Estimating the Spatial Variation of Electricity Consumption Anomalies and the Influencing Factors

Yuyun LIANG, Yao YAO, Xiaoqin YAN, Qingfeng GUAN

School of Geography and Information Engineering, China University of Geosciences, Wuhan 430078, *China*

Abstract: Effective detection of abnormal electricity users and analysis of the spatial distribution and influencing factors of abnormal electricity consumption in urban areas have positive effects on the quality of electricity consumption by customers, safe operation of power grids, and sustainable development of cities. However, current abnormal electricity consumption detection models do not consider the time dependence of time-series data and rely on a large number of training samples, and no study has analyzed the spatial distribution and influencing factors of abnormal electricity consumption in urban areas. In this study, we use the Seasonal-Trend decomposition procedure based on Loess (STL) based time series decomposition and outlier detection to detect abnormal electricity consumption in the central city of Pingxiang, and analyze the relationship between spatial variation and urban functions through Geodetector. The results show that the degree of abnormal electricity consumption in urban areas is related to geographic location and has spatial heterogeneity, and the abnormal electricity users are mainly located in areas with highly mixed residential, commercial and entertainment functions in the city. The results obtained from this study can provide a reference basis and a theoretical foundation for the detection of abnormal electricity consumption by users and the arming of electricity theft devices in the power grid.

Key words: abnormal electricity user detection; spatial autocorrelation; abnormal electricity usage in urban areas; points of interest enrichment factor; Geodetector

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With the continuous development of the social economy and the diversity of electricity demand, urban power grid operation is under increasing pressure, among which the more serious is the abnormal electricity consumption behavior of users, which not only affects the quality of electricity consumption of users and the safe operation of the urban power grid, but also the spatial gathering of abnormal electricity users will have a greater impact on the sustainable and healthy development of urban areas [1-3]. Therefore, it is important to detect the existence of abnormal power consumption behavior and analyze the spatial distribution characteristics of abnormal power consumption in the city for the decision of power grid personnel to improve economic efficiency and promote the development and progress of the power grid.

However, with the development and widespread use of smart meters, grid companies can obtain fine-scale data on the actual electricity consumption of customers, making it possible to study customer electricity consumption anomaly detection and spatial distribution characteristics driven by electricity data [4-5]. Among them, user electricity anomaly detection includes clustering-based methods and deep learning-based methods. Literature [6] proposed a fuzzy clustering based on C-means to detect and identify consumption anomalies of users by fuzzy classification of their electricity consumption data, as well as normalization and ranking of distance

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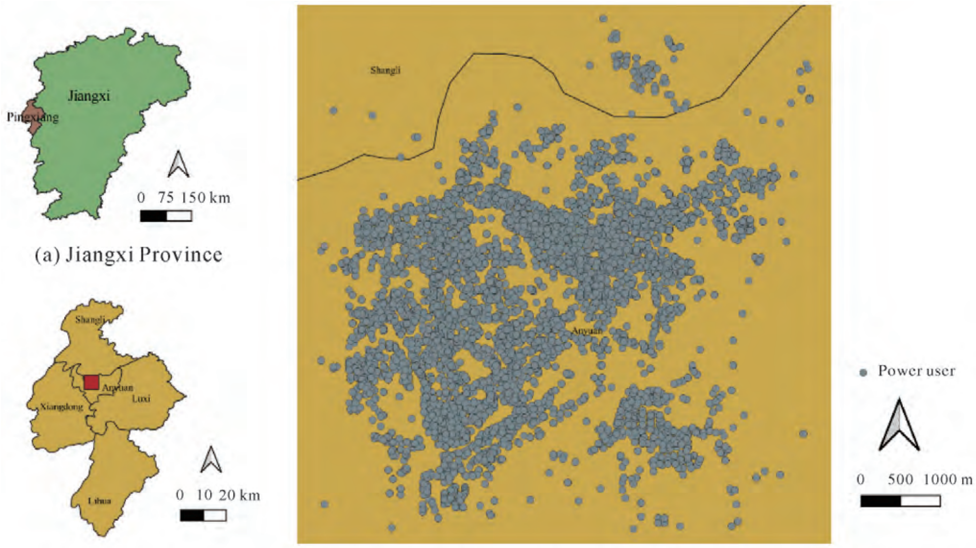
First author: Yuyun LIANG
E-mail: 20161000196@cug.edu.cn
Corresponding author: Yao YAO
E-mail: yaoy@cug.edu.cn

