Coupling Machine Learning and Cellular Automata-Markov Chain to Model Urban Expansion in a Fast Developing Area: A Case Study of Liangjiang New District of Chongqing, China

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Abstract

Timely monitoring and modeling of landuse change is vital to manage land resources effectively and to rectify defective land use policies, especially in rapidly urbanizing areas. Our research is applied to an annual land use dataset in order to simulate urban expansion in a fast developing area, through a hybrid model coupling Artificial Neural Networks (ANNs), cellular automata (CA), and Markov Chain (MC). The ANNs were optimized to create the urban suitability index (USI) map that was then integrated with CA-MC to spatially allocate urban expansion cells. Two ANNs, multiple-layer perceptron (MLP) and long short-term memory network (LSTM), were implemented comparatively. Since LSTM is able to take into account more temporal information, it outperformed MLP in modelling urban expansion process over a short temporal interval. The results, validated using kappa and fuzzy kappa simulation, indicate that the integration of ANNs with CA-MC can capture the possible nonlinear relationship between urban expansion and its drivers, hence it can accurately simulate and predict urban expansion in the study area.

Keywords: urban expansion, artificial neural network, long short-term memory network, multiple-layer perceptron, cellular automata, Markov Chain

1. Introduction

Since the economic reform in the late 1970s, China has been experiencing a rapid economic development and urbanization driven partially by a dramatic increase in urban population (DÉMurger *et al*., 2002; Deng *et al*., 2008; Zhang *et al*., 2014; Engelfriet and Koomen, 2017; He *et al*., 2017). However, the fast but unsustainable urban development in the past decades has caused many pressing issues that became obvious in recent years. The massive and chaotic urban expansion caused inefficient and irrational use of limited land resources, polluted the environment, damaged or destroyed the sensitive ecosystem, and degraded agricultural and forest land (Jat *et al*., 2008; Huang *et al*., 2009; Shafizadeh Moghadam and Helbich, 2013 and 2015). Naturally, many researches has done to monitor and model such changes (Sudihar *et al*., 2004; Liu *et al*., 2005a; Deng *et al*., 2009, Seto *et al*., 2011; Jiang *et al*., 2012).

Current urban expansion modeling is limited by a coarse temporal resolution owing to the lack of suitable data. Many of the empirical studies treated the temporal increment as five-year intervals or longer for the urban expansion model, due to the normal life cycle to form a new urban area from an existing one (Deng *et al*., 2009; Ma and Xu, 2010; Shafizadeh Moghadam and Helbich, 2013 and 2015; Arsanjani *et al*., 2013). However, this temporal resolution does not allow urban expansion in rapidly developing cities to be detected timely, especially in some industrial districts (Seto *et al*., 2011; Xu *et al*. 2012). Thus, it is impossible to assess unanticipated effects of land use policies abruptly promulgated by central and local governments (Zhang *et al*., 2014; Liu *et al*., 2015; Zhan *et al*., 2017), let alone remedy the problems arising from them. Therefore, a shorter temporal interval is highly desirable in modeling and analysing urban land use change to reveal more frequently updated details both spatially and non-spatially, hence to better explain the dynamic process within a rapidly growing urban area (Yue *et al*., 2013).

Another issue in urban expansion modeling is the limited predictive ability of individual models. In recent years, due to the extensive use of geo-informatic technologies, studies on urban expansion have advanced from static descriptions to spatial dynamic simulation modelling. GIS-based models with a spatial scope, such as Cellular Automata (CA) (Batty *et al.* 1999, Li and Yeh 2000, Sudhira *et al.* 2004, Aburas *et al.* 2016), Multi-Agent Model (Arsanjani *et al.* 2013b, Zhang at al. 2015), Land Transformation Model (Pijanowski *et al.* 2002) and SLEUTH (Jat *et al.* 2017), have been used to simulate urban expansion processes. They all attempt to capture the complex nonlinear relationship between driving factors and urban expansion, via the 'bottom-up' model approach and various transition rules. Among these models, Cellular Automata with Markov Chain (CA-MC) is found to be one of the most frequently used since it can be easily integrated with analytic hierarchy process (AHP) and logistic regression (LR) models to create the urban suitability index (USI) map and predict the urban expansion demand based on Markov chain (MC). It can also spatially allocate the amount of urban land based on CA by taking fewer variables into consideration than other models. However, the self-adaptive ability of CA-MC to model the nonlinear relationship between drivers and the urban dynamic process is still not completely reliable (Arsanjani et al. 2013, Arbus et al. 2016, Gosh *et al.* 2017).

