https://doi.org/10.1016/j.scitotenv.2018.11.136

Title: Neighborhood-based subjective environmental vulnerability index for community health assessment: Development, validation and evaluation

Authors: Hung Chak Ho[1,2], Man Sing Wong[2, 3], Ho Yin Man[2], Yuan Shi[4], Sawaid Abbas[2]

Affiliations:

1. **Department of Urban Planning and Design, The University of Hong Kong, Hong Kong**
2. **Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hung Hom, Hong Kong**
3. **Research Institute for Sustainable Urban Development, The Hong Kong Polytechnic University, Hung Hom, Hong Kong**
4. **School of Architecture, The Chinese University of Hong Kong, Sha Tin, Hong Kong**

Corresponding Author: Man Sing Wong, Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hung Hom, Hong Kong, email: lswong@polyu.edu.hk

Abstract

Neighborhood-based environmental vulnerability is significantly associated with long-term community health impacts. Previous studies have quantified environmental vulnerability using objective environmental datasets. However, environmental cognition among a population may influence subjective feelings of environmental vulnerability, and this can be associated with community health risk.

In this study, a mixed-methods approach was applied to estimate neighborhood-based environmental vulnerability based on objective environmental measures and subjective environmental understanding from a local population. The synergistic use of both qualitative and quantitative data resulted in a subjective environmental vulnerability index which can demonstrate environmental deprivation across Hong Kong. The resultant maps were compared with a mortality dataset between 2007 and 2014, based on a case-series analysis. The case-series analysis indicated that using a subjective environmental vulnerability index as an approach for neighborhood mapping is able to estimate the community health risk across Hong Kong. In particular, the following types of cause-specific mortality have significant association with the subjective environmental vulnerability index: 1) mortality associated with mental and behavioral disorders, 2) cardiovascular mortality, 3) respiratory mortality, and 4) mortality associated with diseases of the digestive system.

In conclusion, the use of a subjective environmental vulnerability index can be implemented within a community health planning program, especially to reduce long-term adverse impacts on population with mental impairment.

Keywords: environmental vulnerability; environmental measures; environmental cognition; community health; spatial analytics; deprivation index

Introduction

Neighborhood-based environmental impact is a major factor that can influence community health risk across a city. Previous studies have demonstrated significant impacts from intra-urban air pollution on morbidity and mortality (Ho et al., 2018a); as well as the influence of spatial variations in extreme heat on short-term health risk (Beyer et al., 2014; Ho et al., 2017; Krstic et al., 2017). In addition, the lack of greenspace and higher urban density are the community factors that can modify the health risk of vulnerable populations (Wheeler et al., 2015; Wong et al., 2017).

In order to evaluate environmental impacts on local health, previous studies have commonly applied a cross-sectional analysis or a case-series analysis along with objective environmental data to estimate potential environmental influences on health risk (Hondula, et al., 2012; Woo et al., 2017). The objective environmental data are mainly derived from spatial buffers of the environmental dataset, without linkage to, or inclusion of human perception associated with the environmental experiences. There are also several environmental vulnerability indices derived based on objective environmental data for health risk estimation and prevention (Rugel et al., 2017). These studies aim to develop a more comprehensive framework for identifying neighborhoods with potentially higher health risk, as protocols for community planning.

The aforementioned studies have advocated the use of objective environmental data for public health analyses. However, recent studies have indicated that subjective feelings about a community by a person can play an important role in influencing his/her health status. For example, subjective social scores can identify the neighborhood vulnerability (Wong et al., 2008), and such scores have been found to have significant relationships to actual health risk. In addition, several subjective neighborhood scores have been defined for measuring deprivation of a built environment (Saelens et al., 2003), and some studies have found that these subjective scores were useful in long-term health prediction.

Therefore, environmental cognition by a local population may alter their potential health risk. Differences in environmental cognition of different aspects of geophysical environment (e.g. built environment, air pollution and temperature) can also cause the variations of subjective environmental statues, and the negative feelings from the subjective environmental statuses can further affect the level of environmental vulnerability that can further influence human health. We hereby defined this environmental vulnerability from the subjective and negative feelings of the environmental statuses as “subjective environmental vulnerability”.

The understanding of subjective environmental vulnerability is essential in a compact city with high-density living, since variations in urban morphologies across neighborhoods may significantly influence environmental cognitions among the local populations. In order to consider all factors to better understand negative effects of environmental cognitions among local population, previous studies have administered short-form questionnaires to map the subjective environmental vulnerability across a city (Nichol & Wong, 2009; Faisal & Shaker, 2017), however such approaches have not been validated with actual health data for the potential use of community health applications.