measures. Literature [7] proposes an optimal path forest clustering method and analyzes and compares the detection performance with algorithms such as k-mean clustering, Gaussian mixed model clustering, and attractor propagation clustering. Literature [8] used a hybrid deep neural network with long and short-term memory networks and multilayer perceptron for abnormal electricity usage detection and showed that they have higher accuracy than other classifiers. In Literature [9], a model with an attention mechanism based on particle swarm optimization and long-term short-term memory was proposed and its effectiveness and higher accuracy were verified by comparing with other classifiers. Regarding the analysis of spatial distribution and its drivers, Geographically Weighted Regression (GWR) models [10], Multiscale Geographically Weighted Regression (MGWR) [11] and Geodetector, among which Geodetector have the advantage of being able to detect single-factor and multi-factor interactions without considering multicollinearity problems [12-13]. In addition, Geodetector can detect both numerical and qualitative data, as well as the way the two factors interact on the dependent variable [14-16]. However, Geodetector are rarely not applied on the spatial variation of urban electricity consumption anomalies.

Although all the above studies have proposed solutions to detect abnormal electricity consumption of urban grid users, unsupervised algorithms based on clustering, the detection effect often depends on thesetting of parameters and does not have good inspiration, and the time dependence of time-series data is not considered, and the deep learning-based methods are complicated to model and have the problem of relying on a large number of known abnormal training samples. Meanwhile, the spatial distribution characteristics of urban electricity anomalies and their driving factors are not further explored in the current study. Therefore, in order to take into account the time-dependence of electricity data, this study introduces STL into the detection of abnormal electricity users, and proposes a method to detect the discrete degree of residual terms after time series decomposition of electricity data to detect urban abnormal electricity users. This method is used to detect the abnormal electricity users in urban areas and obtain the degree of abnormal electricity consumption in urban areas. Then, we analyze the spatial distribution of urban abnormal electricity consumption by spatial autocorrelation, and analyze the specific influence of each variable on the degree of abnormal electricity consumption in urban areas by using Geodetectors.

1 Study Area and Data

Pingxiang City, as the economic development center of western Jiangxi Province, is a member of the middle reaches of the Yangtze River city group, with a regional GDP of 96.360 billion in 2020. With the growth of population and the development of various industries, the rapid increase in the number of power users and the great changes in the composition of power users in Pingxiang City have brought impacts on the safe and healthy operation of the power grid and the sustainable development of the city. This paper selects the central city of Pingxiang City as the study area, which is mainly located in the central area of Anyuan District. The electricity data for this study were obtained from the electricity consumption data of 181 330 users in the central urban area of Pingxiang City, Jiangxi Province, from September 15, 2020 to February 8, 2021 for a time interval of 1 day for data collection. Each data includes information such as user number, user name, address of electricity consumption, date, and daily electricity consumption, and the address information of users is geocoded to obtain the latitude and longitude information of users. The study area and the spatial distribution of electricity users are shown in Fig.1. Meanwhile, in order to facilitate the exploration of the spatial differentiation of abnormal electricity consumption in the city, the study area was divided into a grid of about 300 m×300 m [17], of which there were 264 grids with electricity users.



(a) Jiangxi Province (b) Pingxiang City (c) Pingxiang City Central District and the distribution of electricity users

Fig.1 Distribution of study area and power users

Because of the accessibility of POIs and their ability to effectively present regional functions, the enrichment factors of each type of POI were selected as explanatory variables in this study to investigate the relationship between various urban functions and the spatial distribution of the degree of abnormal urban electricity use. Tourism, research and education, residential communities, financial services, shopping, restaurants and buildings. Unlike the POI density, which may be biased due to the high density of some POI categories in the whole city, the POI enrichment factor can be well used to characterize each grid study unit [18]. The POI enrichment factor is calculated as follows

$$EF_i^q = (N_i^q / N_i) / (N^q / N) \quad (1)$$

Where, EF_i^q is the enrichment factor of class q POI in grid i; N_i^q is the number of class q POI in grid i; N_i is the number of POI in grid i; N^q is the total number of class q POI in the whole study area; and N is the total number of POI in the whole study area.

