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Analysis of the relationships between environmental noise and urban morphology☆

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ABSTRACT

Understanding the effects of urban morphology on urban environmental noise (UEN) at a regional scale is crucial for creating a pleasant urban acoustic environment. This study seeks to investigate how the urban morphology influences the UEN in the Shenzhen metropolitan region of China, by employing remote sensing and geographic information data. The UEN in this study consists of not only regional environmental noise (RN), but also traffic noise (TN). The experimental results reveal the following findings: 1) RN is positively correlated with the nighttime light intensity (NTL) and land surface temperature (LST) ($p < 0.05$). More interestingly, landscape composition and configuration can also significantly affect RN. For instance, urban vegetation can mitigate the RN ($r = -0.411$, $p < 0.01$). There is a reduced RN effect when fewer buildings exist in an urban landscape, in terms of the positive relationship between building density and RN ($r = 0.188$, $p < 0.01$). Given the same percentage of building area, buildings are more effective at reducing noise when they are distributed across the urban scenes, rather than being spatially concentrated ($r = -0.205$, $p < 0.01$). 2) TN positively relates to large ($r = 0.520$, $p < 0.01$) and small–medium ($r = 0.508$, $p < 0.01$) vehicle flow. In addition, vegetation along or near roads can alleviate the TN effect ($r = -0.342$, $p < 0.01$). TN can also become more severe in urban landscapes where there is higher road density ($r = 0.307$, $p < 0.01$). 3) Concerning the urban functional zones, traffic land is the greatest contributor to urban RN, followed by mixed residential and commercial land. The findings revealed by this research will indicate how to mitigate UEN.

1. Introduction

Urbanization, which has been taking place at a dramatic rate over the past few decades, is having an increasingly strong impact on the Earth's environment, including biodiversity, energy flows, and biogeochemical cycles, as well as environmental noise and human health (Chi et al., 2012; Han et al., 2014; Peters and Bratton, 2016). Among these effects, urban environmental noise (UEN) has recently drawn much attention (Tenailleau et al., 2016; Wang et al., 2016; Halonen et al., 2017). In general, the acoustic environment is made up of both natural sounds, referring to animal vocalizations and, for instance, the sounds arising from the geophysical environment (wind, thunder, etc.); and environmental sounds created by humans, generated from the various human activities. Nonetheless, accompanied by the accelerated urbanization process, environmental or anthropogenic sounds have come to dominate the urban acoustic environment (Pijanowski et al., 2011).

Noise pollution produced by anthropogenic sounds profoundly influences biodiversity and ecosystem functions. It has been proven that UEN degrades the habitat for many wildlife species, and thereby affects biodiversity and ecosystem functions (Ware et al., 2015). At the same time, increasingly annoying noise interferes in our daily activities such as study, work, leisure, and rest (Freedman et al., 2001; Tassi et al., 2010; Engel and Zannin, 2014), and affects our health (Miedema and Oudshoorn, 2001; Chang and Merzenich, 2003; Min and Min, 2017). Therefore, the study of urban noise is essential for ecology in an urban context (Pijanowski et al., 2011; Schnell et al., 2016).

To date, many acoustic studies have focused on noise model prediction (Doygun and Gurun, 2008; Paz and Zannin, 2010; Morley

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and Gulliver, 2016; Lu et al., 2017) or related factor analysis, such as the urban fabrics of different types of building blocks (Salomons and Pont, 2012), construction density, open spaces, and the position of buildings (Guedes et al., 2011; Wang and Kang, 2011) and outdoor vegetation (Van Renterghem and Botteldooren, 2016). These related factors have significant roles when considering noise propagation. However, to the best of our knowledge, these studies have only investigated one or several city blocks or neighborhoods. Recently, Ryu et al. (2017) presented a statistical model for predicting the noise level of road traffic over residential areas in Cheongju (153.44 km^2) of South Korea. The data used in this study was noise map predicted by the RLS90 model that is embedded in SoundPLAN® (Diniz and Zannin, 2004; SoundPLAN, 2010). However, the in-situ measurement data including RN and TN, and comprehensive and in-depth analysis of environmental noise are relatively lacking in the current literature, especially over a relatively large area (e.g., an entire city).

On the other hand, the collection of sounds emanates from and interacts with urban landscapes, the characteristics of which have a great effect on the acoustic environment. Therefore, the study of the acoustic environment cannot be isolated from the underlying urban morphology. In particular, urban morphology is considered as the study of urban fabrics, which comprise coherent neighborhood morphology (e.g., open spaces, buildings), as well as functions which result from human activity, as a means of discerning the environmental level closely correlated with urban planning. Urban morphology represents not only the physical form or spatial structure, but also social forms which are expressed in the physical layout of a metropolitan area or city. To better characterize the urban morphology, many studies have relied on remote sensing data, due to its wall-to-wall coverage of entire urban areas, which can explicitly reveal the spatial pattern of ground features in a recurrent and consistent way (Li et al., 2011). However, as far as urban noise is concerned, there have, as yet, been few attempts to comprehensively relate urban morphology to environmental noise, especially over an entire city area.

In this study, based on the above considerations, we took Shenzhen (1997 km^2), one of the mega cities in China, as an example, and statistically analyzed the measured noise data. The data were acquired from 248 RN and 101 TN monitoring stations of the Human Settlements and Environment Commission of Shenzhen Municipality. RN and TN are separately measured and recorded with significantly different monitoring purposes and layout of monitoring stations. Specifically, in order to evaluate noise intensity and urban acoustic environment of the whole city, urban built-up areas are divided into a set of non-overlapped square grids, and RN monitoring stations are placed at or near the center of each grid. The noise sources of RN vary among industry, construction sites, traffic, and social activities (such as entertainment, shopping, etc.). TN focuses on evaluating intensity of traffic noise, and monitoring stations are set at locations along the main roads of the city. Moreover, we aimed to investigate how different underlying urban morphology affects environmental noise in the following aspects.