Reliability can be improved by replacing AHP and LR with Artificial Neural Networks (ANNs). ANNs have advantages in simulating urban expansion owing to their ability to model complex non-linear relationships between the dependent and independent variables while involving fewer statistical assumptions than LR (Islam *et al.* 2018, Hagenauer and Helbich 2012, Pijanowski *et al.* 2014). The 'learning' power of ANNs enables CA-MC to be self-adaptive, and the automatic approximation of non-linear functions by ANNs is especially important when the relationships between variables are not known in advance (Paliwal and Kumar 2009). For this reason, ANNs have been independently incorporated into other models to simulate and predict urban expansion despite the difficulties in properly parameterizing and optimally configuring an ANN model. Xu et al. (2019a, 2019b) integrated ANN with CA-MC to simulate and predict urban expansion in the U.S. and Auckland, New Zealand. Results from those studies have demonstrated that such innovative integration can improve the accuracy of simulation. Therefore, the main objective of this paper is to integrate two ANNs into CA-MC for simulating spatiotemporal dynamics of urban expansion in a fast developing area and assess the model capability.

2. Study area and data

2.1. Study area

The Liangjiang New District of Chongqing, Southwest China is chosen as the study area because it has been experiencing rapid growth since 2009. It comprises three industrial zones (Longxing, Yufu, Shuitu), two duty-free ports (an airport and a harbour), plus several counties (Figure 1). Characterized by an area of 1172 km², it has been designated as the first hinterland development and a showcase zone for Southwest China. Thus, this district plays a very critical role in the regional economic development. It enjoys both local and national incentivized land use policies that, in conjunction with the open investment environment and promising future development plan, catapulted the district to unprecedented urban expansion, consuming a significant amount of land resources. The population of the district was projected to reach 3.5 million within a 350 km² built-up urban area by 2020. However, the actual built-up area is expected to surpass the targeted area in a short time since the number had already reached 344 km^2 in 2014, with an average annual growth rate at 7.5%. Thus, further development will have to rely on a more intensive use of the land. Therefore, it is very critical to model, allocate, and plan new urban areas judiciously from now on.