2 Method

The specific process of this paper on the spatial divergence of urban electricity consumption anomalies and the influencing factors is shown in Fig.2. Firstly, the time-series electricity consumption data of users are decomposed into period terms, trend terms and residuals, and the abnormal electricity users are determined by the box-line diagram method; then the spatial divergence of urban electricity anomalies is analyzed; finally, the degree of influence of each type of POI enrichment factor on the spatial layout of urban electricity anomalies is analyzed using a Geodetector.

2.1 Detection of abnormal urban electricity users

The abnormal electricity consumption of power users will cause significant changes in the normal electricity consumption pattern. To obtain the detection results of abnormal electricity consumption of users with high accuracy, this paper performs the detection of abnormal electricity consumption users based on time-dependent time series decomposition. Firstly, the time-series electricity consumption data of users are decomposed by STL [19] time-series decomposition algorithm, and the electricity consumption data Y_v of users at a certain moment is decomposed into trend component, period component and residual, and the equation is as follows

$$Y_v = T_v + S_v + R_v \quad v = 1, 2, \cdots, n \quad (2)$$

Where, T_v is the trend component; S_v is the period component; and R_v is the residual.

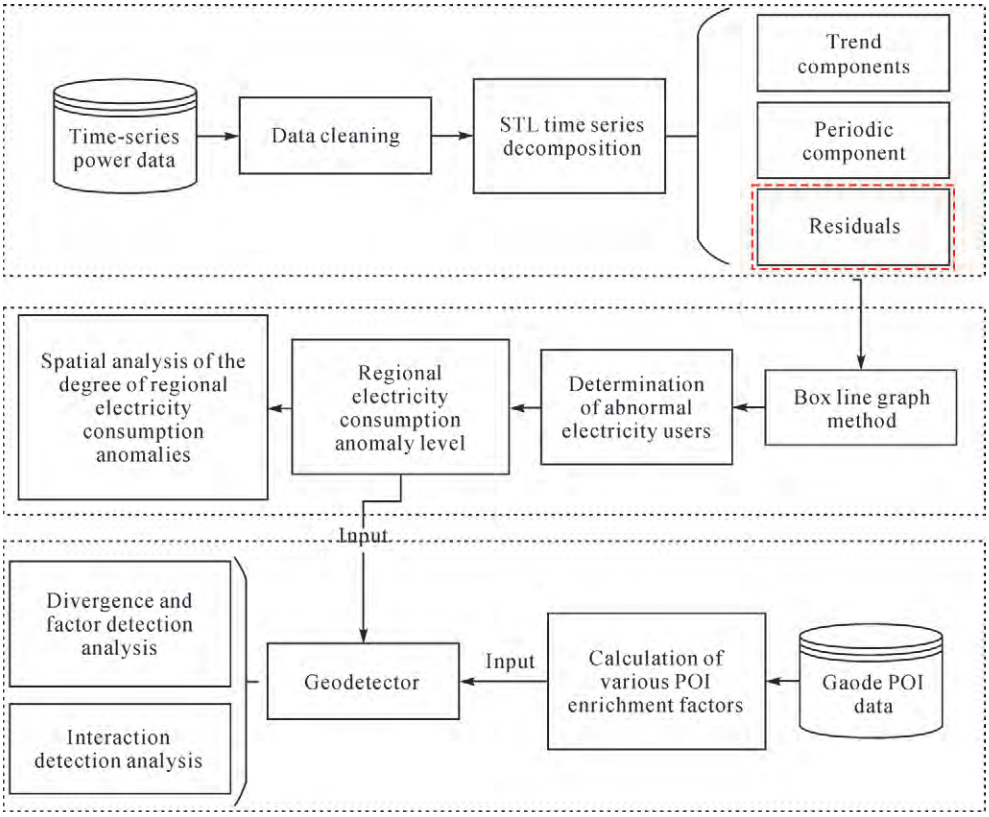


Fig.2 Technology roadmap

STL is divided into inner and outer loops, where the inner loop is mainly used for trend fitting and calculation of the period component. The outer loop is mainly used to adjust the robustness weights. If there are outliers in the customer electricity consumption series, the residuals will be larger. The residuals are defined as follows

