GEOSPATIAL ANALYSIS OF ATMOSPHERIC HAZE EFFECT BY SOURCE AND SINK LANDSCAPE

Tiantian YU [a], Kai XU [a*], Zhaoxiang YUAN [b]

a. Faculty of Information Engineering, China University of Geosciences (Wuhan), Wuhan 430070, m13618650845_1@163.com;

b. China State Power Economic Research Institute, Beijing 100010, 55272598@qq.com.

Commission IV, WG IV/3

KEY WORDS: haze; aerosol optical thickness (AOD); scale effect; source and sink landscape; spatial lag model; spatial error model; geo-weighted regression

ABSTRACT:

Based on geospatial analysis model, this paper analyzes the relationship between the landscape patterns of source and sink in urban areas and atmospheric haze pollution. Firstly, the classification result and aerosol optical thickness (AOD) of Wuhan are divided into a number of square grids with the side length of 6 km, and the category level landscape indices (PLAND, PD, COHESION, LPI, FRAC_MN) and AOD of each grid are calculated. Then the source and sink landscapes of atmospheric haze pollution are selected based on the analysis of the correlation between landscape indices and AOD. Next, to make the following analysis more efficient, the indices selected before should be determined through the correlation coefficient between them. Finally, due to the spatial dependency and spatial heterogeneity of the data used in this paper, spatial autoregressive model and geo-weighted regression model are used to analyze atmospheric haze effect by source and sink landscape from the global and local level.

The results show that the source landscape of atmospheric haze pollution is the building, and the sink landscapes are shrub and woodland. PLAND, PD and COHESION are suitable for describing the atmospheric haze effect by source and sink landscape. Comparing these models, the fitting effect of SLM, SEM and GWR is significantly better than that of OLS model. The SLM model is superior to the SEM model in this paper. Although the fitting effect of GWR model is more unsuited than that of SLM, the influence degree of influencing factors on atmospheric haze of different geography can be expressed clearer. Through the analysis results of these models, following conclusions can be summarized: Reducing the proportion of source landscape area and increasing the degree of fragmentation could cut down aerosol optical thickness; And distributing the source and sink landscape evenly and interspersedly could effectively reduce aerosol optical thickness which represents atmospheric haze pollution; For Wuhan City, the method of adjusting the built-up area slightly and planning the non-built-up areas reasonably can be taken to reduce atmospheric haze pollution.

[*] Corresponding author

https://doi.org/10.5194/isprs-archives-XLII-2-W7-1437-2017

1. Introduction

Recently, with the rapid development of urbaneconomy, urban haze occurs frequently. Haze is an atmospheric phenomenon traditionally where dust, smoke and other dry particles obscure the clarity of the sky. For the haze pollution, Landscape ecology pointed out that, the source landscape increases the concentration of haze, and the sink landscape inhibits the haze concentration from ascension and cuts down the air pollution. In the process of urbanization, the unbalanced distribution of source and sink landscape can affect the diffusion rate and concentration distribution of pollutants in the city. And it leads to the change of urban atmospheric composition, which can cause the deterioration of urban atmospheric environment. Reasonable planning of the source and sink landscape pattern in city reduce the haze pollution and restrain the atmospheric environment from negative changes caused by the city construction.

At present, most of the atmospheric haze pollution studies focused on the following three aspects: the influence of meteorological factors on the formation and development of haze; the concentration and chemical composition of haze; and the transmission trajectory of persistent haze pollution. While the study on the relationship between source and sink landscape pattern and atmospheric haze in urban is insufficient. Aerosol optical thickness (AOD) can well be used to estimate the haze concentration in the atmosphere. This paper takes the aerosol optical thickness and landscape pattern of Wuhan as the research objects to study the atmospheric haze effect by the source and sink landscape.

Due to the spatial dependency and spatial heterogeneity of the data used in this paper, it is necessary to take into account these spatial characteristics when use the analysis model to make the simulation more accurate. Spatial autoregressive model (SAR) is global model which introduce the items that describe the spatial autoregressive based on the regression model, which greatly improves the prediction accuracy. Geographic Weighted Regression Model (GWR) is a local linear regression model, which embeds the spatial position into the regression parameter. That is, it uses the weight matrix to represent the adjacency relation of the spatial units. The regression model can be adjusted with the change of the spatial position of the sampling points. This model can well reflect the non-stationary space of the dependent variable caused by the independent variable. Spatial autoregressive model and geo-weighted regression model are suitable for analyzing the relationship between the least relevant landscape indices and AOD. Through the selection and application of these models, the relationship between spatial distribution of haze and landscape pattern can be discussed from the global and local level, which reflects the influence of source and sink landscape pattern on atmospheric haze pollution. The results of the analysis provide theoretical reference for reasonable planning of urban source and sink landscape pattern and improves urban atmospheric environment.