Firstly, from the socioeconomic aspects, we tested the potential associations between urban noise and socioeconomic factors, e.g., nighttime light intensity (NTL), land surface temperature (LST), gross domestic product (GDP), and demographic data. In many studies, NTL intensity (Zhang and Seto, 2011), LST (Li et al., 2011), GDP (Wu et al., 2013), and demographic data (Pham et al., 2017) have been widely used to depict the urban social forms, and can therefore be used to portray human activities.

We then explored if landscape structure affects urban noise, including RN and TN. Considering that urban scenes are characterized by different land−cover types having their own surface characteristics, and forming patch mosaics, we assumed that landscape composition and configuration can affect sound generation and propagation, and thus the characteristics of the acoustic environment. To represent the spatial pattern or structure of urban scenes, landscape metrics based on land cover data have been developed and widely used to quantify landscape composition and configuration (Frohn and Hao, 2006).

Finally, we conducted an investigation into the noise characteristics of different urban morphology types in terms of urban functional zones, and their effects on urban noise. The acoustic environment mainly comprises sounds generated by anthropogenic activities with different intensities among different urban functional zones. These urban functional areas, in terms of land-use forms in large areas, are generally made up of residential, commercial, industrial, education land, etc., with different kinds of human activities, along with different noise intensity. As such, the change in urban functional areas affects local and regional biodiversity, and is therefore one of the major components of urban environmental changes (Grimm et al., 2008). Understanding the characteristics of urban noise and its relationship with urban morphology in Shenzhen has important implications for many other cities that suffer from urban noise.

2. Materials and methods

2.1. Study area

The city of Shenzhen (113°46′−114°37′E, 22°27′−22°52′N), located in Guangdong province, was chosen as the study area, considering its fast economic development and rapid urbanization in both scope and intensity during the past (Fig. 1). Since Shenzhen became China's first special economic zone (SEZ) in 1979, it has transformed from an unknown fishing village to one of the most prosperous cities in China. During this period, Shenzhen's population has increased from less than 100,000 in 1979 to over 10 million in 2015, accompanied by huge migration from all over the country. Consequently, Shenzhen belongs to a young immigrant city. Compared to other coastal cities, the Shenzhen SEZ has unique location advantages due to its geographical proximity to Hong Kong. By means of tax relief and favorable land, Shenzhen has attracted massive domestic and foreign investments, resulting in its rapid urbanization. Under this circumstance, GDP reached $253.6 billion in 2015. With the development, Shenzhen has been a “window” for economic, scientific, and technological exchanges.

Shenzhen is a “linear city” with a moderately hilly terrain, extending 49 km along the east-west axis and 7 km along the north-south axis. The topography of the city is undulating, particularly in the southeastern part, which shields it from typhoons in summer. Shenzhen has a subtropical monsoon climate with a mean annual temperature of 22.4 °C, and a mean annual precipitation of 1933.3 mm. The rainy season runs from May to September. Native vegetation is mainly composed of tropical evergreen monsoon forest and south subtropical evergreen broad-leaved forest.

Along with the rapid urbanization, Shenzhen has experienced environmental problems, particularly noise pollution. In 2015, according to the bulletins on environmental situations from the Human Settlements and Environment Commission of Shenzhen Municipality, there were 24,663 complaints about noise from residents, accounting for approximately 60% of all the environmental complaints. In addition, the Shenzhen local government has laid noise-reduction pavement, and optimized transportation management at the transport nodes with excessive complaints. Thus, research into environmental noise in Shenzhen is urgently required for urban planning and land-use management, to give some suggestions about possible UEN mitigation strategies.

