ORIGINAL ARTICLE

Type 2 diabetes mellitus and neighborhood deprivation index: A spatial analysis in Zhejiang, China

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ABSTRACT

Aims/Introduction: Many studies have reported that socioeconomically disadvantaged people or people who live in deprived areas are more vulnerable to diabetes complications. However, few such studies were carried out in China. The present study examined the spatial association between the incidence of type 2 diabetes mellitus and neighborhood deprivation in Zhejiang, China, from a spatial epidemiology perspective.

Materials and Methods: Type 2 diabetes mellitus data (2012–2016) in the present study were derived from a population-based diabetes registry system maintained by Zhejiang Provincial Center for Disease Control and Prevention. Principal components analysis was used to combine different socioeconomic variables together into a composited Neighborhood Deprivation Index. We applied the global Moran's *I* and Anselin's local Moran's *I* statistics to explore the spatial patterns of type 2 diabetes mellitus incidence and Neighborhood Deprivation Index.

Results: Type 2 diabetes mellitus incidence (Moran's *I*: 0.531, *P* < 0.001) and Neighborhood Deprivation Index (Moran's *I*: 0.772, *P* < 0.001) showed positive statistically significant global Moran's *I* index values, showing a tendency towards clustering. The local Moran's *I* analyses showed that type 2 diabetes mellitus incidence hot spots were mainly located in urban centers, and type 2 diabetes mellitus incidence cold spots appeared in the provincial capital area (Hangzhou city) and western and south-western regions of Zhejiang; the hot spots of the less deprived areas were concentrated in urban centers (except Lishui city), and the cold spots of the most deprived areas were clustered in western and south-western regions of Zhejiang.

Conclusions: The study showed that the incidence of type 2 diabetes mellitus was higher in affluent areas than the deprived areas across the study period. It will be significant to focus preventive efforts on the least deprived areas.

INTRODUCTION

With economic development and increased living standards, type 2 diabetes mellitus is on the rise worldwide, which is estimated to be the third most challenging disease threatening human health after cancer and cardiovascular disease[1]. China has >110 million people with diabetes, the highest number of any country in the world[2]. According to the International Diabetes Federation, the yearly cost of diabetes in China is

$25 billion. It is estimated that these costs will constantly increase and reach more than $47 billion in 2030[2,3]. Zhejiang is one of the high prevalence areas in China, and there has been >150,000 reported type 2 diabetes mellitus cases every year since 2009[4]. Thus, preventive strategies are urgently required to prevent the development of type 2 diabetes mellitus.

Accumulating evidence shows that diabetes is inversely associated with socioeconomic status (SES) in developed countries[1]. Type 2 diabetes is more prevalent in relatively lower SES groups. Socioeconomic disparities in the prevalence of diabetes are not only limited at the individual level, but also extend to

the contextual (neighborhood) level. Increasingly, Western studies on the measurement of specific characteristics of the economic, social and built environment within relatively small areas, conceptualized as 'neighborhood deprivation,' show that neighborhood deprivation could shape the level of diabetes incidence and prevalence[5]. However, China has witnessed extremely rapid economic development during recent decades, and economic disparities exists within and between areas, but it is not clear how this is associated with diabetes.

Due to the absence of fine-level socioeconomic data, studies on the relationship between SES and type 2 diabetes mellitus at the neighborhood level in China are sparse. Two pilot studies attempted to explore the neighborhood SES–health relationship within a city region, but their findings were not convincing, as there were just 57 districts (samples) included in the studies[6,7]. With the development of remote sensing technology, increasing data (e.g., night-time light data and built environment data) could be aggregated for constructing the neighborhood deprivation index at a fine geographical resolution (sub-districts and townships level), which could improve the neighborhood deprivation measures and the understanding of the neighborhood SES–health relationship in China.

Meanwhile, Geographic Information System has taken giant steps forward in the recent decade, which makes it possible to undertake a sophisticated visual approach to data analysis in public health fields[8,9]. The mapping technology could help us to understand the distribution of disease; spatial autocorrelation analysis is carried out to detect significant differences from a random spatial distribution. Spatial cluster analysis is carried out to identify whether cases of disease are geographically clustered. For policymakers, these applications are significant in that the spatial epidemiology technology could be useful for carrying out regional prevention and control strategies. To our knowledge, however, no studies have explored the spatial epidemiology of type 2 diabetes mellitus in China.

Therefore, the main objective of the present study was to investigate the association between neighborhood deprivation and the incidence of type 2 diabetes mellitus in China, based on a spatial epidemiology perspective. We initially created a neighborhood deprivation index (NDI) at a township level, and then carried out Geographic Information System-based spatial analysis for type 2 diabetes mellitus incidence and NDI.

METHODS
Study site
Zhejiang, one of the most relatively affluent coastal provinces in China, includes nine municipalities comprising of 90 counties with a population of 54 million. There are a total of 1,531 sub-districts ('Jiedao') and townships ('Xiangzhen') across the whole of Zhejiang, which are called the townships level and defined as the smallest formal administrative divisions in China. In the present study, the data were aggregated and analyzed at this level.

