The traditional cellular automata (CA) model can realize the simulation of land use change under various scenarios through system dynamics or Markov chain to control the long-term demand forecasting. However, this type of model ignores the filtering of noise data from imageries and increases uncertainty of the system. Therefore, based on the Future Land Use Simulation (FLUS) model, this paper integrates Kalman filter to control the stochastic process of the state-space system, and predicts the spatio-temporal evolution of land use change impacted by metro system in Nanjing from 2019 to 2035. The results show that: (1) The proposed CA-Kalman filter model can realize the optimized simulation of land use change with good accuracy; (2) Urban patches impacted by metro system will emerge from the existing urban boundaries at the cost of occupation of cultivated land, although there is still significant expansion of urban land and construction land, it will reach the upper limit in 2050.

keywords: Land use change; Metro scenario analysis; Cellular automata; Kalman filter; Spatiotemporal evolution
1 Introduction

At the end of year 2020, Caojiawan Station near the city of Chongqing in China suddenly attracted great attention across the globe, for its contrasting nearby image against five years ago. The place where it has been constructed is embracing flourishing developments since the opening of metro exits, which arouses people’s concern about how the neighboring environment responds to metro construction and development? Will this process exacerbate urban sprawl in the long run?

It is estimated that 70% of the world’s population will live in urban areas by 2050. As a result, metro system is increasingly viewed as one of solutions to address the demand for more resilient space and dependable infrastructure. Metro system intertwines through urban areas and expands to the fringe of city, burden with population migration and intangible capital flow. As the urban traffic axes and development axes of Urban Underground Space (UUS), metro system should make city compact and better. Thus, it appeals to scholars and stakeholders into its planning and governance. Account for direct relationship with land use planning, current researches pertaining to metro system are mainly focused on socioeconomic aspects of urban center or downtown area. Of which quantified the volumes and depths of functional use in Alexanderplatz, Germany; specified the driving factors and predicted the demand of UUS in Xinjiekou, China; identified the quantitative relationship of UUS area, passenger flow rate and land price in Osaka, Japan.

Nevertheless, there are two points need to be emphasized: (1) the investigation extent of metro system can be considered broader to the city suburb. Meanwhile, it shows that urban area is not constantly stationary, instead it expands simultaneously in accordance with city
development. (2) It remains mystery about the metro system’s influence on the built environment. Apparently, the rapid developments of cities promote the formation of metro networks, which in turn affect the environment. However, with unprecedented construction of metro in China, the invisible aspects of metro construction and incidental impacts to cities’ environment are far less researched. Therefore, for the sake of sustainable development, quantitative characterization of large-scale impacts of metro system on city’s environment become necessary and imminent.

Researches have shown that land use change is directly associated with environmental and ecological effects manifested by remote sensing imagery, reflecting environmental crises and regional ecological safety like carbon emission, soil degradation, climate change, etc. Its dynamic simulation is useful in elaborating correlated driving factors, including metro networks, and its scenario prediction will aid decision-makers in multiple land use planning. The spatiotemporal analysis of metro scenario-based land use change is crucial not only in quantitative geography, but also in environmental, spatial planning and sustainability studies.

In addition, it is widely acknowledged that cellular automata (CA) are a prudent way to achieve this exploration, considering both the spatial and temporal extent of vast land. Cellular automata was proposed by Von Neumann in the late 1940s, for the first time it exhibited self-reproduction characteristics in computer, and gradually established fundamental role in the theory of complex system. CA-based models have been applied in the simulation of urban growth since the 19th century. Taking advantage of GIS platform, CA model can simulate non-linear and complex results close to reality from local rules. It discretizes time and space, assigns values to cells in the bottom-up framework. In recent years, many scholars have
combined CA models with artificial neural network, data mining, logistic regression, etc.

Some representative CA models are as follows: DUEM, CLUE-S, Dinamica EGO, Metronamica, SLEUTH, and so forth.

Merging metro system into CA model will enhance simulation accuracy and make the prediction more reliable. Since Nanjing metro system has been planned for long term until 2035 (www.njmetro.com.cn), it is an ideal research area for exploring its impact on land use. To that end, Kalman filter, derived from the optimal state estimation method, is integrated with CA model to simulate land use change from 2005 to 2019. Then the model verifies the land use pattern of the study area in 2015 and 2019, and predicts the two scenarios of Nanjing city (with new planned metro lines or not) in 2035, providing reference for exploring the impact of metro planning.

2 Methodology

In this paper, the model integrates top-down Kalman filter with bottom-up ANN-based CA model to predict land use change of Nanjing in 2035. This paper chooses Future Land Use Simulation (FLUS) model as a framework of CA model. The FLUS model is a hybrid model mainly consisting of artificial neural network (ANN) and cellular automata (CA). FLUS model can simulate the interaction and transition of multiple land use types at the grid cell. It employs self-adaptive inertia and competition mechanism to guide the simulation of multiple land uses on the right trajectory. However, as a CA model, FLUS model requires an external source to regulate evolution of cells, such that the amount of land use types can be in line with the real macro-scale demands and city planning. The top-down Kalman filter therein plays an important role from a macro-scale perspective. The Kalman filter is used to identify future demand for
land uses for each year, and then allocates the amounts of land use types to the FLUS model. Only when the cells of land use types in the FLUS model meets the demanded amounts determined by Kalman filter, can the simulation result be generated at one certain iteration. In a word, the CA-Kalman filter model is integrated in a bottom-up and top-down framework where land use quantities and local allocations mutually feed back in the time series. The schematic workflow of proposed integrated model is illustrated in Fig. 1.