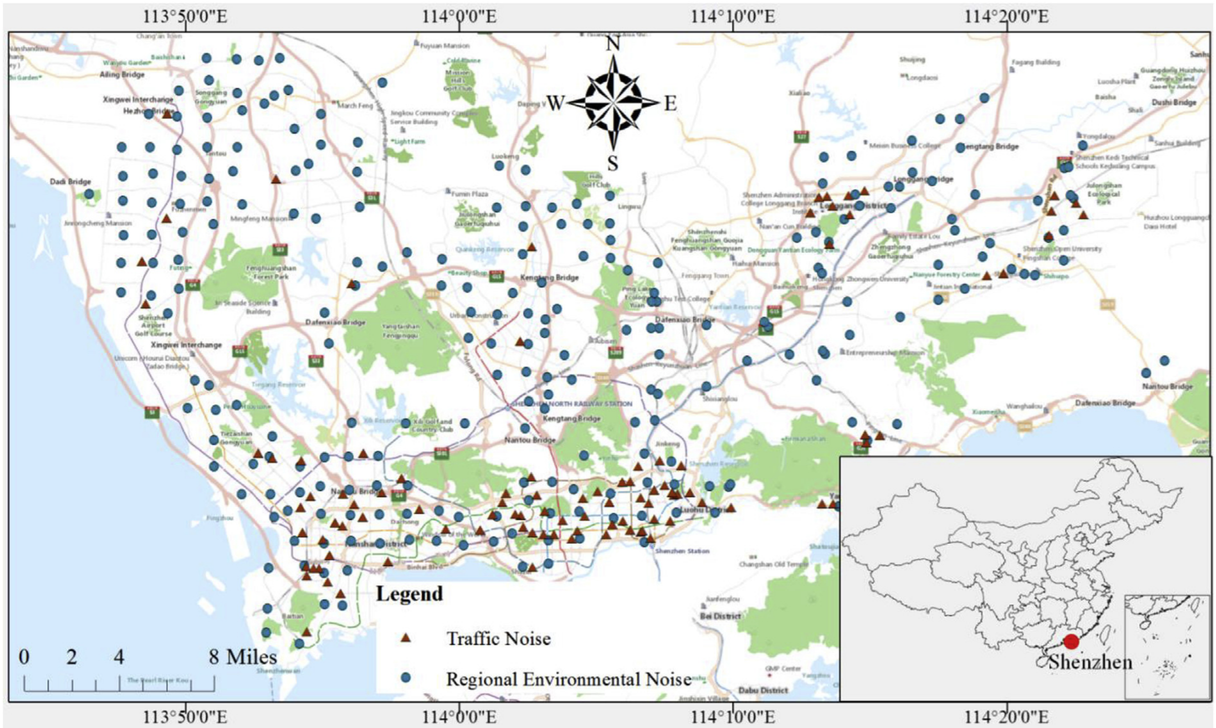

Fig. 1. The spatial distribution of noise measurement sites (including regional environmental noise (RN) and traffic noise (TN)). The inset shows the location of the Shenzhen area in China.

2.2. Noise data

Noise data including RN and TN used in this study were recorded in March 2015 by the Human Settlements and Environment Commission of Shenzhen Municipality, which is an official environmental management department of China. The noise measuring times exclude the rush-hour times (07:00–09:00, 12:00–14:00, and 17:00–19:00), to avoid the extreme noise values induced by rush-hour traffic. It should be mentioned that RN and TN must be separately measured and recorded, with significantly different monitoring purposes and layout of monitoring stations, according to the technical specifications formulated by Ministry of Environmental Protection of the People's Republic of China (2012).

RN focuses on evaluating noise intensity and urban acoustic environment of the whole city. In order to measure RN, urban built-up areas are divided into a set of non-overlapped square grids, and monitoring stations are placed at or near the center of each grid, with a measuring height of 1.2–4.0 m. It should be noted that monitoring stations cannot be laid directly on the roadsides. For RN, the noise sources vary among industry, construction sites, traffic, and social activities (such as entertainment, shopping, etc.). The Shenzhen area is divided into 248 grids of 1.8×1.8 km in size and, therefore, a total of 248 RN monitoring stations are used.

TN only focuses on evaluating intensity of traffic noise which is one of the main sources of noise pollution. Monitoring stations are set at locations along the main roads of the city with a measuring height of 1.2–6.0 m, and they should be located 20 cm away from sidewalks. Traffic flow and road conditions must be recorded at the same time, which facilitates the subsequent analysis of the relationship between TN and traffic conditions. In addition, the measurement of TN should avoid the interference from non-traffic noise, and the noise measuring instrument should be towards the roads. In order to characterize the distribution of TN along the main roads of Shenzhen, a total of 101 TN monitoring stations are equipped.

In this study, both RN and TN use the equivalent-continuous sound pressure level (Leq) as the measurement metric of the noise level at each monitoring station (Guedes et al., 2011). Noise levels often fluctuate over a wide range with time, and Leq is the preferred method to describe sound levels that vary over time. Leq refers to the single decibel value of a steady sound which has the same total sound energy as the time-varying sound over the period of interest, which is expressed in units called decibels (dB). TN data include not only the noise level (Leq) in dB, but also information about vehicle flow, the covered population, and road grade (e.g., urban main road and urban secondary trunk road). In particular, "covered population" refers to the census for residential areas along the sides of the roads.

2.3. Urban morphology

Urban morphology considers human settlements as generally unconscious outcomes, through the accumulation of continuous generations of building activity (Batty, 2009). On the one hand, urban morphology can be used to study the physical form and the spatial structure of a city, by examining the patterns and relationships of the components of the city. Another focus of urban morphology is on the various socioeconomic forms. As the result of the accrual of successive generations of human activity, urban socioeconomic forms have attracted much interest and attention (Wu et al., 2013; Pham et al., 2017). In this regard, it has been demonstrated that urban morphology can profoundly influence the socioeconomic process within or beyond the city boundaries (Luck and Wu, 2002). Recently, the availability of remotely sensed data has facilitated the study of urban morphology. In this study, NTL, LST, GDP and Demographic data are used to depict the socioeconomic morphology of the urban area. In addition, landscape metrics are employed to comprehensively characterize the geographical landscape.

2.3.1. Nighttime light (NTL) data

Many studies have shown the potential of NTL to estimate socioeconomic indictors and urbanization dynamics (Chen and Nordhaus, 2011; Li et al., 2013). In this study, we used NTL composite data which were collected in March 2015 from the Visible Infrared Imaging Radiometer Suite (VIIRS) day-night band carried by the Suomi National Polar-orbiting Partnership (NPP) satellite, termed "NPP-VIIRS", with a resolution of 15 arc-seconds (about 500 m). The NTL data measure light on the Earth's surface, such as that generated by human settlements, gas flares, fires, and illuminated road vehicles. Therefore, NTL data can be used as a proxy for economic and human activity.

