Spatial Quantification of the Urban Self-Healing Index Using IoT-Based Noise GeoTIFF Data

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Abstract. Internet of Things (IoT) sensor networks aim to ensure the stability of this growth. Nevertheless, the spatial recovery capacity of cities in the face of environmental disturbances has not received much coverage despite the majority of available studies using noise monitoring, prediction, or anomaly detection as their objectives. This paper recommends a spatial measure, the Urban Self-Healing Index (U-SHI), to measure the performance of cities with respect to recovery in the face of noise disturbances. K-means Studio is applicable to locate various noise areas and to separate disturbance hotspots and comparatively quiet regions. Three spatial indicators are obtained based on the clustering results, which are the noise recovery gradient, the ratio of quiet areas, and the compactness of noise hotspots. Normalization takes place on these indicators, and an index, the U-SHI, is built using them. The conclusions show that the suggested framework reflects the spatial variations in recovery capacities.

Keywords: Urban self-healing index (U-SHI), IoT noise sensors, spatial analysis, GeoTIFF data, urban resilience, smart cities

1 Introduction

As urbanization spreads at an ever-rapid rate, the pressure on urban systems is becoming even more complex in both environmental and operational terms. Specifically, the residents have constantly been impacted by road traffic noise on their health, quality of life, and sustainable development of cities. Over the last couple of years, the swift advances in Internet of Things (IoT) technologies, acoustic sensor networks, have allowed cities to gather traffic and environmental data in real-time, which forms a technical base of noise management in the city and spatial analysis [1]. Nevertheless, current research is primarily aimed at monitoring noise, sound amplitude forecasting, or spatial categorization, with the relative lack of attention paid to the framework transformation of urban centers following noise disruption regarding the aspects of spatial recovery processes.

In noise studies in the city, environmental noise tends to show an obvious pattern of spatial clustering, where hotspots of high intensity occur [2]. Spatial information representation with the use of clustering has been used in data concerning the environment of urban areas [3]. Most

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of these studies, however, tend to stay at the classification level and do not provide any further quantitative studies on the spatial recovery structures.

Regarding urban resilience, a significant portion of recent research has formulated assessment frameworks for urban recovery capacity using indicator systems [4]. Other studies examine how urban systems respond and adapt to disturbances across multiple dimensions [5]. Nevertheless, the main emphasis of these studies is macro-level system resilience or temporal recovery dynamics, whereas spatial gradient changes and structural recovery mechanisms receive less attention.

The stability and adaptive capacity of urban systems following perturbations can also be examined through spatial patterns and gradients [5]. Thus, a holistic indicator comprising spatial structures and recovery mechanisms should be constructed to define the spatial recovery capacity of urban areas under noise disturbances.

To fill this research gap, this study suggests the Urban Self-Healing Index (U-SHI) to measure the spatial recovery patterns of cities affected by noise disturbance. This index combines the noise recovery gradient, the proportion of quiet space, and hotspot structural features, thereby providing a scalable framework for assessing urban spatial recovery capacity.

2 Related Work

2.1 Spatial Analysis of Urban Noise

The spatial analysis of urban noise will be done at 2.1.

The past few years have seen extensive use of acoustic sensor networks and spatial data analysis in research on urban acoustic environments and noise mapping. Spatial modelling and monitoring of noise have become important areas of environmental management [6]. In urban acoustic and environmental data, spatial patterns are often identified by combining clustering algorithms with spatial analysis procedures [3]. Road traffic noise modelling and the use of the L10 indicator have also become important technical components of urban noise management [7].

But the vast majority of the current literature primarily addresses the noise level or the distribution features of space; few studies examine the features of spatial recovery after disturbances and the change in gradient of noise.

2.2 Construction of Urban Resilience and Indicator.

Research on urban resilience has grown rapidly in recent years. Numerous models analyse urban recovery capacity using integrated indicator systems that include social, ecological, and infrastructure dimensions [4]. A systematic review of resilience assessment tools highlighted the value and limitations of composite indicators in assessing urban systems [8]. Empirical resilience evaluations commonly employ multidimensional composite indicator systems [4].