![Fig. 1. Workflow chart of CA-Kalman filter model](image)

### 2.1 Framework of CA model of FLUS

#### 2.1.1 Artificial neural network

Artificial neural network (ANN) is one member of machine learning (ML) family. It is well acknowledged that ANN can deal with uncertainties emerged from non-linear system, without designating model structure, conversion rule, and other parameters. It is comprised of an input layer, a hidden layer and an output layer, where multiple neurons connecting inputs and outputs
learn features and relationships of a number of variables. In FLUS model, each neuron in the
input layer represents driving factors that need training, while each neuron in the output layer
corresponds to a specific land use type. The signal in the input layer can be written as:

\[ X = [x_1, x_2, \ldots, x_m]^T \] (1)

Where \( x_i \) is the \( i \) th neuron in the input layer. The signal received by neuron \( j \) in the hidden
layer on cell \( p \) at time \( t \) is estimated as an adaptive weight based equation:

\[ \text{ann}_j(p,t) = \sum w_{ij} \times x_i(p,t) \] (2)

Where \( \text{ann}_j(p,t) \) is the signal received by neuron \( j \) in the hidden layer; \( x_i(p,t) \) is the \( i \)
th variable associated with the input neuron \( i \) on cell \( p \) at training time \( t \); and \( w_{ij} \) is an
adaptive weight between the hidden layer and output layer. The connection between hidden
layer and output layer is controlled by a sigmoid function, mapping values of variables to the
range between 0 and 1. The sigmoid activation function adds to non-linear characteristics in the
output layer, which is expressed as follows:

\[ \text{sigmoid}(\text{ann}_j(p,t)) = \frac{1}{1 + e^{-\text{ann} f(p,t)}} \] (3)

At last, the probability of occurrence \( P(p,k,t) \) at cell \( p \) for land use type \( k \) at training
time \( t \) is calculated in the output layer as follows:

\[ P(p,k,t) = \sum_j w_{j,k} \times \text{sigmoid}(\text{ann}_j(p,t)) = \sum_j w_{j,k} \times \frac{1}{1 + e^{-\text{ann} f(p,t)}} \] (4)

Where \( w_{j,k} \) is an adaptive weight between the hidden layer and the output layer.

2.1.2. Self-adaptive inertia and competition mechanism

The land use change is booting up under the condition of various factors which exert varying
degree of impacts. In order to reflect the real state and process of cell conversion for different land use types, namely remain unchanged or convert to another, the model takes into consideration neighborhood effect, the conversion cost, and competition mechanism.

There are many neighborhood windows proposed by scholars in their CA models, such as Von Newmann, Moore, Margolus, etc. The final patterns and emergence are found largely derived from the initial set of window shape \(^{18,29}\). The neighborhood dominance at cell \(p\) for land use type \(k\) is defined as:

\[
\Omega_{p,k}^t = \frac{\sum_{N \times N} \text{con}(c_{p}^{t-1} = k)}{N \times N - 1} \times w_k
\]  
(5)

Where \(\sum_{N \times N} \text{con}(c_{p}^{t-1} = k)\) represents the total number of cells occupied by the land use type \(k\) at the last iteration time \(t-1\) within the \(N \times N\) window. \(w_k\) is the variable weight among the different land use types, which is mainly determined based on expert knowledge.

Meanwhile, it is necessary to adjust the transition state of cell in accordance with future demand of land use. As a result, a self-adaptive inertia is used to enhance the inheritance of previous land use types when there exists contradiction. For instance, if more urban land parcels are required according to master plan, whereas the cell inclines to avoiding being urban land, the inertia will regulate this unfavorable trend onto the right trajectory. The inertia coefficient is expressed as follows:

\[
\text{Inertia}_k^t = \begin{cases} 
\text{Inertia}_k^{t-1} & \text{if } |D_k^{t-1}| \leq |D_k^{t-2}| \\
\text{Inertia}_k^{t-1} \times \frac{D_k^{t-2}}{D_k^{t-1}} & \text{if } D_k^{t-1} < D_k^{t-2} < 0 \\
\text{Inertia}_k^{t-1} \times \frac{D_k^{t-1}}{D_k^{t-2}} & \text{if } 0 < D_k^{t-2} < D_k^{t-1}
\end{cases}
\]  
(6)

Where \(\text{Inertia}_k^t\) denotes the inertia coefficient for land use type \(k\) at iteration time \(t\). \(D_k^{t-1}\) denotes the difference between the macro demand and designated amount of land use type \(k\).
at last iteration time $t - 1$, and so is $D_k^{t-2}$.

The inertia coefficient can be altered with the dynamic trend of developing contradiction: (1) If the macro demand for the specific land use type $k$ equals to the current allocated amount, then the inertia coefficient at iteration time $t$ will stay unchanged; (2) If the macro demand for the specific land use type $k$ is less than the current allocated amount, then the inertia coefficient at iteration time $t$ will decrease slightly by multiplying the previous coefficient by $D_k^{t-2} / D_k^{t-1}$; (3) If the macro demand for the specific land use type $k$ is greater than the current allocated amount, then the inertia coefficient at iteration time $t$ will increase slightly by multiplying the previous coefficient by $D_k^{t-1} / D_k^{t-2}$.

Besides, the model takes in the conversion cost from the perspective of nature of land, i.e. the intrinsic difficulty to convert land use type. It is determined based on expert experience, works the same as the inertia to promote or inhabit the growing trend of current land use type. For each land use pair $c$ and $k$, the cost of the land use change from $c$ to $k$ is denoted as $s_{c \rightarrow k}$. The value of the conversion cost $s_{c \rightarrow k}$ varies between the range of $[0,1]$. Larger values indicate a greater conversion difficulty, and a value of 1 means that the conversion is nearly impossible. For example, the urban land is unlikely to convert to forest, because the region with intense economic activities is unlikely to develop backward in common sense, so the conversion cost would be 0$^{30}$.

2.1.3. Roulette wheel selection

By considering aspects above, the combined probability of a cell being occupied by a specific land use type is estimated. The combined probability of a cell being occupied by a specific land
use type is estimated using the following equation:

\[ TP'_{p,k} = P_{p,k} \times \Omega'_{p,k} \times \text{Inertia}'_k \times (1 - sc_{c\rightarrow k}) \]  

(7)

Where \( TP'_{p,k} \) denotes the combined probability of grid cell \( p \) to covert from the original land use type to the target type \( k \) at iteration time \( t \); \( P_{p,k} \) denotes the probability-of-occurrence of land use type \( k \) on grid cell \( p \); \( \Omega'_{p,k} \) denotes the neighborhood effect of land use type \( k \) on grid cell \( p \) at iteration time \( t \); \( \text{Inertia}'_k \) denotes the inertia coefficient of land use type \( k \) at iteration time \( t \); and \( sc_{c\rightarrow k} \) denotes the conversion cost from the original land use type \( c \) to the target type \( k \).