2.3.2. Land surface temperature (LST) data

Due to the lack of data for March 2015, and in order to avoid the influence of seasonal variation on the estimation of the LST (Li et al., 2011), a cloud-free Landsat-8 Thermal Infrared Sensor (TIRS) image from 26 March 2016 was acquired from the United States Geological Survey (USGS, http://glovis.usgs.gov). The downloaded image was then preprocessed and further used for the estimation of LST (Jiménez-Muñoz et al., 2014).

2.3.3. Gross domestic product (GDP) data

Grid data of the national GDP in 2010 were obtained from the Data Center for Resources and Environmental Sciences at the Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). The resolution of this dataset is 1 km, and each pixel value represents the GDP value per square kilometer. It should be mentioned that this dataset is the latest available grid GDP data of China.

2.3.4. Demographic data

The grid data of population with the spatial resolution of approximately 160 m, acquired by the National Bureau of Statistics of the People's Republic of China in 2010, was used in our study. Again, this data set is the latest available demographic data of China.

2.3.5. Landscape metrics

Landscape metrics are mainly composed of two categories: composition and spatial configuration (Gustafson, 1998; Urban, 2006). To be specific, landscape composition metrics measure the presence and percentage of each land-cover type within the landscape, while configuration metrics measure the spatial distribution and pattern of patches in urban scenes. Landscape composition and configuration can provide complementary information to better quantify the landscape structure. In this paper, we selected seven commonly used landscape metrics (Table 1), calculated by FRAGSTATS software (Mcgarigal et al., 2002). These compositional metrics were adopted to describe three aspects of the urban landscape: area, shape complexity, and spatial distribution (Seto and Fragkias, 2005; Fang et al., 2016). Area is characterized by three indices: percentage of landscape (PLAND), largest patch index (LPI), and mean patch size (MPS). PLAND is a landscape composition measure which quantifies the proportional abundance of each land-cover type in the landscape. LPI quantifies the percentage of total landscape area comprised by the largest land-cover patch and, therefore, this metric can be used to highlight the dominant type in an urban scene. The MPS describes the relative size of the patches in the landscape. A landscape with a high MPS value is usually in possession of more aggregated, less-fragmented, and continuous spatial patterns (Fang et al., 2016). The shape complexity of an urban landscape is described by LSI (landscape shape index) and MSI. LSI provides a standardized measure based on the total length of edges and the landscape area. The LSI value of a square is 1, and it increases as the shape becomes more irregular. Since LSI is standardized, it is only meaningful relative to the size of the landscape, in contrast to total edge. MSI is an average measure of the shape complexity of each kind of land-cover patch within the landscape. Similar to the LSI metric, the more irregular and complex the shape of the corresponding land-cover patches, the higher the value of MSI. In addition, both SPLIT and DIVISION are used to measure the spatial distribution of the patches of each land-cover class. They are defined as measures of landscape fragmentation, but with different sensitivities and focuses with respect to the fragmentation processes (Jaeger, 2000).

Calculation of the landscape metrics was based on the high-resolution land-cover data, which were derived from Map World with a 1.1 m spatial resolution (Chen et al., 2013). It is noteworthy that Map World is the first official free mapping service of China, with the purpose of offering the most comprehensive mapping services to the public (http://www.tianditu.cn/). The urban land-cover classes, e.g., buildings, roads, and vegetation could be accurately extracted over the Shenzhen area. Google Earth high-resolution imagery was used as the reference layers to assess the accuracy of the land-cover product. A total of 267 random points were generated for comparing the land-cover product and reference data. The overall accuracy (OA) and Kappa were approximately 93.6% and 0.902, indicating that the land-cover product was reliable. Finally, the landscape metrics were computed at both the class and landscape levels from the derived land-cover data. Class-

Table 1
Landscape pattern metrics used in this study.

Landscape metric	Abbreviation	Calculation	Description
Percentage of landscape	PLAND	$PLAND = p_i = \frac{\sum_{j=1}^{n} a_{ij}}{A}(100)$	p_i is the percentage of landscape occupied by patch type i; n is the number of patches for class i; a_{ij} is the area (m^2) of patch ij; and A is the total landscape area (m^2)
Largest patch index	LPI	$LPI = \frac{\max(a_{ij})_{j=1}^{n}}{A}(100)$	a_{ij} is the area (m^2) of patch ij; A is the total landscape area (m^2)
Mean patch size	MPS	$MPS = \frac{\sum_{j=1}^{n} a_j}{n}$	a_j is the area (m^2) of patch j; n is the number of patches
Landscape shape index	LSI	$LSI = \frac{0.25 \times \sum_{j=1}^{n} e_{ij}}{\sqrt{A}}$	e_{ij} is the total length of edge for class i and patch j; A is the total landscape area (m^2)
Mean shape index	MSI	$MSI = \frac{\sum_{i=1}^{n} \left(\frac{p_i}{a_i}\right)}{n}$	p_i and a_i are the perimeter and area of patch i, respectively; n is the number of patches within the landscape
Splitting index	SPLIT	$SPLIT = \frac{A^2}{\sum_{i=1}^{n} a_i^2}$	A is the total landscape area (m^2); a_i is the area (m^2) of patch i and n is the number of patches within the landscape.
Landscape division index	DIVISION	$DIVISION = \left[1 - \sum_{j=1}^{n} \left(\frac{a_i}{A}\right)^2\right]$	a_i is the area (m^2) of patch i; A is the total landscape area (m^2).

level metrics represent the amount and spatial distribution of a given land cover class, and landscape-level metrics describe the overall spatial patterns of all land cover classes (Mcgarigal et al., 2002).