Here we applied a systematic approach to analyze subjective environmental vulnerability among urban population, and evaluated the potential use of a subjective environmental vulnerability index for community health planning. The specific objectives of this study include to 1) collect information on subjective environmental vulnerability among an urban population based on an online cohort; 2) evaluate the weight and importance of each subjective environmental vulnerability item with factor analysis; 3) develop a subjective environmental vulnerability index based on the results of factor analysis; 4) map the intra-urban subjective environmental vulnerability based on the constructed index; and 5) evaluate the potential use of this spatial index for analyzing long-term health impacts, with using a case-series analysis to estimate associations between the index and cause-specific mortality. The results of this study can be used to improve public health surveillance by locating high-risk areas for community planning. The identification of high-risk areas can also be useful to improve the environmental dimension of sustainability (Marques et al. 2015; Molinos-Senante et al., 2016).

Data and Methods

Online Cohort Data

An online cohort with 120 subjects from Hong Kong was examined in this study. This cohort was approved by the Human Subjects Ethics Sub-committee of The Hong Kong Polytechnic University (Reference Number: HSEARS20180124002). All data of this cohort were collected between Feb 14, 2018 and Mar 13, 2018, including the demographic information about each subject, and an 8-item survey for rating the subjective environmental statuses that can influence environmental vulnerability. The followings are specific questions of the 8-item survey: 1) "do you think traffic-related air pollution is a serious environmental problem?", 2) "do you think regional-based air pollution is a serious environmental problem?", 3) "do you think light pollution is a serious environmental problem?", 4) "do you think lack of vegetation or greenspace is a serious environmental problem?", 5) "do you think high city/building density is a serious environmental problem?", 6) "do you think summer heat is a serious environmental problem?", 7) "do you think lack of open space or parks is a serious environmental problem?", and 8) "do you think anthropogenic heat is a serious environmental problem?". Each subject ranked the questions in five-scales, in which "1" indicates the "least serious" and "5" indicates the "most serious". The selection of these eight items was based on a literature search, given that all items were associated with adverse health effects (Chepesiuk et al., 2009).

Spatial Data

Based on each environmental item in the online cohort, eight sets of environmental data associated with the subjective vulnerability were further used in this study.

For the traffic-related air pollution, a very fine resolution map at 10 m illustrating the spatial variation of black carbon (BC) across Hong Kong was used (Barrett et al., 2018; Lee et al., 2017). This spatial variation of BC was estimated based on a land use regression, a technique commonly used for air pollution mapping in public health studies (Krstic et al., 2017; Shi et al., 2018).

To demonstrate the regional air pollution within the city, a map of fine particulate matter ($PM_{2.5}$) map at 500 m resolution, derived from 142 cloud-free Moderate Resolution Imaging Spectroradiometer (MODIS) Aerosol Optical Depth (AOD) datasets between 2007 and 2009, was used (Ho et al., 2018b). This $PM_{2.5}$ map was estimated based on the algorithm from Bilal et al. (2017), which was proven to be promising for local use over Hong Kong (R = 0.78).

Light pollution was demonstrated based on a radiance dataset retrieved from a 2015 nighttime Visible Infrared Imaging Radiometer Suite (VIIRS) with 750 m resolution. VIIRS image was acquired from the National Oceanic and Atmospheric Administration (NOAA) and can represent the typical nighttime light scenario across Hong Kong. The light pollution map and the regional air pollution map were masked by the land boundary and non-water areas of Hong Kong for further modelling.

The dataset of open space was derived from the 2012 land use map from the Hong Kong Planning Department. Vegetation data were separately derived from land use and land cover information from the Planning Department of Hong Kong and satellite images (Ho et al., 2018b). These maps were converted from vector-based to a raster-based format (10 m resolution) for further analysis.

We also derived a map of urban sky view factor (SVF) with 10 m resolution to represent urban building density over Hong Kong (Yang et al., 2015). SVF denotes the proportion of the sky viewed from the ground (Hodul et al., 2016). The SVF map was derived from airborne lidar data and a building map of Hong Kong, following the high-accuracy method by Zakšek et al. (2011). In brief, higher SVF indicates a higher sky view and lower building density in the surrounding environment, and lower SVF means a lower sky view and high building density in the surroundings.

The spatial distribution of summer temperature was mapped based on a land use regression (Shi et al., 2018b) with urban morphometric data and local weather information. Map of anthropogenic heat was derived from two satellite-derived maps (Wong et al., 2015) to demonstrate annually averaged daytime anthropogenic heat fluxes across Hong Kong.

Data for Community Health Applications

In order to examine the relationship between subjective environmental vulnerability and adverse health impacts, mortality data between 2007 and 2014 from the Hong Kong Census and Statistics Department were used in this study. This dataset includes the following information: 1) date of death, 2) age, 2) gender, 3) type of employment, 4) location of residence, and 5) cause of death based on the 10^{th} version of International Statistical Classification of Diseases and Related Health Problems (ICD-10). Location of residence was recorded based on the “Tertiary Planning Unit” (TPU), which is the finest spatial scale for mortality datasets in Hong Kong, and is well-used in local planning.

