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SIMULATING LAND USE CHANGE IN URBAN RENEWAL AREAS:

A CASE STUDY IN HONG KONG

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1. INTRODUCTION

Land use change is a both locally and globally significant ecological issue (Agarwal et al., 2002). Considerable effort has been made to explore its mechanisms and impacts. Vitousek (1994) indicated that land-use/land-cover change is one of three well-documented global changes, and Foley et al. (2005) published a review paper on the global consequence of land use. Some researchers have focused on land use change problems globally (e.g., Houghton, 1994; Turner et al., 1994) while others have focused on the issues at a continental or national level. For example, Zhao et al., (2006) identified the most pervasive land use changes in Asia and discussed their ecological consequences. Reginster and Rounsevell (2006) applied a multilevel analysis to constructing four scenarios of future urban land use in Europe. Spatial land use change in China from 1995 to 2000 was explored by using remote sensing data from that period (Liu et al., 2003). At the regional level, Pijanowski and Robinson (2011) analyzed spatial and temporal land use change in the Upper Great Lakes states of the USA. The spatial patterns of urban sprawl in the Flanders-Brussels region of Belgium were studied, as one of the most urbanized regions in Europe (Poelmans & Van Rompaey, 2009). At the city level, land use change involves urbanization and redevelopment processes. A better understanding of land use change mechanisms and dynamics can provide guidance for future urban development and redevelopment. For example, land use change in Beijing, China, was investigated and predicted by combining remote sensing, Geographic Information System (GIS), and other methods (Wu et al., 2006). Land use planning aims at influencing future land use change and achieving a balance between environment and stakeholder needs (Verburg et al., 2002). Simulating the degree and mechanism of land use change can facilitate the planning process (Agarwal et al., 2002; Batty, 2001). For example, regional land use change simulation was conducted to support local government to make decision on the prioritization of land development, land utilization, land harness and land protection under the background of development priority zoning (DPZ-led) strategy in China (Wu et al., 2012).

Land use change detection in urbanization/urban growth/urban sprawl (e.g. Zanganeh Shahrakj et al., 2011; Xiao et al., 2006; Henríquez et al., 2006; Alphan, 2003), as well as ecological and environmental impacts of land use change (e.g. Pauleit, et al., 2005; Tang et al., 2005; Zhao et al., 2004) were the main themes of previous studies. Urban renewal, as one valuable opportunity to re-use land and further improve urban sustainability, has attracted much research interest (e.g. Wang et al., 2014; Zheng et al., 2014). The land within the boundary of the redevelopment project is necessarily re-planed for future use when a redevelopment project is started (Bagaeen, 2006). However, since few researchers have paid attention to it, there is a potential for research on land use change mechanisms in the urban renewal process.

Hong Kong, like many developed cities, is facing urban problems such as urban decay, the shortage of land supply, and environmental deterioration. Urban renewal has been proposed as a policy approach to solve these problems. For example, Hong Kong's Urban renewal Authority has undertaken more than 50 redevelopment projects since 2001 (Development Bureau, 2011). However, decision-making must be improved at the local level for the sustainability (Allen et al., 1999). This research was therefore conducted with the aim of simulating land use change in the Yau Tsim Mong (YTM) district of Kowloon, Hong Kong, which is a developed area and has experienced fast development and redevelopment in recent decades. The Markov chain prediction model was employed to predict temporal land use change. The Conversion of Land Use and its Effects at Small regional extent (CLUE-S) model was selected to conduct spatial simulation. This model is appropriate for small-scale land use change simulation and is able to simulate changes of different land use types simultaneously. Additionally, land use and planning policies, which cannot be easily considered in other models, have significant influence on the trend of land use change; the CLUE-S model allows for these spatial policies in its settings. This research used a series of historical land utilization data (the years of 2000, 2003, 2006, and 2009), which were prepared by using Geographic Information System technology, to develop, calibrate and validate the combined simulation model. To further facilitate decision-making on land use of urban renewal, future land use patterns in 2018 under four different scenarios were simulated by the validated model. The results of this study contribute to a comprehensive understanding of complex mechanisms of land use change and offer a valuable reference for land use planning and management in urban renewal districts.

2. LAND USE CHANGE MODEL

Various models are widely applied for exploring land use dynamics and predicting future land use change in order to enhance decision-making. Models are helpful tools for understanding the complex mechanisms of social, economic and physical variables that influence land use change, and for evaluating land use change impacts (Braimoh & Onishi, 2007; Verburg et al., 2004), both of which facilitate informed decisions (Costanza & Ruth, 1998) and improve land use planning and land-related policies (Braimoh & Onishi, 2007). Some models can also support decision makers in predicting future scenarios (Verburg et al., 2004; Agarwal et al., 2002).

Cellular automata (CA) are often applied to simulate spatio-temporal land use change (Vaz et al., 2012; Liu, 2012; Al-Ahmadi et al., 2009; Stevens & Dragicevic, 2007). The current state of cell depends on its previous state and its neighborhood based on a set of rules (Santé et al., 2010). A cellular automata model has the advantages of spatial explicitness defined by rules and powerful computation ability obtained from artificial intelligence, thus can be developed through a combined method (Liu et al., 2014). It was firstly applied to geographic modeling in the 1970s (Tobler, 1979). In the 1980s, some researchers have begun to investigate urban expansion by applying CA-based models (Batty & Xie, 1994; Couclelis, 1985). Among various applications of CA, studies on the transition rules have obtained much attention since the transition rules are the core component for CA modelling. Many techniques are developed to capture the transition rules, ranging from logistic regression (Wu, 2002), colony algorithm (Liu et al., 2008), Simulated annealing (SA) algorithm (Feng & Liu, 2013) and support vector machines (Huang et al., 2009). This approach is appropriate for short-term predictions although it cannot predict changes when the demands for different land-use types change. The CA approach can only simulate the conversion of one land use type in most cases (Verburg et al., 2002).

