

Dataset of Land Use and Proximity Variables in Panyu District, Guangzhou (1999, 2008)

Zhang, Y. H. Qiao, J. G.*

School of Geography and Tourism, Guangdong University of Finance and Economics, Guangzhou 510320, China

Abstract: Studies have shown that urban expansion is often related to a series of proximity variables. Therefore, ArcGIS software is used to obtain proximity variables, such as, distance from the district center, distance from the metro lines, distance from the metro stations, distance from the roads, and distance from town centers. These proximity variables can be used to build an urban expansion CA model. They also can be used to analysis parameter sensitivity of model. As the Geospatial Data Cloud (<http://www.gscloud.cn/>) provides free Landsat remote sensing data, this paper selects the data in 1999 and 2008. And then orthorectification, atmospheric correction and supervised classification are performed to obtain the classification results, which are used for start and verification images of the urban expansion CA model. By using the map service provided by the National Geographic Information Public Service Platform (<http://www.tianditu.gov.cn/>), the metro stations, metro lines and roads in the study area were digitized, and the district center and town center were obtained to form the vector dataset. These vector datasets were applied to Euclidean distance analysis to obtain the spatial variables of the study area. All the spatial variables were normalized to facilitate the comparative analysis. The dataset is archived in .txt, .img, .xml, and .rrd formats, which is mainly composed of 24 files, and the file size is 1.81 MB. The analysis results of dataset are published on the *Journal of Remote Sensing* in 2018 (No. 6, Vol. 22).

Keywords: urban expansion; cellular automata; parameter sensitivity; Journal of Remote Sensing

1 Introduction

Urban expansion is the most popular part of land use change and the hotspot of global change research^[1-2]. Some scholars pay attention to the spatial pattern of urban expansion, however some scholars pay attention to the process of urban expansion^[3-4]. The process of urban expansion often uses raster data (remote sensing image) as the data source. The structure characteristics of raster data and the Cellular Automaton (CA) models are consistent with each other. Therefore, many scholars use them to study the process of urban expansion

Received: 08-04-2019; **Accepted:** 10-06-2019; **Published:** 25-09-2019

Foundations: Department of Education of Guangdong Province (2016KTSCX045); Natural Science Foundation of Guangdong Province (2014A030313605, 2016A030313806)

***Corresponding Author:** Qiao, J. G. F-7553-2019, School of Geography and Tourism, Guangdong University of Finance and Economics, qjg821@263.com

Data Citation: [1] Zhang, Y. H., Qiao, J. G. Dataset of land use and proximity variables in Panyu district, Guangzhou (1999, 2008) [J]. *Journal of Global Change Data & Discovery*, 2019, 3(3): 284-289. DOI: 10.3974/geodp.2019.03.09.

[2] Zhang, Y. H., Qiao, J. G. Land use and the spatial distances dataset of Panyu district, Guangzhou city of China (1999, 2008) [DB/OL]. Global Change Research Data Publishing & Repository, 2018. DOI: 10.3974/geodb.2019.03.10.V1.

3 Methods

3.1 Study Area

This paper takes the Panyu district of Guangzhou city in the Pearl River Delta as the research area. This study area is located in the center of the Dawan district of Guangdong, Hong Kong and Macao, with a total area of 529.9 km². Panyu district is in the south-central part of Guangzhou, adjacent to the Pearl River in the east, facing the city of Dongguan across the river. its south is Nansha district, adjacent to the Nansha Free Trade Zone, the west to Foshan city and Zhongshan city and north to the Haizhu district of the core city of Guangzhou. Panyu district governs 10 streets and 6 towns. According to the Guangzhou Statistical Yearbook, the permanent population of Panyu district reached 1,171,300 (2017). The urban land area of Panyu was 134.6 km² in 1999 and it increased to 255.60 km² in 2008. The annual growth rate of urban expansion is as high as 6.8%.

3.2 Technical Route

The Geospatial Data Cloud (<http://www.Gscloud.cn/>) provides free Landsat remote sensing data. The data in 1999 and 2008 were selected, and the processes of orthorectification, atmospheric correction and supervised classification were carried out^[13]. The classification results can be used to as start and terminated images in urban expansion CA model. The metro stations, metro lines, roads, district center and town based on the map service provided by the National Geographic Information Public Service Platform (<http://www.Tianditu.gov.cn/>) were digitized and then Euclidean distance was carried out to obtain proximity variables^[3-4]. In order to facilitate the comparative analysis, all the proximity variables were normalized and input into urban expansion CA model. The flowchart for generating the dataset is shown in Figure 1.

