Influencing Factors of Spatial Heterogeneity of Land Surface Temperature in Nanjing, China

Qiang Fan, Xiaonan Song, Yue Shi, and Rui Gao

***Abstract*—The environment and climate significantly affect the land surface temperature (LST) of a city. Previous studies have revealed that LST exhibits significant spatial heterogeneity primarily caused by a combination of natural factors and human activities. Based on this, the introduction of point of interest data of the "production–living–ecological space" divides the influencing pattern into a comprehensive description of human activities supplemented by natural factors, resulting in the precise influencing factors of spatial heterogeneity of LST. Taking Nanjing (Jiangsu Province, China) as a case study, this study uses Landsat-8 remote sensing images, point of interest data, and other data to establish a geographically weighted regression model that combines natural factors and human activities. The main research results are as follows: First, the LST of Nanjing ranged from 19.9 °C to 47.6 °C, whereas the distribution trend was "low at both ends and high in the middle." Second, there is no multicollinearity of the influencing factors, the fitting degree of LST and each influencing factor reached 0.87. The regression coefficients were high and exhibited both positive and negative values, implying that spatial heterogeneity exists among the influencing factors and LST. Finally, the ranking of how all factors influence the LST followed the order of water area > forest and grassland > ecological space > slope > production space > elevation > living space. The research results have practical significance for improving the quality of life of urban residents and providing a critical theoretical basis for optimizing urban human settlements.**

***Index Terms*—Geographically weighted regression (GWR), human settlements, land surface temperature (LST), Nanjing, spatial heterogeneity.**

I. Introduction

In April 2020, the World Meteorological Organization released the report on the State of the Global Climate in 2015–2019, highlighting that the global average temperature in 2019 was 1.1 °C higher than the estimated preindustrialization average temperature. Moreover, the temperatures in the past five years had been the highest since the establishment of a temperature record. Since the foundation of the People's Republic of China till 2019, the Chinese urban population has increased from 57.65 million to 848.43 million, with the national urban proportion increasing from 10.64% to 60.60%. Due to the rising urban population, large amounts of greenhouse gases have been released into the atmosphere; additionally, vegetation, water bodies, and other natural features have been degraded by construction [1], thereby changing the land surface temperature (LST). Research has revealed that LST can potentially indicate the ecological environment in cities. Many urban ecological and social issues, such as biological phenology, ecosystem evolution, human living environment, and human health, have been concerning [2]–[6]. Thus, the analysis of the influencing factors of LST from multiple perspectives is essential for improving the quality of life in cities.

In recent years, scholars have increasingly researched the influencing factors of LST. The research objects primarily included land-use types [7]–[11], landscape patterns [12]–[14], surface biophysical index [15]–[17], and artificial and policy factors [18]–[20]. Zhao *et al.* [21] explored the relationships between LST and rivers, accumulated snow, and glaciers. Yang and Yue *et al.* [22]–[24] analyzed the influences of industrial suburbanization, building density, urban ventilation, and urban green land on LST. Qiao *et al.* [25] investigated the relationship between LST and other satellite-derived land surface parameters Li *et al.* [13] utilized the semiparametric geographically weighted regression (GWR) model to determine that the landscape structure exerts a greater influence on LST than the landscape composition. Deng *et al.* [26] revealed that the normalized difference vegetation index (NDVI) is inversely correlated with LST distribution. Parvez *et al.* [27] found that the population density is an influencing factor of LST. Overall, previous research has revealed the influences of human activities and natural factors on LST. However, the indicators have been studied separately, which fails to reflect the actual conditions in nature. Additionally, most LST data are either moderate resolution imaging spectroradiometer (MODIS) images with a resolution of 1 km [28]–[30] or Landsat Thematic Mapper ^{TM} images with a resolution of 150 m [31]. Therefore, descriptions about LST are not comprehensive.

The production–living–ecological space includes the production, life, and ecological spaces. Research on the production–living–ecological space helps optimizing space, governing resources and environment, and promoting ecological development. Research has revealed that the distribution of the production–living–ecological space strongly correlates with the living quality, utilization of space, and the ecological environment [32]–[34]. Currently, only a few studies have revealed the correlation between the production–living–ecological space and LST, and the correlation degree remains unknown.

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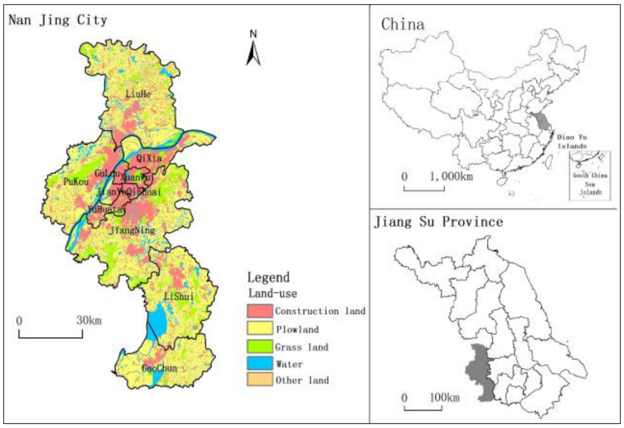

Fig. 1. Location of study area.

In summary, exploratory research on the influencing factors of LST must comprehensively classify the indicator and select indicators that best reflect the nature to explore its actual influencing factors. This study performed an inversion of LST based on Landsat-8 operational land imager (OLI) data and classified its influencing factors into the following two categories: natural and human activity elements. The natural elements include the elevation, slope, forest and grassland, and water. The human activity elements are identified using the point of interest (POI) data of the production–living–ecological space. Both elements are considered to explore the influencing factors of the LST in all districts of Nanjing City to provide a reference for improving the life quality of urban populations.