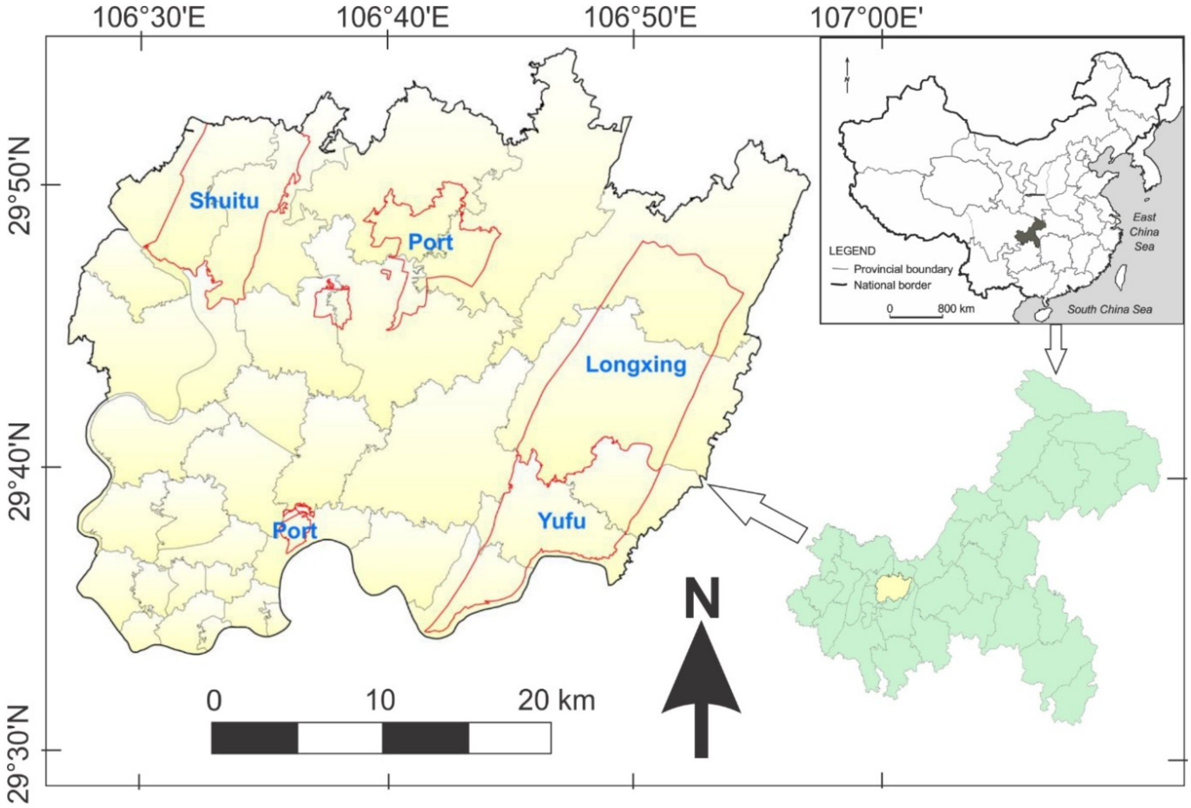


Figure 1**:** Location of the study area, the Liangjiang New District of Chongqing in Southwest China. Red lines: boundaries of industrial zones and the duty-free ports; grey lines: county boundaries.

2.2. Data

The National Annual Land Use Survey Database was used in this study, in which land use was mapped at different levels. The database is updated annually using a land use transformation monitoring approach involving remote sensing and field survey data (Ministry of Land Resource, China, 2007). Such an annual database enables land use change to be monitored periodically so as to plan urban growth effectively. We simplified the data from the original 25 classes to 9 categories (farmland, orchard, forest, grassland, transport, water bodies, bare land, urban land, and other land use).

In addition, for every grid cell in question during the modelling, its neighbourhood effects in different years were also calculated because they would affect the cell status in future years. Other urban expansion drivers, such as distance to existing urban areas, road network, and utilities were also considered as independent attributes for every cell during modelling (Table 1).

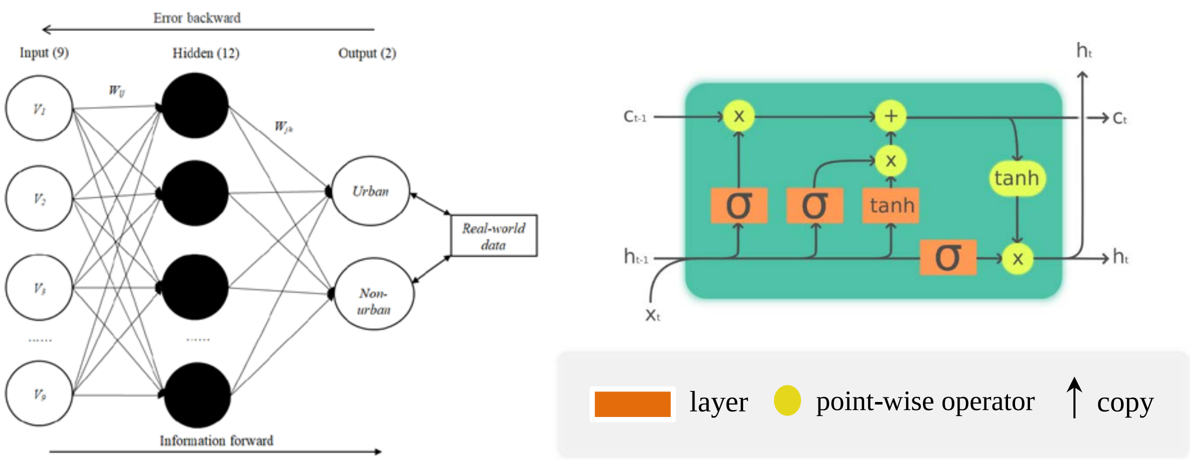
Variable	Description
Dynamic variables	
Distance to existed urban	Euclidean distance between the target cell and existed urban cell
Distance to new road	Euclidean distance between the target cell and newly built roads
Cell neighbourhood	The proportion of different land use cells within 3x3 Moore neighbourhood
Static variables	
DEM	Physical factor, elevation
Slope	Physical factor, slope
Distance to Motorway	Euclidean distance between the target cell and entrance or exit of Motorway
Distance to Arterial Road	Euclidean distance between the target cell and arterial road
distance to urban major road	Euclidean distance between the target cell and urban major road
Distance to urban medium road	Euclidean distance between the target cell and urban medium road
Distance to urban small road	Euclidean distance between the target cell and urban road
Distance to school	Euclidean distance between the target cell and school
Distance to transport	Euclidean distance between the target cell and bus stop, train station, and ferry port
Distance to hospital	Euclidean distance between the target cell and hospital
Distance to market	Euclidean distance between the target cell and market