The most important part of the model is the roulette selection, because it endows allocation opportunity to the land use types, which possess lower combined possibilities. This equal treat is designed out of the perception of competition. That is, even though the specific land use type is eligible to occupy the cell, it may well not be capable of eliminating other land use type when it comes to similar competence or the fortune factor in reality. Therefore, a roulette wheel is proposed where the area of a sector representing a land use type is proportional to the combined probability. With a uniformly distributed random number ranging from 0 to 1 falling into the area of a sector, the corresponding land use type is determined. Generally speaking, a land use type with a higher combined probability is still more likely to be selected at iteration time, but those with lower probabilities have a chance to be allocated.

2.2 Land use demand prediction using Kalman filter

The FLUS model calculates the probability of transition within the bottom-up framework, however it needs a top-down method to predict future amount of land use types for each year. The commonly utilized methods are Markov chain and system dynamics, both of which are
from macro-level perspective. System dynamics (SD) is another tool originated from complex system, could have been an optimal choice to be integrated. However, SD requires a variety of massive data across time, which would be a hurdle for pooling data, let alone complex processes of adjusting parameters. As to Markov chain, it is an incidence-based method commonly used to predict the variance of future phase. It deploys state transition probability to estimate the transition trend of certain pixels, but cannot distinguish noises from actual signals. The noise of simulation is initially derived from the classification of land use in the satellite imagery most of the time. The cells may be mistaken as other kind of land use by the Deep Learning techniques. It is crucial to identify real amount of grid cells for typical land use types, and then incorporate it into the CA model, to minimize the accumulated error and uncertainty during simulated time series. Therefore, this paper improves predictive methods by integrating Kalman filter with the state transition probability of Markov chain, governed by the premise that the amount of pixels remain the same during transition.

Kalman filter is an algorithm of data fusion in the theory of optimal state estimation. It is based on minimizing the mean-square error, can support estimations of past, present, and future states, which has been widely used in the field of dynamics and control over the past three decades. proposed to use extended Kalman filter and unscented filter to calibrate magnetometer. used adaptive Kalman filter algorithm (AKF) to improve the performance of the robot's speed and heading angle. estimated the target scattering coefficients in an adaptive radar system based on Kalman filter (KF) with waveform optimization. developed a new extended interval Kalman filter (EIKF) for tracking the missile system. implemented the integration of GPS with INS using an extended Kalman filter. proposed a fuzzy multi-sensor
data fusion Kalman model to help reduce integrated vehicle health maintenance system (IVHMS) failure risk. \(^{38}\) estimated the state space model of time varying parameter approach (TVP) by Kalman filter, which is used for estimating the effect of energy consumption on economic growth over period 1967-2009 in Iran. In a word, Kalman filter in its various forms is clearly established as a fundamental tool for analyzing and solving a broad class of estimation problems.

Kalman filter involves the process state and a sequence of noisy measurements, in which the modeled system is filled with uncertainty. The equations for Kalman filter fall into two parts: time update equations and measurement update equations \(^{39,40}\). The time update equations are responsible for projecting forward the current state and error covariance estimates to obtain the \textit{a priori} estimates for the next time step (Eqs. (19) and (21)). The measurement update equations are responsible for the feedback, in other words, for incorporating a new measurement into the \textit{a priori} estimate to obtain an improved \textit{a posteriori} estimate (Eqs. (15), (17), and (18)).

It begins by assuming the random process to be estimated in the form:

\[
x_{k+1} = \Phi_k x_k + w_k
\]

Where \( x_k \) is a \( n \times 1 \) process state vector at time \( t_k \); \( x_{k+1} \) is a \( n \times 1 \) process state vector at time \( t_{k+1} \); \( \Phi_k \) is a \( n \times n \) matrix relating \( x_k \) to \( x_{k+1} \) in the absence of a forcing function; \( w_k \) is a \( n \times 1 \) vector assumed to be a white sequence with known covariance structure. It is the input white noise contribution to the state vector for the time interval \((t_k, t_{k+1})\).

The measurement of the process is assumed to occur at discrete time points in accordance with the linear relationship:

\[
z_k = H_k x_k + v_k
\]
Where $z_k$ is a $m \times 1$ vector measurement at time $t_k$; $H_k$ is a $m \times n$ matrix giving the ideal (noiseless) connection between the measurement and the state vector at time $t_k$; $v_k$ is a $m \times 1$ measurement error assumed to be a white sequence with known covariance structure.

The covariance matrices for $w_k$ and $v_k$ vectors are given by:

$$E[w_k w_j^T] = Q_{kj}$$

(10)

$$E[v_k v_j^T] = R_{kj} \delta_{kj}$$

(11)

$$E[w_k v_j^T] = 0$$

(12)

If $k = j$, then $\delta_{kj} = 1$. If $k \neq j$, then $\delta_{kj} = 0$.

We assume we have an initial estimate of the process at the point $t_k$, and it is based on all our knowledge about the process prior to $t_k$. This a priori estimate will be denoted as $\hat{x}_k^-$. Where the “hat” denotes estimation, and the “super minus” is a reminder that this is our best estimate prior to assimilating the measurement at $t_k$. We also assume that we know the error covariance matrix associated with $\hat{x}_k^-$. That is, we define the estimation error to be:

$$e_k^- = x_k - \hat{x}_k^-$$

(13)

In addition, the associated error covariance matrix is:

$$P_k^- = E[e_k^- e_k^-^T] = E[(x_k - \hat{x}_k^-)(x_k - \hat{x}_k^-)^T]$$

(14)

With the assumption of a priori estimate $\hat{x}_k^-$, we now seek to use the measurement $z_k$ to improve it. We choose a linear blending of the noisy measurement and the a priori estimate in accordance with the equation

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H_k \hat{x}_k^-)$$

(15)

Where $\hat{x}_k$ is a updated estimate; $K_k$ is Kalman gain (yet to be determined).