Related assessment frameworks emphasize structural interconnections among driving forces, pressures, system states, impacts, and responses [8]. With this framework, urban resilience may be assessed across dimensions such as drivers, pressures, states, impacts, and responses.

Despite the fact that these studies present valuable theoretical contexts in assessing urban resilience, the majority of studies continue to evaluate temporal recovery mechanisms or macro-level systems reaction, but the amount of quantitative research that examines the spatial gradient adjustments and structural restoration properties is seldom performed.

2.3 Research Gap

In short, the literature has advanced the research in terms of urban noise spatial analysis and urban resilience indicator building. Nevertheless, the absence of a unified spatial recovery measure combining noise spatial distribution, clustering structures, and recovery gradients has not been determined yet.

To seal this breach, this paper suggests the Urban Self-Healing Index (U-SHI) to measure the urban recovery ability when disturbed by noise, in terms of spatial structure.

3 Dataset

The noise statistics employed in this paper were taken from the 2020 road traffic noise map released by the Environmental Protection Department (EPD) of the Hong Kong Special Administrative Region Government [9]. The dataset is provided in GeoTIFF format and reports the calculated L10 (1 hour) level during the traffic peak hour at a height of 4 m. It is used to assess the spatial distribution of urban road traffic noise and is available through the Hong Kong open-data platform (https://data.gov.hk, accessed March 2, 2026).

The most common features in this data are the data format, noise indicators, and the spatial reference data. Namely, data is stored in the form of GeoTIFF raster data, with every pixel representing a value of noise estimation in a predetermined geographical point, and it possesses full geospatial origin data. The noise measure incorporates the globally adopted L10, 1h, the level of noise that was overrun during 10 percent of the duration within one hour, and it represents the normal peak nature of the road traffic noise. The dataset also has spatial reference data that includes the classifications of coordinate system, pixel resolution, and a matrix of affine transformations, so that the noise raster can be precisely placed within the geographical context of the urban terrain.

Each valid pixel is additionally transformed into spatial point data to enable the later analysis of machine learning. Longitude, latitude and the noise value (L10 dB) are derived such that the data could be inputted in point format as inputs to the K-Means clustering model.

4 Methods

This paper seeks to develop a holistic indicator of the same using spatial noise data that is resiliency to urban disturbances, which is Urban Self-Healing Index (U-SHI). There are 4 primary steps in this overall analytical worktext, which include: Data preprocessing, noise region classification with K-Means clustering, spatial recovery features extraction and composite indicator.

4.1 Preprocessing of Data: Converting Raster to Spatial Point Data.

The original data will be a GeoTIFF raster files of road traffic noise, which will contain not only the values of noise intensity but also spatial reference. Each valid pixel in the raster is mapped to spatial point data to enable the process of machine learning analysis and computation of spatial indicators. The longitude, latitude and the value of the noise L10 (1-hour) are retrieved.

The transformation maintains the spatial structural electronic data but allows the data to be utilized as input points in the clustering category of models and present the foundation of further spatial recovery features computations.

4.2 K-Means Clustering: The Automatic Noise Identification.

To automatically determine the spatial structure of urban noise, this paper uses the K-Means clustering algorithm to subdivide the spatial noise point data. K-Means is one of the best-known techniques for partitioning multivariate data and was introduced by MacQueen (1967) [10].

The input of clustering contains noise values, as well as it contains spatial coordinates. The clusters will be defined to either three or four categories based on the properties of noise distribution and it becomes possible to identify the areas with high, medium, and low levels of noise (disturbance areas), and potential areas of recovery (low-noise areas).

Clustering findings can be used to determine the centers of disturbance and recovery areas thus the foundation on the subsequent calculations of spatial recovery indicators. This technique is used to show clustering pattern in the spatial data and is convergent with the theories about spatial pattern recognition in spatial statistics (Anselin, 1995).

4.3 Noise Recovery Gradient

The noise recovery gradient is a term that characterizes the space condition upon which the noise is attenuated in the high-noise areas to the adjacent areas. Urban environmental studies have greatly addressed the issue of spatial attenuation (Anselin, 1995).