Table 1： Variables considering in the modelling

3. Method

3.1. Artificial neural networks

ANNs are widely used modelling techniques with self-adapting, self-organizing, and self-learning abilities (Li and Yeh 2002, Park *et al.* 2011, Berberoğlu *et al.* 2016). In this study, two ANNs are integrated with CA-MC: MLP and LSTM. The MLP is considered as the most frequently used and constructed with the efficient feed-forward, error Back-Propagation Three-Layer Perceptron (BP-TLP) ANN architecture (Figure 2a). It was adopted to simulate urban expansion owing to its simplicity, ease of training, and its abilities for reasonable associative memory and prediction (Rumelhart *et al.* 1986). While LSTM is explicitly designed to avoid the long-term dependency problem and has a strong focus on temporal (sequential) scale, it can be combined with CA-MC to extract spatial information (Lipton, 2015). Instead of feed-forward, it is a recurrent neural network including a delayed input, also known as the feedback of output that creates a chain of repeating modules of the neural network (Figure 2b). For both ANNs, the most important criteria of their architecture is the number of hidden nodes in each hidden layer, which significantly affects ANNs performance (Hagan et al. 1996). Too few nodes will cause a significant prediction error, while too many will prolong the training process and lead to overfitting. The networks were trained stepwise iteratively with a targeted mean square error (MSE) of 0.01 between the model output and the real-world data. However, reaching this MSE threshold might cause overfitting, which was avoided by setting the number of training epochs to 500, and the maximum fail number to 15. These two parameters reduced the possibility of overfitting by early stopping. In addition, the training bitch size of LSTM also impacts the final result that it usually set to be an integral times of the data time.



(a) (b)

Figure 2: (a) The architecture of MLP (the BP-TLP) ANN adopted in this study. V is the input, W_{ij} and W_{jk} are the connecting weights. (b) The architecture of LSTM. $\boldsymbol{X}$ is the vector input; $\boldsymbol{h}$ is a hidden state vector also known as the memory output vector of the LSTM unit; $\boldsymbol{c}$ is the cell state vector, σ and tanh are the activation functions.

3.2. ANNs Markov Chain – Cellular Automata

The Markov Chain (MC) model determines the expected amount of non-urban land transition to urban use in future urban expansion. It calculates the land use change process through the transitions of different land use types at a temporal interval of one year. Two results are generated from MC: a transition area matrix, which shows the absolute amount of change from different non-urban land uses to urban land, and a transition possibility matrix, which reveals the likelihood of the transition.

CA uses the current cell status and the cell's neighbourhoods to predict the future cell status, as expressed in Equation 1:

$$S^{t+1} = f(S^{t}, N, R) \quad \text{Equation 1}$$

In which S^{t+1} and S^{t} denote the cell state at time *t* and *t+1*, respectively; *N* is the effect of a cell's neighbourhood; *R* is the transition rule; and *f* is the state transition function. For regular MC-CA, *R* is the transition possibility matrix produced from MC, which shows only the numeric results from two land use datasets without any information on the spatial distribution of the modelled changes. This problem is solved by using the USI map generated from MLP (Equation 2) and LSTM (Equation 3).

$$USI\_MLP = f_{MLP}(V_1, V_2, \dots, V_i) \prod C \quad \text{Equation 2}$$

Where f_{MLP} is the activation function of ANNs; V_i is the i^{th} input variable, and *C* represents the constraint with a binary value of 0 or 1.

$$USI\_LSTM_t = f_t * USI\_LSTM_{t-1} + i_t * S_t \quad \text{Equation 3}$$

Where f_t is the forget function of LSTM; i_t is the scaling down function for input variables and cell state S_t, it is usually sigmod or tahn.

Hence, the final state (urbanized or not) of $cell_{ij}$ in this ANN-CA-MC will be represented as Equation 4:

$$S^{t+1}_{ij} = f_{ca}(S^{t}_{ij}, A^{t+1}, USI_{ann}, N_{multiple}) \quad \text{Equation 4}$$

Where A^{t+1} is the expected amount of expansion predicted by MC, and USI_{ann} is the USI generated from either the MLP or LSTM network, and $N_{multiple}$ represents different land use neighbourhood effects at cell (i, j) (*i* - row, *j* - column). The CA transition rules are now the combination of USI and *N*.