The problem now is to find Kalman gain $K_k$ that yields an updated estimate which is
optimal because it minimizes the trace of \textit{a posteriori} error covariance $P_k$.

\[ P_k = E\left[ e_k e_k^T \right] = E\left[ (x_k - \hat{x}_k)(x_k - \hat{x}_k)^T \right] \quad (16) \]

Next, we substitute the resulting expression for $\hat{x}_k$ into Eq. (16)

\[ P_k = (I - K_k H_k)P_k (I - K_k H_k)^T + K_k R_k K_k^T \quad (17) \]

We proceed to differentiate the trace of $P_k$ with respect to $K_k$:

\[ K_k = P_k H_k^T (H_k P_k H_k^T + R_k)^{-1} \quad (18) \]

The updated estimated $\hat{x}_k$ is easily projected ahead via the transition matrix. We are justified in ignoring the contribution of $w_k$ in Eq. (16) because it has zero mean and is not correlated with any of the previous $w$’s. Thus, we have

\[ \hat{x}_{k+1} = \Phi_k \hat{x}_k \quad (19) \]

The error covariance matrix associated with $\hat{x}_{k+1}$ is obtained by first forming the expression for the \textit{a priori} error

\[ e_{k+1}^- = x_{k+1}^- - \hat{x}_{k+1}^- = \Phi_k e_k + w_k \quad (20) \]

We now note that $w_k$ and $e_k$ have zero cross correlation, because $w_k$ is the process noise for the step ahead of $t_k$. Thus, we can write the expression for $P_{k+1}^-$ as

\[ P_{k+1}^- = E\left[ e_{k+1}^- e_{k+1}^{T} \right] = \Phi_k P_k \Phi_k^T + Q_k \quad (21) \]

Equations (15), (18), (19), and (21) comprise the Kalman filter recursive equations. The time update equations can also be regarded as predictor equations, while the measurement update equations can be thought of as corrector equations. Once the loop is entered, it can proceed on \textit{ad infinitum} recursively. With the aid of updated Kalman gain, the updated estimation is resulted from the \textit{a priori} estimate of process state assimilating the measurement as shown in Fig. 2.
3 Case study

3.1 Study area

Nanjing is the capital city of Jiangsu Province in East China, situated in the lower reaches of the Yangtze River. It is located at the range between 31° 14′ ~ 32° 37′ N and 118° 22′ ~ 119° 14′ E, with the total area of 6,587.02 square kilometers, and the residential population of 8.335 million. Known as a historic and cultural city to the world, it boasts a picturesque scenery integrating with ancient relics across six ancient dynasties. As the largest city in Yangtze River Delta, Nanjing ranked 11th among national cities with the GDP of 143 billion RMB in 2019 (http://www.stats.gov.cn). In the same year, it was rated as one of 12 new first-tier cities of China (https://www.cbnweek.com/articles/magazine/23576), showing its nimble competitiveness in lots of international rankings.

Nanjing consists of 11 municipal districts, with its downtown area occupying 6 main districts,
and has district centers distributed in downtown, sub-cities, new cites, and new towns, as Fig. 3 (a) depicts. The booming economy of whole city flows through the transportation vessels of highways, railways, and metro lines that have bolstered population migration for years. Fig. 3 (b) illustrates existing metro lines that are principally built along riverside districts. The density of metros in different administrative districts indicates unbalanced development and short-term planning emphasis, which will pose different impacts on land use pattern from the perspective of territory spatial planning.

![Study area and layout of existing metro lines](image)

**Fig. 3.** Study area and layout of existing metro lines

### 3.2 Data sources for spatial database

#### 3.2.1 Data acquisition

The data of existing metro lines come from the website of Amap, and data for the planned lines come from the website of mapbar. Both of them are in the form of attribute table including
the name and location of metro stations that could be precisely projected in the study area. The operation years of metro lines are classified into four periods by three year-sections, as mentioned in Section 2. Table 1 shows all metro lines of Nanjing City, including the planned ones. Based on each operation year, three year-sections (2010, 2015, and 2019) are determined, dividing time span into four phases (2005-2010, 2010-2015, 2015-2019, and 2019-2035). The ultimate year turns out to be 2035, for two reasons: (1) as Table 1 indicates, the clear operation year for planned lines is 2030, it is better to leave a 5-year interval for the metro fusion with surrounding land; (2) the official master plan of Nanjing City envisions the future to the year 2035.

Table 1

| NO. | Operation year | Length (km) | NO. | Operation year | Length (km) |
|-----|----------------|-------------|-----|----------------|-------------|
| 1   | 2005           | 38.90       | S6  | 2021           | 26.31       |
| 2   | 2010           | 37.95       | S4  | 2022           | 8.15        |
| 10  | 2014           | 21.60       | 6   | 2023           | 32.40       |
| S1  | 2014           | 37.30       | 9   | 2023           | 19.67       |
| S8  | 2014           | 45.20       | 11  | 2023           | 27.00       |
| 3   | 2015           | 44.90       | S5  | 2025           | 14.15       |
| 4   | 2017           | 33.80       | 13  | 2030           | 36.40       |
| S3  | 2017           | 36.22       | 14  | 2030           | 34.20       |
| S9  | 2017           | 52.42       | 15  | 2030           | 31.40       |
| S7  | 2018           | 30.16       | 16  | 2030           | 25.16       |
| 5   | 2020           | 37.40       | 8   | NAN            | 62.30       |
| 7   | 2021           | 35.49       | 12  | NAN            | 24.30       |

Note: (1) The planned extensions of existing lines are not considered in this paper. (2) For trans-provincial lines, the length of which beyond Nanjing is excluded.

Remotely sensed data have drawn considerable attention in the analysis and modelling of land use change. In this regard, the remote sensing imageries are acquired from the open-source platform EarthExplorer. In order to match the broad extent of area, to maintain the same
resolution of images in time span, and to be of relatively high quality among other types of
satellites, Landsat TM5 imageries are chosen to present land use change. With a resolution of
30m, Landsat TM5 imageries are widely deployed in the modelling and simulation of
geological cellular automata\textsuperscript{41,42}. Because of long-term sequence, this paper makes two
validations after simulation based on the imageries of 2015 and 2019.