In order to minimize any potential bias in the modelling, daily information on temperature and air pollution were retrieved and used in this study. Hourly temperature data were obtained from the weather station located at headquarters of the Hong Kong Observatory and were averaged to a daily basis. Air pollution data used in this study are as follows: particulate matters (PM_{10}), nitrogen oxides (NO_x), ground-level ozone (O_3), and sulfur dioxide (SO_2). These air pollution data were the average of daily air quality information from seven air monitoring stations (Central Western, Sham Shui Po, Sha Tin, Tai Po, Tsuen Wan, Kwai Chung, and Tap Mun) operated by the Hong Kong Environmental Protection Department. These stations covered both urban and rural areas of Hong Kong.

Development of Subjective Environmental Vulnerability Index

We first applied a factor analysis to construct the empirical index of subjective environmental vulnerability for community health estimation. A varimax rotation was applied to the first two factors for estimation of factor loadings, and the sum of factor loadings for these two factors was assigned to be the weight for each variable.

For mapping subjective environmental vulnerability across the city, all spatial datasets were first resampled to a 10 m resolution for subsequent analysis. In addition, to standardize the data for vulnerability mapping, data of nighttime light, regional air pollution, traffic-related air pollution, anthropogenic heat, and summer heat were stretched between 0 to 100 based on the following equation: (pixel value – min) *100 / (max – min). The SVF was multiplied by 100 for data standardization.

Since statistical bias from scaling effects of the Modifiable Areal Unit Problem (MAUP) on community health analysis has been well documented (Cebrecos et al., 2018), a pixel-by-pixel spatial averaging with focal statistics of ESRI ArcGIS was applied to retrieve the average values from spatial buffers of 250 m, 500 m, 750 m, and 1000 m. This approach minimizes the potential issue of MAUP caused by scaling and zoning in community health planning (Ho et al., 2015), while the multiscale data can provide higher flexibility in the data analysis.

Based on the focal statistics, all datasets have turned into the following spatial parameters: 1) average regional air pollution, 2) average traffic-related air pollution, 3) average light pollution, 4) percentage of vegetation cover 5) average sky view factor, 6) average summer temperature, 7) percentage of open space, and 8) average anthropogenic heat. This analysis determines the adverse effect caused by environment, in which higher values should hypothetically be areas with lower environment quality, while 4), 5) and 7) have high values as better environment. Therefore, we inversed the values of these spatial layers of 4), 5) and 7) to match with the hypothesis based on the following equation to: 100 – pixel.

With the use of processed datasets for all corresponding spatial parameters, we then applied the index to map four versions of subjective environmental vulnerability within the land boundary of Hong Kong.

Case-Series Analysis

We applied a case-series analysis to evaluate the use of the subjective environmental vulnerability index in estimating long-term health impacts. Case-series analysis is a common epidemiological design to directly differentiate environmental effects between various groups of health data. This design has been commonly used in environmental epidemiological studies to analyze air pollution and temperature effects on community health (Hondula, et al., 2012).

In this study, we selected the following groups of decedents as "case": 1) cardiovascular mortality (ICD-10 I00-I99), 2) respiratory mortality (ICD-10 J00-J99), 3) mortality associated with mental and behavioral disorders (ICD-10 F00-F99), 4) mortality associated with diseases of nervous systems (ICD-10 G00-G99), 5) mortality associated with diseases of the genitourinary system (ICD-10 N00-N99), 6) mortality associated with diseases of the digestive system (ICD-10 K00-K93), and 7) cancer-related mortality (ICD-10 C00-C97). Each "case" group was subjected to a logistic regression individually, with accidental mortality (ICD-10 V01-X59) as the "control" group, to determine whether the subjective environmental vulnerability index would be useful in community health assessment.

Mortality data with missing location of residence and death date were excluded to reduce potential statistical bias. Mortality data from the last two days of 2014 were also excluded in order to prevent potential bias from delay in reporting. In addition, the decedents lived in a remote TPU without information on subjective environmental vulnerability were excluded from the analytic dataset.

The basic form of logistic regression is written as the following:

$$Case\ (1,0)\ \sim\ \beta_0 + \beta_1(\ Vulnerability) +\ \ \beta_2 Unemployed\ \ (1,0) + \beta_4(Age)$$
$$+ \beta_5(Gender\ \ (1,0)) + \beta_6(Hot\ \ Day\ \ (1,0)) + \beta_7(Cold\ \ Day\ \ (1,0))$$
$$+ \beta_8(High\ \ PM_{10}\ \ Day\ \ (1,0)) + \beta_9(High\ \ NO_x\ \ Day\ \ (1,0))$$
$$+ \beta_{10}(High\ \ O_3\ \ day\ \ (1,0))\ \ + \beta_{11}(High\ \ SO_2\ \ day\ \ (1,0)) +\ \ \beta_{12}(DOW)$$
$$+ \beta_{13}(Month)$$