Type 2 diabetes data
The type 2 diabetes mellitus data analyzed in the present study came from a population-based diabetes registry system maintained by Zhejiang Provincial Centre for Disease Control and Prevention (Zhejiang CDC). Type 2 diabetes mellitus cases between 2012 and 2016 were routinely reported to the Zhejiang CDC diabetes surveillance system and verified by the provincial Non-Communicable Disease program. All cases had elevated blood glucose according to at least one of the following World Health Organization criteria[10]: (i) random plasma glucose ≥11.1 mmol/L; (ii) fasting plasma glucose ≥7.0 mmol/L; or (iii) 2-h plasma glucose value after the oral glucose tolerance test ≥11.1 mmol/L; and presented classic symptoms and were diagnosed as diabetes. A number of confirmed cases were geocoded and matched to the township level layers of the polygon in terms of their residential addresses using the ArcGIS v10.1 software (ESRI, Redlands, CA, USA). The annual type 2 diabetes mellitus incidence (2012–2016) was calculated by dividing the number of annual cases by the corresponding population and multiplied by 100,000 at the township level. As a consequence of the diabetes surveillance coverage issue in Zhejiang, there were 1,299 out of 1,531 sub-districts and townships with type 2 diabetes mellitus incidence. The Jenks natural break was used in the classification of all choropleth maps in ArcGIS v 10.1, which is a data classification method designed to place variable values into naturally occurring data categories. Natural breaks in the data are identified by finding points that minimize the within-class sum of squared differences and maximize the between-group sum of squared differences[11].

Constructing area-based deprivation indictors
The utilization of area-based deprivation measurements in health research is widely accepted by international scholars. A great variety of indicators have been used for measuring area deprivation in relevant studies[12–16], which are usually linked to social deprivation (e.g., illiteracy rate, unemployment rate and population structure) and material deprivation (e.g., gross domestic product [GDP], income and car ownership). In general, they depend on the availability of information in the census and the objective of the study. However, because of the general lack of reliable census information on the small areas, the relevant studies are limited in the Chinese context.

In light of data availability for overall provincial areas, remote sensing data and statistical information were integrated in the present study for measuring deprivation in the Zhejiang area. Satellite-derived night-time light data have been extensively used as an efficient proxy measure for monitoring urbanization dynamics and socioeconomic activity[17]. In the present study, we used night-time light data made available by the US National Oceanographic and Atmospheric Administration. The observations on which the data are assembled were made by the Operational Linescan System flown on the Defense Meteorological Satellite Program satellites[18,19]. An excellent detailed

description of the satellite instrumentation, and the data collection and processing methods was provided by Elvidge *et al.*[17]

Considering all the data consistency in this study, we requested and downloaded the Zhejiang Operational Linescan System/Defense Meteorological Satellite Program night-time light image of 2013 from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, which is shown in Figure 1. Each pixel also has a numerical value, called a digital number, which records the intensity of electromagnetic energy measured for the ground resolution cell represented by that pixel[20]. Digital number values range from 0 to 63. Higher digital number values are associated with more intense lights.

Other area-based socioeconomic data included GDP per capita (2013), the proportion of the population that was illiterate (2010), urban built-up area information (2013), the number of hospital beds (per 1,000 people; 2013) and living space per person (2013) at the township level for Zhejiang province. The data were collected by the local statistics department of Zhejiang. Although the illiteracy rate data had a 3-year lag compared with others, we assumed that the data remained credible and showed correlations among the variables. The descriptive statistics for all the variables are shown in Table S1.

In the present study, principal components analysis was used to combine different socioeconomic variables together into a composite index of deprivation. Kaiser–Meyer–Olkin and

Bartlett's tests were applied to the six variables by using IBM SPSS Statistics for Windows version 22.0 (IBM Corporation, Armonk, NY, USA). The test results ($P < 0.001$) showed strong correlations amongst the variables. The Kaiser–Meyer–Olkin sampling adequacy was 0.736, showing that the principal components analysis method was suitable for the present study. The first two components together explained approximately 79.02% of the total variance of the dataset; therefore, they were used in they present study. Finally, the composited NDI can then be simplified to the following equation (1):

$$NDI = 0.680Z_1 + 0.257Z_2 \qquad (1)$$

where Z_1 and Z_2 were, respectively, the first principal component and the second principal component in this study.

Therefore, compound indices relating to night-time lights index, GDP, the proportion of the population that was illiterate, urban built-up area, hospital beds and living space were generated to describe deprivation at the township level for Zhejiang province in the present study.