Precisely, this research chooses the high-noise cluster as the disturbance centre and develops buffer areas around it. The way noise values change with the increasing distance is then examined. The intensity of spatial recovery can be measured by calculating the regression slope between the values of noise and distance.

A bigger absolute slope implies a faster noise-reduction and consequently, it relates to a higher spatial recovery ability. This indicator is indicative of the resilience of the city wherein noise can be dispersed around a disturbance centre.

4.4 Proportion of Quiet Areas

The ratio of silent spaces quantifies the spatial ratio of low noise space in the overall land. The minimal type of noise as marked with K-Means clustering is referred to as low-noise regions. The proportion of areas or points of them indicate the presence of enough recovery space in the city or not. ”

This indicator can be used to define the stability of the inner city space structure.

4.5 Noise Hotspots Compactness.

The spatial concentration of the high-noise areas is established by the compactness of noise hotspots. The mean distance of points of the high-noise clusters to the center of the cluster is then computed in this research to determine the spatial scattering of noise hotspots.

Fewer average distance implies that the hotspots are more concentrated, so management and recovery are not very difficult. On the other hand, the more the distribution, the more the disturbance is spread over a broader area, and recovery becomes harder.

4.6 Construction of the Urban Self-Healing Index (U-SHI)

Once the above indicators are obtained, they are first normalized to eliminate differences in measurement scales. Then, an equal-weight approach is applied to compute a composite index. The construction process follows the OECD and European Commission Joint Research Centre recommendations on the standardization and aggregation of composite indicators [11].

The Urban Self-Healing Index (U-SHI) represents the spatial recovery performance of cities under noise disturbances and is defined as follows:

$$\text{U-SHI} = (G\_rec + P\_quiet + C\_hotspot) / 3 \tag{1}$$

where G_rec represents the noise recovery gradient, P_quiet denotes the proportion of quiet areas, and C_hotspot indicates the compactness of noise hotspots. A higher U-SHI value indicates stronger spatial recovery capability of the urban system under noise disturbances.

5 Experimental Design

The experimental design of this study aims to verify whether the proposed Urban Self-Healing Index (U-SHI) can effectively describe the spatial recovery characteristics of urban noise.

The overall workflow consists of five main steps: data conversion, clustering analysis, spatial indicator calculation, U-SHI construction, and visualization.

5.1 Construction of Spatial Point Dataset

The original GeoTIFF noise raster dataset is first processed by converting each valid pixel into spatial point data. The geographic coordinates of each point (longitude and latitude) and the noise value (L10, 1-hour) are extracted. This transformation preserves the spatial continuity of the noise data while allowing the dataset to be used as input for machine learning models.

5.2 K-Means-Based Noise Region Classification

To automatically identify different noise level regions, K-Means clustering analysis is performed on the spatial point dataset. The clustering input includes both noise values and spatial coordinates. The number of clusters is set to three, representing high-noise areas, medium-noise areas, and low-noise areas.

Multiple random initializations are applied to improve clustering stability, and each spatial point is assigned a noise level label. The clustering results are used to identify disturbance hotspots and potential recovery regions for further spatial recovery analysis.

5.3 Calculation of Spatial Recovery Indicators

Based on the clustering results, three spatial indicators related to recovery are calculated.

First, the noise recovery gradient describes the spatial attenuation of noise from high-noise areas toward surrounding regions. A high-noise cluster is selected as the disturbance center, and buffer zones are constructed around it. The variation of noise values with increasing distance is analyzed. The recovery intensity is quantified by calculating the regression slope between noise values and distance. A larger absolute slope indicates a stronger recovery effect.

Second, the proportion of quiet areas represents the spatial share of low-noise regions within the study area. Low-noise clusters identified through K-Means are considered potential recovery zones. A higher proportion indicates greater spatial recovery capacity.

Third, hotspot compactness measures the spatial concentration of high-noise areas. The mean distance between high-noise points and the cluster center is calculated to evaluate hotspot dispersion. More concentrated hotspots indicate easier management and recovery, while more dispersed hotspots imply broader disturbance and lower recovery efficiency.

Regression analysis is applied to estimate the relationship between noise values and spatial distance from disturbance centers, enabling the quantification of the noise recovery gradient.