II. Study Area and Research Methods

A. Study Area

Nanjing City (see Fig. 1) is located in Jiangsu Province, China (31°14′–32°37 N, 118°22′–119°14 E). Located in the center of the municipal administrative region bordered by the Ningzhen and Laoshan mountains, Nanjing City is an area with low mountains and hills. It features a subtropical monsoon climate, with four distinctive seasons and a mean annual temperature of 16.2 °C. During 2000–2018, the Nanjing City population increased from 5.4489 million to 6.9694 million. Nanjing City contains 11 districts, including Xuanwu, Qinhuai, Jianye, Gulou, Pukou, Qixia, Yuhuatai, Jiangning, Liuhe, Lishui, and Gaochun. It is an important part of the Yangtze River Delta Urban Agglomerations in China, which has developed rapidly in recent years. With continuous economic development, urbanization has gradually become a prominent problem, and the urban heat island effect has a huge impact on the urban environment and human settlements. Therefore, it is of great significance to select Nanjing City as the study area.

B. Data Sources

The data utilized in this study included POI data, Landsat-8 OLI remote sensing image data, and digital elevation model data. The data sources are presented in Table I. POI data crawled by Baidu Map are cleaned, screened, and classified based on the production–living–ecological space. The production–living–ecological space is a general term for production, living, and ecological space, which are independent of each other and interrelated. The production space element primarily refers to the spatial area used by humans for industries and various associated products. The life space element is the spatial area for daily human activities. The ecological space element is the spatial area for maintaining ecological stability [35]. Table II lists the specific classification rules, which are based on the Ministry of Housing and Urban–Rural Development of the People's Republic of China. The code for the classification of urban land use and planning standards of development land is GB50137-2011. Through random forest supervision classification of Landsat-8 OLI data, the spaces are classified as construction land, forest and grassland, cultivated land, water bodies, and other lands. The kappa coefficient was 0.91, which meets the analysis requirements.

TABLE I
Data Source and Descriptions

Data	Date	Data source
POI data	2019	https://map.baidu.com/
Landsat-8 OLI remote sensing image data	2019	http://www.glovis.usgs.gov/
DEM data	/	http://www.gscloud.cn/

C. Research Methods

1) Mono-Window Algorithm: LST is a critical parameter for reflecting the earth's surface energy. Currently, the inversion of LST is primarily realized using the single-channel [36], mono-window [37], or split-window algorithms [38], [39]. The mono-window algorithm is characterized by high inversion precision and applicability. The Landsat-8 OLI data used in this study exhibit the following two thermal infrared bands: 10th and 11th. According to research, the 10th band exhibits a superior effect on the inversion of LST [40]. Therefore, this study adopted the mono-window algorithm to calculate the LST in Nanjing City based on the 10th thermal infrared band. The calculation formulae are as follows:

$$LST = [a(1 - C - D) + (b(1 - C - D) + C + D)T - D \cdot T_{mn}]/C \quad (1)$$

$$C = \alpha\beta \quad (2)$$

$$D = (1 - \alpha)\,[1 + (1 - \beta)\alpha] \quad (3)$$

where α is the atmospheric transmissivity, β is the surface emissivity, T is the brightness temperature corresponding to the star radiation measurement, T_{mn} is the mean atmospheric temperature, and a and b are the regression coefficients. The unit of LST is *K*.

2) Kernel Density Analysis: Kernel density analysis is a method to determine the gathering area of point elements [41]. The kernel density analysis was performed to output the POI data

TABLE II
RULES FOR CLASSIFICATION OF "PRODUCTION–LIVING–ECOLOGICAL" SPACE BASED ON POI DATA

Major class	Medium class	Subclass
Production	Transportation	Entrance/exit, traffic facilities
	Production Service	Companies, finance
	Management	Governmental authorities
Life	Life service	Real estate, shopping, education training, hotel, beauty, food, life service, auto service, cultural media, leisure and entertainment, fitness, medical treatment
Ecology	Ecological Green land	Tourist attractions, natural features

density situation of all the districts in Nanjing City. Assuming that the POI point data are $a_1, a_2, a_3 \ldots a_n$, the estimation function of the Kernel density is as follows:

$$f_n(x) = \frac{1}{n\pi r^2} * \sum_{i=1}^{n} A\left[\left(1 - \frac{(a-a_i)^2 + (b-b_i)^2}{r^2}\right)\right]^2 \tag{4}$$

where $(a-a_i)^2 + (b-b_i)^2$ is the square of the Euclidean distance from (a_i, b_i) to (a, b), r is the search radius, n is the number of sample points within the search radius, and A is the Kernel function.

3) GWR: Regression analysis is a commonly used data analysis method. The most famous data analysis method is the ordinary least squares (OLS). However, the OLS method only considers the global estimation and does not consider the spatial heterogeneity of the dependent and independent variables [42]. GWR exhibits several advantages, such as a small residual and sufficient local reflection of the results. Therefore, it is suitable for determining the influencing factors (e.g., natural and human activity elements) of the LST in this study. The principle is as follows:

$$Y_i = \alpha_0(u_i, v_i) + \sum_{i=1}^{k} \alpha_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{5}$$

where Y_i is the explanatory value of the dependent variable, (u_i, v_i) is the geographic coordinate of the ith district, x_{ik} $(k = 1, 2 \ldots 10)$ is the explanatory value of the independent variable of the ith district, and ε_i is the error term.

4) Affect Variables: Seven variables were selected as the LST explanatory variables. These encompassed the following two aspects: natural and human activity elements. The natural elements were divided into topographic factors and land cover types. Different topographic relief changes have different effects on LST [43], [44]; therefore, slope and elevation were selected as the influencing variables. In addition, land cover type had a major influence on LST, and the proportion of forest, grass, and water in land-use type was extracted as the influencing variable of LST.