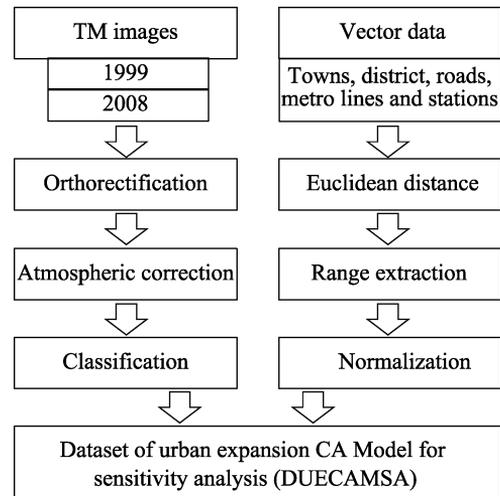


Figure 1 Technical route of the data development

4 Results and Validation

4.1 Data Products

This dataset contains classifications images of 1999 and 2008 in Panyu district. The classifications images of 1999 were used as start image in the simulations of urban expansion CA model, while classifications image of 1999 was used as validation data for simulation results. The dataset also includes proximity variables, such as distance from the district center, distance from the metro lines, distance from the metro stations, distance from the roads, and distance from town centers (Figure 2).

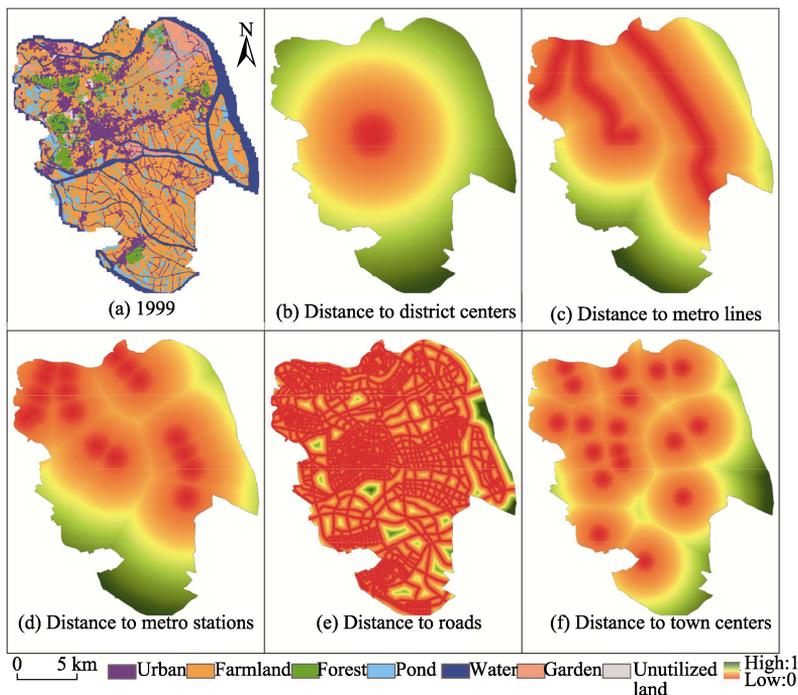


Figure 2 Basic data of urban expansion CA model^[14]

4.2 Validation

First, sampling ratio of the dataset on parameters was analyzed. Monte Carlo sampling method was used in this paper for convenience comparison (Table 2). Samples with different sampling ratios of 1%, 3%, 5%, 10%, 15%, 20%, 25%, 30%, 40% and 50%, were respectively obtained to obtain parameters. Results showed that the parameters became stable as the ratio increased (Figure 3). If higher ratio of sampling is used for training, the amount computation of training will be relatively large. If a smaller sample ratio is used to obtain the parameter, the parameter will have larger error. Secondly, the simulation results of different neighborhood sizes and neighborhood structures were analyzed (Table 3). It can be found that the accuracy of the simulation results could reach 80.57% by using 3×3 neighborhood. The accuracy would be lower and became 80.48% by using 5×5 extended neighborhood. However, the simulation accuracy will reach 80.51% and 80.52% when using 7×7 and 9×9 neighborhood. In general, the simulation accuracy that using the von Neumann neighborhood is slightly lower than that using Moore neighborhood. The