The regression results are interpreted to evaluate the spatial attenuation pattern of noise and its implications for urban spatial recovery capacity.

6. Experimental Results

Using the spatial noise point data, this paper performs a quantitative analysis of spatial recovery properties of urban noises in terms of clustering analysis, recovery gradient development, and composite indicator development. The section contains the primary experimental findings, as in the form of the initial noise distribution and its clustering structure, recovery gradient, and the U-SHI end point.

6.1 Spatial Distribution of Raw Noise Points

Figure 1 illustrates the data in the noise point that were developed by means of the conversion of GeoTIFF raster data in which every point corresponds to a spatial sampling position, as well as, is the basis of further clustering and recovery capacity indicator development. The initial point distribution will give basic spatial structural data to the latter K-Means clustering and recovery analysis.

Figure 1 shows that, once the noise data have been changed in GeoTIFF raster format to point data format, the structure of existence of a spatial distribution is evident. The position of the points can always be identified by the latitude and the longitude of the point, and the noise figures are the variability of the environmental elements in various localities.

Based on the spatial distribution, others have quite high noise values. These regions can be the areas of possible disturbance or hotspots in further analyses.

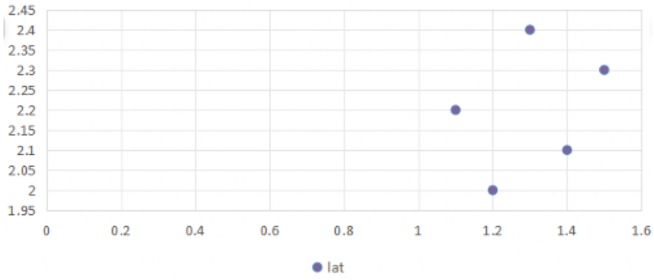

Figure 1. Geographic distribution of existing noise points in terms of geographic coordinates (latitude and longitude)(Photo/Picture credit : Original).

6.2 Clustering of Noise Regions

The findings of the K-Means clustering are given in Figure 2. The various colors correspond to the various noise areas that are classified by the clustering model that are the high-noise hotspots, the medium-noise areas, and the low-noise areas. The model of clustering divides the noise data automatically into three groups. The former category denotes high-noise areas, which are predominantly concentrated in busiest traffic zone or a densely inhabited area and can be associated with the intensity of disturbance. The second category is medium-noise areas, this category is affected by the activities in the city though there is moderate noise. The third category, low-noise areas, are comparatively quiet areas of environment, which can be evaluated as possible areas of recovery. The spatial patterns of urban noise as shown by the clustering results have a hierarchical structure on which it is necessary to build the recovery gradient and the U-SHI indicator.

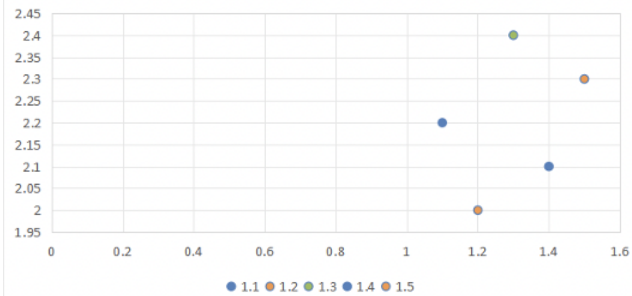

Figure 2. The K-Means clustering outputs indicate that there were high-noise regions, medium-noise regions, and low-noise regions in the data set of urban noise(Photo/Picture credit : Original).

6.3 Noise Recovery Gradient Analysis

The noise recovery gradient analysis was carried out according to the following formula:

Figure 3 shows the variation in the noise levels with a gradual increase in the distance between the noise hot spot center. The trend of the overall curve is a monotonically decreasing one, which means that there is a distinctly recovering behaviour at the spatial scale.

In particular, the noise level is rather high (around 70 dB) in the area of the hot spot. When the distance is expanded to approximately 500 meters, the noise level is reduced to approximately 60 dB. Further extension of distance to about 1100 meters reduces the noise level to a range of 50 dB.