At the micro-level, multi-agent system models are the most popular. These models analyze the decision-making process of key stakeholders in a given system (Parker et al., 2003). Multi-agent models usually work as a function of individual decision-making agents, their interactions and related social process (Matthews et al., 2007). This kind of model enables combination of subsets of various ancillary data and discrete variables (Jokar Arsanjani et al., 2013). The agents can model human behavior more precisely and facilitate better evaluation (Fujita & Kashiwadani, 1989). However, most current multi-agent models only focus on simple systems since the number of interrelated agents is so large that developing comprehensive models is difficult (Verburg et al., 2004). Sufficient data at the individual/household level can improve the effectiveness of these models, but it is difficult to acquire data from individuals at the micro-level.

Some other models based on multidisciplinary considerations and various modeling techniques are classified into integrated models, which are probably best tools to interpret land use change processes (Guan et al., 2011). The Conversion of Land Use and its Effects (CLUE) modeling framework is the most famous one among these integrated models, and its modified version for use in a small regional context is referred to as CLUE-S (Verburg et al., 2002; Veldkamp & Fresco, 1996). This model has been widely used in different regions addressing a wide range of issues including agricultural intensification, deforestation, land abandonment, and urbanization (Verburg & Overmars, 2007).

3. METHODOLOGY

This research simulated land use changes from 2000 to 2009 based on historical changes of land uses during this period. Since Planning Department in Hong Kong updates land utilization maps every three years, data of 2000, 2003, 2006, and 2009 were utilized. By comparing the real land utilization map with the simulated land utilization map in the year 2009, the proposed simulation model was calibrated and validated. Finally, several future scenarios in 2018 were developed based on various development policies or directions. The proposed model consists of two important parts: the Markov chain prediction model and the CLUE-S model. The Markov chain prediction model works on the issue of temporal land use change, namely when and how much land use change will happen, while the CLUE-S model addresses the issue of where these changes will happen. The two models are connected to keep the balance between temporal land demand and spatial allocation. The flowchart of the methodology is shown in Figure 1.

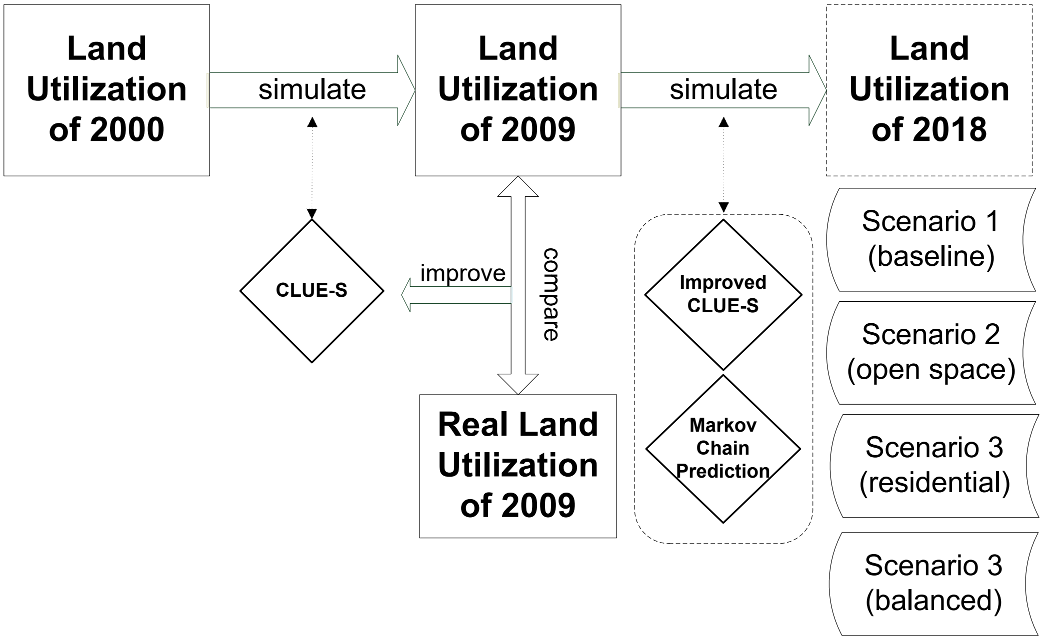

Figure 1 Flowchart of the research methodology

3.1 Study Area and Data Sources

The study area for this research is the Yau Tsim Mong (YTM) district of Kowloon, Hong Kong, which is a highly developed area with scarce land resources. It is located on the Kowloon peninsula, spanning 114°09′-114°11′E and 22°17′-22°19′N. It is bounded by the East Rail Line of the Mass Transit Railway (MTR) to the east, the waterfront to the south and the west, and Boundary Street to the north. Figure 2 shows the location of YTM district. The land area of this district is approximately 8 km^2 and the current population is around 301,800. Economic activities in YTM are mainly commercial, supplemented by tourism and light industries. Land use types in this district include commercial, residential, industrial, government, institutional and community facilities (G/IC), open space[1], vacant land. Although this district is highly developed in most areas, land use still probably changes since vacant land accounts for a large portion of the total area (approximately 15.3% in 2009) and some old areas need to be redeveloped because of decaying conditions.

The raw spatial data was collected from the Lands Department of Hong Kong, including land utilization maps of the study area in 2000, 2003, 2006 and 2009, and digital

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[1] Open space here represents a statutory land use zoning for providing open space and recreation facilities for the entertainment of the general public according to the definition of Planning Department in Hong Kong.

topographic maps. The spatial dataset provides the information of natural conditions, land utilization, facilities, transportation, neighborhood and some social and economic aspects. Non-spatial data includes historical documents on social and economic aspects including population, historical property price and policies such as District Aspiration Study for Urban Renewal in Yau Tsim Mong and Projections of Population Distribution by the Planning Department.

