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Model Simulation of Urban Land Use and Land Cover Change Based on Machine Learning Techniques: A Case Study of Shanghai, China

Hao GONG, Yuji MURAYAMA
Graduate School of Life and Environmental Sciences, University of Tsukuba
Email: <hiro.gonghao@gmail.com>

1. Introduction

A city is considered as a complex system. It consists of numerous interactive sub-systems and is affected by diverse factors including governmental land policies, population growth, transportation infrastructure, and market behavior. To understand the driving forces of the urban form and structure change, the multispectral satellite-based estimates are considered as the appropriate methods to monitor these dynamical change in a long term.

This research focuses on an automated artificial neural network (ANN) with a single hidden layer Multi-layer Perceptron (MLP) neural network module. The ability of automated ANN system with MLP module to perform the future Land cover/use changes based on supervised 6-categories Landsat classification results.

2. Data and Methods

Input layers of the MLP model are the multispectral supervised maximum likelihood classification results of two time periods - 2000 (Landsat 5 Thematic Mapper) and 2015 (Landsat 8 Operational Land Imager) (Table 1). One of the most changing cities in past two decades - Shanghai was selected to test the model. The scale of the study area is 100 x 100 km^2 (Fig.1).

Table 1. LULC changes in Shanghai (2000-2015).

	2000		2015		Net Changes (2000-2015)	
	ha ('000)	% of total	ha ('000)	% of total	ha ('000)	% of 2000
Built-up	270.40	27.03	437.72	43.75	167.32	227.69
Forest	42.99	4.30	8.71	0.87	-34.27	-79.73
Cropland	343.28	34.31	257.94	25.78	-85.34	-24.86
Grassland	59.95	5.99	43.98	4.40	-15.97	-26.64
Other	10.69	1.07	16.47	1.65	5.78	54.11
Water	273.10	27.30	235.58	23.55	-37.51	-13.74
Total	1000.40	100.00	1000.40	100.00		