$$h = 6 \times \text{median}(\ |R_v|)$$

To carry out further detection, the residuals obtained after decomposition are detected as outliers by the box-line diagram method, and the outliers in the residuals that exceed the upper limit or are lower than the lower limit are judged as abnormal electricity consumption points of customers. After the abnormal power consumption points on the power consumption time sequence of power users are detected, it does not directly determine whether the users are abnormal power users. Therefore, considering the investment of human and material resources in the grid to check the abnormal electricity users, this study determines the top 2% of abnormal data points as abnormal users, and the degree of regional abnormal electricity consumption is quantified by the number of regional abnormal electricity users.

2.2 Study on the spatial differentiation of urban electricity consumption anomalies

According to the first law of geography, "everything is related to everything else, but things that are close to each other are more closely related", and the distribution of regional customers' abnormal electricity consumption in geographic space also has a certain correlation, in order to assess this correlation, we adopt global spatial autocorrelation analysis. The global spatial autocorrelation analysis measures the spatial autocorrelation based on the location of the study unit and the degree of abnormal electricity consumption of the study unit users. The global Moran's I index, which measures the spatial autocorrelation, can be expressed as follows

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{S_0 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n} z_i^2} \tag{3}$$

Where, z_i is the deviation of the attribute value of study unit i from its mean value; w_{ij} is the spatial weight between study units i and j; n is the total number of study units; and S_O is the aggregation of all spatial weights.

$$S_O = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \tag{4}$$

Where the number of study units and the variance of all data values for a given data set are known, their z-scores and p-values can also be calculated and used to verify that this result is statistically significant.

After exploring the correlation between the degree of abnormal electricity consumption of regional customers and their geographical locations, this study further investigates whether there is spatial heterogeneity using local spatial autocorrelation analysis. The evaluation index of local spatial autocorrelation is the local Moran's I index, which can specifically reflect the specific spatial aggregation phenomenon of the abnormal electricity consumption degree of customers and classify the obtained aggregation types into four categories: high-high cluster, low-low cluster, high-low outlier, and low-high outlier.

2.3 Analysis of factors influencing spatial differentiation of anomalous users based on Geodetectors

The occupants of different urban functions have different electricity consumption patterns, and the urban functions are closely related to the abnormal electricity consumption of the city [20-21]. As a statistical method to detect spatial dissimilarity and reveal its drivers, the Geodetector is used to determine whether each explanatory variable is similar in spatial distribution by determining whether they have a significant effect on the dependent variable [22]. The Geodetector has four detector tools: variance and factor detection, interaction detection, risk area detection, and ecological detection. In this study, the divergence and factor detection tool and the interaction detection tool are used to analyze the intensity of each type of POI enrichment factor on the spatial layout of the abnormal electricity consumption of regional customers, and thus analyze the relationship between various urban functions and the spatial distribution of the abnormal electricity consumption of cities.

The divergence and factor detection tool is able to detect the intensity of the explanation of the spatial divergence of each type of POI enrichment factor on the degree of abnormal electricity consumption of regional users, which is measured by the q-value and calculated as follows

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^{L} N_h \sigma_h^2 \tag{5}$$

Where, $h = (1, 2, 3, \cdots, L)$ is the stratification of regional customer abnormal electricity consumption degree or each category of POI enrichment factor, and each factor is discretized into 3 categories in this paper; N_h and N are the number of cells in layer h and study area; σ_h^2 and σ^2 are the variance of regional customer abnormal electricity consumption degree in layer h and study area. The higher q value indicates that the higher the influence of this category of POI enrichment factors on the spatial distribution of the degree of abnormal electricity consumption of regional customers.

The interaction detector can assess whether two classes of POI enrichment factors acting together enhance or diminish the explanatory power of the degree of abnormal electricity use by regional customers, or whether they are independent of each other. The relationship between the two factors can be classified into five categories: non-linearly attenuated, single-factor non-linearly attenuated, two-factor enhanced, independent, and non-linearly enhanced.