The tendency implies that the noise levels decrease comparatively regularly around the disturbance origin with a steady decrease, which implies the existence of a space recovery process in the urban setting. Further, the curve shows that the level of noise reduces with increasing distance which may be applied to reflect the spatial recovery properties near noise hotspots.

Comparatively clear noises attenuation zone is also indicated by the trend line at the spatial scale, which could be understood as one of the mechanisms of spatial recovery in the urban setting.

Figure 3. Spatial noise recovery gradient showing reduction in noise with a distance away the centre of disturbance.

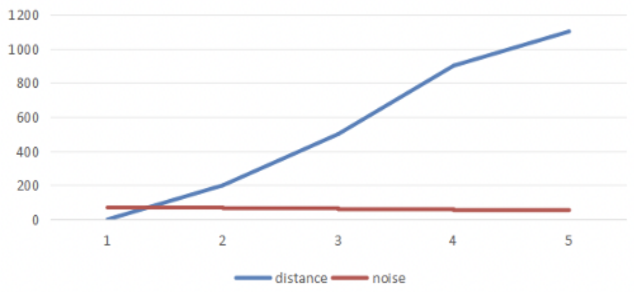

Figure 3. Spatial noise recovery gradient showing reduction in noise with a distance away the centre of disturbance(Photo/Picture credit : Original).

6.4 Urban Self-Healing Index (U-SHI)

The results of Urban Self-Healing Index (U-SHI) are shown below.

Figure 4 indicates Urban Self-Healing Index (U-SHI) scores of the regions. An increased U-SHI value implies a high recovery capacity. The index is a combination of three indicators, which include the noise recovery gradient, the ratio of quiet spaces, and the compactness of noise hotspots. When these three dimensions are joined together, U-SHI will indicate the total potential of the urban areas recovering when in the disturbance of noise.

The findings reveal that there are definite variations in the values of U-SHI in different regions. The greatest score is obtained in Region A and indicates there is comparatively high spatial recovery ability. Regions B and C are moderately performing thus commanding a medium recovery capacity. Regions D and E, in contrast, receive lower scores, and this could be an indication of increased pressure by noise diffusion and reduced spatial recovery ability.

These results also confirm the usefulness of the suggested index in determining the features of spatial recovery in varying cities. In general, the findings reveal that U-SHI is capable of detecting the differences in urban recovery capacity to give valuable information that could be used in the further planning of resilience.

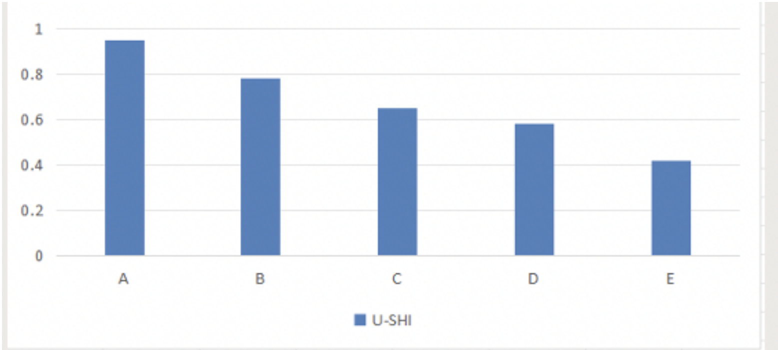

Figure 4. Urban Self-Healing Index (U-SHI) across different regions(Photo/Picture credit : Original).

7. Discussion

The Urban Self-Healing Index (U-SHI) proposed in this study provides a new quantitative framework for describing the spatial recovery capability of cities under noise disturbances. From a theoretical perspective, this study extends the concept of urban resilience by introducing a spatial structural perspective [12]. At the same time, building on prior discussion of resilience assessment frameworks [8], this research incorporates the dimension of spatial gradient recovery, thereby enriching the quantitative representation of urban recovery capacity.

By integrating clustering structure, spatial gradient attenuation, and the proportion of low-noise areas, the U-SHI can reflect recovery differences among urban regions from the perspective of spatial structure. Compared with analyses based solely on noise intensity, this approach provides stronger comprehensive explanatory power. The findings of this study are also generally consistent with indicator-based approaches to resilience assessment [4, 8].