3.3. Model implementation

Figure 3 illustrates the detailed steps of how to integrate these two machine learning based ANNs with CA-MC to model the urban expansion. Annual land use data and spatial data such as DEM, slope, road network, and facility locations (Table 1) were collected to create a geodatabase in the GIS environment, from which the urban expansion areas and related driving factor values were extracted. Afterwards, both changed and unchanged cell samples were selected using the maximum dissimilarity distance algorithm (MDDA) or random sampling. The selected samples were used to train MLP and LSTM and to create the USI map. Also the annual land use data were fed to CA-MC to predict the expected amount of urban expansion. The ANN-CA-MC simulated the urban expansion at a certain time from the expected amount of expansion and the USI map output from either MLP or LSTM, taking into account the multiple neighbourhood land use effect. The output model results were validated against the actual land use data using kappa simulation. Only when the modelled results passed the validation process was the properly configured and trained model then used to predict future urban expansion that can provide convincing information for modifying land use policies and plans.

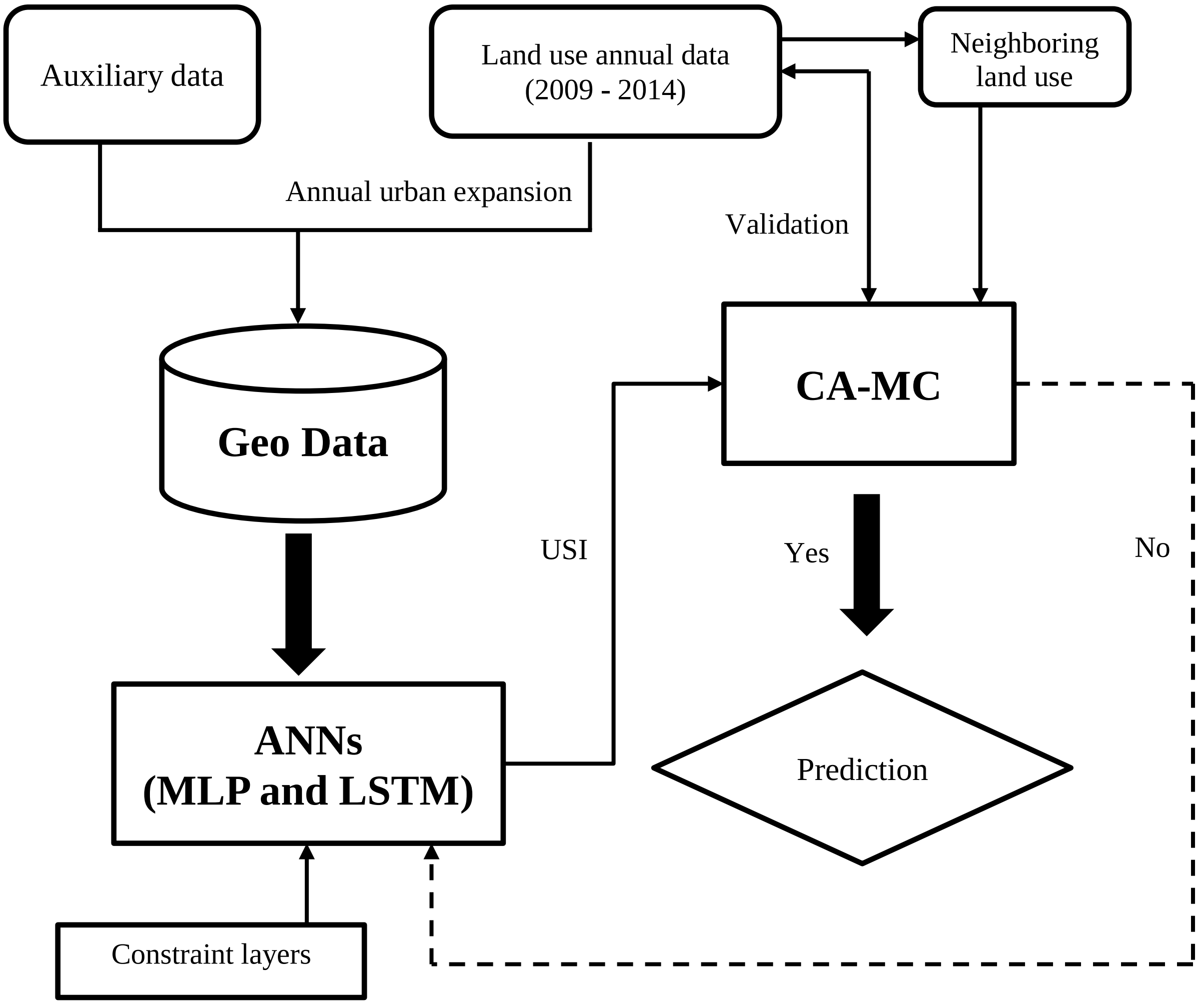


Figure 3. Flowchart of the ANN-CA-MC method in modelling urban expansion in Liangjiang District of Chongqing, China.