2 Data and materials

Surface cover categories include buildings, woodlands, waters, arable land, shrubs (as shown in Figure 1).
The aerosol optical thickness distribution is shown in Fig.2.

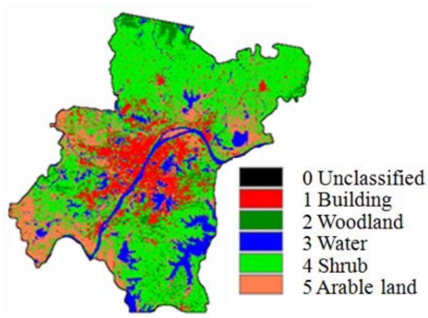


Fig.1 Classification result of Wuhan

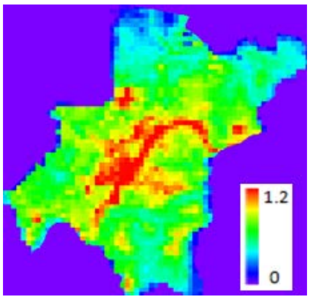


Fig.2 AOD distribution of Wuhan

3 Identification of source and sink landscape

Scale effect is a special feature for landscape pattern, it affects the interpretation of landscape to environment. The heterogeneity of the landscape determines the importance of the landscape spatial pattern. Therefore, this paper analyzes the overall landscape heterogeneity index of 2 ~ 9km to select the optimal scale to identify the source and sink landscape. The results of the normalized heterogeneity index at different scales are shown in the figure 3.

Fig.3 shows that normalized heterogeneity indices reached the maximum at 6km except SHEI reached the maximum at 5km. So this paper considers 6km as the optimal scale.

Landscape indices of category level can reflect the distribution characteristics of various type landscapes, so they can be used to identify the source and sink landscape of atmosphere haze pollution. In this paper, the classification results of land cover and AOD distribution in Wuhan are divided into square grid with side length of 6 km.

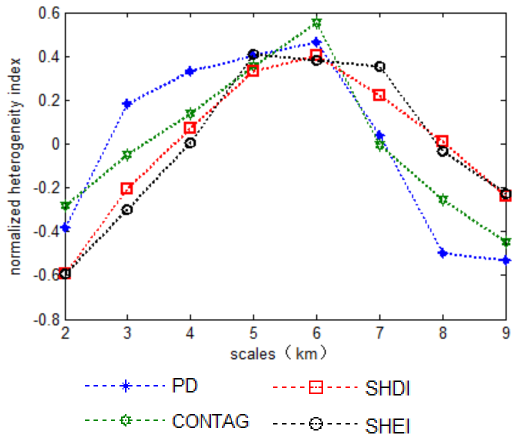


Fig.3 normalized heterogeneity index at different scales

Then the index that can fully express the characteristics of each category of landscape are selected and calculated in each grid. The selected category level landscape indices are shown in Table 1. The mean value of the pixels in each grid is regarded as the value of the grid's center. Finally, using the correlation coefficients between the indices and AOD identify source and sink landscape. The correlation coefficients are shown in Table 2.

Landscape indices of category level	meaning
Percent of landscape（PLAND）	The ratio of the total area of a patch type to the entire landscape area.
Patch density（PD）	Reflecting the distribution uniformity (fragmentation) of a landscape patch.
Fractal dimension（FRAC_MN）	A non-integer dimension that describes the complexity of the patch or landscape inlay geometry，The closer to 1 the value is, the more regular of the shape。
Patch cohesion（COHESION）	Measure the physical connectivity of the corresponding patch type，The greater the value, the better the connectivity
Largest patch index（LPI）	The proportion of the largest plaque in a category throughout the landscape

Table 1 Landscape index selected in this paper

category	PLAND	PD	LPI	FRAC_MN	COHESION
Building	0.654**	-0.565**	0.489**	0.321**	0.58**
Water	0.017	-0.225**	-0.077	-0.121	0.338**
Woodland	-0.646**	-0.582**	-0.499**	-0.329**	-0.639**
Shrub	-0.566**	-0.495**	-0.467**	-0.307**	-0.71**
Arable land	-0.065	-0.094	-0.148**	0.074	0.335**

** indicate that it is significantly correlated at the 0.01 level

Table 2 Correlation analysis results of landscape indices and AOD

Table 2 shows that, for building, the indices of PLAND, LPI, FRAC_MN, COHESION are positively correlated with AOD, while PD is negatively correlated. For woodland and shrub, the indices are negatively correlated with AOD. Therefore, it can be considered that the source landscape of haze pollution is buildings, and the sink landscapes are woodland and the shrub.