where *Case (1,0)* is a binary variable indicating whether the decedents were died from a corresponding specific cause-of-death; *Vulnerability* is the average value of the subjective environmental vulnerability index of each TPU; *Age* is a continuing variable indicating the age of death; *Gender (1,0)* is a binary variable indicating gender of a decedent, with male as "1" and female as "0"; and *Unemployed (1,0)* is a binary variable indicating employment status, in which decedents classified as "economically inactive" were "1" and others were "0". In addition, *Hot Day (1,0)* represents the date of death with temperature >= 95th percentile between 2007 and 2014, while Cold Day (1,0) indicates that date of death with temperature <= 5th percentile. *High PM_{10} Day (1,0)*, *High NO_x Day (1,0)*, *High O_3 Day (1,0)*, and *High SO_2 Day (1,0)* were binary variables indicating the date of death with PM_{10}, NO_x, O_3, or SO_2 >= 95th percentile.

Age, *Gender (1,0)*, *Unemployed (1,0)*, *Hot Day (1,0)*, *Cold Day (1,0)*, *High PM_{10} Day (1,0)*, *High NO_2 Day (1,0)* and *High O_3 Day (1,0)* were the confounders of this study, together with a category variable of *DOW* indicating the day of week for controlling the weekday/weekend effect and a category variable of *Month* indicating seasonal effects.

In this study, we repeated the test for four versions of the subjective environmental vulnerability index individually, in order to evaluate whether each version of the vulnerability index can be used for predicting long-term health impacts. For each test, each "case" group was compared with the "control" group, separately. The odds ratio (OR) and the 95% confidence interval (CI) were reported from each model to determine the association between the subjective environmental vulnerability index and each type of cause-specific mortality. Based on each regression, the OR was used to evaluate the difference between two mortality groups in a 10-units increment in the subjective environmental vulnerability index.

Results

Data Summary

In general, the online cohort had a balanced sample size and included subjects with a dynamic demographic profile. Of the subjects, 40.8% were male and 59.2% were females; and 46.7% were younger than 30 years old while 53.3% were aged 30 or above. In addition, 51.7% had lower income (monthly income <= HKD$20,000), and 48.3% had higher income. Noted that the cutoff of HKD$20,000 is approximately to USD$2,000. A total of 68.3% declared themselves as urban residents, while 31.7% of them declared as sub-rural or rural residents. There were also 25.0% who declared themselves as outdoor workers or manual labors and 75.0% as indoor workers.

Based on the raw score (1 to 5) retrieved from the online cohort (Table 1), traffic-related air pollution was the factor that most of the subjects generally weighted the highest. The average score for the question of "do you think traffic-related air pollution is a serious environmental problem?" was 4.13 out of 5, with a standard deviation of 0.89. It was followed by the influence of high building density. For the question of "do you think high city/building density is a serious environmental problem", the average score was 4.11 with a standard deviation of 1.00. In contrast, subjects from the online cohort generally weighed vegetation amount and availability of open space lower than other factors. The average score for the question “do you think lack of open space or park is a serious environmental problem” was 3.53 out of 5, with a standard deviation of 1.00, and the average score for “do you think lack of vegetation or greenspace is a serious environmental problem” was 3.68 out of 5 with a standard deviation of 1.03. Since standard deviations of scores retrieved from all factors were generally large, this suggested that simply using the average of raw scores to determine the importance of each factor may not be appropriate.

To evaluate the use of the subjective environmental vulnerability index for neighborhood-level health estimation, 259,514 decedents between 2007 and 2014 from the mortality dataset were examined in this study. Of these, there were 60,004 decedents from cardiovascular mortality, 63,357 decedents from respiratory mortality, 5,521 decedents from mortality associated with mental and behavioral disorders, 2,252 decedents from mortality associated with diseases of nervous systems, 15,404 decedents from mortality associated with diseases of the genitourinary system, 11,161 decedents from mortality associated with diseases of the digestive system, and 98,247 decedents from cancer-related mortality. There were also 3,568 accidental decedents used as controls in the case-series analyses.

Subjective Environmental Vulnerability Index

Based on the first factor loadings after varimax rotation, anthropogenic heat, regional air pollution and summer heat were the most severe factors that first engaged the environmental concerns of the local population (Table 2). Higher building density and traffic-related air pollution were also associated with the first insights of environmental vulnerability in the local population, while lack of vegetation and open space appeared not to initially increase the environmental concerns among the population.