2.4. Data analysis

We identified the spatial clusters and outliers in terms of noise values using the spatial cluster and outlier analysis algorithm (Koteeswaran et al., 2012). This algorithm is based on the local Moran's I value, in which a positive value indicates a spatial cluster and a negative value represents a spatial outlier (Zhang et al., 2008). The identified statistically significant spatial clusters, either with a high value (HH) or with a low value (LL), indicate that there are neighboring features with similarly high or low noise values. However, the identified outliers have neighboring features with dissimilar noise values: a high value surrounded primarily by low values (HL) or a low value surrounded by high values (LH).

The study of urban structure with landscape metrics requires the city to be partitioned into homogenous units of analysis (Herold et al., 2005). According to Kurze and Anderson (2006), most outdoor sound propagation distances are within approximately 400 m. Given the 1.1 m spatial resolution of the land-cover data, a grid cell size of 440 m by 440 m (corresponding to 400 by 400 pixels) was adopted in our study, which could capture the urban environmental characteristics while considering the heterogeneous noise distribution (Tenailleau et al., 2015). Because we only focused on the ambient environment around each noise measurement site, landscape metrics were calculated from the land-cover information of the noise-site centered grid. Each grid was defined as a landscape unit of the analysis, and was used as a data point for further Pearson correlation analysis between the urban morphology parameters and urban noise. The significance of each calculated correlation coefficient was determined using a two-tailed Student's *t*-test (Adler and Parmryd, 2010). The general work flow is shown in Graphical abstract.

3. Results

3.1. Spatial characteristics of RN and TN

The spatial characteristics of RN are shown in Fig. S1, in which the high or low spatial clusters and outliers are indicated with different colors. Overall, most of the noise sites show a non-significant spatial distribution (termed “not significant” in Fig. S1 and Fig. S2). Low-value noise clusters (LL) are mainly located in the middle and upper right part of the city, while high-value noise clusters (HH) concentrate in the upper left. There are six spatial outliers, two of which are low-value outliers (LH) and the remaining four are outliers of high value (HL). In addition, we selected two sample scenes for each cluster category for further investigation (Fig. S1). In general, for urban scenes of high-value noise, either HH or HL, there are more buildings or roads. In contrast, there is more vegetation coverage in the LL or LH urban landscape. A similar phenomenon can be observed for TN (Fig. S2). There are neither HL nor LH outliers in the TN cluster and outlier analysis results. LL clusters in the upper part of the city, while HH locates near the bottom part of the city.

3.2. The relationship between RN and urban morphology

Urban noise, including RN and TN, can be significantly affected by urban morphology parameters. Correlation coefficients between urban socioeconomic morphology and RN are given in Table 2(A). It can be seen that RN is positively correlated with NTL and LST ($r = 0.147$, $p < 0.05$ and $r = 0.165$, $p < 0.05$). This occurs because the areas with high NTL and LST values are more likely to be affected by human activity, which induces more noise effect (Votsi et al., 2017). In order to corroborate our results, we examined astronaut photography taken from the International Space Station (ISS), searching for available images using the “Cities at Night Atlas” (http://citiesatnight.org/). These nighttime images were downloaded from https://eol.jsc.nasa.gov/. These images can be used for visual inspection at medium spatial resolution (30–100 m) (Fig. S3). It can be observed that the areas with high NTL values are more likely to be urban transport land or industrial land, both of which are under intensive human activity and are the main sources of urban noise.

The relationships between RN and landscape metrics at both the class and landscape levels are given in Table 2(B). At the class level, RN is correlated with the landscape metrics for buildings and vegetation. For buildings, RN is positively associated with PLAND, MPS, and LPI. These indices primarily reflect the form of buildings from the area aspect, thereby corresponding to the intensity of human activity. Thus, high values of these indices imply the enhancement of urban noise. However, RN is inversely related to the DIVISION, MSI, and SPLIT of buildings ($p < 0.01$). This indicates that the scattered distribution and irregular shape of buildings can help mitigate urban noise and, inversely, aggregated and concentrated forms of buildings strengthen it. For vegetation, RN is positively correlated to DIVISION and SPLIT, but is negatively correlated with PLAND, MPS, and LPI ($p < 0.01$). It can be inferred that urban vegetation can mitigate the effect of environmental noise. In particular, the higher the connectivity and the greater the aggregation of urban vegetation morphology, the quieter the environment tends to become. RN is not correlated to any of the landscape

Table 2
Pearson correlation coefficients between urban morphology parameters: **(A)** Socioeconomic parameters, **(B)** Landscape metrics, and RN.

(A)

Socioeconomic data	NTL	LST	GDP	Demographic
	0.147*	0.165*	0.007	0.010

(B)

Landscape metric		PLAND	MPS	LPI	DIVISION	MSI	SPLIT	LSI
Class-level	Building	0.188**	0.174**	0.166**	−0.202**	−0.166**	−0.205**	−0.055
	Road	0.082	0.038	0.013	−0.013	0.001	−0.013	−0.009
	Vegetation	−0.411**	−0.217**	−0.410**	0.443**	0.113	0.221**	0.083
Landscape-level		–	−0.297**	−0.339**	0.353**	−0.135*	0.103	−0.105

*Correlation is significant at the 0.05 level (two-tailed).
**Correlation is significant at the 0.01 level (two-tailed).

pattern metrics of road. At the landscape level, there are negative correlations between RN and the MPS, LPI, and MSI metrics, indicating that urban scenes with less-fragmented and complex-shape patches generally tend to suffer less from RN effects. However, the positive association existing between RN and DIVISION ($p < 0.01$) exhibits the opposite trend, i.e., urban scenes with a scattered distribution suffer more from noise. It should be noted that, at the class level, the signs of buildings and vegetation, with regard to the MPS, LPI, and DIVISION metrics, are the opposite. However, the combined effects (buildings, roads, and vegetation) make the signs of these correlation coefficients consistent with vegetation at the landscape level (Table 2(B)).