3 Results and Analysis

3.1 Analysis of the spatial distribution of urban abnormal electricity users

The time-series electricity consumption data of power users in the study area are input into the detection model of abnormal electricity users proposed in this paper, and the detected abnormal electricity users in the city are overlaid on the vector layer of the grid of the study area for spatial connection, and the number of abnormal electricity consumptions in the grid is assigned to the degree of abnormal electricity consumption of users in the grid area, finally, the degree of abnormal electricity consumption in the central urban area of Pingxiang City is obtained as shown in Fig.3. The distribution map is shown in Fig.3. In this study, the spatial autocorrelation analysis is performed for the degree of abnormal electricity consumption in the central urban area of Pingxiang City. The global Moran's I index is 0.166, the corresponding p-value is 0.000, and the z-score is 10.978. A p-value less than 0.01 indicates statistical significance, and a z-score greater than the corresponding critical value of 2.58 indicates that the degree of abnormal electricity consumption in the urban area shows a clustering phenomenon, and a global Moran's I greater than 0 indicates that the degree of abnormal electricity consumption in the urban area shows a clustering phenomenon's I greater than 0 indicates a positive spatial correlation.

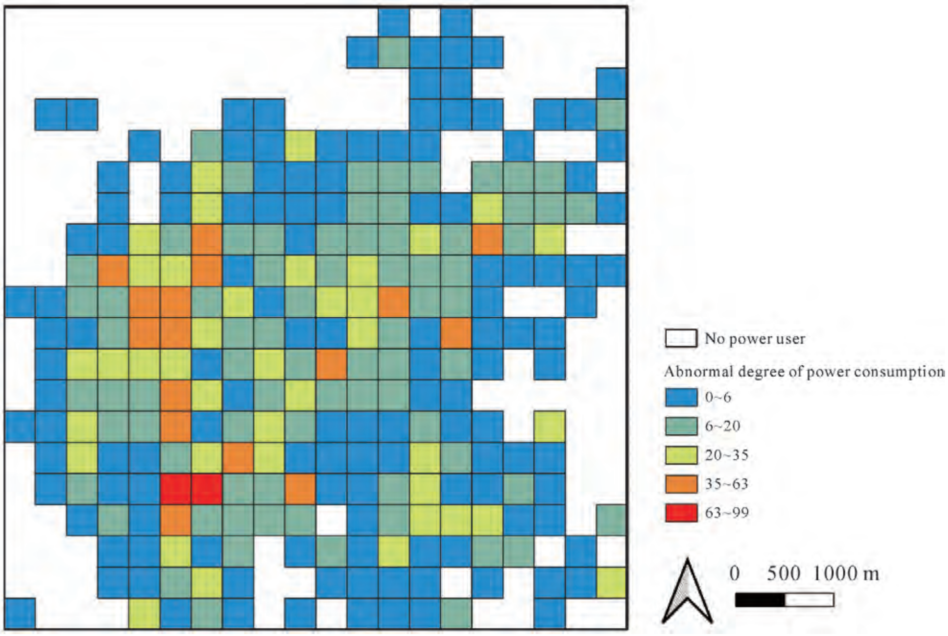


Fig.3 Distribution of the degree of abnormal electricity consumption in urban area

In order to further study the spatial clustering of the abnormal electricity consumption degree in urban areas, this study uses local spatial autocorrelation analysis to derive the spatial clustering of the abnormal electricity consumption degree in the central urban area of Pingxiang City. As can be seen in Fig.4, the analysis results show less high-low outlier and low-high outlier, indicating that the distribution of the degree of abnormal electricity consumption in the central urban area of Pingxiang City has obvious heterogeneity. The high-high cluster areas of the abnormal electricity consumption degree in the central urban area of Pingxiang City are mainly distributed in the central area of the study area, where a large number of residents and small stores are gathered, and the number and type of electricity users are more complicated, with larger electricity demand and more concentrated use, which are the areas with high abnormal electricity consumption. The low-low cluster area is located in the north of the study area, near the gathering area of some factories and plants, with a smaller number of users. Factory users are generally dedicated users, powered by a special transformer, and there are fewer cases of abnormal power consumption.