However, although lack of vegetation and open space may not be the first environmental risk factor to raise public concern, these were identified as hidden factors that reinforce peoples' sense of environmental vulnerability after initial alert from the first factor, when we considered the second factor loadings of varimax rotation (Figure 1). This indicated that these hidden factors should not be omitted in determining the subjective environmental vulnerability, as they are factors act synergistically with the first factors to induce adverse environmental cognitions in the local population. Other than lack of vegetation and open space, higher building density is also a potential second factor that can influence the subjective environmental vulnerability among local population. In contrast, light pollution did not threaten the local population, as both the first and second factor loadings of light pollution were low. Based on the sum of the first and second factor loadings, the subjective environmental vulnerability index was constructed as follows:

$$Vulnerability = 0.646 \times Traffic + 0.840 \times Regional + 0.432 \times Light + 0.919 \times LowVeg + 0.979 \times BuildingDensity + 0.836 \times SummerHeat + 1.018 \times LowOpenSpace + 0.907 \times AnthroHeat$$

where *Vulnerability* is the final score of the subjective environmental vulnerability index; *Traffic* is the normalized traffic-related air pollution scored from 0 to 100; *Regional* is the normalized regional air pollution scored from 0 to 100; *Light* is the normalized light pollution scored from 0 to 100; *LowVeg* is the inversed percentage of vegetation coverage scored from 0 to 100; *BuildingDensity* is the inversed percentage of sky view scored from 0 to 100; *SummerHeat* is the normalized values of summer air temperature scored from 0 to 100; *LowOpenSpace* is the inversed percentage of open space scored from 0 to 100; and *AnthroHeat* is the normalized values of anthropogenic heat scored from 0 to 100.

Comparing all versions of subjective environmental vulnerability maps, the range of index values from the map generated by the 250 m spatial buffer was the greatest (Figure 2), with the highest maximum value and the lowest minimum value. The index range fell when the radius of the spatial buffer increased. However, although ranges of all the maps were different, the spatial variabilities of subjective environmental vulnerability from all versions of maps were similar.

In general, subjective environmental vulnerability is generally higher across the urban areas. Suburban areas (e.g. Tsuen Wan) and "New Towns" in Hong Kong (e.g. Tseung Kwan O, Tin Shui Wai) also obtained relatively high subjective environmental vulnerability, while the vulnerability decreases when moving outward from the town center into suburban areas. There is also a considerable urban-rural difference in subjective environmental vulnerability across Hong Kong, in which there is a sharp decrease to low vulnerability at the boundary of the rural areas.

Validation with case-series analysis

Our results indicate that the subjective environmental vulnerability index is useful to determine neighborhood risk from four of the seven causes of mortality (Figures 3 – 6).

The most significant cause-specific mortality that can be estimated based on subjective environmental vulnerability index is the mortality associated with mental and behavioral disorders. Compared with accidental deaths, the decedents with mental and behavioral disorders generally resided in neighborhoods with higher subjective environmental vulnerability. The results are consistent with four versions of the subjective environmental vulnerability index. In 10-units increase of subjective environmental vulnerability index, OR from the average of the 250 m map is 1.022 [1.011, 1.032], OR from the average of the 500 m map is 1.022 [1.011, 1.033], OR from the average of the 750 m map is 1.022 [1.011, 1.034], and OR from the average of the 1000 m map is 1.022 [1.011, 1.034], while controlling for gender, age, short-term weather, short-term air pollution, weekday/weekend and seasonal effects.

The second significant cause-specific mortality is cardiovascular mortality, and followed by respiratory mortality as third. In 10-units increase of subjective environmental vulnerability index, OR for the comparison between cardiovascular mortality and accidental deaths from the average of the 250 m map is 1.011 [1.004, 1.019], controlling for gender, age, short-term weather, short-term air pollution, weekday/weekend and seasonal effects. In addition, OR from the average of the 500 m map is 1.012 [1.005, 1.020], OR from the average of the 750 m map is 1.013 [1.005, 1.020], and OR from the average of the 1000 m map is 1.013 [1.006, 1.021].

Based on the comparison between respiratory mortality and accidental deaths, in 10-units increase of subjective environmental vulnerability index, the ORs from average of 250 m, 500 m, 750 m and 1000 m maps are 1.010 [1.002, 1.017], 1.010 [1.002, 1.018], 1.010 [1.002, 1.018], and 1.010 [1.002, 1.018], respectively.

In addition, we found a low but significant result showing that deaths from diseases of the digestive system are 0.9% to 1.0% more likely to reside in a neighborhood with higher subjective environmental vulnerability, when compared with accidental deaths. Based on the case-series analysis, we did not find any significant spatial difference between the following decedents and accidental deaths: cancer deaths, deaths from mortality associated with nervous diseases, and deaths from mortality associated with genitourinary diseases.

Discussion

This study demonstrated on the environmental quality mapping technique using several urban environmental factors to locate areas with higher or lower subjective environmental vulnerability. The new subjective environmental vulnerability index was spatially integrated with mortality data to evaluate its potential use in community health risk estimation. The results indicated that the subjective environmental vulnerability index developed with spatial data was appropriate to locate areas with higher non-accidental mortality, specifically, mortality associated with mental and behavioral disorders, cardiovascular mortality, respiratory mortality, and mortality associated with diseases of the digestive system.