Assessment of spatial pattern

Global Moran's *I* is a measure of spatial autocorrelation across an entire study area, developed by Moran. Spatial autocorrelation indicates that neighbored observations of the same phenomenon are correlated[21]. The values of the Moran's *I* range
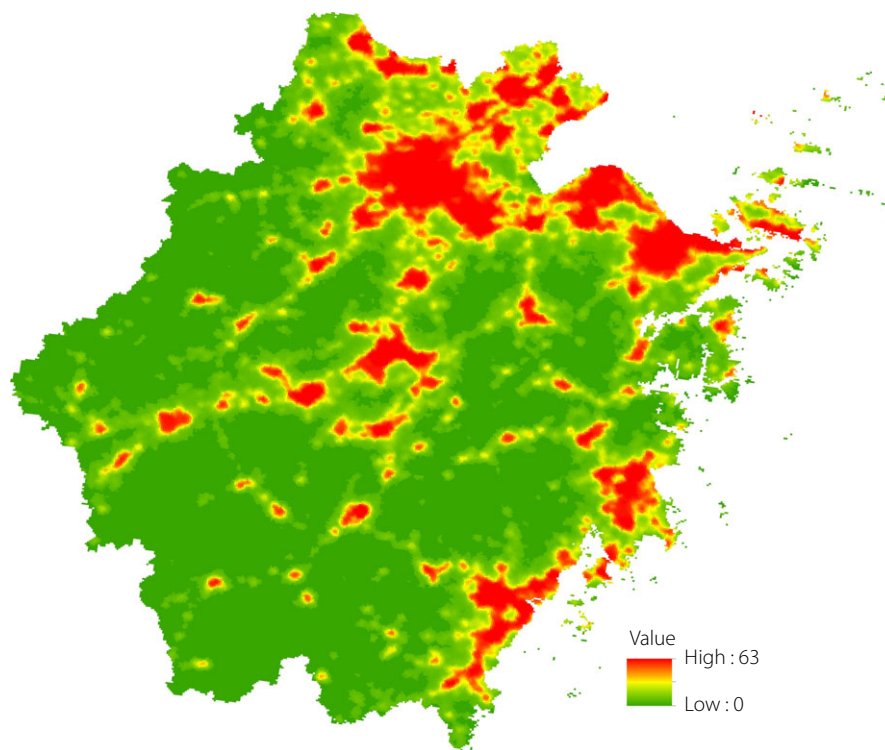

Value
High : 63
Low : 0

Figure 1 | Operational Linescan System flown on the Defense Meteorological Satellite Program night-time light image of Zhejiang province (2013).

between −1 and 1, with 1 for maximum positive association and −1 for maximum negative association. A zero value indicates a random spatial pattern; a higher positive value indicates a stronger spatial autocorrelation and vice versa for negative values. We applied this method to identify the global pattern of type 2 diabetes mellitus incidence and NDI at the townships level in ArcGIS v10.

Moran's I identifies the type and strength of spatial autocorrelation for overall data, but it does not show the actual location of significant spatial clusters and outliers. Therefore, local indicators of spatial association (LISA) were used in the present study to detect spatial clusters and outliers[22]. A LISA map can produce four different types of spatial association. The types high-high (HH) and low-low (LL) indicate spatial clusters (hot spots and cold spots, respectively), whereas the types high-low (HL) and low-high (LH) mean spatial outliers[22]. For instance, the HH type means that an area with high incidence is surrounded by neighboring areas also with high incidence; whereas the LH type means that an area with low incidence is surrounded by neighboring areas with high incidence. The first order queen spatial weight was used to identify neighbors for the spatial features. The first order queen weight defines neighbors as areas (polygons) that share either a common border or a vertex with a given area. The final LISA map was based on 999 permutations and a pseudo-significance level of $P = 0.05$.

Ethical review

In the present study, type 2 diabetes data were collected as part of routine disease surveillance and control activities. We did not carry out any human subject research; therefore, institutional review board approval was not required.

RESULTS

Type 2 diabetes mellitus incidence and NDI mapping

There were a total of 934,385 type 2 diabetes cases reported in Zhejiang Province, China, between 2012 and 2016 (Table 1). Annualized average type 2 diabetes mellitus incidence at the township level ranged from 196.710 to 278.986 per 100,000

(Table 2). The geographical distribution of type 2 diabetes mellitus incidence from 2012 to 2016 at the township level is shown in Figure 2. Type 2 diabetes mellitus incidence varied by years, and thus the cut-off values could not be same. The highest incidence rates were respectively found in Ningbo, Shaoxing, Quzhou, Jinhua and Huzhou. The relatively low incidence rates appeared in the provincial capital city of Hangzhou, and the west and south hilly parts of the province (e.g., Lishui and Quzhou).

The NDI was produced for 1,299 sub-districts and townships in Zhejiang, ranging from 0 to 1. NDI scores were divided into quintiles, with the first quintile (Q1) including the deprived areas, and the sixth quintile (Q6) including the least deprived areas. The distribution of NDI scores is shown in Figure 3.

Spatial autocorrelation analysis of type 2 diabetes mellitus incidence and NDI

The global spatial autocorrelation analyses for type 2 diabetes mellitus incidence (2012–2016) and NDI (2013) in Zhejiang showed that the Moran's I was significant (see Table 3), implying that type 2 diabetes mellitus incidence and NDI were spatially autocorrelated in Zhejiang. The township scale LISA measures for type 2 diabetes mellitus incidence and NDI were calculated, and the significant cluster (HH, LL, HL and LH) is shown in Figures 4 and 5. The HH category indicates clustering of high type 2 diabetes mellitus incidence and relatively affluent areas (high NDI value), whereas the LL category indicates clustering of type 2 diabetes mellitus incidence and less affluent areas (low NDI value).