3.2 Analysis of the results of factors influencing the spatial variation of urban electricity consumption anomalies

The mapping visualizes the spatial differentiation of the abnormal electricity consumption degree in urban areas, but further quantitative analysis of each driver of the spatial differentiation of the abnormal electricity consumption degree in urban areas is needed. Since the Geodetector is used to analyze the category variables, the 13 POI enrichment factors are discretized and the factors are discrete into 3 categories by the natural breakpoint method. In this study, the number of customers with abnormal electricity consumption in the grid is used as the dependent variable, and the enrichment factors of each category of POI in the grid are used as explanatory variables, which are input into the Geodetector for the analysis of the relationship between various urban functions and the spatial distribution of the degree of abnormal urban electricity consumption.

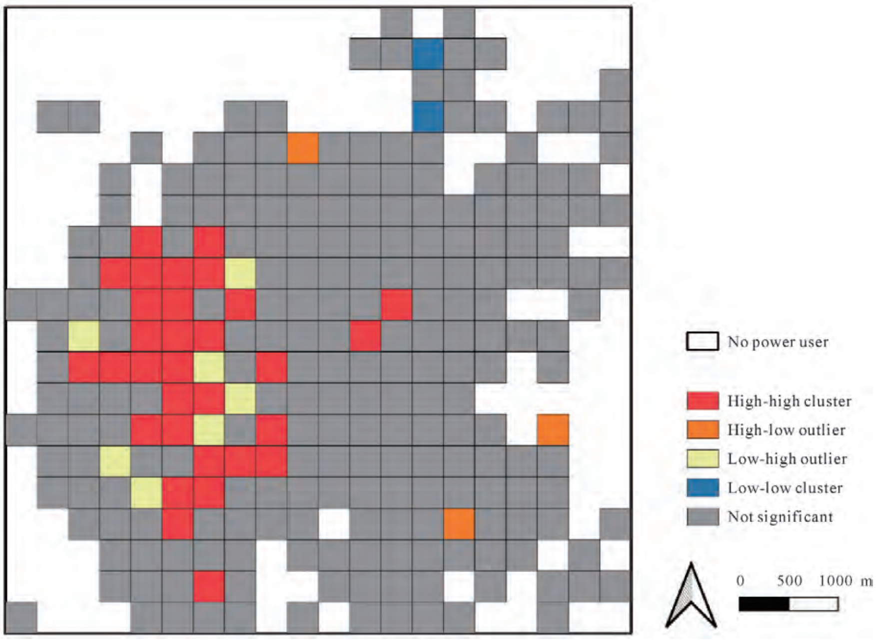


Fig.4 Local spatial autocorrelation analysis of the degree of abnormal electricity consumption in urban area

The results of the divergence and factor detection in the Geodetector are shown in Tab.1. The larger the q-value indicates the greater the degree of influence of this type of POI on the distribution of the degree of abnormal electricity consumption in the city. As can be seen from the table, the q-values of restaurants, accommodation, leisure and entertainment, residential community, financial services and living services are all greater than 0.2. These POI categories are mainly located in areas with highly mixed residential, commercial and entertainment functions in the city, with a large user base and complex personnel composition, which are prone to abnormal electricity consumption. The impact degree of public facilities, scientific research and education, shopping, government agencies, buildings, and medical services are all lower than 0.2, indicating that abnormal electricity consumption is less in public service areas, industrial areas, and business areas in the city. Most of these areas are dedicated users, powered by special transformers, and users have better electricity consumption habits, resulting in less abnormal electricity consumption. The influence of tourism is at the lowest level of 0.005, and the areas of tourism are generally suburban areas with fewer users, so there are few cases of abnormal electricity consumption.

Tab.1 Geodetector divergence and factor detection results

Impact factor	q-value	Impact factor	q-value
Restaurants	0.263***	Scientific research education	0.180***
Accommodation	0.262***	Shopping	0.173***
Leisure and entertainment	0.259***	Government offices	0.164***
Residential neighborhoods	0.256***	Mansions	0.163***
Financial services	0.242***	Medical services	0.111***
Life services	0.208***	Travel	0.005
Public facilities	0.182***		

Significant codes: 0"***"0.001"**"0.01"*"0.05"."0.1.