The land use is strongly driven by geophysical, socioeconomic, and institutional conditions
\textsuperscript{43}. It is impossible to make simulation that absolutely resemble the reality, but only sufficiently
close to that by choosing most representative driving factors. This paper considers topology,
transportation, and socio-economy as strong driving factors, aims to incorporate them to arrive
at reasonable simulation and prediction. The topology aspect includes DEM and slope that
discern elevation of study area and correspond to physical geo-restrictions and development
costs. It indicates the terrain's suitability for urban development. The transportation aspect
shows the proximity to residential settlement and population flow, which are strongly associated
with spatial planning of transportation infrastructure. The socio-economy aspect reveals
population density and GDP density, reflecting the macro policy influence on urban
development. It suggests the possibility of the nonurban-to-urban transformation. It should be
emphasized that transportation factor here only contains metro information, excluding roads
and railways. Because by ruling out other types of transportation, the metro effect could be
ideally extracted (using scenario subtraction) in case of multiple redundant intersections. At the
cost of overall accuracy declination, the idea of subtraction of scenarios proves worthy in the
following sections. The raw data of DEM and slope can be obtained from the open-source
platform Earthdata. The transportation aspect contains distance to city center, distance to district
center, and distance to metro lines, which are made out of original geo-points after Euclidean
distance analysis and resampling process. The city center refers to Xinjiekou that located at the
intersection of Gulou District, Xuanwu District and Qinhua District. The district center refers
to the administrative center of each district. It should be noted that the administrative centers
(of city/district) went through changes in Feb. 2013 according to official documents, which
would subsequently influence the visualization of distance to district center and other factors
for year 2005, 2010, 2015, and 2019. For instance, Qinhua District and Baixia District were
merged into new Qinhua District; Gulou District and Xiaguan District were merged into new
Gulou District; Lishui and Gaochun were updated from county to district administratively.
However, the alteration concerning merge and rename would not cause significant changes to
DisDist visualization. Because the merged districts were adjacent to each other, moreover, they
covered quite small area in the city core area. Given that, we use the method called Euclidean
distance analysis to illustrate the distance to District centers without having to produce DisDist
(2005, 2010, 2015, 2019). As to the distance to metro lines, GDP and population, the same
processing is also applied. While it is important to count GDP and population according to the
changes of districts before and after year 2013, for GDP and population are not in the same
magnitude as the distance when it comes to map visualization using Euclidean distance analysis.
As a result, we need to produce GDP and Pop separately and differently for each year section
(2005, 2010, 2015, 2019). Table 2 sums up the preparation of data before simulation.

Table 2

| Type            | Abbr. | Statement                  | Res. | Source                | Purpose |
|-----------------|-------|----------------------------|------|-----------------------|---------|
| Land use        | LandUse | Remote sensing images      | 30m   | earthexplorer.usgs.   | Input   |
| Driving factors | classification | gov                      | Topology impact |
|-----------------|---------------|--------------------------|-----------------|
| DEM Slope       | Elevation    | earthdata.nasa.gov      |                 |
| DisCity         | Dis. to city center | www.amap.com   | Transporta-
| DisDist         | Dis. to district center | www.mapbar.com | tion impact   |
| DisLine         | Dis. to metro line in 2005-2019 | www.mapbar.com |                 |
| Pop             | Population density in 2005-2019 | www.worldpop.org | Socioecono-
| GDP             | GDP density in 2005-2019 | tjj.nanjing.gov.cn | mic impact    |

Note: the scope of study area is 5103x2793

### 3.2.2 Data visualization

To begin with, the scope of study area is clipped at 5103 rows and 2973 columns in ENVI software. After some necessary pre-processes, the land use is categorized into five types by means of supervised classification, namely forest, urban land, construction land, cultivated land, and water area. Supervised classification is a commonly used method based on subjective sampling of naked eye that demands prior experience and knowledge for each land use type. Then an amount of samples are trained according to maximum likelihood of bands combination, thus all cells find their own categories thanks to special spectrum feature, as is depicted in Fig. 4.
Fig. 4. Presentation and classification of Landsat imagery of Nanjing city

(a: Landsat remote sensing imagery; b: categorical map based on supervised classification)

Compared with 2005, the categorical map of 2010 reveals an increase in construction land and a decrease in urban land in downtown area. It can be ascribed to urban redevelopment in a way. As points out, that urbanization is inexorable for no existing urban areas are subjected to deurbanization. The disappearance of urban patches can be observed during urbanization, owing to local redevelopment. A land transformation from urban built area to demolished land can be identified as short-term decrease of impervious surface coverage by remote sensing. Theoretically speaking, such a phenomenon occurs at a point of time span, but soon phases out
or be masked in a long interval.

When pooling driving factors for simulation, quantification and visualization is always the priority. Factors like industrialization, slope and elevation, land use policy and urban planning, infrastructure are proved feasible with regard to data source and mapping. Meanwhile, for the sake of dimension effect, the normalization method of is adopted, shown is the visualization of driving factors in Fig. 5.

![Fig. 5. Driving factors for land use change in 2005, 2010, 2015, 2019](image)

### 3.3 Model simulations

#### 3.3.1 Parameter adjustment

Before calculating the transition probability of land use types in the FLUS model, an ANN based training is executed where the number of hidden layer is set to 7, and the sampling rate is set to 0.2%, which is tested as optimal result after multiple trials. Next, by adding prepared raster files of seven driving factors, integrating with the categorical maps, the transition probabilities in the year 2010, 2015 are respectively generated. Note that the year 2005 is not
included because the data of the former year 2000 is unavailable here, so that the Kalman filter could not produce corresponding data of year 2010 to estimate whether the transition has reached the demand or not. In addition, the year 2019 is ruled out because it is merely for prediction in Section 3.3.3.

Then, during the self-adaptation and competition of cells with three neighbors designated, the model will iterate at most 300 times. In case of slow operation due to broad extent of area, specified are the value of accelerator as 0.1, as well as the running thread as 8. A few restrictions are posed taking into account of reality rules. The cost matrix for each land use type is as Table 3 shows. When one type of land use is able to convert to another type, the cost coefficient would be 1, otherwise turns to be 0. In addition, the weights of neighborhood of forest, urban land, construction land, cultivated land, and water area are 0.5, 1.0, 1.0, 1.0, and 0.1, respectively. The parameter adjustment for neighborhood weights is based on trial-and-error, by comparing the expansion performance of cells with real satellite imageries during multiple trials of coefficient combinations. The greater the value of weights, the stronger the expansion ability of specific type cells would be.