The hot spots of type 2 diabetes mellitus incidence were shown to be dynamic in space and time. Three persistent hot spots were found in the urban centers of Ningbo, Shaoxing and Jiaxing. The cold spots were always observed in Hangzhou (urban and rural areas) and south of Quzhou and Lishui. After 2012, the hot spots in Jinhua disappeared, but the other hot spots were detected in urban areas of Quzhou, Taizhou and Wenzhou from 2013 to 2016.

Table 1 | Distribution of type 2 diabetes mellitus cases in Zhejiang, China from 2012 to 2016

	2012	2013	2014	2015	2016	Total
Sex						
Male	90,191 (49.22)	98,786 (50.26)	105,333 (51.39)	97,822 (52.43)	87,103 (53.42)	479,235
Female	93,038 (50.78)	97,763 (49.74)	99,628 (48.61)	88,771 (47.57)	75,950 (46.58)	455,150
	183,229	196,549	204,961	186,593	163,053	934,385
Age						
0–15 years	69 (0.04)	81 (0.04)	96 (0.05)	73 (0.04)	112 (0.07)	431
15–30 years	2,425 (1.32)	3,008 (1.53)	3,331 (1.63)	3,361 (1.80)	3,247 (1.99)	15,372
30–45 years	21,353 (11.65)	24,198 (12.31)	25,767 (12.57)	22,632 (12.13)	19,664 (12.06)	113,624
45–60 years	70,883 (38.69)	76,400 (38.87)	80,770 (39.41)	72,795 (39.01)	62,724 (38.47)	363,572
>60 years	88,500 (48.30)	92,862 (47.25)	94,997 (46.35)	87,732 (47.02)	77,295 (47.40)	441,386

Data presented as n (%).

Table 2 | Type 2 diabetes mellitus incidence at the township level, Zhejiang, China (per 100,000 persons)

Year	Min.	Max.	Mean	SD
2012	19.796	768.320	245.876	184.591
2013	20.899	801.376	233.364	198.364
2014	22.706	796.271	278.986	168.985
2015	25.225	759.770	227.169	179.521
2016	21.983	771.562	196.710	140.710

Min., minimum; Max., maximum; SD, standard deviation.

As expected, the result of LISA analysis for NDI suggested the hot spots persisted in eight cities' centers, except Lishui city; the cold spots were detected in the west and south of Zhejiang, which were considered as the relatively deprived areas.

Visual comparison of the spatial pattern of type 2 diabetes mellitus incidence with NDI pattern, we can clearly see that the risk of type 2 diabetes mellitus was roughly prevalent in the relatively affluent areas, consistent with the results shown in Figure 6. The differences between Q1 (deprived areas) and Q6 (the least deprived areas) were substantial: the risk of type 2 diabetes mellitus increased with decreasing neighborhood deprivation. However, the risk of type 2 diabetes mellitus in the least deprived areas decreased slightly.

DISCUSSIONS

In the present study, we initially attempted to construct a composite neighboring deprivation index based on integrating remote sensing data and socioeconomic statistical data. The spatial analysis was used to quantify the spatial pattern of type 2 diabetes mellitus incidence and NDI at the township level. In contrast to existing studies, the present investigation took the spatial variation into account to explore the association between diabetes and area deprivation[23,24]. It is significant in that it made an approach to this study based on the area level, whereas most previous studies were carried out at the individual level. It is therefore expected that the present study could contribute to neighborhood SES–health studies.

Traditionally, area socioeconomic assessment is based on statistics collected by local governments[25]. However, there are limits to local socioeconomic census data in China, as it could generate a huge amount of economic costs. In addition, considering national political issues, some socioeconomic census data at the small census units are not allowed to be announced to the public; for example, the income and employment rate. Therefore, we integrated the night-time light data as a main proxy for measuring area socioeconomic status at the local level in the present study. Although international studies have proven that the night-time light data is capable of providing a strong estimation of GDP[26,27] and income[28], its application for relevant studies in China is still innovative.

The significant positive spatial autocorrelation and the significant local clusters confirmed the spatial variances of type 2 diabetes mellitus incidence from 2012 to 1016. We found that the persistent hot spots for type 2 diabetes mellitus emerged in the city centers, but the cold spots for type 2 diabetes mellitus were found in the rural areas. People who live in affluent areas are more likely to suffer from diabetes. It is consistent with the findings of previous studies in China. One study approximated economic development using data on the provincial GDP per capita, showing higher diabetes prevalence in developed urban (12%) and rural (12%) areas and in underdeveloped urban areas (10.4%), but lower prevalence in underdeveloped rural areas (5.8%)[29]. Similarly, a study from Xu *et al.*[30] reported the prevalence of diabetes was higher in urban residents and in persons living in economically developed regions.

Diabetes is considered to be a so-called 'disease of affluence' in developing countries[31]. Along with the urban transition, the lifestyle of the Chinese has changed, obviously as a result of engaging in less physical activity and consuming a diet rich in high-fat food[32]. A national study in China showed that just 18% of urban participants reported they carry out moderate or vigorous physical activity in their leisure time[33]. Residents in urban areas were more sedentary and more exposed to high-calorie foods than residents of rural areas[34].