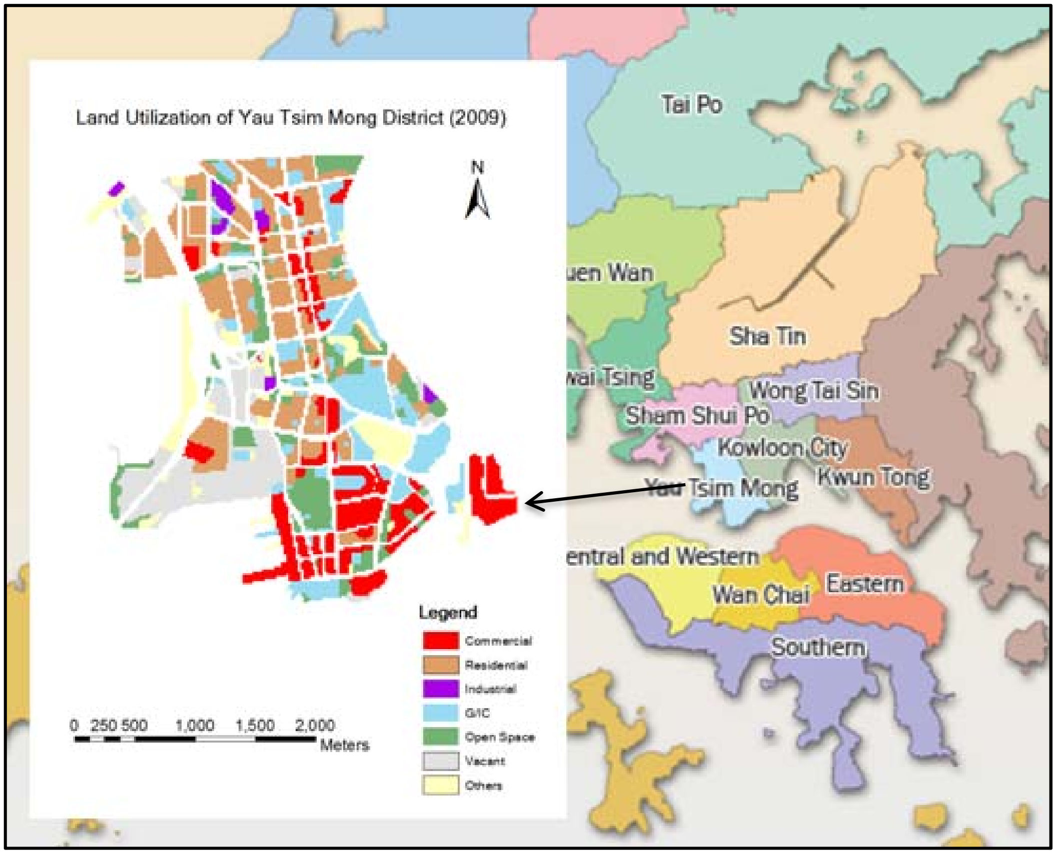


Figure 2 Location of the Yau Tsim Mong district

3.2 Markov Chain Prediction Model

The Markov chain prediction model calculates temporal land use demand in the year 2018 for the baseline scenario. Markov chain models have been widely applied to temporal land use change prediction in a considerable number of studies (e.g. Xia et al., 2013; Reveshty, 2011; Muller & Middleton, 1994). *"Markov chain models are essentially projection models that describe the probabilistic movements an individual in a system comprised of discrete states." (Iacono et al., 2012: 4)*. The Markov process models a system in which probability distribution over next state is supposed to be decided by current status, not by previous ones (Pijanowski et al., 2002; Fischer & Sun, 2001). In the dynamic process of land use change, the transition rate of land use is comparatively stable during certain periods, different land types may change into each other in a certain region and many incidents that are difficult to capture may be included in the conversion process between different land use types. As the land use change process of the study area conforms to the aforementioned conditions and characteristics, it is appropriate to use the Markov chain prediction model for temporal land-use change in this research (Guan et al., 2011).

The transition probability matrix of land use type needs to be provided before applying the Markov chain. Its mathematic expression is as follows:

$$p = (p_{ij}) = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \cdots & & & \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix}$$

In the above matrix, P_{ij} represents the transformation probability of the i th land use type into the j th land use type from previous status to next status; n is the land use type of study area. P_{ij} should meet the following requirements:

$$0 \leq p_{ij} \leq 1 (i, j = 1, 2, 3 \cdots, n)$$

$$\sum_{i=1}^{n} p_{ij} = 1 (i, j = 1, 2, 3 \cdots, n)$$

Based on a transition probability matrix and Bayes' theorem of conditional probabilities, the Markov chain prediction model is defined as: $P_{(n)} = P_{(n-1)} P_{ij}$, in which $P_{(n)}$ is the state probability of any times and $P_{(n-1)}$ is the previous state probability (Chen & Zhang, 2011; Guan et al., 2011).

The rate and behavior of historical land use change were calculated by using the function of spatial analysis in ArcGIS 10. Since the prediction period is from 2009 to 2018, the change data from 2000 to 2009 was employed to calculate the conversion probability matrix, which is an essential part of the Markov chain prediction model. Finally, future land use demands under other scenarios were set according to different conditions.