3.3. The relationship between TN and urban morphology

The correlations between TN and the measurement data are shown in Table 3(A). The large and small–medium vehicle flow significantly contribute to TN ($r = 0.520$, $p < 0.01$ and $r = 0.508$, $p < 0.01$). Urban main roads produce more TN than urban secondary trunk roads ($r = -0.209$, $p < 0.05$), due to their larger traffic volume. There is also a positive relationship between TN and covered population along the sides of the roads ($r = 0.204$, $p < 0.05$). The road length and width have no significant effect on TN.

The correlations between TN and the landscape metrics are given in Table 3(B). Overall, at least two landscape metrics of each land-cover class are significantly associated with TN. TN is significantly correlated with the MSI ($r = -0.321$, $p < 0.01$) and LSI ($r = -0.235$, $p < 0.05$) of buildings, which indicates that the irregular shapes of buildings along the sides of the roads alleviate the TN. Buildings with contiguous and connected forms tend to form irregular shapes in urban areas. For roads, TN is clearly associated with PLAND ($r = 0.307$, $p < 0.01$). This means that a greater road percentage in the landscape can lead to more TN. Urban main roads tend to have larger LSI and MSI values than urban secondary trunk roads. Accordingly, positive relationships exist between TN and LSI ($r = 0.293$, $p < 0.01$), and between TN and MSI ($r = 0.237$, $p < 0.05$). There are negative relationships between TN and PLAND/MPS ($r = -0.342$, $p < 0.01$ and $r = -0.427$, $p < 0.01$, respectively), whereas there is a positive relationship between TN and the LSI ($r = 0.350$, $p < 0.01$) of vegetation. This indicates that a high density, aggregated distribution, and regular shape of vegetation can help to mitigate noise effects. TN is more closely correlated with the landscape metrics of vegetation than the other land-cover classes. At the landscape level, MPS and LSI are positively correlated with TN ($r = 0.322$, $p < 0.01$, and $r = 0.229$, $p < 0.05$, respectively), while SPLIT is negatively correlated with TN ($r = -0.216$, $p < 0.05$).

3.4. The relationship between urban functional zones and RN

Urban morphology comprises neighborhood morphology as well as its functions, which refer to human activity (Batty, 2009). The formation of urban functional zones, such as residential, commercial, and industrial land, has been viewed as the results of urbanization and modern civilization (Chen et al., 2017). In a metropolis, these functional zones provide people with the various urban functions to meet their different needs (e.g., shopping, entertaining). In this context, we explored the RN distribution characteristics for the different urban functional zones by taking advantage of points of interest, Baidu street view (http://map.baidu.com/), high-resolution satellite images in Google Earth, and 2-m WorldView-2 images acquired on 25 March 2012. We visually inspected each RN scene (440×440 m) and manually classified its semantic categories. According to the land-use classification standards of the Ministry of Land and Resources, the urban functional zones consist of 14 categories (Fig. S4).

The acoustic environment (RN) intensity was divided into four categories, i.e., "high", "sub-high", "sub-low", and "low", using the Jenks natural breaks classification method in ArcGIS 10.1, in which classes are established among the largest breaks in the data array (Weng et al., 2008). We then conducted an investigation into the proportions of the four categories among the different urban functional zones (Fig. 2). Low and sub-low categories dominate in the *Green Space* category, and the *High-grade Residential Area* category belongs to the most comfortable acoustic environment. There is an obvious decrease of sub-low RN for the mixed *Commercial and Residential Area* category (less than 25%) compared to *Commercial Land* (approximately 100%) and *Residential Area* (greater than 70%). The *Transportation and Education Sites* category refers to education sites surrounded by urban main roads with a large traffic volume. Sub-high RN dominates this type of functional zone. In the *Transportation Land* category, sub-high and high RN account for 50%. The *First-class Industrial Land* category is mainly made up of sub-low RN, while the *Second-class Industrial Land* category is primarily composed of high and sub-high RN. Sub-high RN occupies a large proportion in the *Entertainment* category.

4. Discussion

4.1. Effect of urban morphology on RN

Previous studies have shown the potential of NTL or LST data for the estimation of socioeconomic indictors and urbanization dynamics (Chen and Nordhaus, 2011). Our results reveal that these socioeconomic morphology parameters, such as NTL and LST data, are associated with RN magnitude, to some extent (Table 2(A)). On

Table 3
Pearson correlation coefficients between urban morphology parameters: **(A)** Road measurement data, **(B)** Landscape metrics, and TN.

(A)

Road measurement data	Large vehicle flow	Small–medium vehicle flow	Road grade	Population	Length of road	Width of road
	0.520**	0.508**	−0.209*	0.204*	−0.191	0.179

(B)

Landscape metric		PLAND	MPS	LPI	DIVISION	MSI	SPLIT	LSI
Class-level	Building	0.033	0.021	0.086	−0.116	−0.321**	−0.106	−0.235*
	Road	0.307**	0.037	0.115	−0.182	0.237*	−0.182	0.293**
	Vegetation	−0.342**	−0.427**	−0.051	0.146	0.160	0.010	0.350**
Landscape-level		–	0.322**	0.157	−0.196	0.014	−0.216*	0.229*

*Correlation is significant at the 0.05 level (two-tailed).
**Correlation is significant at the 0.01 level (two-tailed).