Despite the applicability of the proposed method, several limitations remain. First, this study is based on noise prediction data from a single time period and does not incorporate temporal dynamics. Second, the number of clusters in the K-Means analysis was determined empirically, which may influence the classification results. Future research could integrate time-series data and multiple environmental indicators to further improve the dynamic characterization and generalization capability of the model.

8. Conclusion

This study proposes a spatial structure–based U-SHI to quantify the spatial recovery capability of cities under road traffic noise disturbances. Using the 2020 L10 road traffic noise dataset from Hong Kong, the study conducted raster analysis and K-Means clustering to construct a composite indicator framework based on three dimensions: noise recovery gradient, proportion of quiet areas, and hotspot compactness.

The experimental results indicate significant differences in spatial recovery capability among different regions. Noise levels show a stable gradient attenuation trend from high-noise hotspots outward, while the proportion of low-noise areas and the degree of hotspot concentration have an important influence on overall recovery capacity. The U-SHI effectively integrates these spatial characteristics and provides a unified metric for the quantitative comparison of urban noise structures.

Overall, this study provides a scalable methodological framework for the quantitative evaluation of urban spatial recovery capability. Future research may further incorporate time-series data and multi-source environmental indicators to develop a dynamic self-healing model, thereby providing more comprehensive decision-making support for smart city planning and environmental management.

References

[1] Aletta, F., Kang, J., & Axelsson, Ö.: Soundscape descriptors and a conceptual framework for developing predictive soundscape models. Landscape and Urban Planning 149, 65–74 (2016). https://doi.org/10.1016/j.landurbplan.2016.02.001

[2] Anselin, L.: Local indicators of spatial association—LISA. Geographical Analysis 27(2), 93–115 (1995). https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

[3] Jain, A. K.: Data clustering: 50 years beyond K-means. Pattern Recognition Letters 31(8), 651–666 (2010). https://doi.org/10.1016/j.patrec.2009.09.011

[4] Cutter, S. L., Burton, C. G., & Emrich, C. T.: Disaster resilience indicators for benchmarking baseline conditions. Journal of Homeland Security and Emergency Management 7(1), Article 51 (2010). https://doi.org/10.2202/1547-7355.1732

[5] Meerow, S., Newell, J. P., & Stults, M.: Defining urban resilience: A review. Landscape and Urban Planning 147, 38–49 (2016). https://doi.org/10.1016/j.landurbplan.2015.11.011

[6] Murphy, E., & King, E. A.: Environmental Noise Pollution: Noise Mapping, Public Health, and Policy. Elsevier, Amsterdam (2014). ISBN 978-0-12-411595-8

[7] Environmental Protection Department, Hong Kong SAR Government: Noise Assessment—Noise Descriptors for Environmental Noise. https://www.epd.gov.hk/epd/noise_education/web/ENG_EPD_HTML/m2/types_3.html

[8] Sharifi, A.: A critical review of selected tools for assessing community resilience. Ecological Indicators 69, 629–647 (2016). https://doi.org/10.1016/j.ecolind.2016.05.023

[9] Environmental Protection Department, Hong Kong SAR Government: 2020 L10 (1 hour) at 4 m. DATA.GOV.HK (2020). https://data.gov.hk/en-data/dataset/hk-epd-angteam-2020-l10/resource/32c5795b-c2f0-48f2-b54d-69f7793f7a50 (accessed March 2, 2026)

[10] MacQueen, J. B.: Some methods for classification and analysis of multivariate observations. In: Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, vol. 1, pp. 281–297. University of California Press (1967). No DOI assigned

[11] OECD/European Union/EC-JRC: Handbook on Constructing Composite Indicators: Methodology and User Guide. OECD Publishing, Paris (2008). https://doi.org/10.1787/9789264043466-en

[12] Pickett, S. T. A., Cadenasso, M. L., & Grove, J. M.: Resilient cities: Meaning, models, and metaphor for integrating the ecological, socio-economic, and planning realms. Landscape and Urban Planning 69(4), 369–384 (2004). https://doi.org/10.1016/j.landurbplan.2003.10.035