By contrast, the results from studies carried out in developed countries were quite divergent from Chinese studies, showing higher diabetes prevalence in disadvantaged areas than in affluent areas. In an analysis from Germany, the diabetes prevalence in the most deprived municipalities was clearly higher compared with the least deprived municipalities[35]. Other studies from Scotland[36], Australia[37] and Spain[38] also well established the positive association between neighborhood deprivation and the risk of diabetes. We might argue that this discrepancy between the developed counties and the developing counties could be attributed to the level of economic development, but few empirical studies further support the point.

Also of importance is the fact that the direction of the association between neighborhood deprivation and type 2 diabetes mellitus incidence is not stationary in the present study. Once exceeding a certain threshold level of socioeconomic development, the overall level of type 2 diabetes mellitus incidence might be slightly decreased (Figure 6). Spatial analysis also confirmed that there were persistent spatial clusters of low type 2 diabetes mellitus incidence in Hangzhou (urban and rural areas), which is a provincial city and considered as the most affluent area in Zhejiang province. Hangzhou's GDP per capita already reached over $20,000 in 2017[39]. All kinds of collective infrastructural resources (e.g., health education, medical care facility and public health service) are densely concentrated in Hangzhou. Additionally, the Hangzhou government has included diabetes prevention and control in its community-based chronic disease management program for long-term supervision and intervention since 2009[40]. Most community health centers started to educate people on diabetes, screen those at risk and put in place a patient management system[41]. The Hangzhou government put a great deal of effort into
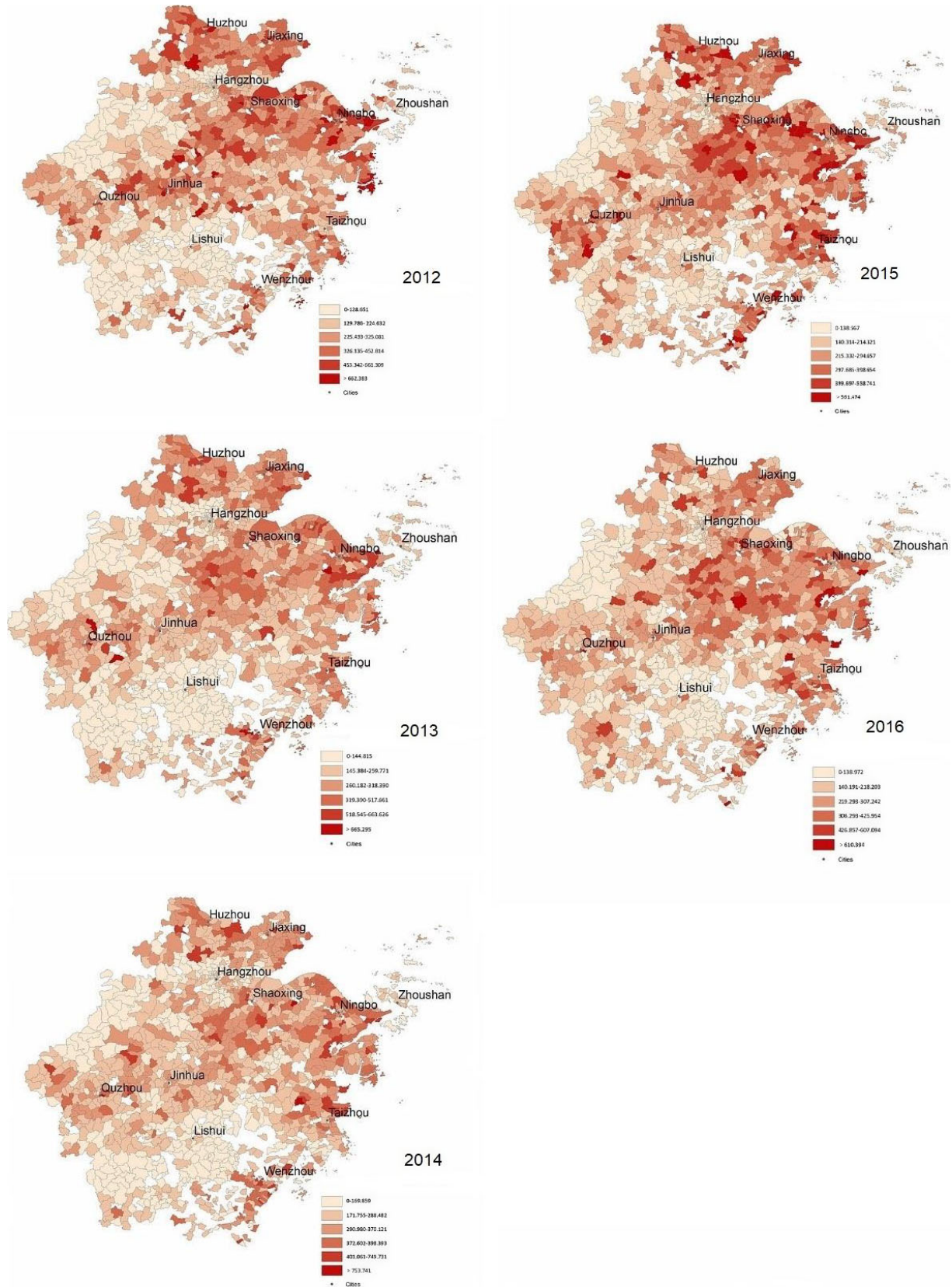
Figure 2 | The geographical distribution of type 2 diabetes mellitus incidence from 2012 to 2016.
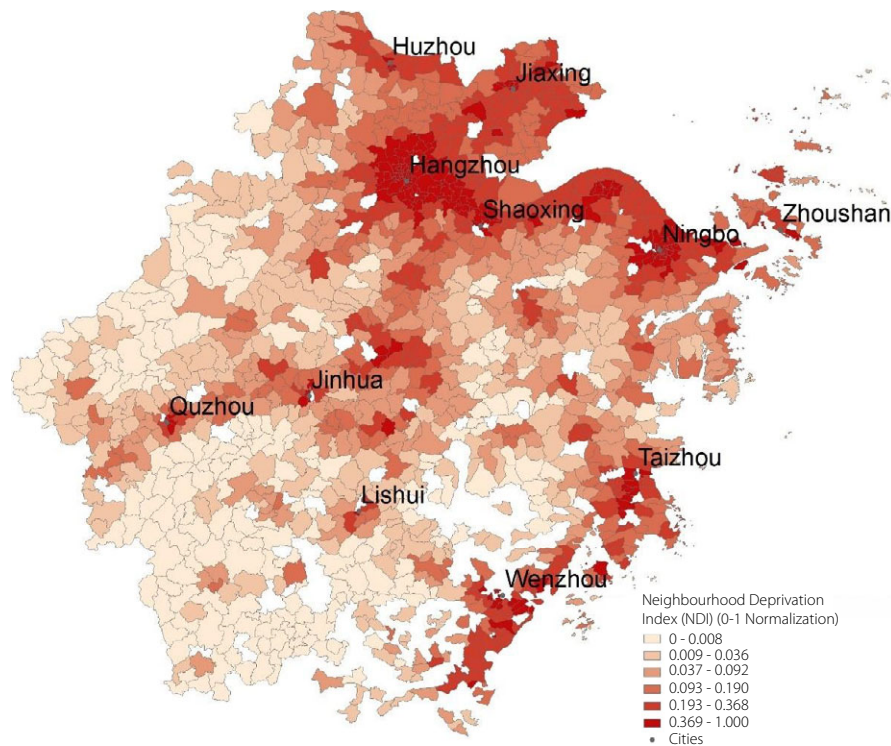
Figure 3 | A composited Neighborhood Deprivation Index in Zhejiang.