LST is related to land cover types and topographic factors and is greatly influenced by human activities [45], [46]. Therefore, to effectively describe the impact of human activities on LST, this study divided the POI into "living space," "production space," and "ecological space" according to different types of POI and considered the densities of the above-mentioned three factors as the variables affecting the spatial heterogeneity of LST.

III. RESULTS AND ANALYSIS

A. Spatial Distribution Pattern of LST

This study utilizes the mono-window algorithm to invert the LST in Nanjing City. The results are shown in Fig. 2(a). According to the statistical analysis, the mean LST was 27.5 °C, 26.8 °C, 26.6 °C, 26.3 °C, 26.2 °C, 26.2 °C, 25.9 °C, 25.7 °C, 25.4 °C, 25.3 °C, and 24.9 °C for Qinhuai, Gulou, Yuhuatai, Pukou, Xuanwu, Jianye, Qixia, Jiangning, Gaochun, Lishui, and Liuhe districts, respectively. The LST in Nanjing City was lower on the periphery and higher in the center. The LSTs in the five districts in the center were high, and the LST declined gradually from the five central districts.

B. Spatial Distribution Pattern of Influencing Factors

The slope (see Fig. 2(b)) is a primary indicator for measuring the geography and landform of a district. The slope difference of all the districts in Nanjing City was large; however, the mean slope was 5–8.5°. The mean slopes of the five districts in the center of Nanjing City were large: 8.192°, 7.104°, 6.682°, 6.364°, and 5.720° for Xuanwu, Yuhuatai, Gulou, Qinhuai, and Jianye districts, respectively. In contrast, the mean slopes of the urban fringe districts of Nanjing City were 5.818°, 5.668°, and 5.421° for Liuhe, Gaochun, and Lishui districts, respectively. The mean slopes of the three districts surrounding the central five districts were as follows: 7.563°, 6.925°, and 5.634° for Pukou, Jiangning, and Qixia districts, respectively. Nanjing City is at a low altitude. The city elevation distribution is illustrated in Fig. 2(c). The mean elevations of all the districts were as follows: 54.0340 m, 34.093 m, 33.675 m, 27.488 m, 22.754 m, 22.437 m, 22.190 m, 21.783 m, 18.604 m, 17.982 m, and 7.992 m for Xuanwu, Jiangning, Lishui, Pukou, Liuhe, Yuhuatai, Gulou, Gaochun, Qixia, Qinhuai, and Jianye districts, respectively. The elevation differences among the Yuhuatai, Gulou, Gaochun, Qixia, Qinhuai, and Jianye districts were small.

Nanjing City was deemed a "national forest city" by the China Green Committee and the Forestry Administration of China, in 2013, encouraging Nanjing City to develop into a green, ecological, and suitable city for living. Through the visual interpretation of remote sensing images, we obtained

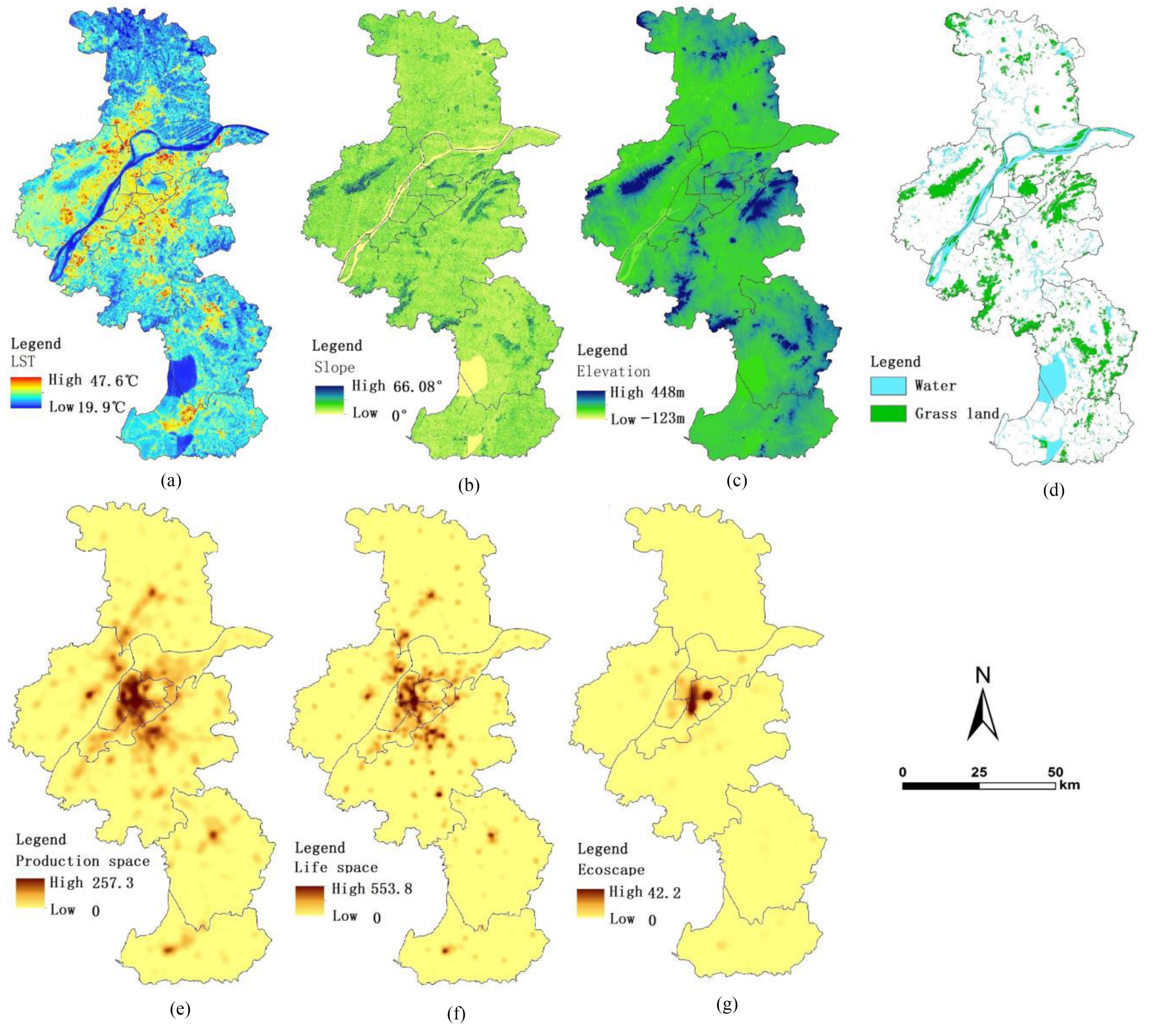

Fig. 2. Spatial heterogeneity of the LST and influencing factors.