3.3 CLUE-S Model

The CLUE-S model was applied in this research to capture land use changes spatially. It was developed at Wageningen University in the Netherlands and first published in 1996 (Veldkamp & Fresco, 1996). CLUE-S is used for the spatially explicit simulation of land use change on the basis of location suitability as well as the dynamic modeling for competition and interactions between different land use types (Verburg et al., 2002). The adapted simulation process of the combined model is shown in Figure 3. Specifically, spatial considerations (including spatial patterns of land use, location factors, conversion elasticity and matrix, as well as spatial policies and restrictions) decide the land allocation spatially, which needs to be consistent with the land demand calculated by the Markov chain prediction model.

Logistic regression for land use is an essential step in the simulation process, which aims to examine the relationships between location factors and different land use types. The land allocation probability depends not only on location factors, but also on the conversion capability of different land use types. In the conversion settings of the model, conversion elasticity and conversion matrix need to be set accordingly. The conversion elasticity reflects the relative elasticity for change from one land use type to any other land use type in the model (Verburg et al., 2002), which was obtained from experts' experience and then modified by calibration of the model. The conversion matrix shows the probability of land use change (Verburg et al., 2002).

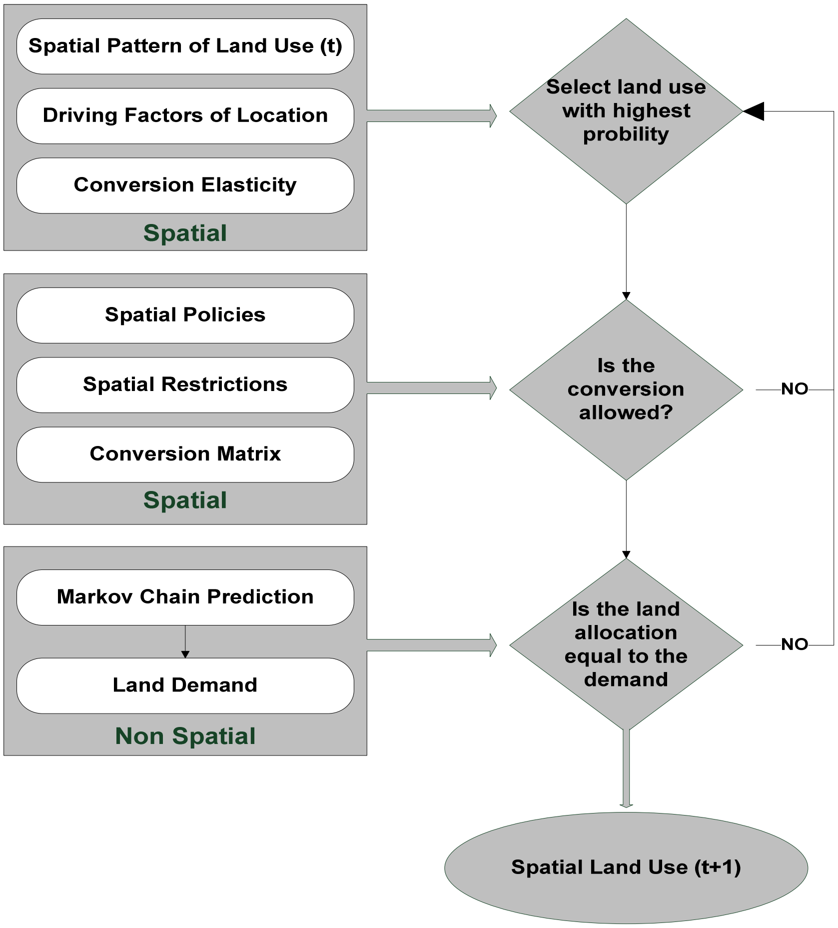


Figure 3 Land allocation process (adapted from Verburg, 2008)

3.4 Other Important Considerations

Future scenario is speculation about how the future might unfold, which can be expressed in both words and numbers (Lead et al., 2005). These scenarios provide images of the future through exploration of drivers of change, past and current tracks, and opportunities for engagement (Raskin et al., 1998) . The aim of scenario analysis is not predicting the future, but getting a better understanding of uncertainties that can provide a robust basis for decision-making. In this research, four scenarios were produced in the simulation process. The first scenario is the baseline scenario, which means following the historical process of land use change and not taking into account any future measures to limit or encourage land use change. Land demand under the baseline scenario was calculated using the Markov chain model. The other three scenarios are policy-based scenarios.

Supplying more housing and improving the quality of the environment are two main objectives proposed by the government. One of the urban renewal objectives in Hong Kong is "*to offer more open space for the benefit of our urban communities*" (URS, 2011). The second scenario is thus aimed at providing more open space at the district level, named as the open space scenario. According to the projections made by the Planning Department in November 2008, there would be 3.39 m^2 per person provision of open space if all sites planned as open space were developed. Therefore, the demand of open space will be calculated based on 3.39 m^2 per person and the projected population of 345,900 in 2018 by the Planning Department. The balance of open space will be compensated by vacant land and other land use under this scenario. The third scenario is the residential scenario, which is assumed to provide more land for residential use in YTM. Based on the maximum plot ratio (7.5) assigned for Kowloon by the Planning Department and the average floor space per capita in the UK (35 m^2) in 2007 (Rector, 2007), the demand for residential land was determined accordingly. The balance of residential land is compensated by vacant land. The fourth scenario aims at achieving the balance of the improvement of housing and the sufficient provision of open space; therefore the demands of open space and residential land were calculated based on the standards in scenario 2 and scenario 3 respectively. And the increased land supply of residential land and open space is from G/IC, vacant land, and others.

The precondition of land use change by running the model restricts land use change of historical sites because heritage preservation is one of the most important considerations for urban renewal in Hong Kong (URS, 2011). There are four historical sites in YTM, the land use change of which were restricted in the simulation process. Similarly, some particular sites were restricted due to the redevelopment of residential sites. As YTM is a district of Kowloon, it is necessary to consider neighborhood effects on the land use. Therefore, data of neighborhood facilities were included in the analysis of location factors.