Table 3 | Global Moran's *I* test for the spatial autocorrelation of type 2 diabetes mellitus incidence (2012–2016) and Neighborhood Deprivation Index (2013)

	Moran's *I*	*P*-value	Pattern
Type 2 diabetes mellitus incidence 2012	0.439	<0.001	Cluster
Type 2 diabetes mellitus incidence 2013	0.422	<0.001	Cluster
Type 2 diabetes mellitus incidence 2014	0.398	<0.001	Cluster
Type 2 diabetes mellitus incidence 2015	0.387	<0.001	Cluster
Type 2 diabetes mellitus incidence 2016	0.363	<0.001	Cluster
NDI 2013	0.593	<0.001	Cluster

NDI, Neighborhood Deprivation Index.

combating diabetes and has been a flagship city for preventing the non-communicable disease in China, which could partially explain why the spatial pattern of type 2 diabetes mellitus incidence in Hangzhou is different to other developed cites.

Studies have more commonly focused on how individual socioeconomic characteristics influence health[42]. However, there is a growing consensus that socioeconomic characteristics of neighborhoods could have an effect on the health of the residents[43]. The present study extends the existing literature on neighborhood SES–health, while considering spatial heterogeneity in the relationship between area deprivation and type 2

diabetes mellitus. This is a typical ecological study. The findings from the results are best not interpreted at the individual level, thus avoiding the ecological fallacy. Because of the absence of data at the individual level, we are unable to differentiate between SES effects at the individual and at the neighborhood level; that is, to carry out multilevel analyses. However, the present study does not refute the impact of individual characteristics and behaviors on health. The findings indirectly reveal that, to a large extent, individual unhealthy behavior and lifestyle might be responsible for the high incidence of type 2 diabetes mellitus in urban areas.