These results suggest that subjective environmental vulnerability maps are suitable for estimation of community health risk at the small-district-level (e.g. TPUs in this study). Considering the scaling effects that can be caused by the MAUP, the demonstrated robustness of case-series analyses from four versions of maps have demonstrated that even applying datasets derived from different spatial buffers can be useful for the estimation of community health risk. This further indicates that the small district is an appropriate neighborhood-level for community planning and health monitoring, as the characteristics of the built environment are fully represented at such a small district level.

In addition, our results indicate that subjective environmental vulnerability does not influence all types of diseases, but has the highest association with mental impairment, and secondarily with cardiorespiratory and digestive diseases. These results imply that subjective environmental vulnerability is very likely to influence mental health issues, or to affect chronic diseases indirectly controlled by the mental status of a person. Specifically, cardiovascular and respiratory diseases are likely related to physical activities and walkability, while previous studies have demonstrated that environmental conditions can influence attitudes and practices of physical activities and walkability of a person (Handy et al., 2002). Therefore, a person with long-term expose to an environment causing negative cognitions can accumulate a significant adverse effect on their cardiorespiratory health. There is also literature indicating the effects of low environmental quality on the diet and metabolism of a person (Ghosh et al., 2018; Yang et al., 2017), in which adverse environmental cognition may increase such negative effects on local population, resulting in increased prevalence of digestive diseases. It is notable that approximately 99.0% of decedents with mental and behavioral disorders in this analytic dataset were people who died from dementia. This result implies environmental conditions can directly influence people with dementia through cognitive functions, and can directly influence this population through the interaction between adverse environmental cognitions, depression, frailty, physical activities, walkability, and other chronic diseases. Indeed, recent literature has indicated that air pollution and environmental changes can be factors contributing to dementia (Cioffi et al., 2007; Chen et al., 2017).

Based on our study, the following protocols are suggested to reduce adverse effects on community health through using the subjective environmental vulnerability index: 1) locating neighborhoods with higher subjective environmental vulnerability with the use of our index; 2) establishment of more community support for the local population, especially for people with chronic diseases associated with subjective environmental vulnerability, for the improvement of their quality of life and health status; 3) to deliver health education to vulnerable people, in order to improve their health status through enhancing their knowledge, attitude and practice for mitigating environmental risk and 4) to improve the environmental quality of high-risk neighborhoods through community planning (e.g. urban greenery) and environmental monitoring (e.g. local warning system and air quality monitoring stations). These actions should be undertaken immediately, and evaluated every three to five years, in order to maintain the effectiveness of healthcare and risk mitigation.

Although there are advantages of using neighborhood-level subjective environmental vulnerability index as a tool to estimate community health risk, some limitations of our study should be noted. First, environmental cognition is highly influenced by local experience and cultures, thus the results of this study may not be able to represent other cities. Therefore, our study was focused on the effectiveness of measuring subjective environmental vulnerability as a tool for community health assessment, instead of defining our results from mortality analyses as global guidelines for community planning. Second, spatial datasets from this study were synoptic datasets. These synoptic datasets hypothesized environmental vulnerability as a typical scenario, but subjective environmental vulnerability may be a spatiotemporal component in reality. Time-series of data may enhance the data modelling, but can also create a large statistical bias from ecological fallacy, since the mobility of a person within a day cannot be included in a traditional time-series dataset. In order to solve this problem, a future study using mobile apps for health reporting is suggested here. This method can enhance the measurement of subjective environment vulnerability, since the location-based service can help to identify the actual location and time that influence the environmental cognition of a person. However, human ethics is the greatest obstacle of such application. Based on the level of ethical approval that we could obtain, the approach of using synoptic dataset as typical scenario is still appropriate.

Conclusions

A mixed-method approach was applied to develop a subjective environmental vulnerability index. This index was used to map the neighborhood-based environmental vulnerability based on the adverse environmental cognition of a local population, and was evaluated with mortality data. The results indicate that this subjective environmental vulnerability index is significantly associated with the mortality disparity of the local population, and can be used for health planning and community risk management.

Acknowledgement

This research was supported in part by a grant from the General Research Fund (Project ID: 15205515); a grant from the Hong Kong Polytechnic University (Grant PolyU 1-ZE24); and a grant PolyU 1-BBWD from the Research Institute for Sustainable Urban Development, the Hong Kong Polytechnic University. We also thank the support from the Hong Kong Census and Statistics Department, the Hong Kong Environmental Protection Department, and the Planning Department of Hong Kong for the mortality, air pollution, and land use and land cover data.

References

Beyer, K. M., Kaltenbach, A., Szabo, A., Bogar, S., Nieto, F. J., & Malecki, K. M. (2014). Exposure to neighborhood green space and mental health: evidence from the survey of the health of Wisconsin. International journal of environmental research and public health, 11(3), 3453-3472.