**Table 3**

Cost matrix for each land use type

|           | Forest | Urban land | Constr. land | Cultiv. land | Water area |
|-----------|--------|------------|--------------|--------------|------------|
| Forest    | 1      | 1          | 1            | 1            | 0          |
| Urban land| 0      | 1          | 0            | 0            | 0          |
| Constr. land| 0    | 1          | 1            | 0            | 0          |
| Cultiv. land| 1    | 1          | 1            | 1            | 1          |
| Water area| 0      | 0          | 0            | 1            | 1          |

As soon as the simulation reaches the maximum iteration, or the result gradually converges
to a value, the probabilities of occurrence in 2015 and 2019 are calculated which are originated
from initial maps of 2010, 2015 respectively. The probability of occurrence for each cell is then
selected by roulette wheel to determine final transition land use type. At this moment, Kalman
filter generates future demand for land use of the two years, to estimate whether the transition
amount has meet the need. If so, the model will generate simulated results. If not, the feedback
from Kalman filter will be given to self-adaptive inertia, to reproduce new probability of
occurrence in multiple iterations.

3.3.2 Validation

By comparing the actual imagery and simulated result, we can make two validations for the
year 2015 and 2019. In this part, three image indicators are adopted to quantify the accuracy of
simulation, namely Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure
(SSIM), and Feature Similarity Index for Image (FSIM). Among them, PSNR is calculated from
the gray value of the image, which can be used as a preliminary characterization of the
comparison between the predicted result and the actual result. In addition, SSIM and FSIM are
used to calculate the similarity between the two images.

The value of PSNR ranges from 20 to 40, the larger the value, the smaller the difference of
two images. It can be expressed as follows:

$$PSNR = 10 \log_{10} \left( \frac{L^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} (I_1(i, j) - I_2(i, j))^2} \right)$$  \hspace{1cm} (22)

Where $M, N$ represent the image size; $I_1(i, j), I_2(i, j)$ represent the gray value of two
images used for comparison at coordinates $(i, j)$; $L$ is the peak signal, for an 8-bit gray
image, $L=2^8-1=255$. 

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In SSIM, structural information is incorporated, i.e. brightness, contrast, and structural similarity. If the value of SSIM is closer to 1, it means highest similarity. Assuming that X and Y are two images for comparison, then we have:

\[
l(X,Y) = \frac{2\mu_X \mu_Y + C_1}{\mu_X^2 + \mu_Y^2 + C_1}
\]

\[
c(X,Y) = \frac{2\sigma_X \sigma_Y + C_2}{\sigma_X^2 + \sigma_Y^2 + C_2}
\]

\[
s(X,Y) = \frac{\sigma_{xy} + C_3}{\sigma_X \sigma_Y + C_3}
\]

Where \( \mu_X \), \( \mu_Y \) are the mean value of image X and Y respectively, denote brightness information; \( \sigma_X \), \( \sigma_Y \) are the variance of image X and Y respectively, denote contrast information; \( \sigma_{xy} \) is the correlation coefficient of image X and Y, denotes the similarity of structural information; \( C_1, C_2, C_3 \) are natural numbers close to 0 to prevent abnormal results when the denominator is zero. Thus, SSIM can be expressed as follows:

\[
SSIM (X,Y) = [l(X,Y)]^\alpha + [c(X,Y)]^\beta + [s(X,Y)]^\gamma
\]

Where \( \alpha, \beta, \gamma \) are used to adjust the proportions of three types of information.

FSIM is an image evaluation index based on traditional image evaluation method, where phase consistency and image gradient are considered for comparison. It bears the assumption that the point with the most count of Fourier component is a feature point, instead of simply taking the biggest gray value change as a feature to simulate human perception and observation of images. If the value of FSIM is closer to 1, it means highest similarity. By obtaining two images’ phase consistency \( PC_1, PC_2 \), and image gradient \( G_1, G_2 \), we have:

\[
S_{FSIM} (X) = \frac{2PC_1(X) \cdot PC_2(Y) + T_1}{PC_1^2(X) + PC_2^2(Y) + T_1}
\]
Thus, FSIM can be expressed as follows:

$$FSIM = \frac{\sum_{x \in \Omega} S_L(x) \cdot PC_m(x)}{\sum_{x \in \Omega} PC_m(x)}$$ (30)

Where $T_1$, $T_2$ are constant; $PC_m = \max(PC_1(x), PC_2(x))$; $\Omega$ represents the extent of image.

**Table 4**

The comparison of image indicators for model simulation accuracy

| Image indicators | Accuracy 2015 | Accuracy 2019 |
|------------------|--------------|--------------|
| PSNR             | 38.0460      | 34.3977      |
| SSIM             | 0.7002       | 0.6534       |
| FSIM             | 0.8795       | 0.8554       |

As Fig. 6 illustrates, the simulated results have common urban tissues with actual ones, yet fail to recognize a certain number of urban patches, as well as construction land. Table 4 shows that three indicators (PSNR, SSIM, and FSIM) are respectively 38.0460, 0.7002, 0.8795 in 2015, and are respectively 34.3977, 0.6534, 0.8554 in 2019. Notwithstanding the accuracy appears slightly satisfactory, it matches other findings in literature when it comes to broad extent of study area with the resolution of 30 meters, let alone single transportation factor metro is involved. Consequently, the cellular automata model can generate relatively real imagery across long term, which will support the prediction of the land use in 2035 in Section 3.3.3, and
extraction of patches with regard to metro effect in Section 3.4.

| 2015 | 2019 |
|------|------|
| ![Actual](image1) | ![Simulated](image2) |
| ![Actual](image3) | ![Simulated](image4) |

**Fig. 6.** Comparison between actual and simulated land use change

### 3.3.3 Prediction

From 2019 to 2035, 14 new metro lines are planned on the basis of existing lines, some of which are currently under construction. The descriptive information and data are collected from the webpage of Nanjing metro in Baidu baike and mapbar, respectively. After projection, calibration, and vectorization in ArcGIS, the driving factor of merged metro lines, including existing lines as of 2019, are incorporated into the coupled model to predict land use change as of 2035.