3.5 Model Validation

A land use change model is often validated by comparing model results of a historic period with the actual changes of land use (Verburg et al., 2004). In this research, kappa statistics is applied to assessing the accuracy of the model. Cohen's kappa measures the agreement between datasets for categorical items (Carletta, 1996). Kappa is more reliable than simple percent agreement calculation because it considers chance agreement. The general equation for k is:

$$k = \frac{\mathrm{P}(a) - \mathrm{P}(e)}{1 - \mathrm{P}(e)}$$

in which P(a) is the relative observed agreement between two maps and P(e) is the hypothetical probability of agreement due to chance. If the two comparing maps are in complete agreement then kappa value is 1; K value above 0.8 represents strong agreement or accuracy between two maps; K value between 0.6 and 0.8 represents high agreement; K value ranging from 0.4 to 0.6 means moderate agreement; and if the K value is below 0.4, the agreement is poor (Landis & Koch, 1977).

The confusion matrix (or contingency table) is the core to calculate the kappa value. The confusion matrix shows how the distribution of categories in simulated map differs from real map. P_{iT} represents the proportion of cells of category j in simulated map whilst P_{Ti} is the rate of cells of category j in real map. And P_{ij} is the proportion of cells of category i of simulated map in category j of real map (Sousa et al., 2002).

Table 1 Confusion matrix (adapted from Sousa et al., 2002)

Simulated map categories	**Real map categories**							
	j=1	**j=2**	**…**	**j=i**	**j=j**	**…**	**j=J**	**total**
j=1	p_{11}	p_{12}	**…**	p_{1i}	p_{1j}	**…**	p_{1J}	p_{1T}
j=2	p_{21}	p_{22}	**…**	p_{2i}	p_{2j}	**…**	p_{2J}	p_{2T}
…	**…**	**…**	**…**	**…**	**…**	**…**	**…**	**…**
j=i	p_{i1}	p_{i2}	**…**	p_{ii}	p_{ij}	**…**	p_{iJ}	p_{iT}
j=j	p_{j1}	p_{j2}	**…**	p_{ji}	p_{jj}	**…**	p_{jJ}	p_{jT}
Total	p_{T1}	p_{T2}	**…**	p_{Ti}	**…**	**…**	p_{TJ}	1

Based on this, the kappa is calculated as: $k = \dfrac{\sum_{i=1}^{J} p_{ii} - \sum_{i=1}^{J} p_{\mathrm{iT}} \times p_{\mathrm{Ti}}}{1 - \sum_{i=1}^{J} p_{\mathrm{iT}} \times p_{\mathrm{Ti}}}$

4 IMPLEMENTATION AND RESULTS

4.1 Temporal Land Use Change

4.1.1 Conversion probability

In order to predict temporal land use change by Markov chain prediction, transition matrix is a crucial instrument. Table 2 shows the matrix of transition probability calculated from land use change from 2000 to 2009. P_{ij} presents the probability of one land use type changing into another from 2000 to 2009.

Table 2 Matrix of transition probability from the 2000 to 2009

2000	**2009**						
p_{ij}	**Commercial**	**Residential**	**Industrial**	**G/IC**	**Open space**	**Vacant**	**Others**
Commercial	0.95	0.05	0.00	0.00	0.00	0.00	0.00
Residential	0.01	0.96	0.00	0.01	0.01	0.01	0.00
Industrial	0.03	0.31	0.66	0.00	0.00	0.00	0.00
G/IC	0.06	0.04	0.00	0.81	0.02	0.04	0.03
Open space	0.00	0.00	0.00	0.22	0.75	0.00	0.03
Vacant	0.11	0.14	0.00	0.04	0.14	0.50	0.07
Others	0.00	0.00	0.03	0.00	0.07	0.00	0.90

4.1.2 Land demands and scenarios

In order to supplement spatial simulation, temporal changes of land use need to be predicted. Markov chain was used to project the demand of the baseline scenario from 2009 to 2018. The demands of other scenarios are calculated by taking into account the baseline scenario and future policies in the study area. Table 3 displays the historical land demand calculated by the software package ArcGIS 10. From 2000 to 2009, the areas of commercial land, residential land, open space and other land increased while industrial land and vacant land decreased; the area of G/IC remained stable. Table 4 presents the land demands under four different scenarios in 2018. Markov chain prediction for the baseline scenario shows that commercial, residential and other land uses will increase continuously by taking up vacant land. The decreasing rate of industrial land is low since industrial land only takes up a small part of YTM.

Table 3 Areas for various land types in history (Unit: ha)

Year	commercial	residential	industrial	G/IC	open space	vacant	Others
2000	70.2617	106.4684	12.1246	87.3023	51.4901	149.3220	34.2637
2003	64.8760	128.6287	6.9258	93.9278	48.8408	130.2163	37.8174
2006	84.0548	131.8941	10.8074	90.7033	51.5202	97.4870	44.7660
2009	89.1069	133.8881	9.0288	89.8417	64.7818	78.4262	46.1593

Note: G/IC means government, institutional and community facilities.