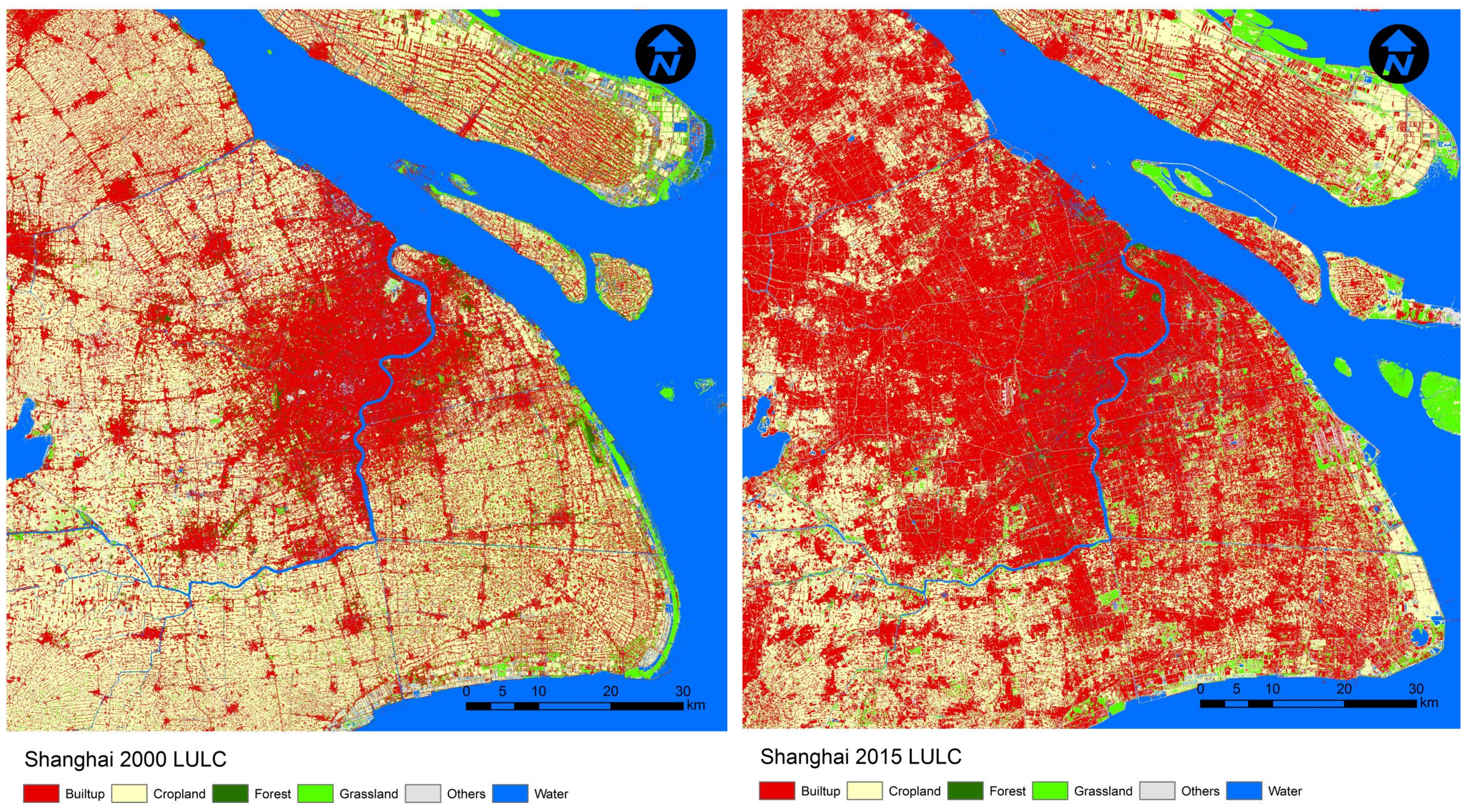

Figure 1. Land use/cover changes in Shanghai (2000-2015).

In the MLP model, we utilized supervised learning techniques (back propagation) for training the network. As a fully connected MLP model (Fig.2), 6 input layer neurons, 6 hidden layer neurons and 2 output layer neurons model were constructed in this study for each sub-model. The batch size (samples per class) is 10,000, and 5,000 times iteration for per sub-model running. Considering the geographical changing pattern, the transition from all categories to built-up was excluded.

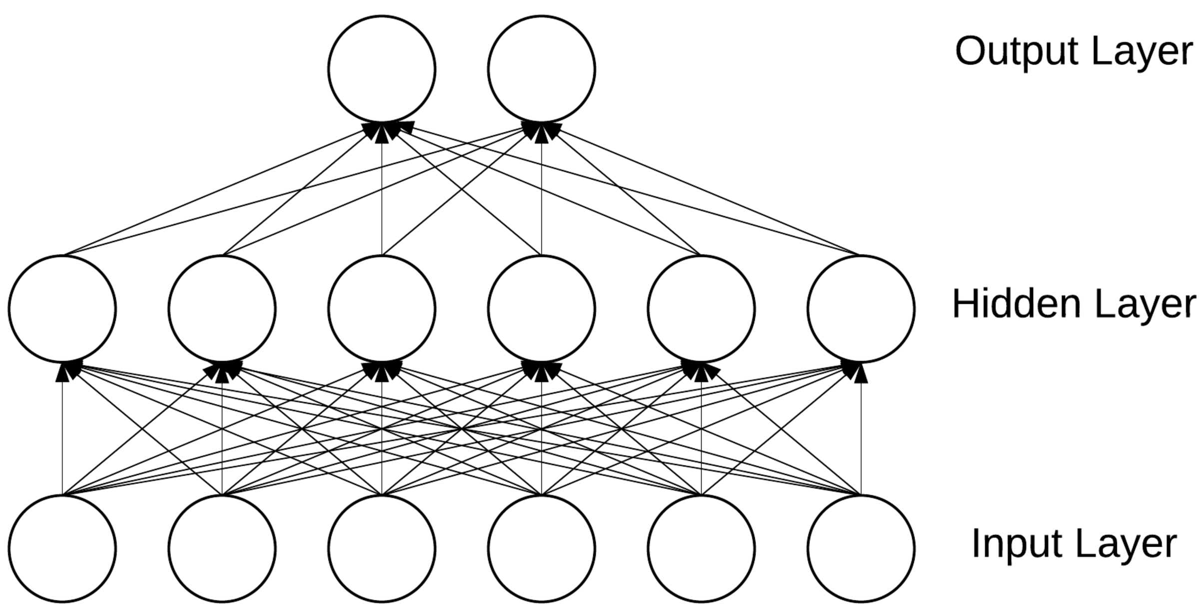

Figure 2. Framework of the single hidden layer Multi-layer Perceptron (MLP) neural network module.

Formally, a single-hidden-layer MLP is a *function* $f: R^D \rightarrow R^L$, where D is the size of input vector x and L is the size of the output vector $f(x)$, such that, in matrix notation:

$$f(x) = G(b^{(2)} + W^{(2)} (s(b^{(1)} + W^{(1)} x))),$$

with bias vectors $b^{(1)}$,$b^{(2)}$; weight matrices $W^{(1)}$, $W^{(2)}$ and activation functions G and s.

The vector

$$h(x) = s(b^{(1)} + W^{(1)} x)$$

constitutes the hidden layer. $W^{(1)} \in R^{D \times Dh}$ is the weight matrix connecting the input vector to the hidden layer. Each column $W_{\cdot i}^{(1)}$ represents the weights from the input units to the i-th hidden unit.