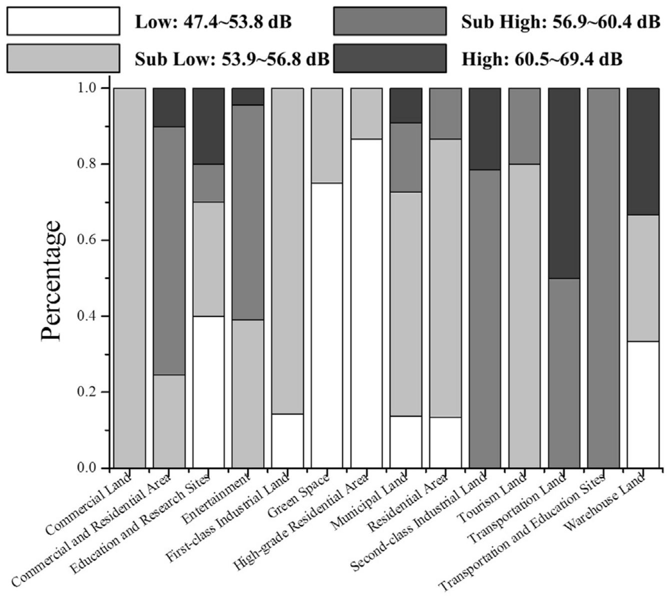

Fig. 2. The proportions of the four RN categories (high, sub-high, low, and sub-low) among the different urban functional zones.

the other hand, RN is influenced by landscape composition and the configuration of both vegetation and buildings. Building density plays a main role in increasing RN, which is contrast to an earlier finding from Amsterdam and Rotterdam (Salomons and Pont, 2012). This may be because people in Amsterdam and Rotterdam walk and cycle more or use public transport more often in areas with high building densities (Salomons and Pont, 2012). However, in Shenzhen, an increase in building density causes an increase in traffic, including not only public transport but also private cars. Furthermore, areas with high building densities may refer to other human activities, such as redevelopment of the neighborhood or urban villages resulting from the complicated socioeconomic development of China (Huang et al., 2015). The shape and spatial arrangement of buildings also have an impact on RN. Contiguous and complete forms of buildings have a positive effect on RN and, conversely, a more scattered distribution helps to mitigate urban noise. This is probably because the scattered spatial distribution of buildings facilitates the attenuation of acoustic energy through its multiple reflections between walls (Kurze and Anderson, 2006). Both previous studies (Liu et al., 2013; Cohen et al., 2014; Margaritis and Kang, 2017) and this study have reported that urban vegetation can help to mitigate the effect of environmental noise. The mitigating effects increase as the areal percentage of vegetation in the landscape increases. Interestingly, our results suggest that the spatial arrangement of vegetation also influences RN. The high-connectivity and less-fragmented spatial configuration of vegetation contributes to alleviating RN effects. The signs of the significant metrics for both buildings and vegetation are exactly opposite, possibly corroborating their distinct roles in RN. This phenomenon is probably caused by the different noise-mitigation performances of buildings and vegetation. On the one hand, scattering and diffusion effects between dense foliage and branches within vegetation can result in noise attenuation (Martens and Michelsen, 1981; Watanabe and Yamada, 1996; Fang and Ling, 2003; Bucur, 2006). Importantly, on the other hand, vegetation can influence the porosity and water content of soils from the aspects of soil temperature, organic and inorganic composition, and animal life (Connelly and Hodgson, 2015). And the effects of soils are also the principal factors in sound attenuation for vegetation (Horoshenkov et al., 2013). High-permeability soils exhibit very high values of acoustic absorption, whereas the absorption coefficient of low-permeability soils is low. However, the presence of vegetation on the low-permeability soils can significantly enhance the acoustic absorption coefficient of such soils (Aylor, 1972; Horoshenkov et al., 2013). With respect to buildings, which are often with impervious surfaces, the absorption coefficient is relatively low, and much noise can reflect between walls (Kang, 2006; Horoshenkov et al., 2013). In streets with tall buildings on both sides, continuous building façades are more likely to cause higher concentration of reflected sound (Kang, 2006; Guedes et al., 2011). Under this circumstance, planting more urban vegetation is an effective approach for noise reduction, since vegetation-soil system can attenuate much noise by scattering and absorption (Kang, 2006). At the landscape level, the combined effects of the land-cover classes existing within the landscape result in the signs of the significant correlation coefficients being consistent with vegetation (Table 2(B)). This indicates the important role of vegetation in noise reduction, which is consistent with previous studies (Connelly and Hodgson, 2015; Margaritis and Kang, 2017). Moreover, it should be noted that vegetation has a more psychological than physical effect on sound attenuation (Kuttruff, 2007).

4.2. Effect of urban morphology on TN

Vehicle flow is the most significant factor affecting TN (Table 3(A)), and a similar trend has been found in other studies (Guedes et al., 2011; Ware et al., 2015; Bastián-Monarca et al., 2016). Furthermore, our results reveal that a positive relationship between TN and population census data along the sides of the roads exists. This is due to the higher traffic demands for areas with more population. This phenomenon is also supported by the relationship between TN and road grades, where traffic volume on urban main roads exceeds that on urban secondary trunk roads.