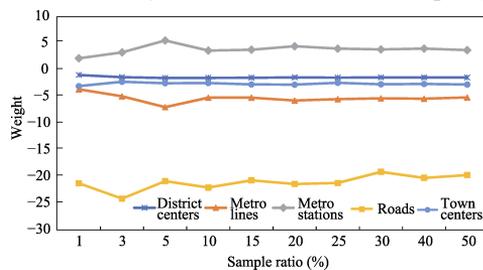


Figure 3 Relationship between sample ratio and parameters

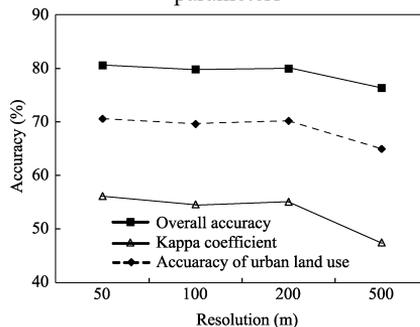


Figure 4 Simulation accuracy in different resolutions^[14]

The

accuracy was 80.43%, 80.47%, 80.50% ,and 80.51%, respectively, when using the extended von Neumann neighborhoods of 3×3 , 5×5 , 7×7 , and 9×9 . Thirdly, we analyze the spatial sensitivity of dataset by using overall accuracy, Kappa coefficient and accuracy of urban area (Figure 4). In general, the overall accuracy, Kappa and accuracy of urban area is reduced as the spatial scale increases. When the spatial scale is increased from 50 m to 200 m, the overall accuracy, Kappa and accuracy of urban area change little, from 80.57% to 79.98%, from 56.11% to 55.04%, and from 70.58% to 70.18%, respectively. However, when the scale is increased from 200 m to 500 m, the indicators decreased significantly, i.e., the overall accuracy decreased from 79.98% to 76.36%, the Kappa coefficient decreased from 55.04% to 47.45%, and the accuracy of urban area decreased from 70.18% to 64.94%. Finally, in order to understand the different spatial scales in micro-level, we count the ratio of urban cells in different resolution of $50 \text{ m} \times 50 \text{ m}$, $100 \text{ m} \times 100 \text{ m}$, $200 \text{ m} \times 200 \text{ m}$ and $500 \text{ m} \times 500 \text{ m}$ in 1999 and 2008.

Table 2 Sampling validation of the dataset^[14]

Ratio (%)	District center	Subway lines	Subway stations	Roads	Town centers	Accuracy (%)
1	-0.90	-3.58	2.23	-21.19	-2.99	80.44
3	-1.31	-4.89	3.34	-24.07	-2.17	80.65
5	-1.45	-6.93	5.57	-20.78	-2.44	80.59
10	-1.42	-5.14	3.69	-21.99	-2.41	80.64
15	-1.40	-5.14	3.83	-20.63	-2.66	80.66
20	-1.35	-5.68	4.49	-21.32	-2.72	80.62
25	-1.38	-5.43	4.04	-21.14	-2.37	80.66
30	-1.34	-5.28	3.89	-19.05	-2.64	80.67
40	-1.37	-5.35	4.04	-20.18	-2.59	80.70
50	-1.36	-5.10	3.78	-19.64	-2.69	80.64

Results showed that with the increase of spatial scale, the ratio of high urban cells (such as, count is 8 or 7) decreased in 1999 and 2008 (Table 4). This suggests that urban development density decreases from high to low by downscaling. It can also be seen from the table that urban cells of 1, 2, 3, and 4 were continuously increased by downscaling. However, the ratio of urban cells (count are 6, 7, and 8) in neighborhood had a tendency to be declined.

Table 3 Validation of neighborhood structure^[14]

Neighborhood size	Accuracy (%)	
	Moore	von Neumann
3×3	80.57	80.43
5×5	80.48	80.47
7×7	80.51	80.50
9×9	80.52	80.51

Table 4 Urban cell ratio of Moore neighborhood in different resolution^[14]