The task of prediction here is for two future scenarios in 2035, namely metro scenario that includes 24 metro lines, non-metro lines that includes 10 metro lines. The scenario for non-metro also needs to be simulated in the coupled model, only by selecting of metro raster files as of 2019 when importing driving factors. By repeatedly following simulation processes mentioned in sections above, the model successfully predicts two land use scenarios of Nanjing
City as of 2035. In this case, the state transition probability is determined as the ratio of transited amount to total amount. Integrating the available transition matrices of four periods, a comprehensive state transition probability matrix is obtained, which then serves as the process state equation \( \Phi_{k+1,k} \) of Kalman filter. The matrix is as follows:

\[
\Phi_{k+1,k} =
\begin{bmatrix}
0.5689 & 0.2473 & 0.0192 & 0.1591 & 0.0055 \\
0.0675 & 0.8014 & 0.0604 & 0.0643 & 0.0064 \\
0.0191 & 0.1308 & 0.8394 & 0.0069 & 0.0038 \\
0.0675 & 0.1432 & 0.0045 & 0.7793 & 0.0056 \\
0.0127 & 0.0877 & 0.0052 & 0.014 & 0.8805
\end{bmatrix}
\]  

(31)

According to equation (21), (18), (17), (15) in Section 2.2, we predefine observation matrix \( H_k \) as [1 1 1 1 1], the column number of which is determined by the number of land use types. In addition, both \( a \) priori estimation error covariance matrix \( P_k^{-} \) and process error covariance matrix \( Q_k \) are defined as a 5×5-identity matrix filled with 10. Here, 10 is thought as a mild increment for iterations. Measurement error covariance matrix \( R_k \) is set as \( 10^5 \), therein we obtain Kalman Gain \( K_k \) through those necessary parameters. Subsequently, the estimation error covariance \( P_k \) is updated with the help of Kalman Gain \( K_k \), the process of which is called from \( a \) priori to \( a \) posteriori in Section 2.2. Finally, we update the estimate \( \hat{x}_k^{-} \) with measurement \( z_k \). The long-term prediction of land use evolution is therefore depicted in Fig. 7.
Based on the prediction of Kalman filter, the FLUS model proceeds to allocate the amount of land use types for 2035. As is shown in Fig. 8, five land use types are exhibiting more complex spatial characteristics. Particularly the urban land and construction land are replacing more other types of land. Nevertheless, these two scenarios look alike, as if there is no land use differences caused by newly added metro lines.

In light of that, more micro-level details are depicted in Fig. 9. Taking urban land as example, new urban patches are distributed approximate existing urban patches, not very crowded, but at a certain scale to form considerable settlements. The concealed information are nearly masked between two scenarios’ maps, showing that the metro effects are in favor of local area. To study moderate increment of grain sizes, it requires enlarging specific area with one scenario as background. At three places of Fig. 9, it indicates the number of urban patches under metro scenario surpass that of non-metro scenario.
Fig. 8. Simulated results for 2035 (a: metro scenario; b: non-metro scenario)
Therefore, three questions emerge: how does land use respond to metro expansion? How to measure the relationship between urban land and metro lines across space and time? How the accumulated metro effects can cast light on territory development plan?

3.4 Results and Discussion

If separately examining the growth of urban land, we shall discover that the urban growth boundaries delineated in each four period are cluttered with patches dotted around the outskirt (Fig. 10). That absorption of neighboring land is meant to reduce the concentration of wealth and culture in the main city area.

According to [44], the evolution of urban area actually includes simultaneous expansion and shrinkage, which can be characterized as oscillated processes of diffusion and coalescence (Fig. 11). The process makes urban patches exhibit three kinds of shrinkage: isolating renewal, adjacent renewal, enclosing renewal. Among them, enclosing renewal is exactly in connection
with urban redevelopment, proving again the evidence found in Section 3.4.1. As is shown in Fig. 10, colored urban patches of four periods have suffered both expansion and shrinkage. Despite of “salt-and-pepper” effects, notable shrinkage happens in the periphery of existing urban land, reflecting intensity of redevelopment near downtown area.

![Diagram of urban renewal processes](image)

**Fig. 11.** The oscillated renewal of urban patch (after 44)

In order to find out the transition mechanism of urban expansion, four transition matrices for land use change in four periods are obtained (Table 5, 6, 7, 8). Derived from that, Sankey diagram can vividly show flow of land use changes across time. As can be seen from Fig. 12, all types of land use flow through year columns, where the amount of fluxes in and out keeps constant. It is in the intervals that the land use transitions occur.

**Table 5**

|                     | Constr. land | Cultiv. land | Forest | Urban land | Water area | Total |
|---------------------|--------------|--------------|--------|------------|------------|-------|
|                | Constr. land | Cultiv. land | Forest | Urban land | Water area | Total  |
|----------------|--------------|--------------|--------|------------|------------|--------|
| Constr. land   | 112.5568     | 138.5992     | 2.483745 | 37.07076   | 1.888615   | 292.5991 |
| Cultiv. land   | 278.5777     | 3993.911     | 98.89591| 203.4437   | 25.86005   | 4600.689 |
| Forest         | 15.12361     | 186.8649     | 355.5045| 6.379493   | 6.200732   | 570.0732 |
| Urban land     | 100.9727     | 174.8352     | 2.660908| 368.0879   | 3.192459   | 649.7492 |
| Water area     | 13.67253     | 61.72074     | 1.765433| 15.30958   | 386.4265   | 478.8948 |
| Total          | 520.9033     | 4555.931     | 461.3105| 630.2914   | 423.5684   | 6592.005 |

Table 6

Transition matrix for 2010-2015 Unit (km²)

|                | Constr. land | Cultiv. land | Forest | Urban land | Water area | Total  |
|----------------|--------------|--------------|--------|------------|------------|--------|
| Constr. land   | 132.6396     | 211.8874     | 3.916026| 165.75     | 6.80069    | 520.9937 |
| Cultiv. land   | 283.4857     | 3874.567     | 140.485| 224.4975   | 32.76978   | 4555.805 |
| Forest         | 11.2351      | 65.09388     | 380.1576| 3.871004   | 0.976144   | 461.3337 |
| Urban land     | 37.53482     | 144.4981     | 2.060864| 439.2687   | 6.936454   | 630.2989 |
| Water area     | 1.743369     | 31.43602     | 2.355814| 6.195052   | 381.783    | 423.5133 |
| Total          | 466.6386     | 4327.482     | 528.9753| 839.5822   | 429.2661   | 6591.945 |