4. Result and discussion

4.1. Urban suitability index map

In the USI map (Figure 4) output from the ANN, the suitability of non-urban cells for urban expansion was graded from 0 (low) to 1 (high), coloured from green to red. This range was categorized into five classes (very high, high, moderate, low, and very low) using an equal interval to show the spatial distribution of these cells (Table 2). Based on the results from MLP (Figure 4A, 4B), we can see that the great majority of non-urban areas in the Liangjiang New District is not suitable for urban development as approximately over 75% of the cells have a suitability index <0.2. Cells having a suitability >0.6 are relatively small in quantity (approximately over 8%). They are located either close to or inside existing urban areas, confirming the "organic urban growth mode" with possible compact development (e.g., as infilling and edge development), all of which were accurately modelled by the MLP-based ANN. The most likely hotspots of future urban expansion are distributed in the industrial development zones, as well as next to the developed counties. The medium suitability value indicates possible future urban expansion. Both maps show that Longxing and Shichuan counties (top right) having this value are the next potential areas to be urbanized. However, both the quantity and spatial pattern of the USI from LSTM are different to those of the MLP network. Over 95% of these non-urban cells are predicted to have a very low likelihood of urbanisation in the future, while only 2.6% of them have a USI > 0.6, much lower than that number of the MLP. In addition, only a very small amount of non-urban cells has a medium USI value (0.2 – 0.6) with less than 0.5% of this area predicted to be transitioned to urban uses based on the LSTM. The spatial patterns of high USI with the LSTM are still close to existing urban cells but more dispersed, with a large amount of high USI cells only distributed in the three industrial zones, and very few outside their boundaries (Figure 4C). This zonal based distribution shows that the LSTM has the ability to capture the land use plan information through the temporal learning process.