No.	1999				2008			
	50 m	100 m	200 m	500 m	50 m	100 m	200 m	500 m
0	69.1	59.5	54.5	44.6	50.5	40.1	32.6	18.7
1	4.0	9.2	15.9	23.2	4.5	8.9	14.3	20.9
2	4.1	8.7	9.2	12.8	4.5	8.9	11.2	16.2
3	5.0	6.9	6.1	7.0	6.0	8.6	8.6	13.5
4	3.7	4.2	4.2	5.2	4.7	6.3	6.6	9.1
5	3.3	3.2	3.2	3.5	4.9	5.7	5.8	8.8
6	2.2	2.5	2.4	2.0	3.6	4.6	5.6	6.2
7	1.8	2.1	2.0	1.1	3.1	4.6	5.8	4.3
8	6.9	3.8	2.5	0.7	18.2	12.2	9.5	2.2

5 Discussion and Conclusion

In order to verify the sensitivity of the urban expansion CA model, we collected relevant data of a rapidly urbanized area, Panyu district in Guangzhou city, and a new dataset with the spatial resolution of 50 m was constructed. Using this dataset, it is easy to analyze the effect of sensitivity of sampling scale, neighborhood structure, and spatial resolution on urban expansion CA model. Results showed that the dataset had good stability for obtaining the weights (parameters) of the CA model. It was also effective for verifying the function of CA model in different neighborhood sizes and neighborhood structures. In terms of spatial scale sensitivity, the dataset can help to understand the simulation result in micro-levels and their relationship with simulation accuracy. In order to analyze the sensitivity and understand the CA model, this paper provided an operational and basic version of dataset for urban expansion CA models or land-use change CA models. Longer time series and more spatial resolution to study the predictive ability of the CA model will be carried out in the next step.

Author Contributions

Qiao, J. G. designed the algorithms of dataset; Zhang, Y. H. contributed to the data processing, data analysis, and paper writing.

References

- [1] Liu, J. Y., Liu, M. L., Zhuang, D. F., *et al.* Analysis on the spatial pattern of land use change in China [J]. *Science China Earth Sciences*, 2002, 32(12): 1031–1040.
- [2] Wang, L., Li, C. C., Ying, Q., *et al.* China's urban expansion from 1990 to 2010 determined with satellite remote sensing [J]. *Chinese Science Bulletin*, 2012, 57(16): 1388–1399.
- [3] Li, X., Yeh, A. G. O. Data mining of cellular automata's transition rule [J]. *International Journal of Geographical Information Science*, 2004, 18(8): 723–744.
- [4] Zhang, Y. H., Li, X., Liu, X. P., *et al.* The CA model based on data assimilation [J]. *Journal of Remote Sensing*, 2011, 15(3): 475–491.
- [5] White, R., Engelen, G. Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns [J]. *Environment and Planning A*, 1993, 25(8): 1175–1199.
- [6] Wu, F. Calibration of stochastic cellular automata: the application to rural-urban land conversions [J]. *International Journal of Geographical Information Science*, 2002, 16(8): 795–818.
- [7] Li, X., Yeh, A. G. O. Neural-network-based cellular automata for simulating multiple land use changes using GIS [J]. *International Journal of Geographical Information Science*, 2002, 16(4): 323–343.
- [8] Ke, X. L., Deng, X. Z., He, S. J. Scale sensitivity and its causality for geo-cellular automata modeling [J]. *Geographical Research*, 2010, 29(5): 863–872.
- [9] Liu, X., Ma, L., Li, X., *et al.* Simulating urban growth by integrating landscape expansion index (LEI) and cellular automata [J]. *International Journal of Geographical Information Science*, 2014, 28(1): 148–163.
- [10] Wu, H., Zhou, L., Shi, W. Z., *et al.* Scale sensitive of cellular automata model for the simulation of land use change based on orthogonal experiment [J]. *Scientia Geographica Sinica*, 2013, 33(10): 1252–1258.
- [11] Zhang, Y. H., Qiao, J. G. Land use and the spatial distances dataset of Panyu district, Guangzhou city of China (1999, 2008) [DB/OL]. Global Change Research Data Publishing & Repository, 2018. DOI: 10.3974/geodb.2018.04.06.V1.
- [12] GCdataPR Editorial Office. GCdataPR data sharing policy [OL]. DOI: 10.3974/dp.policy.2014.05 (Updated 2017).
- [13] Zhao, Y. S. Principles and Methods of Remote Sensing Application and Analysis [M]. Beijing: Science Press, 2003: 166–208.
- [14] Zhang, Y. H., Qiao, J. G., Liu, W. H., *et al.* Parameter sensitivity analysis of urban cellular automata model [J]. *Journal of Remote Sensing*, 2018, 22(6): 1051–1059. DOI: 10.11834/jrs.20187145.