the distributions of forests, grasslands, and water bodies in all districts of Nanjing City (see Fig. 2(d)). The Xuanwu, Yuhuatai, Gulou, Qinhuai, and Jianye districts contained large construction land areas and exhibited high afforestation rates. The east of the Jiangning District contained many forestlands and shrubberies that provided sufficient vegetation coverage. The northeast of the Pukou District was also covered by a large area of forest and grasslands. The south of the Gaochun District was covered with forest and grasslands, and water bodies were found in the north. The north of the Lishui District was mostly covered with a large forest and grassland area, and there were many water bodies in the northwestern part of the district. The entire Liuhe District was covered with paddy fields and water bodies, and forest and grasslands were primarily distributed in the northeast portion of the district. In the Qixia District, forest and grasslands were predominately distributed in the central area, and water flowed from the west to the east.

A kernel density analysis of the POI data in Nanjing City was conducted. POI data were classified according to the production–living–ecological space. The kernel density analysis results are presented in Fig. 2(e)–(g). The centralized distribution area of the production–living–ecological space exhibited different values. However, the areas with a high kernel density value were primarily distributed in the five districts in the center of Nanjing City. The kernel density analysis of the production space revealed that the kernel density was high in the south of the Liuhe District, east of the Pukou District, southwest of the Qixia District, north of the Jiangning and Lishui Districts, and northwest of the Gaochun District. Additionally, this analysis indicated that the area with a high kernel density value was similar to the production space. In contrast, the area with a high kernel density of the life space in the Jiangning and Pukou districts was scattered. The kernel density analysis of the ecological space revealed that areas with a high kernel density value were

TABLE III
REGRESSION COEFFICIENT OF GWR MODEL

Influencing factor	Minimum value	Maximum value	Mean value	Proportion of negative value	Proportion of positive value
Elevation	-0.156065	0.997772	0.021346	40.9434	59.0566
Slope	-0.205846	2.993982	0.132135	34.3879	65.6121
Forest and grass land	-0.000014	0.000013	-1.441052	89.4257	10.5743
Water	-0.000024	0.000029	-1.848331	92.3614	7.6386
Production space	-0.061891	1.146619	0.048777	2.5652	97.4348
Life space	-1.409952	0.083638	-0.006376	74.6045	25.3955
Ecological space	-1.897459	9.437645	0.205397	46.4443	53.5557

primarily distributed in Gulou, Xuanwu, Qinhuai, and Jianye districts, and the Kernel density value in the other districts was low.

C. GWR Analysis

This study utilized the GWR model to explore the spatial heterogeneity of the LST in all Nanjing City districts according to the natural and human activity elements. The calculated variance inflation factor (VIF) was <7.5, establishing that there was no multicollinearity among the selected factors. Fig. 3(a) shows the fitting degree of selected indicators of the GWR model and LST. The R^2 value in each area ranged between 0.442 and 0.929, revealing that the seven influencing factors selected in this study exhibited an explanatory power for the LST, and the explanatory power was stronger for the central districts in Nanjing City than for districts on the urban fringe. This result is primarily because the urbanization rate of all districts in the center of Nanjing City was high; thus, the factors strongly influenced the LST.

The regression coefficient of the GWR model was arranged (see Table III), and the maximum, minimum, and mean values and proportions of positive and negative values were taken as the statistical types. Table III demonstrates that the regression coefficients of the influencing factors greatly differ, with both positive and negative values, indicating the spatial heterogeneity of the influencing factors. The absolute value of the mean value reflects the effect of each influencing factor on the LST: waters > forest and grassland > ecological space > slope > production space > elevation > life space.

D. Analysis of Influencing Factors of LST

The relevant coefficient of each influencing factor in the GWR model was visualized to obtain the spatial distribution of the relevant coefficient of each indicator to analyze the influencing factors of the LST in Nanjing City. The influence of the terrain factor as a natural element on the LST presented a positive correlation, whereas the influence of the natural features on the LST presented a negative correlation. The degree of the influence of natural elements on the LST followed the order of waters > forest and grasslands > slope > elevation. Within the municipal administrative region, the regression coefficient of the slope was small. The regression coefficient in the center was lower than that on the fringe, and a high regression coefficient only occurred to the west of the Liuhe, Pukou, Qixia, and Jiangning districts, the north of the Lishui District, and the west and the south of the Gaochun District. However, the regression coefficient of the central five districts was small, and most areas presented a negative correlation. The influence of elevation (see Fig. 3(c)) on different districts in Nanjing City was significantly large. A negative correlation was presented in the Xuanwu District likely because its mean elevation and the elevation difference were the largest among all districts, and elevation significantly influenced the LST in this area. Comparatively, the Jianye District presented a positive correlation, and the mean value and elevation differences of this area were the smallest. The Jianye, Yuhuatai, Liuhe, Pukou, and Gaochun districts contained many areas that presented a positive correlation. Jiangning District presented alternating positive and negative correlations. The east and the west exhibited a positive correlation, whereas the central area presented a negative correlation.