Bilal, M., Nichol, J. E., & Spak, S. N. (2017). A new approach for estimation of fine particulate concentrations using satellite aerosol optical depth and binning of meteorological variables. Aerosol and Air Quality Research, 17(2), 356-367.

Cebrecos, A., Domínguez-Berjón, M. F., Duque, I., Franco, M., & Escobar, F. (2018). Geographic and statistic stability of deprivation aggregated measures at different spatial units in health research. Applied Geography, 95, 9-18.

Chen, H., Kwong, J. C., Copes, R., Hystad, P., van Donkelaar, A., Tu, K., ... & Wilton, A. S. (2017). Exposure to ambient air pollution and the incidence of dementia: a population-based cohort study. Environment international, 108, 271-277.

Chepesiuk, R. (2009). Missing the dark: health effects of light pollution. Environmental Health Perspectives, 117(1), A20.

Cioffi, J. M., Fleming, A., Wilkes, L., Sinfield, M., & Le Miere, J. (2007). The effect of environmental change on residents with dementia: The perceptions of relatives and staff. Dementia, 6(2), 215-231.

Faisal, K., & Shaker, A. (2017). An Investigation of GIS Overlay and PCA Techniques for Urban Environmental Quality Assessment: A Case Study in Toronto, Ontario, Canada. Sustainability, 9(3), 380.

Ghosh, R., Gauderman, W. J., Minor, H., Youn, H. A., Lurmann, F., Cromar, K. R., ... & McConnell, R.

(2018). Air pollution, weight loss and metabolic benefits of bariatric surgery: a potential model for study of metabolic effects of environmental exposures. Pediatric obesity, 13(5), 312-320.

Handy, S. L., Boarnet, M. G., Ewing, R., & Killingsworth, R. E. (2002). How the built environment affects physical activity. American journal of preventive medicine, 23(2), 64-73.

Ho, H. C., Knudby, A., & Huang, W. (2015). A spatial framework to map heat health risks at multiple scales. International journal of environmental research and public health, 12(12), 16110-16123.

Ho, H. C., Knudby, A., Walker, B. B., & Henderson, S. B. (2017). Delineation of spatial variability in the temperature–mortality relationship on extremely hot days in greater Vancouver, Canada. Environmental health perspectives, 125(1), 66.

Ho, H. C., Wong, M. S., Yang, L., Chan, T. C., & Bilal, M. (2018a). Influences of socioeconomic vulnerability and intra-urban air pollution exposure on short-term mortality during extreme dust events. Environmental Pollution, 235, 155-162.

Ho, H. C., Wong, M. S., Yang, L., Shi, W., Yang, J., Bilal, M., & Chan, T. C. (2018b). Spatiotemporal influence of temperature, air quality, and urban environment on cause-specific mortality during hazy days. Environment international, 112, 10-22.

Hodul, M., Knudby, A., & Ho, H. C. (2016). Estimation of continuous urban sky view factor from landsat data using shadow detection. Remote Sensing, 8(7), 568.

Hondula, D. M., Davis, R. E., Leisten, M. J., Saha, M. V., Veazey, L. M., & Wegner, C. R. (2012). Fine-scale spatial variability of heat-related mortality in Philadelphia County, USA, from 1983-2008: a case-series analysis. Environmental health, 11(1), 16.

Krstic, N., Yuchi, W., Ho, H. C., Walker, B. B., Knudby, A. J., & Henderson, S. B. (2017). The Heat Exposure Integrated Deprivation Index (HEIDI): A data-driven approach to quantifying neighborhood risk during extreme hot weather. Environment international, 109, 42-52.

Lee, M., Brauer, M., Wong, P., Tang, R., Tsui, T. H., Choi, C., ... & Allen, R. (2017). Land use regression modelling of air pollution in high density high rise cities: A case study in Hong Kong. Science of The Total Environment, 592, 306-315.

Marques, R. C., da Cruz, N. F., & Pires, J. (2015). Measuring the sustainability of urban water services. Environmental Science & Policy, 54, 142-151.

Molinos-Senante, M., Marques, R. C., Pérez, F., Gómez, T., Sala-Garrido, R., & Caballero, R. (2016). Assessing the sustainability of water companies: A synthetic indicator approach. Ecological indicators, 61, 577-587.

Nichol, J., & Wong, M. S. (2009). Mapping urban environmental quality using satellite data and multiple parameters. Environment and Planning B: Planning and Design, 36(1), 170-185.

Rugel, E. J., Henderson, S. B., Carpiano, R. M., & Brauer, M. (2017). beyond the Normalized Difference Vegetation Index (ndvi): Developing a Natural Space Index for population-level health research. Environmental research, 159, 474-483.

Saelens, B. E., Sallis, J. F., Black, J. B., & Chen, D. (2003). Neighborhood-based differences in physical activity: an environment scale evaluation. American journal of public health, 93(9), 1552-1558.