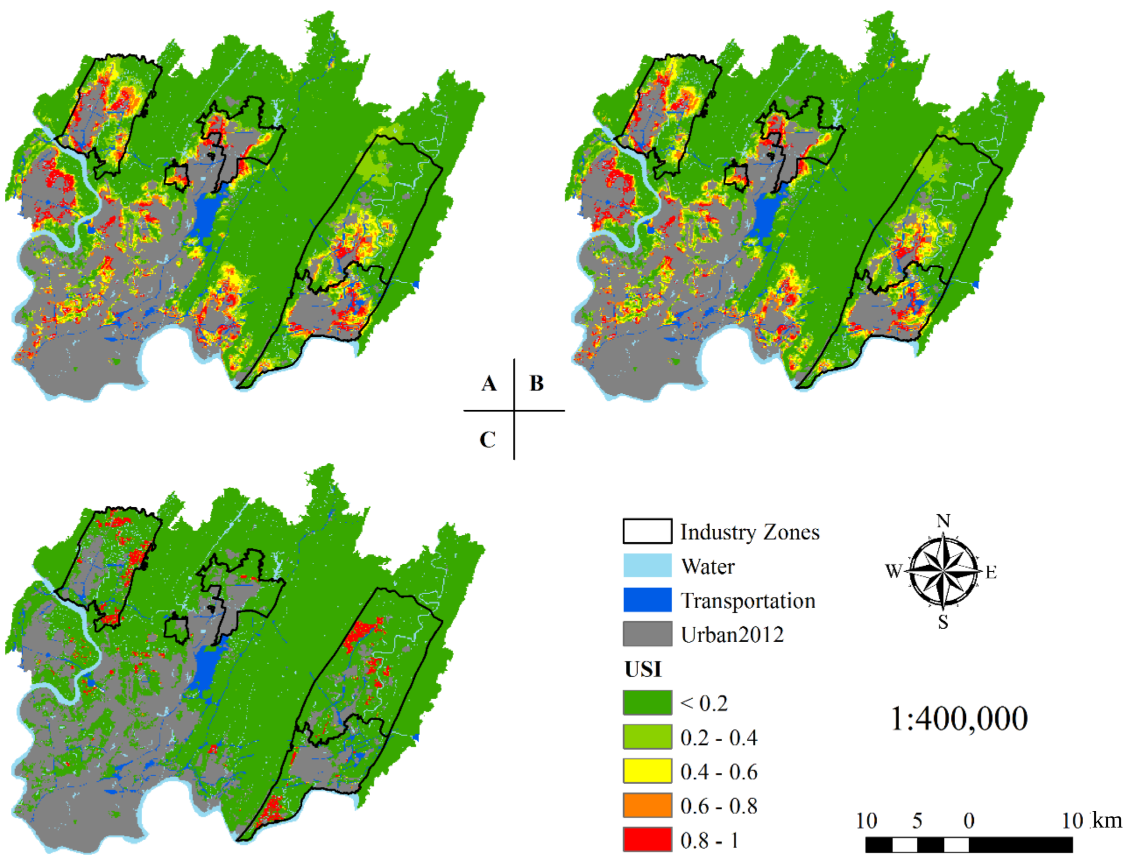


Figure 4: USI map of the study area from ANNs. (A) MLP with random sampling; (B) MLP with MDA sampling; and (C) LSTM.

Range	≥ 0.8	0.8 - 0.6	0.6 – 0.4	0.4-0.2	< 0.2
MLP-Random	31.27 / 3.9%	38.11 / 4.8%	47.94 / 6.0%	79.38 / 10%	596.38 / 75.3%
MLP-MDDA	28.65 / 3.6%	33.92 / 4.3%	44.98 / 5.7%	73.30 / 9.2%	612.23 / 77.2%
LSTM	19.27 / 2.4%	1.54 / 0.2%	0.87 / 0.1%	2.43 / 0.3%	769.00 / 96.9%

Table 2: Proportion of areas at five ranges of USI value predicted with three methods. (Unit: km^2)

4.2. Model validation and comparison

For the purposes of validation, the integrated ANNs-CA-MC model was used to simulate urban expansion in 2014 based on the annual land cover change from 2009 to 2013, and the validated modelling results are shown in Table 3. MC analysis yielded an expected urban expansion by 46.3 km^2 in 2016, against the actually expanded area of 48.78 km^2, leading to a maximum simulation accuracy of 95%. All the models have a high degree of local agreement (kappa > 80%) between the modelled and the reference urban area, which indicates that both MLP (regardless of the sampling method, either random or MDDA) and LSTM can simulate the urban area in 2014 precisely. Judged against (fuzzy) kappa simulation that takes transition/change into account and that corrects the agreement between two maps for the size of class changes and compares the variations instead of the status of the land cover (van Vliet *et al.* 2011), LR has the lowest values indicating its weakest ability to model nonlinear relationship among all the algorithms. LSTM has the highest validation values among the models, and thus the most accurately modelled results because of its capability to learn with a short time interval, which is important in modelling fast growing urban areas.

Method	Kappa	Kappa simulation	Fuzzy kappa simulation
LR	0.818	0.27	0.51
MLP-Random	0.829	0.36	0.64
MLP-MDDA	0.827	0.32	0.53
LSTM	0.857	0.48	0.70

Table 3: Validation results of (fuzzy) kappa simulation of four types of models.

The same model was applied to southern Auckland, New Zealand, using a similar set of geodata. All the model validation values are higher in Auckland than in the Liangjiang New District. With southern Auckland, the ANN-CA-MC could simulate the urban expansion with a very high kappa (0.94) and acceptable kappa simulation (>0.50), demonstrating that both the urban pattern and urban expansion can be modeled at a high certainty level (Xu et al. 2019b). However, in the Liangjiang New District, China, the model is less accurate. The validation results, though still considered acceptable, are not as good as with Auckland. The kappa was only slightly higher than 0.8 and the kappa simulation of MLP was even below the medium level (0.4 -0.6), and 0.48 of LSTM. They suggest that we could still locate the major urban areas (kappa) within the study area, but it is less accurate to simulate the changes of urban areas (kappa simulation). The most significant reason for this discrepancy is the role of land use policies and plan in the simulation that were not taken into account in the model, an issue that has also been identified by other researchers (Deng 2011, Fu et al. 2012, and Fu 2017). The aforementioned Liangjiang New District plays a very important role in the national development strategy of China, where urbanization needs to be fast paced and most of the new urban areas are pre-designated and planned by governments at both the local and national levels. Many policies and rules were used to restrict the location and distribution of future urban areas. Therefore, the urban expansion mode under government directions and guidance is much more complex, the location of urban areas is more definitive, and their spatial distribution is more dispersed, all those added difficulties to simulate and predict their future patterns. Another possible reason to explain the less accurate modelled results is the quality of data supplied to the model. For Auckland, urban information was extracted from aerial photos with a very high spatial resolution (0.5m), but it decreased to 30m for the Liangjiang New District. In addition, the precision of auxiliary data, such as DEM, had been degraded deliberately before they were released for public access from overseas.