The forest and grasslands primarily presented a negative correlation with the LST of Nanjing City. All five districts in the center of Nanjing City presented the same negative correlation level, indicating that LST decreases with increase in the forest and grassland areas (see Fig. 3(d)). This is because green plants undergo transpiration; they can absorb heat from the environment to reduce the temperature. The influence of water (see Fig. 3(e)) on the LST in the north of the Liuhe District, southwest of the Pukou and Jiangning districts, and east and west of the Gaochun District presented a positive correlation, whereas other areas presented a negative correlation. This is primarily because the heat capacity of water is large; heat absorption occurring during evaporation of water decreases the LST more than that of forest and grasslands. This is also the reason for the higher influence of water on the LST than that of the forest and grassland.

In this study, the production–living–ecological space was selected to evaluate human activity elements. The influence of the life space on the LST presented a negative correlation, whereas that of the production and ecological spaces presented a positive correlation. The degree of influence of human activity elements on the LST followed the order of ecological space > production space > life space. A positive correlation effect of the production space (see Fig. 3(f)) on the LST was presented for a large part of the municipal administrative area, including north of the Liuhe District, east of the Qixia and Lishui districts, west

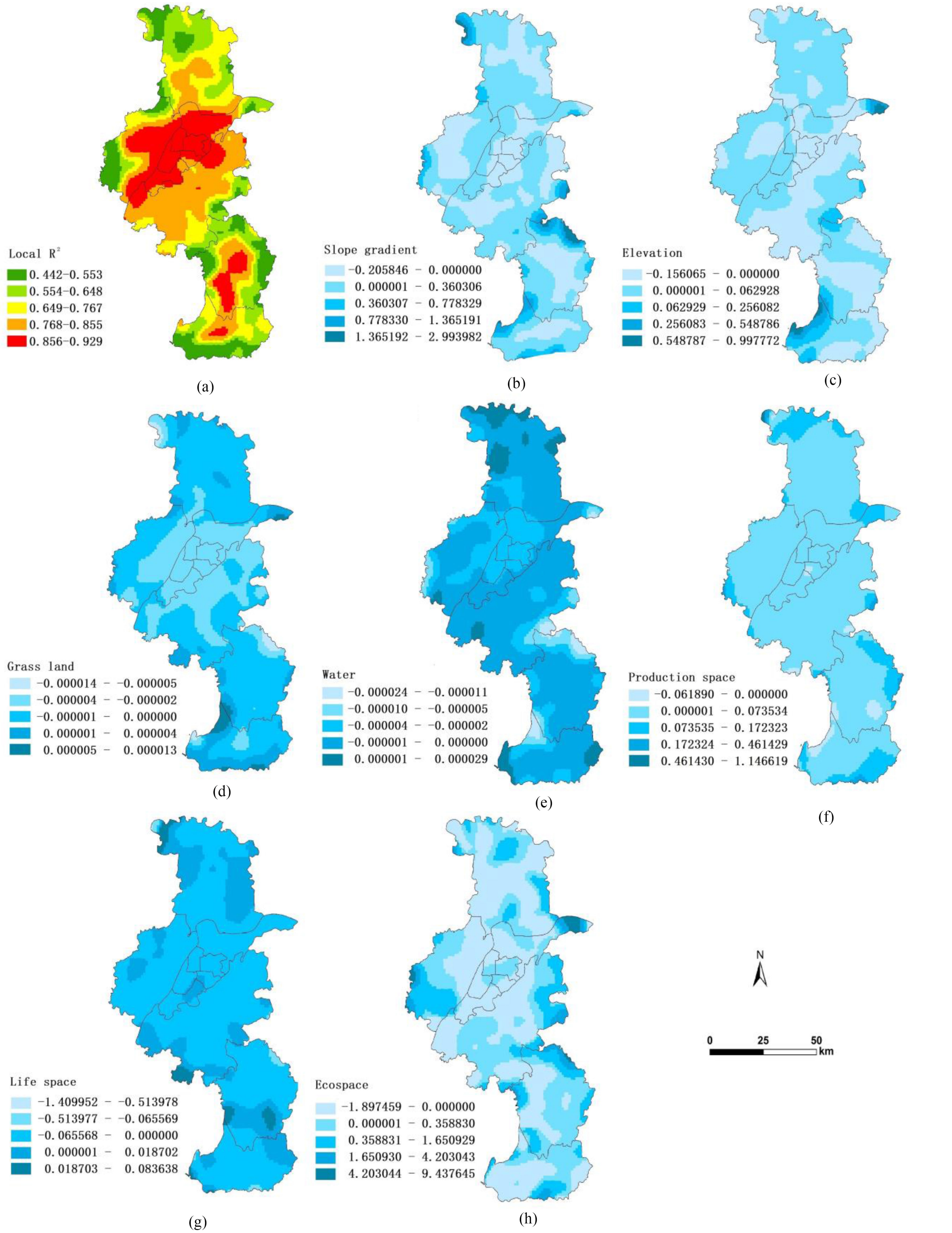

Fig. 3. Fitting degree and coefficient distribution.

of the Pukou District, and south of the Gaochun District. This was primarily because the subclasses of the production space included entrances and exits, traffic facilities, companies, financial institutions, and government authorities. Most subclasses were covered with construction lands, and an increase in the construction lands can increase the LST. A negative correlation effect of the life space (see Fig. 3(g)) element was presented for the entire municipal administrative region. A positive correlation effect was presented in the east and west of the Liuhe District, west of the Pukou District, northeast of the Yuhuatai District, southwest of the Qinhuai and Jiangning districts, south of the Lishui District, and east and west of the Gaochun District. The life space primarily constitutes hotels and beauty and cultural media places. These life service places consider afforestation; thus, the negative correlation of the life space element and LST was presented in a large area. The positive and negative correlations of the ecological space (see Fig. 3(h)) and LST across the entire municipal administrative region were equivalent. The Jianye and Yuhuatai districts, which constituted a large area, presented a negative correlation. The Jiangning, Lishui, and Pukou districts, which encompassed a large area, presented a positive correlation. Among the POI data, the ecological space primarily includes tourist attractions and natural features; its high-density value was predominantly distributed in the five central districts of Nanjing City. The increase in tourist attractions and natural features implies increasing green land and waters, and LST can be reduced accordingly.