There is correlation between landscape indices, which may cause multicollinearity. So the values in table 2 are not very high. Besides, the correlation analysis can only represent that the closely relation between the dependent variable and the independent variable, therefore, this paper introduces the geospatial analysis models.

4 Establishment and comparison of models

The aerosol optical thickness is treated as the dependent variable, and the landscape indices of each category are the independent variables. Through the spatial autoregressive model and geographic weighted regression model, the relationship between spatial distribution of haze and landscape pattern is discussed from the global and local level, which reflects the influence of source and sink landscape pattern on atmospheric haze pollution.

4.1 Spatial autocorrelation analysis of variables

The spatial autocorrelation test of variables is a prerequisite for the use of spatial autoregressive model. The *Moran's I* of AOD is 0.5776, and the *Moran's I* values of each category are shown in table 3.

Spatial autoregressive model belong to global model. They can't describe the spatial distribution discrepancy of variables. Therefore, the GWR model is established to detect the spatial non-stationary of the data.

category	PLAND	PD	COHESION
Woodland	0.6607	0.4447	0.4344
Shrub	0.7714	-0.055	0.1252
Building	0.7709	0.0193	0.1393

Table3 *Moran's I* coefficients of the variables

4.2 Establish models

There is correlation between landscape indices. In order to avoid multicollinearity and improve the fitting accuracy of the model, the least relevant landscape indices are selected based on the correlation coefficients for the following analysis. The correlation between landscape indices of different categories proves that PLAND, PD, and COHESION are well suitable to analyze with AOD for each category.

Spatial autoregressive model includes spatial lag model (SLM) and spatial error model (SEM). Lagrange multiplier statistics should be used to determine which one is more suitable. From the Lagrange multiplier test statistical results (Table 4) of the traditional regression model (ordinary least squares OLS), the superiority of the two models can't be determined, so these two models should be used for regression analysis with AOD.

Lagrange multiplier		LM-lag	Robust LM-lag	LM-error	Robust LM-error
Building	t	127.049	83.4317	60.5676	16.9503
	p	<0.001	<0.001	<0.001	<0.001
Shrub	t	197.0378	22.2912	175.4756	13.3932
	p	<0.001	<0.001	<0.001	<0.001
Woodland	t	125.638	30.9447	100.1178	11.4245
	p	<0.001	<0.001	<0.001	<0.001

Table4 Lagrange multiplier test statistic of standard linear regression

4.3 Comparison

PLAND, PD and COHESION are used to establish models with AOD. Comparing the fitting results of OLS, SLM and SEM model, the conclusion can be obtained that the significance of the fitting results of spatial autoregressive model is higher than that of OLS. All of the fitting results of spatial autoregressive models are significant (P <0.05) or extremely significant (P <0.01).

Comparing the RSS, LIK, AIC and SC (Table 5) of these global models of SEM, SLM and OLS, the SLM and SEM are more applicable than OLS. Considering all the parameters, the fitting result of SLM model is better than that of SEM for analyzing the relationship between the source and sink landscape and atmospheric haze pollution.

GWR model can explain the haze effect of landscape pattern at the local level, its ability for explain building, shrub and woodland is more superb than that of OLS.

5 Analysis results at the global and local levels

From the global level analysis, the regression coefficients of SLM model of each category shows that the PLAND and COHESION of building play a role in increasing AOD, and the PD play a negative role. That is, in a certain area the lager the percent and the patch cohesion of building, the higher the haze concentration is. For landscapes of shrub and woodland, the COHESION is proportional to AOD, and the PLAND and PD are the opposite. That is, in a certain area, increasing the percent of sink landscape area, and distributing them more dispersed, the haze will evacuate faster.