There were some limitations to the present study that are worth mentioning. First, our data relied on official surveillance, and it is possible that some community health centers or hospitals might underreport the number of cases for various reasons. However, this situation is currently being rectified, in that Zhejiang CDC has continuously improved the diabetes surveillance system for decreasing the underreporting rate of diabetes. Second, the spatial analysis of type 2 diabetes mellitus incidence in Zhejiang was carried out based at the township level, but the boundaries are a reflection of administrative needs rather than the actual spatial distribution of epidemiological factors. It might lead to a modifiable areal unit problem. Third, spatial analysis is suitable for visualizing and detecting the spatial patterns of disease, but it could not explain the patterns it showed.
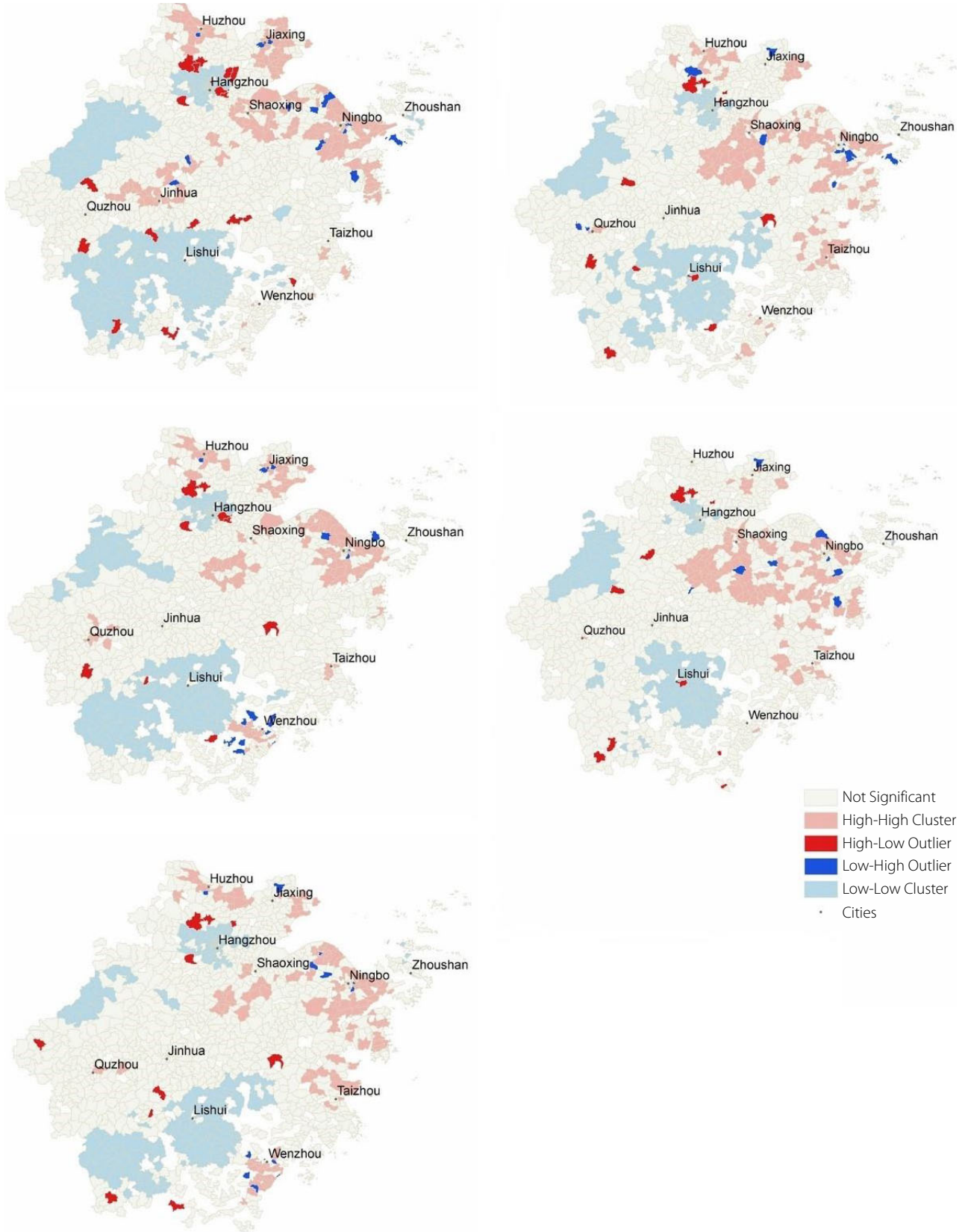
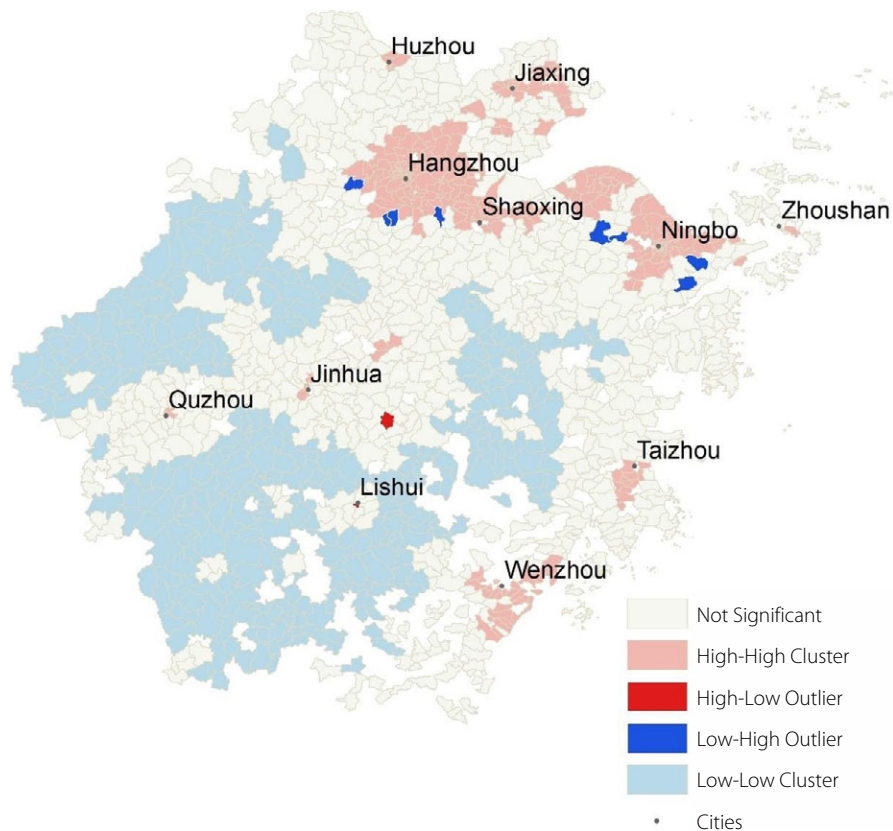**Figure 4** | Local indicators of spatial association map of type 2 diabetes mellitus incidence from 2012 to 2016.