IV. Discussion and Conclusion

A. Discussion

1) Influencing Factors of LST: LST is an indicator of the ecological environment of a city. Analyzing its spatial heterogeneity and influencing factors can help improve urban life quality. Influencing factors of LST can be summarized as natural factors and human activities. Previous studies primarily explored the influences of unitary elements on LST, such as the NDVI [27], ozone pollution [47], and building density [48]. Most LST data are MODIS images with a resolution of 1 km or Landsat TM images with a resolution of 150 m. Additionally, the descriptions of the ground temperature are not typically detailed. In this study, Landsat OLI images with a resolution of 100 m were used to invert the LST data, and the influencing factors of the spatial heterogeneity of LST were explored by analyzing seven natural and human activity elements. Thus, the influencing factors can be comprehensively analyzed. Combining natural and human activity elements with the LST provides a crucial basis for improving the urban living quality and the social development space.

2) Influences of Human Activities on the LST: Human activities exert a great influence on the LST. Recent studies have demonstrated that population density [28], land utilization [49], and city size [50] are the primary influencing factors of the LST. The emergence of POI data facilitates a detailed description of human activities. This study classified the POI data according to the production–living–ecological space. A few existing studies have associated the production–living–ecological space and LST. Incorporating this classification into an LST study can help in exploring the influence of human activities on the LST and optimizing the spatial layout of the production–living–ecological space. Therefore, this research is significant for governmental planning and decision-making departments.

3) Study Limitations: This study still exhibits certain limitations in exploring the influencing factors of the spatial heterogeneity of the LST by combining natural and human activity elements. Research at the municipal level can be sufficiently conducted; however, the effect cannot be fully understood when research is conducted at the national or provincial level due to the cloud quantity and timeliness of the Landsat-8 OLI images. Additionally, the influencing factors selected in this study included both natural and human activity elements (seven influencing factors in total). Other influencing factors can also promote the generation of the spatial heterogeneity of the LST.

B. Conclusions

This research selected Nanjing City, Jiangsu Province, China, as a case study. This study utilized the GWR model and combined natural and human activity elements to determine the spatial heterogeneity of influencing factors of the LST. The primary conclusions are as follows.

1) The LST in Nanjing City was lower on the periphery and higher in the center. The elevation and slope of the districts were low. The central area of Nanjing City underwent rapid economic development and afforestation. Many water bodies, such as the Yangtze River and Shijiu Lake, are located nearby, and the waters are distributed sporadically. This study used the production–living–ecological space to present the human activity distribution. The density distribution declined gradually from the life space to the production space and subsequently to the ecological space.
2) According to the collinearity inspection, the VIF value of the influencing factors was <7.5, indicating no multicollinearity. The fitting degree of the LST and influencing factors reached 0.87, and the effects of the LST influencing factors exhibited strong spatial heterogeneity.
3) The mean coefficients of the influencing factors on the LST were as follows: 0.021 for elevation, 0.132 for slope, -1.441 for forest and grassland, -1.848 for water bodies, 0.049 for production space, -0.006 for life space, and 0.205 for ecological space. Thus, the degree of influence of the factors on the LST followed the order of waters $>$ forest and grasslands $>$ ecological space $>$ slope $>$ production space $>$ elevation $>$ life space.

Exploring the influencing factors of the spatial heterogeneity of the LST using the GWR model is useful for determining its spatial heterogeneity. Moreover, using the production–living–ecological space division model to assess POI data can explain the influences of human activities on the LST for various spatial patterns, providing a strong theoretical basis for the decision-making of governmental authorities. Future research can continue exploring the influencing factors of the LST at the national and provincial levels to improve the urban living environment.

REFERENCES

[1] H. L. Hu, Y. H. Chen, and A. D. Gong, "Advance in the application of remotely sensed data to the study of urban heat island," *Remote Sens. Land Resour.*, no. 3, pp. 5–9+13, 2005.

[2] A. W. Michael, R. N. Ramakrishna, E. T. Peter, and W. R. Steven, "Satellite evidence of phenological differences between urbanized and rural areas of the eastern United States deciduous broadleaf forest," *Ecosystems*, vol. 5, no. 3, pp. 260–273, 2002.

[3] N. B. Grimm *et al.*, "Global change and the ecology of cities," *Sci.*, vol. 319, no. 5864, pp. 756–760, Feb. 2008.

[4] W. Z. Yue, X. Liu, Y. Y. Zhou, and Y. Liu. "Impacts of urban configuration on urban heat island: An empirical study in China mega-cities," *Sci. Total Environ.*, vol. 671, pp. 1036–1046, Jun. 2019.

[5] A. D. Guo *et al.*, "Impact of urban morphology and landscape characteristics on spatiotemporal heterogeneity of land surface temperature," *Sustain Cities Soc.*, vol. 63, Dec. 2020, Art. no. 102443.

[6] B. J. He, Z. Q. Zhao, L. D. Shen, H. B. Wang, and L. G. Li, "An approach to examining performances of cool/hot sources in mitigating/enhancing land surface temperature under different temperature backgrounds based on Landsat 8 image, " *Sustain. Cities Soc.*, vol. 44, pp. 416–427, Oct. 2018.