Table 4 Land demand areas of three scenarios in 2018 (Unit: ha)

2018	Commercial	Residential	Industrial	G/IC	Open space	Vacant	Others
S1	99.621	150.2993	7.3063	92.1780	66.0249	43.5243	52.2790
S2	99.621	150.2993	7.3063	92.1780	117.2600	17.9072	26.6610
S3	99.621	161.4200	7.3063	92.1780	66.0249	32.4036	52.2790
S4	99.621	161.4200	7.3063	80.2300	117.2600	17.9072	27.4883

Note: G/IC means government, institutional and community facilities. S1 means the scenario 1. S2 means the scenario 2. S3 means the scenario 3. S4 means the scenario 4

4.2 Regression Analysis of Land Use

The CLUE-S model requires setting the relationship of location factors and different land uses. Typical driving factors were chosen to analyze the location suitability of these seven land use types. These factors were selected based on relevant literature, including physical, socioeconomic attributes and proxy variables (Wang et al., 2013; Zondag & Borsboom, 2009; Braimoh & Onishi, 2007; Veldkamp & Lambin, 2001). Table 5 shows the selected location factors in CLUE-S model and the analyzed coefficients for the logistic regression. Each land use type has different factors contributing to its location. For example, the location of residential land is related to factors including slope, distance to MTR stations, distance to historical sites, distance to road, distance to school, distance to open space, and population density.

To validate the reliability of the logistic regression, the ROC curve was used. The ROC is used to measure the goodness of fit of the logistic regression mode (Baldwin et al., 1998). All the ROC values in the Table 4 are above 0.7, which indicate that these location variables preferably explain the location of land use.

Table 5 Estimated coefficients of binary logistic regression for different land use types

Driving Factors	Commercial	Residential	Industrial	G/IC	Open Space	Vacant	Others
Slope		0.1599	0.3967	0.0987			
Elevation	0.1135		0.1288	-0.0679	-0.0371	-0.1794	0.1028
Distance to CBD	-0.0181			-0.0032			0.0071
Distance to airport							-1.0436
Distance to MTR stations		-0.0047	0.0071			0.0064	

Distance to bus terminus				-0.0017	0.0016	0.0011	0.0034
Distance to coastline				0.0027			-0.0077
Distance to historic sites		0.0007	0.0033	-0.0010			0.0022
Distance to schools		-0.0024			-0.0009		
Distance to open space		0.0006	-0.0068		-0.0932	-0.0014	
Distance to road		-0.0280	-0.0171		0.0314	-0.0097	
Distance to hospital	0.0020		0.0060	-0.0003			-0.0081
Population density	-20.9384	17.5029		-21.9404		-11.8701	
Property price						0.0001	0.0001
Roc Value	0.9230	0.8580	0.9580	0.7810	0.8700	0.9070	0.8130

4.3 Model Validation

Model parameters were set based on the historical data from 2000 to 2009. The simulated land use pattern of 2009 was achieved on the basis of land utilization map in

2000. Figure 4a shows the land utilization map of 2000. The simulated land utilization map of 2009 (Figure 4b) was achieved based on Figure 4a in the CLUE-S model, and the real land utilization of YTM in 2009 is displayed in Figure 4c. The overall accuracy is 81.53%, which shows the percent of the number of pixels simulated correctly to the total number of pixels. Kappa value calculated by the ENVI 4.7 software is 0.7753, representing a substantial agreement, which indicates the effectiveness of the model's setting to conduct the future simulation. Table 6 shows the contingency table, which is the basis for calculating the kappa value.

Table 6 Contingency table

Simulation (unit: percent)	**Reality (unit: percent)**						
	0	**1**	**2**	**3**	**4**	**5**	**6**
0	86.47	6.59	0.00	1.21	1.77	0.00	2.36
1	4.67	85.43	1.34	3.85	11.03	1.28	6.98
2	0.22	1.40	77.68	0.00	0.00	0.00	0.00
3	4.00	4.29	0.00	79.25	6.09	4.66	4.54
4	4.31	1.49	9.82	12.46	64.53	0.31	9.42
5	0.04	0.00	0.00	1.30	3.35	92.68	5.67
6	0.27	0.80	11.16	1.93	13.22	1.08	71.03

Note: 0 represents commercial land, 1 represents residential land, 2 represents industrial land, 3 represents the zone of government, institutional and community facilities, 4 represents open space, 5 represents vacant land, 6 represents other land uses.