The landscape configuration of the land-cover classes influences TN magnitude (Table 3(B)). Interestingly, contiguous and connected forms and irregular shapes of buildings along the sides of roads mitigate the TN effects. Oliveira and Silva (2010) found that regularity of urban forms decreases the possibility of the formation of a quiet environment. Contiguous and connected forms of buildings are more likely to decrease the regularity of urban scenes. As in the study of Liu et al. (2013), we found that TN increases with the area proportion of roads, and a remarkably higher TN magnitude occurs for areas with a high percentage of roads (Table 3(B)). Moreover, we found that the shape characteristics of road, as quantified by LSI, are positively associated with TN. This is because urban main roads tend to have larger LSI and MSI values than urban secondary trunk roads. Our research suggests that high-density vegetation along the sides of roads can reduce the effects of TN pollution, which is consistent with the findings of previous studies (Liu et al., 2013; Margaritis and Kang, 2017). Through the landscape indices analysis, it is revealed that a less-fragmented distribution and a regular shape of vegetation along the sides of roads can help to reduce the TN effect. At the landscape level, some interesting phenomena can be observed. Firstly, although the MPS of vegetation has a negative impact on TN, the combination of buildings and roads shows the positive role of MPS on TN. Secondly, TN is inversely related to SPLIT. There is no significant relationship between TN and the SPLIT of buildings, roads, and vegetation at the class level. However, their interactions negatively affect TN. Thirdly, TN is positively influenced by LSI, in which the combined effects of roads and vegetation are more significant than that of buildings.

4.3. Comparison between RN and TN

The underlying landscape interacts with both RN and TN, and has important impacts on them. However, to the best of our knowledge, there have been few attempts to compare how RN and TN relate to landscape features. RN is correlated with the landscape composition and configuration of buildings, while TN is related to their shape features and spatial configuration. For RN, the noise sources vary, such as industry, construction sites, etc. Buildings existing in RN scenes might reflect the land-use forms and functions through their composition and spatial configuration. Some studies (Yu et al., 2010; Lu et al., 2014) have regarded buildings as the response to dense business concentration and human activity, which may in turn affect RN magnitude. Furthermore, our results indicate that buildings behave as obstacles to the free propagation of noise by their spatial arrangement and shape characteristics. It has been shown that traffic volume plays a crucial role in determining the magnitude of TN sources (Seong et al., 2011), and hence building configuration rather than composition associates with TN. RN is not correlated with any of the landscape pattern metrics of road, whereas TN is associated with its shape features. This is because the shape features of roads diversify greatly among the different grades corresponding to different amounts of traffic flow. In terms of vegetation, both RN and TN are related to PLAND and MPS, confirming that contiguous and less-fragmented forms are preferable for reducing RN and TN effects. In addition, a regular and simple shape of vegetation along the sides of roads is more beneficial to reducing TN effect.

4.4. Implications for urban noise reduction

The relationships between urban noise and urban morphology parameters have important implications for city planning and urban functional zone management. From the land-cover viewpoint, vegetation can act as an acoustic barrier and help to mitigate environmental noise. However, it should be noted that vegetation can also transmit the noise, and it has a more psychological than physical effect (Kuttruff, 2007). The vegetation fraction is an important factor influencing its alleviating effect (Liu et al., 2013; Margaritis and Kang, 2017). The spatial configuration of vegetation can also affect the alleviating effect. Our results reveal that contiguous and less-fragmented forms of vegetation are preferable for reducing RN and TN magnitude. Vegetation with a regular shape along roads has a better sound insulating effect for TN. At the landscape level, vegetation contributes more to environmental noise than other land-cover categories, indicating the important role of green spaces in our cities. It is well known that green spaces have been recognized as providing valuable ecosystem services, such as climate regulation, air purification, water filtration, and mitigating the effect of urban heat island (UHI). When buildings within the urban scenes are irregular, this is more effective at reducing noise effects than when they are regular. In terms of urban functional zones, *Transportation Land* and *Second-class Industrial Land* are the main contributors of environmental noise. Future city planning should take this into consideration when choosing the locations for school or research institutions. Planning and restriction of heavy vehicle traffic is considered as an effective way to mitigate the traffic noise (Bunn and Zannin, 2015). If railroads pass through the city, three alternatives can be used to control the noise pollution generated by railway traffic: exclusion of the train horn, inclusion of acoustic barriers, and removal of the railway tracks from the urban perimeter (Bunn and Zannin, 2016). In addition, in urban functional zones with high noise, we should take some steps to control the environmental noise. For example, construction of road pavements made of noise-absorbing materials is suggested by Vázquez et al. (2016). Inclusion of open spaces in recreational areas with high urban density can help to control urban noise as well (Paneto et al., 2017).

5. Conclusions

The main purpose of this paper was to analyze the influence of urban morphology on environmental noise, including regional environmental noise (RN) and traffic noise (TN). Urban morphology parameters were evaluated from both socioeconomic and geographical landscape aspects. From the results of this study, it is demonstrated that there are significant relationships between urban morphology and RN/TN.

The landscape in this study was quantified with landscape metrics calculated on high-resolution land-cover data (including buildings, vegetation, and roads), at both the class level and landscape level. Both the composition and configuration of buildings significantly relates to RN. Scattered distributions and irregular shapes of buildings facilitate the attenuation of RN. Only the configuration of buildings is correlated with TN, and contiguous and connected forms of buildings along the sides of roads are more effective at mitigating the TN effects. Both the composition and configuration of vegetation are correlated with RN and TN, and high-percentage, aggregated, and less-fragmented vegetation is more effective at ameliorating the RN and TN. The findings of this study have the potential to be used to mitigate UEN.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.envpol.2017.10.126.

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