Different POI category enrichment factors were combined, and the interaction effects of each factor were analyzed by the cross-action detector in the Geodetector. The results show that the interactions between the POI enrichment factors of each category have a higher impact on the distribution of the degree of abnormal urban electricity consumption than that of a single factor alone. The type of interaction between tourism and lifestyle services and tourism and medical services is nonlinearly enhanced, and the interaction between the remaining two factors is bifactor enhanced.

4 Conclusion and Discussion

4.1 Conclusion

Previous studies on the detection of abnormal electricity consumption of urban electricity users failed to consider the time dependence of electricity series data, and did not explore the relationship between the degree of abnormal electricity consumption and its spatial location in urban areas, as well as did not quantitatively analyze the degree of influence of urban functions on the distribution of the degree of abnormal electricity consumption in urban areas. This study constructs an abnormal electricity consumption detection model based onthe STL time series decomposition, and analyzes the relationship between the abnormal electricity consumption degree and its spatial location in urban areas, as well as quantitatively analyzes the influence of various types of POI enrichment factors on the distribution of abnormal electricity consumption degree in urban areas. The main conclusions including:

① The user abnormal electricity consumption detection method proposed in this study can well decompose the abnormal electricity consumption data points of users in time sequence from the perspective of time dependence, and then detect them abnormally through the dispersion degree of residuals, so as to well determine whether the users are abnormal electricity users. The effective detection of urban abnormal electricity users can reduce the losses of power companies and maintain the safe operation of power grids, and at the same time can provide protection for users' daily electricity safety and reduce their electricity consumption risks.

② By analyzing the influence of various POI enrichment factors, we found that urban area functions have an important influence on the degree of abnormal electricity consumption in urban areas. The abnormal electricity consumption in the city mainly occurs in residential areas and areas with a high mixture of residential, commercial and entertainment users, while the abnormal electricity consumption is less in areas with a concentration of dedicated users such as factories, public service areas and business areas. At the same time, spatial autocorrelation analysis reveals that there are spatial distribution differences in the degree of abnormal electricity consumption in the central city of Pingxiang, with high-high clusters located in or around the city center and low-low clusters located in the suburban areas at the edge of the city, further indicating that geographical location factors have a great influence on the degree of abnormal electricity consumption in urban areas. It helps to accurately monitor the spatial development of the city and put the anti-theft equipment into specific areas to achieve the purpose of accurate deployment [23].

4.2 Discussion

This paper has obtained certain research conclusions and has some research value, but there are also shortcomings in the research process. The influence factor dataset used for the Geodetector in this study only uses POI enrichment factors reflecting urban functions, but does not consider the influence of socio-economic features and underlying geographic features [24-25], and subsequent studies analyzing the potential correlation between these features and the degree of abnormal electricity consumption in urban areas can be conducted.

References

[1] BREUNIG M M, KRIEGEL H P, NG R T, et al. LOF: identifying density-based local outliers [C] // Proceedings of the 2000 ACM SIGMOD International Conference on Management of Data. Texas: ACM, 2000: 93-104.

[2] WANG Yi, CHEN Qixin, HONG Tao, et al. Review of smart meter data analytics: applications, methodologies, and chal-

lenges [J]. IEEE Transactions on Smart Grid, 2019, 10(3): 3125-3148.

[3] BUZAU M M, TEJEDOR-AGUILERA J, CRUZ-ROMERO P, et al. Detection of non-technical losses using smart meter data and supervised learning [J]. IEEE Transactions on Smart Grid, 2019, 10(3): 2661-2670.

[4] MICHELI G, SODA E, VESPUCCI M T, et al. Big data analytics: an aid to detection of non-technical losses in power utilities [J]. Computational Management Science, 2019, 16 (1-2): 329-343.

[5] JOKAR P, ARIANPOO N, LEUNG V C M. Electricity theft detection in AMI using customers' consumption patterns [J]. IEEE Transactions on Smart Grid, 2016, 7(1): 216-226.

[6] ANGELOS E W S, SAAVEDRA O R, CORTÉS O A C, et al. Detection and identification of abnormalities in customer consumptions in power distribution systems [J]. IEEE Transactions on Power Delivery, 2011, 26(4): 2436-2442.

[7] JÚNIOR L A P, RAMOS C C O, RODRIGUES D, et al. Unsupervised non-technical losses identification through optimum-path forest [J]. Electric Power Systems Research, 2016, 140: 413-423.