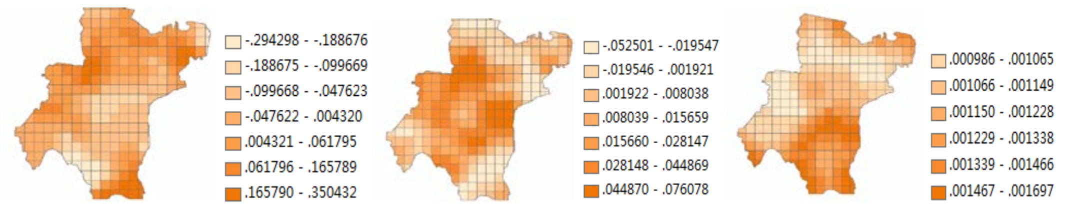
From the local level analysis, the spatial distribution discrepancy of variables is described. Figure 4(a) shows that the regression coefficients of PD are negative in the main urban area and are positive in the suburbs area. Figure 4(b) shows that the PLAND coefficients are almost all positive. And in figure 4(c) the COHESION coefficients are all positive. It is due to the large patch of building in the main urban. Although the patch density of building is low, its proportion is very large, so the corresponding values of AOD are high. In suburbs, the building is mixed with other categories, so its patch density increases, at the same time the building area is just a small amount of total area, so the corresponding values of AOD are low.

Fig. 5 (a) and (b) show that the patch density in the main urban area is high, but the percent of the shrub area is very small, so PLAND plays the dominate role in effecting AOD. In the suburbs, the percent of shrub is not so much, so the PD holds the main factor.

For woodland, Figure 6 shows that the effect of woodland on haze is almost the same as that of shrub, but in the main city its distribution is limited.

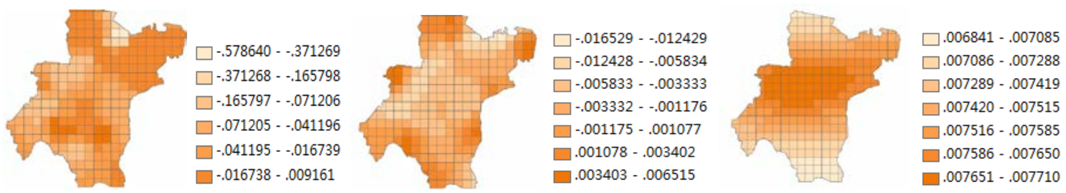
category	models	R^2	Preudo R^2	RSS	LIK	AIC	SC
building	OLS	0.5066	--	7.4903	101.711	-195.422	-181.014
	SLM	--	0.7974	3.0751	192.464	-374.928	-356.917
	SEM	--	0.7735	3.4383	168.613	-329.226	-314.817
	GWR	0.7521	--	3.7635	--	-231.4728	--
shrub	OLS	0.209	--	12.1136	36.577	-65.146	-50.737
	SLM	--	0.7783	3.3695	168.933	-327.866	-309.86
	SEM	--	0.7758	3.4067	164.277	-320.555	-306.15
	GWR	0.7708	--	3.4832	--	-261.589	--
woodland	OLS	0.5851	--	8.2619	88.4258	-168.852	-154.443
	SLM	--	0.7684	4.6117	154.25	-298.5	-280.49
	SEM	--	0.7804	4.3735	150.2182	-292.436	-278.028
	GWR	0.6769	--	6.4383	--	-112.6157	--

Table 5 Comparison of Model Parameters



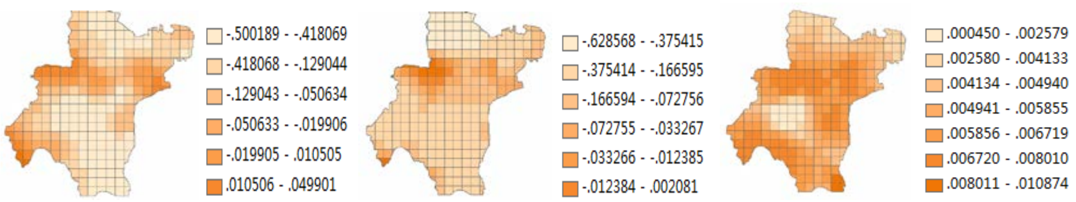
（a）Regression coefficients of PD （b）Regression coefficients of PLAND （c）Regression coefficients of COHESION

Fig.4 geographical weighted regression analysis results of Building category



（a）Regression coefficients of PD （b）Regression coefficients of PLAND （c）Regression coefficients of COHESION

Fig.5 Geographic weighted regression analysis results of shrub category



（a）Regression coefficients of PD （b）Regression coefficients of PLAND （c）Regression coefficients of COHESION

Fig.6 Geographic weighted regression analysis results of forest category

6 Results and conclusions

Based on the selection of source and sink landscape of haze, this paper discusses the relationship between spatial distribution of haze and landscape pattern from the global and local level. And the research indicates that：

(1) The source landscape of atmospheric haze pollution is the building, and the sink landscape are shrub and woodland.

(2) The SLM model is superior to the SEM model in this paper. Although the fitting effect of GWR model is more imperfect than that of SLM, the influence degree of influencing factors on atmospheric haze of different geography can be expressed clearer.