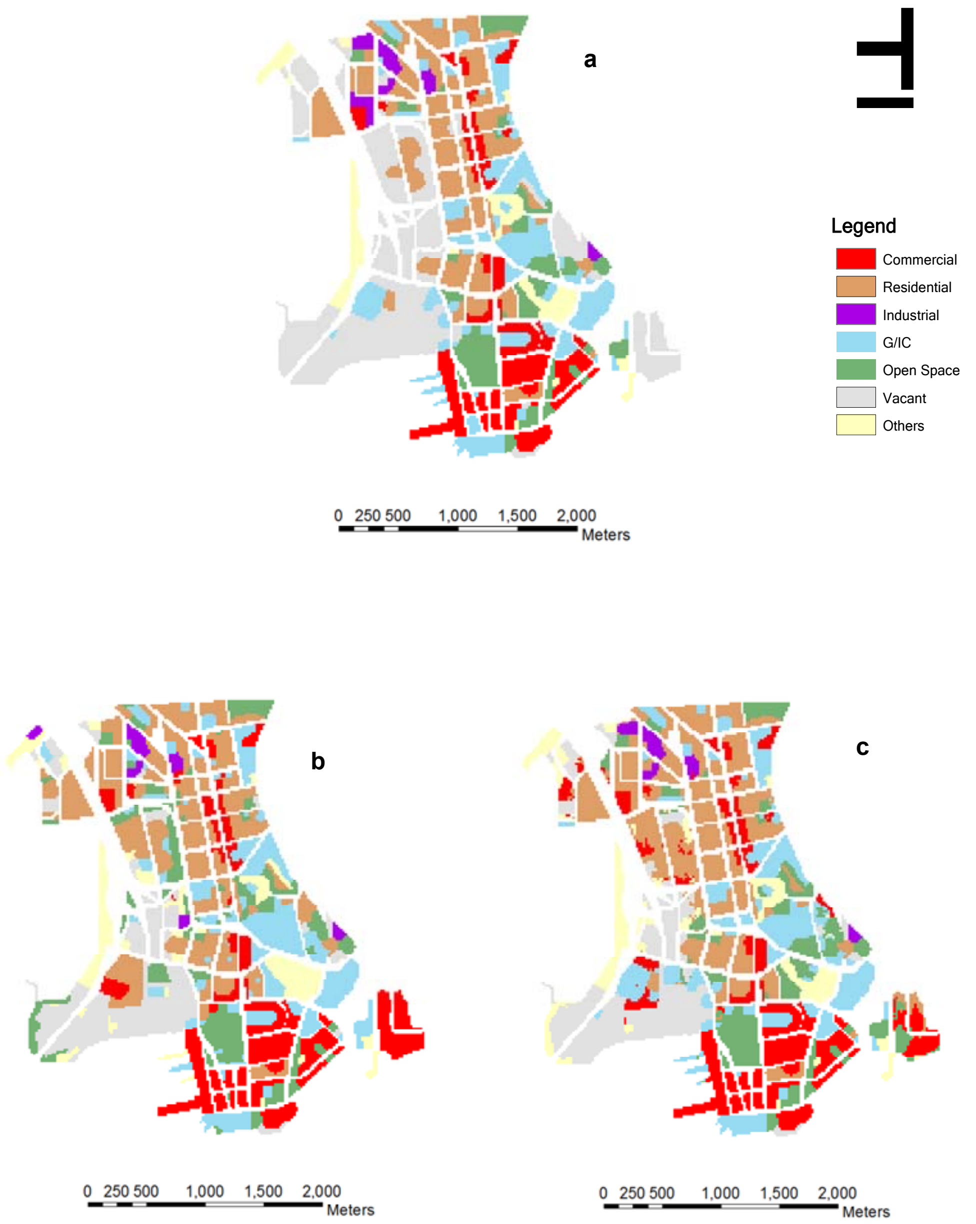
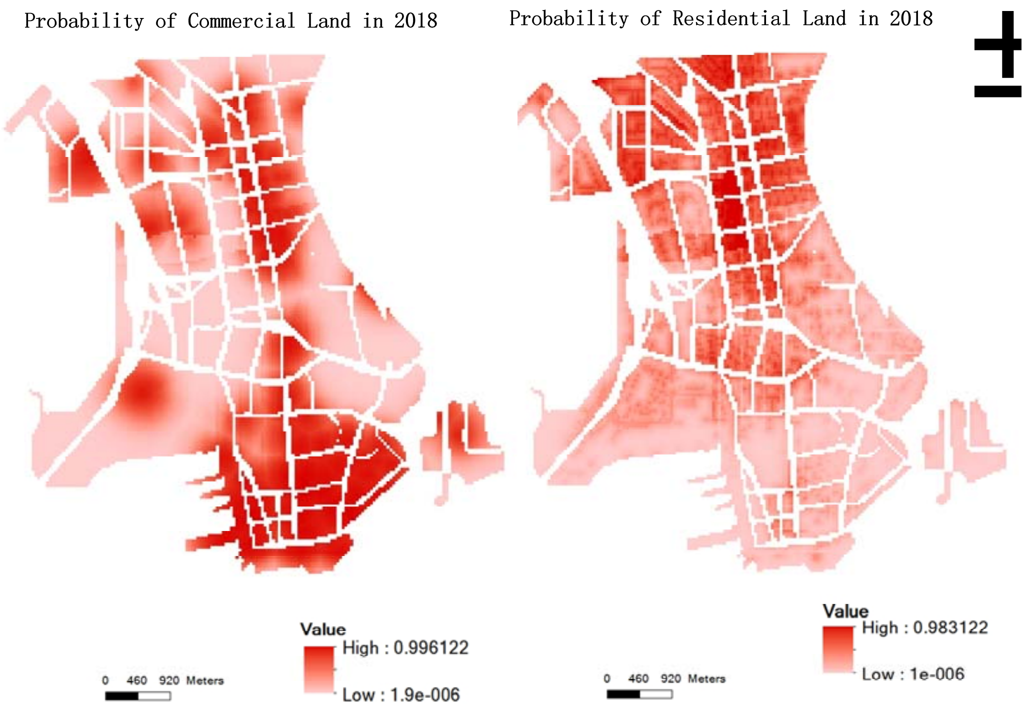


Fig. 4 **(a)** Real land utilization map of year 2000, **(b)** real land utilization map of year 2009, and **(c)** simulated land utilization map of year 2009

4.4 Simulation Results

4.4.1 Probability maps of different land use types

After validating the proposed model, the validated model was used to simulate future land use in 2018. By using the function of calculating probability maps in the CLUE-S model, seven probability maps for different land use types (commercial, residential, industrial, G/IC, open space, vacant, and others) were produced accordingly (see Figure 5). Commercial land has a higher probability of being located at the south part of YTM, which is near the coastline, while residential land is more likely to be located at the north part of YTM, which is the old district of Kowloon. Industrial land has a low probability of being located at most parts of YTM, except in a small part near Tai Kok Tsui in the northwest of YTM. G/IC is more likely to be located at districts near King's Park and Kowloon Park. Open space has a comparatively equal probability of location except the northwest part with a lower probability, which implies a need for open space in these districts. Vacant land has a higher probability of locating at the west part of YTM, which is associated with the reality that developed land may not change back to vacant land for a long time.