5. Conclusion

In this study, we built two ANN-based CA-MC to model the urban expansion inside the Liangjiang New District. The obtained results demonstrate the possibility of using machine learning, such as ANNs, to improve the capability of CA-MC simulation of urban expansion. The ANNs-CA-MC outperformed LR-CA-MC with higher kappa and kappa simulation values. In simulation, the most important layer, USI map, can be efficiently created by MLP or LSTM, and it provides critical information on potential future urban areas. LSTM is more powerful at capturing temporal information, hence is more reliable than other two MLP CA-MC models with different sampling methods in simulating fast annual urban expansion process for the study area. Overall, the proposed modelling approaches can be used to yield relevant and useful information for urban planners and local government decision makers. However, the simulation results of the Liangjiang New District are not as good as in other urban areas, even with the same model and similar dataset. Unlike the urban class patterns, the changes cannot be well simulated possibly because the important role of land use policies from different levels of governments in urban development was not considered in the modelling. The effects of the government directed land use directives were randomly distributed land use patterns with an ambiguous expansion mode or trend that is very difficult to model and predict. Therefore, an integrated model is still needed to overcome the limitation in simulating human behaviour / policies at different scopes. In future research, multi-scenario modelling should be attempted to address the prediction uncertainty related to land use policies more appropriately (Arsanjani *et al.* 2013a, Shafizadeh Moghadam and Helbich 2013, Mustafa *et al.* 2017). In addition, socioeconomic factors, such as population density, income, and GDP, should also be considered to produce more reliable modelling outcome in future.

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Response Letter

----------------------- REVIEW 1 ---------------------
SUBMISSION: 3
TITLE: Coupling Machine Learning and Cellular Automata-Markov Chain to Model Urban Expansion in a Fast Developing Area: A Case Study of Liangjiang New District of Chongqing, China
AUTHORS: Tingting Xu, Jay Gao and Giovanni Coco

----------- Overall evaluation -----------
SCORE: 1 (accept)
----- TEXT:
An interesting paper and relevant to the conference. Some comments below.

Check capitalisation of "environment" in address

"much research has gone"?

"from existing one" -> "from an existing one"

Fig 2b. "pointwize"

"Only when the modelled results passed the validation process, the properly configured and trained model was then used"
-> "Only when the modelled results passed the validation process was the properly configured and trained model then used"

Fig 4. Scale bar should be in "km", not "KM". Remove scale text as it is unlikely to be correct after insertion of map into the document.

Table 3. Caption should be on same page as the table.

Rephrase: "causing it very difficult to model"

All these pointed out problems have been addressed with the revised file.

----------------------- REVIEW 2 ---------------------
SUBMISSION: 3
TITLE: Coupling Machine Learning and Cellular Automata-Markov Chain to Model Urban Expansion in a Fast Developing Area: A Case Study of Liangjiang New District of Chongqing, China
AUTHORS: Tingting Xu, Jay Gao and Giovanni Coco

----------- Overall evaluation -----------
SCORE: 1 (accept)
----- TEXT:
Interesting combination of CA and ANNs for modeling urban expansion.
Yet, the novelty and aim of the study could be formulated in a crispier way.

The initialism MC needs to be defined in the paper

Done

I am not too familiar with the USI but how can reliability be improved by replacing AHP and LR by ANNs?

A comparison study with these three models was done with a paper – “Simulation of urban expansion via integrating artificial neural network with Markov chain – cellular automata” (Xu et al., 2019) and revealed that it is quite reliable to use ANNs rather than AHP and LR in urban expansion model due to its capability to simulate the non-linear relationship.

Figure 2. what is pointwize op?

Revised it as “point wize”

Would it be possible to briefly describe the criteria used to define the architecture of the ANNs?

Due to the word limitation, we can only add some briefly descriptions. However, we can extent this part with more details if it is going to be published.

Table 3. caption and table are in different pages. can this be fixed?
Fixed.

Finally, please double check that the layout of your paper matches the one used in the provided template.

Thanks for the suggestion, we have double checked the format and now it matches the template.