[7] B. Feizizadeh and T. Blaschke, "Examining urban heat island relations to land use and air pollution: Multiple endmember spectral mixture analysis for thermal remote sensing," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 6, no. 3S1, pp. 1749–1756, Jun. 2013.

[8] X. Luo, J. Yang, W. Sun, and B. J. He, "Suitability of human settlements in mountainous areas from the perspective of ventilation: A case study of the main urban area of Chongqing," *J. Clean Prod.*, vol. 310, 2021, Art. no. 127467.

[9] Y. T. Lu, P. H. Wu, X. S. Ma, H. Yang, and Y. L. Wu, "Monitoring seasonal and diurnal surface urban heat islands variations using Landsat-scale data in Hefei, China, 2000–2017," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 13, pp. 6410–6423, Oct. 2020.

[10] Z. Q. Zhao, B. J. He, L. G. Li, H. B. Wang, and A. Darko, "Profile and concentric zonal analysis of relationships between land use/land cover and land surface temperature: Case study of Shenyang, China," *Energy Build.*, vol. 155, pp. 282–295, Sep. 2017.

[11] Z. Qiao, L. Liu, Y. W. Qin, X. L. Xu, B. W. Wang, and Z. J. Liu, "The impact of urban renewal on land surface temperature changes: A case study in the main city of Guangzhou, China," *Remote Sens.*, vol. 12, pp. 794–609, 2020.

[12] R. C. Estoque, Y. Murayama, and S. W. Myint, "Effects of landscape composition and pattern on land surface temperature: An urban heat island study in the megacities of Southeast Asia," *Sci. Total Environ.*, vol. 577, pp. 349–359, Jan. 2017.

[13] W. F. Li, Q. W. Cao, K. Lang, and J. S. Wu, "Linking potential heat source and sink to urban heat island: Heterogeneous effects of landscape pattern on land surface temperature," *Sci. Total Environ.*, vol. 586, pp. 457–465, May 2017.

[14] S. H. Du, Z. Q. Xiong, Y. C. Wang, and L. Guo, "Quantifying the multilevel effects of landscape composition and configuration on land surface temperature," *Remote Sens. Environ.*, vol. 178, pp. 84–92, Jun. 2016.

[15] D. L. Sun and M. Kafatos, "Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America," *Geophys. Res. Lett.*, vol. 34, Dec. 2007.

[16] C. Y. Wu *et al.*, "Understanding the relationship between urban blue infrastructure and land surface temperature," *Sci. Total Environ.*, vol. 694, Dec. 2019, Art. no. 133742.

[17] C. Phompila, M. Lewis, B. Ostendorf, and K. Clarke, "MODIS EVI and LST temporal response for discrimination of tropical land covers," *Remote Sens.*, vol. 7, pp. 6026–6040, May 2015.

[18] J. Yang, Y. C. Wang, C. L. Xiu, X. M. Xiao, J. H. Xia, and C. Jin, "Optimizing local climate zones to mitigate urban heat island effect in human settlements," *J. Clean Prod.*, vol. 275, Dec. 2020, Art. no. 23767.

[19] X. Li, W. Li, A. Middel, S. L. Harlan, A. J. Brazel, and B. L. Turner, "Remote sensing of the surface urban heat island and land architecture in phoenix, Arizona: Combined effects of land composition and configuration and cadastral–demographic–economic factors," *Remote Sens. Environ.*, vol. 174, pp. 233–243, 2016.

[20] X. Huang and Y. Wang, "Investigating the effects of 3D urban morphology on the surface urban heat island effect in urban functional zones by using high-resolution remote sensing data: A case study of Wuhan, Central China," *ISPRS J. Photogramm.*, vol. 152, pp. 119–131, Jun. 2019.

[21] W. Zhao, J. L. He, Y. H. Wu, D. H. Xiong, F. P. Wen, and A. N. Li, "An analysis of land surface temperature trends in the central Himalayan region based on MODIS products," *Remote Sens.*, vol. 11, pp. 900–918, Apr. 2019.

[22] W. Z. Yue, S. S. Qiu, H. Xu, H. L. Xu, and L. L. Zhang, "Polycentric urban development and urban thermal environment: A case of Hangzhou, China," *Landscape Urban Plan.*, vol. 189, pp. 58–70, Sep. 2019.

[23] J. Yang *et al.*, " Contribution of urban ventilation to the thermal environment and urban energy demand: Different climate background perspectives," *Sci. Total Environ.*, vol. 795, Nov. 2021, Art. no. 148791.

[24] J. Yang, Y. X. Yang, D. Q. Sun, C. Jin, and M. X. Xiao, "Influence of urban morphological characteristics on thermal environment," *Sustain. Cities Soc.*, vol. 72, 2021, Art. no. 103045.

[25] Z. Qiao, J. D. Zhang, X. L. Xu, and L. Liu, "Robustness of satellite-derived land surface parameters to urban land surface temperature," *Int. J. Remote Sens.*, vol. 40, pp. 1858–1874, 2019.

[26] Y. H. Deng *et al.*, "Relationship among land surface temperature and LUCC, NDVI in typical karst area," *Sci. Rep.*, vol. 8, Jan. 2018, Art. no. 641.

[27] I. M. Parvez and Y. A. Aina, "Exploring the influence of land use type and population density on urban heat island intensity," in *Proc. Conf. Arabian J. Geosci.*, 2019, pp. 113–115.

[28] Y. B. Yan *et al.*, "Driving forces of land surface temperature anomalous changes in North America in 2002–2018," *Sci. Rep.*, vol. 10, pp. 1–13, Apr. 2020.

[29] S. M. Jaber and M. M. Abu-Allaban, "MODIS-based land surface temperature for climate variability and change research: The tale of a typical semi-arid to arid environment," *Eur. J. Remote Sens.*, vol. 53, pp. 81–90, Jan. 2020.