Shi, Y., Ho, H. C., Xu, Y., & Ng, E. (2018). Improving satellite aerosol optical Depth-PM2. 5 correlations using land use regression with microscale geographic predictors in a high-density urban context. Atmospheric Environment, 190, 23-34.

Shi, Y., Katzschner, L., & Ng, E. (2018b). Modelling the fine-scale spatiotemporal pattern of urban heat island effect using land use regression approach in a megacity. Science of the Total Environment, 618, 891-904.

Wheeler, B. W., Lovell, R., Higgins, S. L., White, M. P., Alcock, I., Osborne, N. J., ... & Depledge, M. H. (2015). Beyond greenspace: an ecological study of population general health and indicators of natural environment type and quality. International journal of health geographics, 14(1), 17.

Wong, S. Y., Mercer, S. W., Woo, J., & Leung, J. (2008). The influence of multi-morbidity and self-reported socio-economic standing on the prevalence of depression in an elderly Hong Kong population. BMC Public Health, 8(1), 119.

Wong, M. S., Ho, H. C., Yang, L., Shi, W., Yang, J., & Chan, T. C. (2017). Spatial variability of excess mortality during prolonged dust events in a high-density city: a time-stratified spatial regression approach. International journal of health geographics, 16(1), 26.

Woo, J., Yu, R., Leung, J., Wong, M., Lau, K., Ho, H. C., ... & WL, D. (2017). Urban Characteristics Influencing Health of Older People: What Matters. International Journal of Innovative Research in Medical science, 12(2), 1561-1568.

Yang, B. Y., Qian, Z. M., Li, S., Fan, S., Chen, G., Syberg, K. M., ... & Yang, M. (2018). Long-term exposure to ambient air pollution (including PM1) and metabolic syndrome: The 33 Communities Chinese Health Study (33CCHS). Environmental research, 164, 204-211.

Captions of Figures

Figure 1 – Factor loadings based on varimax rotation from factor analysis

Figure 2 – Environmental vulnerability across Hong Kong mapped based on subjective environmental status of all subjects from the online cohort

Figure 3 - Odds ratio (OR) and the 95% confidence interval (CI) reported from the results of 250-m map to determine the association between the subjective environmental vulnerability index and each type of cause-specific mortality. Based on each regression, the OR was used to evaluate the difference between a cause-specific mortality and accidental mortality in a 10-units increment in the subjective environmental vulnerability index.

Figure 4 - Odds ratio (OR) and the 95% confidence interval (CI) reported from the results of 500-m map to determine the association between the subjective environmental vulnerability index and each type of cause-specific mortality. Based on each regression, the OR was used to evaluate the difference between a cause-specific mortality and accidental mortality in a 10-units increment in the subjective environmental vulnerability index.

Figure 5 - Odds ratio (OR) and the 95% confidence interval (CI) reported from the results of 750-m map to determine the association between the subjective environmental vulnerability index and each type of cause-specific mortality. Based on each regression, the OR was used to evaluate

the difference between a cause-specific mortality and accidental mortality in a 10-units increment in the subjective environmental vulnerability index.

Figure 6 - Odds ratio (OR) and the 95% confidence interval (CI) reported from the results of 1000-m map to determine the association between the subjective environmental vulnerability index and each type of cause-specific mortality. Based on each regression, the OR was used to evaluate the difference between a cause-specific mortality and accidental mortality in a 10-units increment in the subjective environmental vulnerability index.

Table 1 – Average score and standard deviation of each question ranked by all subjects of the online cohort

Questions	**Mean**	**SD**
do you think traffic-related air pollution is a serious environmental problem?	**4.13**	**0.89**
do you think regional-influenced air pollution is a serious environmental problem?	**3.81**	**1.03**
do you think whether light pollution is a serious environmental problem?	**3.70**	**1.06**
do you think lack of vegetation or greenspace is a serious environmental problem?	**3.68**	**1.03**
do you think high city/building density is a serious environmental problem?	**4.11**	**1.00**
do you think summer heat is a serious environmental problem?	**3.73**	**1.20**
do you think lack of open space or park is a serious environmental problem?	**3.53**	**1.00**
do you think anthropogenic heat is a serious environmental problem?	**3.84**	**1.02**

Table 2 - Factor loadings after varimax rotation based on factor analysis

Questions	**D1**	**D2**
do you think traffic-related air pollution is a serious environmental problem?	**0.412**	**0.234**
do you think regional-influenced air pollution is a serious environmental problem?	**0.635**	**0.205**
do you think light pollution is a serious environmental problem?	**0.393**	**0.039**
do you think lack of vegetation or greenspace is a serious environmental problem?	**0.080**	**0.839**
do you think high city/building density is a serious environmental problem?	**0.462**	**0.517**
do you think summer heat is a serious environmental problem?	**0.594**	**0.242**
do you think lack of open space or park is a serious environmental problem?	**0.259**	**0.759**
do you think anthropogenic heat is a serious environmental problem?	**0.650**	**0.257**