The output vector is then obtained as:

$$o(x) = G(b^{(2)} + W^{(2)} h(x))$$

To train an MLP model, we learn all parameters of the model, and here we use Stochastic Gradient Descent with mini batches. The set of parameters to learn is the set $\theta = \{b^{(1)}, b^{(2)} , W^{(1)}, W^{(2)}\}$. Obtaining the gradients can be achieved through the back-propagation algorithm (a special case of the chain-rule of derivation).

3. Results and Conclusions

Through this study, the prediction of future land use/cover changes was simulated for 3 separated stages, 2016, 2018 and 2020 (Fig.3). In order to control the unpredictable factors, water body was fixed in the model. The deeper color in the potential map, then the higher possibility that the remaining land use/cover will be transferred to the built-up category. Furthermore, with the automated ANN-MLP model, future changes can be predicted with reasonable results and relatively good accuracy.

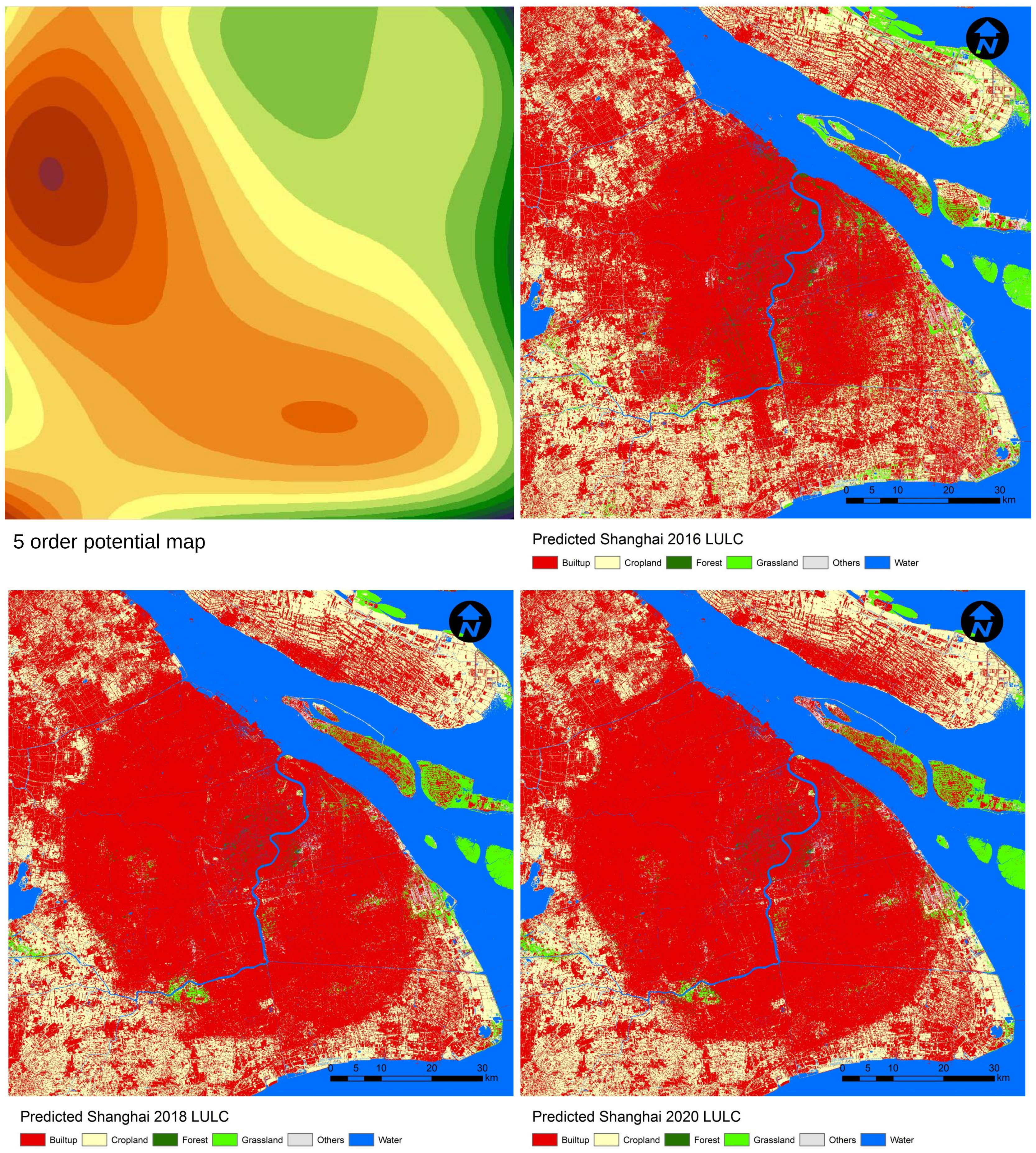

Figure 3. Prediction results for the future land use/cover changes by MLP model.