Probability of Commercial Land in 2018

Probability of Residential Land in 2018

Fig. 5 Probability maps of different land use types in 2018

4.4.2 Simulation maps

The land use demands in 2018 for four scenarios were input into the CLUE-S model separately (see Table 4). After running the CLUE-S model with the calibrated model settings, land use patterns under four scenarios were simulated (see Figure 6). The baseline scenario indicates that the supply of new land is from vacant land mainly in West Kowloon. The simulation results display the differences between the four scenarios. There are more open space areas in western Kowloon by taking up vacant land and other land uses under the open space scenario. There is more residential land in the west part of YTM under the residential scenario compared with the baseline scenario. Compared with the historical data in 2009, the increased land supply of residential is mainly from some vacant land and G/IC land. For scenario four, the location of open space is similar compared with that under the open space scenario. And there is more residential land in the northwest part than that under the second scenario.

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Fig. 6 Simulated scenarios of land use in 2018

5. DISCUSSION

This research combined the CLUE-S model and the Markov chain prediction model to analyze land use change from both spatial and temporal dimensions. The model parameters were based on the historical land use data from 2000 to 2009. Comparing the simulated land use with the actual land use in 2009 validated the model. The kappa value is 0.7753, demonstrating the reliability of the model simulation. The simulation results of future land use in 2018 display the future land use alternatives under four different scenarios. This research is a pilot study for applying simulation model to explain land use change in urban renewal areas. Also, while previous studies on land use change tended to focus on large-scale renewal, this research is at the district level, which is a proper scale for decision-making. Furthermore, the selected factors for land use change are more comprehensive.

The model developed in this research considers land use allocation factors including physical, locational, social and economic attributes, which are comparatively comprehensive. Policy factors, which are difficult to capture and express in some other models, are reflected in this model. In Hong Kong, policy plays a crucial role in land use allocation. For example, in order to solve the problem of residential land shortage, the government proposed “Hong Kong land for Hong Kong people”, which means one specific parcel of land is restricted to residential use for Hong Kong permanent residents only. In the simulation, historical sites and parks were restricted to stable land use. Similarly, some particular sites were restricted due to spatial policies, such as urban redevelopment of residential sites. This shows the possibility of using models to simulate land use change in urban renewal areas instead of simply discussing or analyzing land use change qualitatively.

Temporal land use change in history is associated with the fact that there is more commercial and residential land supply in YTM after the handover of Hong Kong to China. The possible reasons are: (1) more immigrants move to Hong Kong, which stimulate developers to construct more residential housing with rising property price in Hong Kong; (2) government has been being striving to provide more residential housing during the past decade; (3) the development of tourism after the handover of Hong Kong to China explains why there are more commercial land. Based on Markov chain prediction, which means following the historical trend, there will be more supply of commercial and residential land in 2018. The probability maps for different land use types provide an explicit understanding of land allocation probability spatially.

Decision-makers for urban renewal could understand the direction of future land use, discover possible problems of land use, and then make more informed decisions. For instance, the probability value of open space is low in the northwest region, indicating that attention should be paid to this area for sustainability. The simulated scenarios show that land development in YTM often takes place by occupying vacant land or industrial land. The results are reasonable for two reasons: (1) developed land always has constant inertia, which means that it tends to follow its original use; (2) land use change occurs when new land use type is able to provide more value especially economic value in a free market. And compared with developed land, vacant land has lower value. To improve sustainability, redeveloping some old sites or brownfield sites may be more favorable. From a practical perspective, the main benefits of simulated scenarios can reveal problems resulting from interventions of different policies, indicate the trend of land use change, and provide a more comprehensive understanding of land use mechanisms in urban renewal areas, all of which can serve as important references for decision-making in relation to sustainable land use in the urban renewal process.

However, the kappa value (0.7753) implies a limitation of the proposed model, since only a K value above 0.8 represents strong agreement or accuracy. The urban land system is very complex and no single model can capture all aspects of the land use change mechanism (Verburg et al., 2008). This is especially so in the case of Hong Kong's history of land reclamation, high density, developed land, and system of land management. As some social and economic data cannot be obtained at a district scale, such as economic output of each land unit, density of land use, and employment density, some variables of land allocation were ignored in this research. For future related research, methods of obtaining such data for small-scale urban renewal could be developed. Also, as some qualitative factors, such as land ownership and land lease cannot be reflected in this kind of model, combining qualitative and quantitative analysis is a potential direction for future research. Urban renewal in Hong Kong associates with land use density change more rather than land use type change, investigation on this issue can provide a better understanding of urban renewal in Hong Kong. Therefore, it is suggested to touch this issue in future research. Finally, as actual land use may take a multitude of directions in the future, further studies could simulate more alternative scenarios by adjusting the model's settings.

6. CONCLUSIONS

A comprehensive understanding of land use change mechanisms and directions is crucial for land use planning decisions. Land use planning for urban renewal areas is different from planning new towns since the land sites in renewal area have been developed for many existing uses (Wang et al., 2013) . However, previous research on land use change often overlooked urban renewal districts. This research proposed a combined model to explore land use change mechanism in one renewal area of Hong Kong.

Considering both spatial and temporal dimensions, a land use change model (combining the CLUE-S model and the Markov chain prediction model) was developed and validated to simulate four land use scenarios in 2018. The simulation results indicate that land use change is influenced by physical, locational, socio-economical, and political factors, and the selected 14 factors (see Table 4) can explain land use allocation to a large extent. This can be a complement to qualitative analysis on the mechanism of land use change in urban renewal areas. The results also show that vacant land has a higher priority of being utilized when a development is required. To improve sustainability, it is necessary to consider redeveloping decaying sites rather than developing new land. Due to data limitations and the complexity of the urban land system, land use change analysis depending on this proposed model may not be enough, and more factors and scenarios should be included and generated in the model to better facilitate the decision-making process.

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