(3) Reducing the proportion of source landscape area and increasing the degree of fragmentation could cut down aerosol optical thickness; And distributing the source and sink landscape evenly and interspersedly could effectively reduce aerosol optical thickness which represents atmospheric haze pollution.

(4) For Wuhan City, the method of adjusting the built-up area slightly and planning the non-built-up areas reasonably can be taken to reduce atmospheric haze pollution.

REFERENCES

Wu D. J., 2012. A Summary Studies on China's Haze in Recent Ten Years. Journal of Environmental Science, 32 (2), pp. 257-269.

Chen L M, Fu B J, Zhao W W. J., 2006. Source and sink landscape theory and its ecological significance. Journal of Ecology, 26 (5), pp. 1444-1449.

Li Lin, D., 2016. Study on thermal environmental effects of urban landscape pattern changes in Chengdu. Sichuan Normal University.

Chen L, Sun R H, Liu H. L, J., 2013. Research progress in ecological environment effects of urban landscape pattern evolution. Journal of Ecology, 33 (4), pp. 1042-1050.

Tanaka T, Moriyama M, J., 2011, Urban Environmental Climate Maps for supporting Environmental and urban planning works in local in local government [J]. AIJ Journal of Technology and Design. 17(36), pp. 687-692.

Sun R H, Xu Z L, Chen L M, et al, J., 2012. Basic theoretical framework and technical framework of urban ecological landscape research. Journal of Ecology, 32 (7), pp. 1979-1986.

Li Lan, Zhang Kai, et al, J., 2017. Analysis of temporal and spatial distribution characteristics of low visibility weather and change rules of meteorological factors in central region of Liaoning. Chinese Journal of Environmental Engineering. 11(4), pp. 2330-2336.

Zhang Zhe, Ding Jianli, et a, J., 2017. Aerosol optical properties over Ebinur region in spring. China Environmental Science. 37(2), pp. 467-475.

Hu Yadong, Ma Anzhou, et al, J., 2017. Community Charateristics of Cultivable Bacteria in Fine Particles (PM2.5) of Beijing and Baoding. Environmental Science. 38(4), pp. 1327-1337.

Han Y, Zhou Z X, J., 2015. Estimation ecosystem service of green landscape in Xi'an and its spatial pattern. Geography Research. 34 (7), pp. 1247-1258.

Fameli K M, Assimakopoulos V D, Kotroni V, et al. J., 2013. Effect of the land use change characteristics on the air pollution patterns above the Greater Athens Area(GAA) after 2004. Global Nest Journal, 15(2), pp.169-177.

ZHANG Y H , LI Z Q, HOU W Z, et al, J., 2013. Retrieval of aerosol optical depth based on high spatial resolution CCD of HJ-1. Journal of Remote Sensing , 17(4), pp.959-969.

Ning X H, Guo L,Zhang H T, J., 2013.Comprehensive degree of land-use at different scales based on spatial autocorrelation regression and geographically weighted regression models. Journal of Huazhong Agricultural University, 32(4), pp. 48-54.

Kelejian H H, Prucha I R, J., 2010. Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances.

Journal of Econometrics, 157(1), pp. 53-67.

Kazar B M, Celik M, M., 2012. Spatial autoregression (SAR) model: Parameter estimation techniques. Springer Science and Business Media.

Liu Q F, Li M D, Duan J N, et al, J., 2013, Analysis on influence factors of soil Pb and Cd in agricultural soil of Changsha suburb based on geographically weighted regression model. Transactions of the Chinese Society of Agricultural Engineering, 29(3), pp. 225－234.

Chi Y，Shi H H，Wang E K，Guo Z，Feng A P Ma D M, J., 2017. Landscape pattern characteristics and ecological effects on five northern islands of Miaodao Archipelago．Acta Ecologica Sinica， 3 7(4) , pp. 1270-1285．

QIN Dong, CHEN Huiyan, J., 2017. Application of spatial autoregressive model in prediction of high slop deformation. Journal of Hohai University(Natural Science). 45(2), pp. 104-108.

Drukker D M,Egger P, Prucha I R, J., 2013. On two-step estimation of a spatial autoregressive model with autoregressive disturbances and endogenous regressors. Econometric Reviews, 32(56), pp. 686-733.

Wu L, Hou X Y, Xu X L, J., 2014. Analysis of spatial pattern of farmland and its impacting factors in coastal zone of Circum Bohai. Transactions of the Chinese Society of Agricultural Engineering. 30(9), pp. 1-10.