[8] BUZAU M M, TEJEDOR-AGUILERA J, CRUZ-ROMERO P, et al. Hybrid deep neural networks for detection of non-technical losses in electricity smart meters [J]. IEEE Transactions on Power Systems, 2020, 35(2): 1254-1263.

[9] BIAN Jiahao, WANG Lei, SCHERER R, et al. Abnormal detection of electricity consumption of user based on particle swarm optimization and long short term memory with the attention mechanism [J]. IEEE Access, 2021, 9: 47252-47265.

[10] BRUNSDON C, FOTHERINGHAM A S, CHARLTON M E. Geographically weighted regression: a method for exploring spatial nonstationarity [J]. Geographical Analysis, 1996, 28 (4): 281-298.

[11] FOTHERINGHAM A S, YANG Wenbai, KANG Wei. Multiscale geographically weighted regression [J]. Annals of the American Association of Geographers, 2017, 107 (6): 1247-1265.

[12] LUO Lili, MEI Kun, QU Liyin, et al. Assessment of the geographical detector method for investigating heavy metal source apportionment in an urban watershed of eastern China [J]. Science of the Total Environment, 2019, 653: 714-722.

[13] SHRESTHA A, LUO Wei. Analysis of groundwater nitrate contamination in the Central Valley: comparison of the geodetector method, principal component analysis and geographically weighted regression [J]. ISPRS International Journal of Geo-Information, 2017, 6(10): 297.

[14] XU Li, DU Hongru, ZHANG Xiaolei. Driving forces of carbon dioxide emissions in China's cities: an empirical analysis based on the geodetector method [J]. Journal of Cleaner Production, 2021, 287: 125169.

[15] WANG Jinfeng, LI Xinhu, CHRISTAKOS G, et al. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China [J]. International Journal of Geographical Information Science, 2010, 24(1): 107-127.

[16] WANG Jinfeng, ZHANG Tonglin, FU Bojie. A measure of spatial stratified heterogeneity [J]. Ecological Indicators, 2016, 67: 250-256.

[17] YAO Yao, ZHANG Jiaqi, QIAN Chen, et al. Delineating urban job-housing patterns at a parcel scale with street view imagery [J]. International Journal of Geographical Information Science, 2021, 35(10): 1927-1950.

[18] ZHAI Wei, BAI Xueyin, SHI Yu, et al. Beyond Word2vec: an approach for urban functional region extraction and identification by combining Place2vec and POIs [J]. Computers, Environment and Urban Systems, 2019, 74: 1-12.

[19] CLEVELAND R B, CLEVELAND W S, MCRAE J E, et al. STL: a seasonal-trend decomposition procedure based on loess [J]. Journal of Official Statistics, 1990, 6(1): 3-73.

[20] CHOU J S, TELAGA A S, CHONG W K, et al. Early-warning application for real-time detection of energy consumption anomalies in buildings [J]. Journal of Cleaner Production, 2017, 149: 711-722.

[21] LEONG K, LEUNG C, MIAO Chunyan, et al. Detection of anomalies in activity patterns of lone occupants from electricity usage data [C] // Proceedings of the 2016 IEEE Congress on Evolutionary Computation (CEC). Vancouver: IEEE, 2016: 1361-1369.

[22] WANG Jinfeng, XU Chengdong. Geodetector: principle and prospective [J]. Acta Geographica Sinica, 2017, 72(1): 116-134.

[23] ZHANG Xinchang, LI Shaoying, ZHOU Qiming, et al. Logical and innovative construction of digital twin city [J]. Journal of Geodesy and Geoinformation Science, 2021, 4(4): 113-120.

[24] ZHANG Tianning, SONG Hongquan, ZHOU Boyan, et al. Effects of air pollutants and their interactive environmental factors on winter wheat yield [J]. Journal of Cleaner Production, 2021, 305: 127230.

[25] ZHANG Xiangxue, NIE Juan, CHENG Changxiu, et al. Spatial pattern of the population casualty rate caused by super typhoon Lekima and quantification of the interactive effects of potential impact factors [J]. BMC Public Health, 2021, 21 (1): 1260.