[30] F. Tian, G. Y. Qiu, Y. H. Yang, Y. J. Xiong, and P. Wang, "Studies on the relationships between land surface temperature and environmental factors in an inland river catchment based on geographically weighted regression and MODIS data," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 5, no. 3, pp. 687–698, Jun. 2012.

[31] G. H. Guo, Z. F. Wu, and Y. B. Chen, "Complex mechanisms linking land surface temperature to greenspace spatial patterns: Evidence from four southeastern Chinese cities," *Sci. Total Environ.*, vol. 674, pp. 77–87, Jul. 2019.

[32] X. Li, B. Fang, R. M. Yin, X. Xu, and T. Y. Chen, "Spatial pattern and association of production–living–ecological function and life quality on the village scale: A case of Yangzhou City, Jiangsu Province," *Acta Geographica Sinica*, vol. 40, pp. 599–607, 2020.

[33] C. Wei, Q. W. Lin, L. Yu, H. W. Zhang, S. Ye, and D. Zhang, "Research on sustainable land use based on production–living–ecological function: A case study of Hubei Province, China," *Sustainability,* vol. 13, 2021, Art. no. 996.

[34] Y. Y. Yang, W. K. Bao, Y. H. Li, Y. S. Wang, and Z. F. Chen, "Land use transition and its eco-environmental effects in the Beijing–Tianjin–Hebei urban agglomeration: A production–living–ecological perspective," *Land*, vol. 9, 2020, Art. no. 285.

[35] G. D. Li and C. L. Fang, "Quantitative function identification and analysis of urban ecological-production–living spaces," *Acta Geographica Sinica*, vol. 71, pp. 49–65, 2016.

[36] J. C. Jimenez-Munoz, J. Cristobal, J. A. Sobrino, G. Soria, M. Ninyerola, and X. Pons, "Revision of the single-channel algorithm for land surface temperature retrieval from Landsat thermal-infrared data," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 1, pp. 339–349, Jan. 2009.

[37] Z. H. Qin, M. H. Zhang, A. Karnieli, and P. Berliner, "Mono-window algorithm for retrieving land surface temperature from Landsat TM 6 data," *Acta Geographica Sinica*, vol. 4, pp. 456–466, 2001.

[38] O. Rozenstein, Z. H. Qin, Y. Derimian, and A. Karnieli, "Derivation of land surface temperature for Landsat-8 TIRS using a split window algorithm," *Sensors*, vol. 14, pp. 5768–5780, Apr. 2014.

[39] J. C. Jimenez-Munoz, J. A. Sobrino, D. Skokovic, C. Mattar, and J. Cristobal, "Land surface temperature retrieval methods from Landsat-8 thermal infrared sensor data," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, no. 10, pp. 1840–1843, Oct. 2014.

[40] M. Montanaro, A. Gerace, A. Lunsford, and D. Reuter, "Stray light artifacts in imagery from the Landsat 8 thermal infrared sensor," *Remote Sens.*, vol. 6, pp. 10435–10456, Nov. 2014.

[41] S. Wang, G. Xu, and Q. S. Guo, "Street centralities and land use intensities based on points of interest (POI) in Shenzhen, China," *ISPRS Int. J. Geo-Inf.*, vol. 7, pp. 425–439, Nov. 2018.

[42] D. C. Wu, "Spatially and temporally varying relationships between ecological footprint and influencing factors in China's provinces using geographically weighted regression (GWR)," *J. Clean Prod.*, vol. 261, 2020, Art. no. 121089.

[43] J. He, W. Zhao, A. Li, F. Wen, and D. Yu, "The impact of the terrain effect on land surface temperature variation based on Landsat-8 observations in mountainous areas," *Int. J. Remote Sens.*, vol. 40, pp. 1808–1827, 2019.

[44] X. Peng, W. Wu, Y. Zheng, J. Sun, T. Hu, and P. Wang, "Correlation analysis of land surface temperature and topographic elements in Hangzhou, China," *Sci. Rep.*, vol. 10, 2020, Art. no. 10451.

[45] B. Yang *et al.*, "Modeling the impacts of urbanization on summer thermal comfort: The role of urban land use and anthropogenic heat," *J. Geophys. Res., Atmos.*, vol. 124, pp. 6681–6697, 2019.

[46] S. Chen *et al.*, "Characterizing spatiotemporal dynamics of anthropogenic heat fluxes: A 20-year case study in Beijing–Tianjin–Hebei region in China," *Environ. Pollut.*, vol. 249, pp. 923–931, 2019.

[47] Y. Y. Wang, H. Y. Du, Y. Q. Xu, D. B. Lu, X. Y. Wang, and Z. Y. Guo, "Temporal and spatial variation relationship and influence factors on surface urban heat island and ozone pollution in the Yangtze River Delta, China," *Sci. Total Environ.*, vol. 631-632, pp. 921–933, Aug. 2018.

[48] J. C. Song, W. Chen, J. J. Zhang, K. Huang, B. Y. Hou, and A. V. Prishchepov, "Effects of building density on land surface temperature in China: Spatial patterns and determinants," *Landscape Urban Plan.*, vol. 198, Jun. 2020, Art. no. 103794.

[49] Y. Feng, S. Du, S. W. Myint, and M. Shu, "Do urban functional zones affect land surface temperature differently? A case study of Beijing, China," *Remote Sens.*, vol. 11, pp. 1802–1826, 2019.

[50] J. Yang, Y. X. Zhan, X. M. Xiao, J. H. C. Xia, W. Sun, and X. M. Li, "Investigating the diversity of land surface temperature characteristics in different scale cities based on local climate zones," *Urban Climate*, vol. 34, pp. 100700–100711, Dec. 2020.

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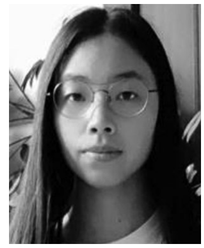

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