Table 7

Transition matrix for 2015-2019 Unit (km²)

|                | Constr. land | Cultiv. land | Forest | Urban land | Water area | Total  |
|----------------|--------------|--------------|--------|------------|------------|--------|
| Constr. land   | 169.9787     | 156.32       | 27.44262| 110.0352   | 2.860328   | 466.6369 |
| Cultiv. land   | 545.8737     | 3104.223     | 311.6591| 318.4189   | 46.909     | 4327.083 |
| Forest         | 17.08505     | 50.48425     | 456.1169| 3.637992   | 1.705446   | 529.0296 |
| Urban land     | 70.42236     | 131.8793     | 7.642882| 622.1443   | 7.503453   | 839.5924 |
| Water area     | 6.929806     | 44.86672     | 4.084645| 2.133693   | 371.2811   | 429.296  |
| Total          | 810.2896     | 3487.773     | 806.9461| 1056.37    | 430.2594   | 6591.638 |

Table 8

Transition matrix for 2019-2035 Unit (km²)

|                | Constr. land | Cultiv. land | Forest | Urban land | Water area | Total  |
|----------------|--------------|--------------|--------|------------|------------|--------|
| Constr. land   | 774.2862     | 10.13516     | 6.211778| 19.82076   | 0.025448   | 810.4793 |

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In the four phases, the augmented urban land mainly comes from construction land and cultivated land. The construction land can be large or small sometimes, and inclines converting into urban land and cultivated land. Cultivated land, which has always accounted for the largest proportion in all phases, has been decreasing year by year. In 2015, a large part of it went to construction land, and in 2019, a large proportion of it went to forest and urban land. In general, the total amount of green space (forest and cultivated land) has not changed much, and the water area has basically remained unchanged, which has a lot to do with urban ecological protection policies.

The conversion focus of each phase is also different. Since 2005, although the conversion of cultivated land to urban land has always been the main theme, the focus of 2010-2015 is the conversion of cultivated land to construction land. The focus of 2015-2019 has added the conversion of cultivated land to forest. The focus of 2019-2035 will follow the same trend. This change of orientation shows that urban growth has shifted from increments to stocks, not because the vitality of the metro is gradually declining, but the invisible effects under the intervention of the master plan are gradually being guided.
In effect, when using the Kalman filter to predict the amount of future land use, it is found that in 2050 or so, urban land parcels will become saturated, as will construction land. Perhaps a small amount of construction land (for industry, tourism) will contribute to urban land continually, and this balance will not be broken in the short run. On the basis of the land use in 2035 under the metro scenario (because there is no real reference in 2035), the urban land change brought about by metro is minimal compared with the previous years. It is basically a slight expansion at the edge of the existing urban periphery to enhance connectivity. To a certain extent, it shows that the metro's vitality to drive urban sprawl has an upper limit, and it is not an endless incursion of other land to achieve transformation.

Through calculations, the urban growth rate brought by the metro during four periods of
2005-2010, 2010-2015, 2015-2019, 2019-2035 are 0.27, 0.38, 0.29, 0.08 respectively.

Assuming that the predicted amount under the metro scenario is 0.7 times the actual amount, then the rate of 0.08 will be converted to 0.11, which is still less than the ideal value 0.3. In other words, taking into account the forecast errors, the growth rate of urban brought by the metro from 2019 to 2035 is still less than the expected value, which has a lot to do with the upper limit of urban parcels mentioned above.

4 Conclusion

This paper studies the metro impact on Nanjing city’s environment from the perspective of land use change over 30 years. Based on FLUS model of CA, this paper incorporates kalman filter, originated from optimal state estimation theory to distinguish information from noise in state-space system. The simulation and prediction results of proposed integrated model can provide reference for policymaking and spatial planning. The shortcoming of this paper lies in only considering limited driving factors and no comparisons of other models, so the geo-simulation will be improved by incorporating up-to-date data and integrating more precise prediction methods.

The main conclusions of this study are as follows:

(1) Comparing the two scenarios in the future 2035 (with/without new metro lines), it shows that the newly expanded urban patches in the metro scenario are mostly scattered on the edge of existing urban land, such that promote patch connectivity and personnel mobility. The amount of urban parcel is predicted to reach saturation in 2050, which approximate that in 2035. Construction land and other land use types will be in a dynamic balance, and urban boundaries will basically be shaped. The development focus of future urban parcel is meant
to be in new city and new town along the Yangtze river and metro axis;

(2) The simulation and prediction results demonstrate that in the four phases of 2005-2010, 2010-2015, 2015-2019, and 2019-2035, the transition fluxes of five land use types are flowing in and out mutually, and the transition focus of each phase gradually deviates towards more environmental friendly development. The prevailing transition trend is still the conversion of cultivated land into urban land. Metro stations have played an important role in enhancing the expansion intensity of nearby construction land, so it is necessary to protect the ecological red line, by implementing more stringent basic cultivated land protection policies;

(3) With the metro lines expanding year by year, the CA model can assist city planners in scenario prediction and decision-making. In addition, the simulation of long-term series (in a 5-year step) using Kalman filter, can analyze uncertainty of state-space system with good accuracy, which is beneficial to understand the temporal and spatial evolution of land use coupled with metro and sort out the symbiotic relationship between them.

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**Figure captions**

Fig. 1. Workflow chart of CA-Kalman filter model

Fig. 2. Kalman filter loop

Fig. 3. Study area and layout of existing metro lines

Fig. 4. Presentation and classification of Landsat imagery of Nanjing city

Fig. 5. Driving factors for land use change in 2005, 2010, 2015, 2019

Fig. 6. Comparison between actual and simulated land use change

Fig. 7. Land use prediction using Kalman filter from 2005 to 2050

Fig. 8. Simulated results for 2035

Fig. 9. Comparison of urban land under two scenarios for 2035

Fig. 10. Urban growth boundary as of four year-sections

Fig. 11. The oscillated renewal of urban patch

Fig. 12. Sankey diagram of land use transitions from 2005 to 2035

**Table captions**

Table 1 The operating and planned metro lines of Nanjing

Table 2 Data preparation for land use change simulation

Table 3 Cost matrix for each land use type

Table 4 The comparison of image indicators for model simulation accuracy

Table 5 Transition matrix for 2005-2010

Table 6 Transition matrix for 2010-2015

Table 7 Transition matrix for 2015-2019

Table 8 Transition matrix for 2019-2035