Figure 5 | Local indicators of spatial association map of Neighborhood Deprivation Index.
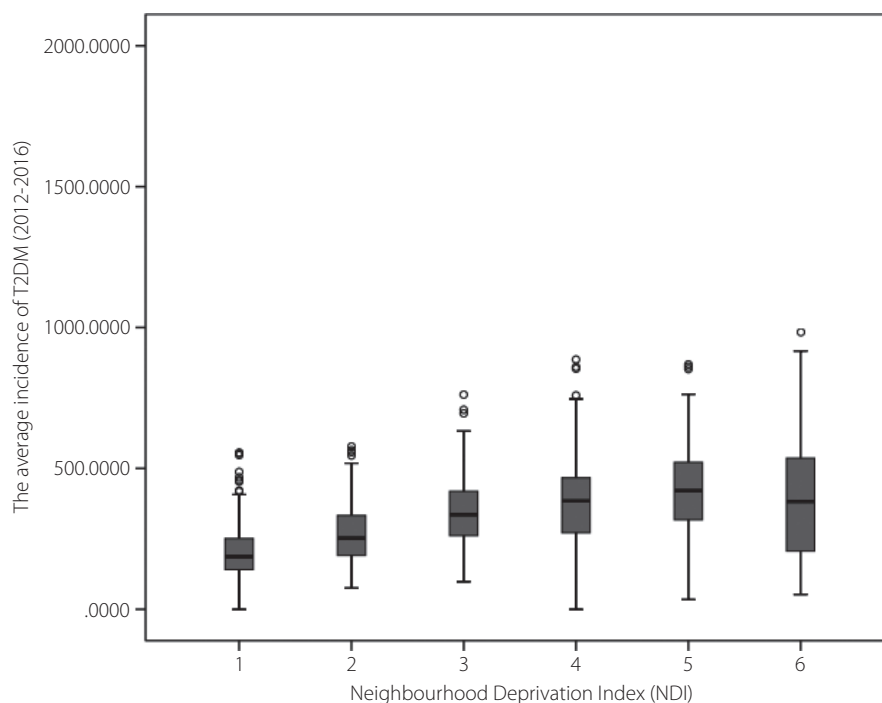

Figure 6 | Box plot of type 2 diabetes mellitus (T2DM) incidence by the different level of neighborhood deprivation.

Thus, further work is necessary to incorporate the statistical models to improve the research.

In summary, the present study showed spatial variation in type 2 diabetes mellitus incidence and neighborhood deprivation index at the finest scale in Zhejiang. The spatial and place-based methods aid future investigators to improve understanding of the association between neighborhood deprivation and type 2 diabetes mellitus in developing countries. It is very intriguing that type 2 diabetes mellitus incidence is higher in affluent areas than the deprived areas across the study period. The implication is that health prevention and programs can be focused to specific neighborhoods of high risk to better meet their health needs. There is not a one-size-fits-all strategy for all neighborhoods within a large-scale area. The policymakers should enhance the public knowledge of the risk factors for type 2 diabetes mellitus and strongly promote community-based chronic disease management programs for urban areas. Meanwhile, we should also realize that a non-trivial proportion of people living with diabetes in rural china has not been diagnosed[29]. Diabetes detection was not proportional to the underlying incidence. Therefore, improving the quality of the local public health service and reinforcing access to routine health checks in the relatively deprived rural areas could be a key priority for policymakers and practitioners.

ACKNOWLEDGMENT

DISCLOSURE
The authors declare no conflict of interest.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S1 | Descriptive statistics for the variables at the township level, Zhejiang, China.