

1 Title: Neighborhood-based subjective environmental vulnerability index for community health

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4 assessment: development, validation and evaluation

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10 Authors: Hung Chak Ho^{1,2}, Man Sing Wong^{2,3}, Ho Yin Man², Yuan Shi⁴, Sawaid Abbas²

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16 Affiliations:

- 17
18
19
20 1. Department of Urban Planning and Design, The University of Hong Kong, Hong Kong
- 21
22
23 2. Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University,
- 24
25
26 Hung Hom, Hong Kong
- 27
28
29 3. Research Institute for Sustainable Urban Development, The Hong Kong Polytechnic
- 30
31
32 University, Hung Hom, Hong Kong
- 33
34
35
36 4. School of Architecture, The Chinese University of Hong Kong, Sha Tin, Hong Kong

37
38
39
40
41
42 Corresponding Authors:

- 43
44
45 1. Man Sing Wong, Department of Land Surveying and Geo-Informatics, The Hong Kong
- 46
47
48 Polytechnic University, Hung Hom, Hong Kong, email: lswong@polyu.edu.hk
- 49
50
51
52 2. Hung Chak Ho, Department of Urban Planning and Design, The University of Hong
- 53
54
55 Kong, Hong Kong, email: hcho21@hku.hk
- 56
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Replies to Reviewer 1:

Comment 1: The paper is a good contribution to the literature and relevant conclusions are achieved. The authors applied mixed-methods to estimate neighbourhood-based environment vulnerability. The paper has potential, however some comments must be taken into account before being considered for publication:

Reply: We would like to thank the reviewer for his/her hard work and scrutiny of our manuscript.

Comment 2: The title can be improved, but I will leave it to the authors

Reply: Thank you for the comment. The title is now changed to "Neighborhood-based subjective environmental vulnerability index for community health assessment: development, validation, and evaluation."

Comment 3: The keywords should also be improved, including, for example, replace the word "objective environmental measures";

Reply: We have replaced the word of "objective environmental measures" to ""environmental measures" based on the suggestion of reviewer.

Comment 4: Introduction can be improved, for example including a paragraph presenting the organization of the paper

Reply: Thank you for the comment. The organization of this paper is now added and highlighted in the Lines 87 – 94 of the revised manuscript.

Comment 5:

In the introduction, the authors could emphasise the importance of sustainability (see Marques et al, 2015);

Reply: Thanks for the comment. We have emphasized the importance of sustainability and added the reference suggested by the reviewer in Lines 95 - 97.

Comment 6: The novelty and contributions of the paper must be highlighted in the text;

Reply: The contribution of this paper is now highlight in Lines 94 - 97 in the section of introduction.

Comment 7: A paragraph presenting the organization of the paper can be added in the end of the introduction

Reply: Thank you for the comment. The organization of this paper is now added and highlighted in the Lines 87 – 94 of the revised manuscript.

Comment 8: All abbreviations must be presented in the text;

Reply: Details of all abbreviations has now been presented and highlighted in the manuscript (e.g. Line 126, Line 127, Line 131, Line 132, Line 141).

Comment 9: Explain better the potential and limitations of using indexes (see Molinos-Senante et al., 2016);

Reply: Thank you for the suggestions. We have added more information regarding potential and limitations of using indexes in Lines 403 - 419. The reference suggested by the reviewer is also added in Line 97.

Comment 10: All sources of information have to be detailed in the text

Reply: We have edited all references based on the comment of reviewer 1 and the manuscript guideline of the “Science of the total Environment”.

Comment 11: Justify the methodology adopted and explain the contents of the variables used; Try to explain better the contents of the variables taken into account;

Reply: Thanks for the suggestion. The epidemiological design is based on statistical analyses for similar previous studies. We have added the information with reference in Lines 201 - 205.

Comment 12: Include the units of the variables;

Reply: Thank you for the comments. Most variables of the case-series analysis are binary variables and therefore they are “unitless”.

Comment 13: Add the conversion of the monetary values to US\$ and the date;

Reply: Based on the comment of reviewer 1, we have added the approximate values in U.S. dollars in Lines 256 - 257.

Comment 14: Include a statistical analysis to the results;

Reply: Thank you for the comment. A statistical analysis with mortality data is now included in the results (Lines 327 - 353)

Comment 15: After the discussion the authors should include a chapter for the "Conclusions"

Reply: A section of conclusion is added in Lines 421 - 426 based on the comment of reviewer 1.

Comment 16: More recommendations for decision-makers were expected in the conclusions;

Reply: Thank you for the comments. More recommendations for decision-maker are now added in Lines 391 - 402.

Comment 17: The references must be improved and homogenized and in line with author guidelines. For example, some issues are missing.

References:

MARQUES, R.; DA CRUZ, N.; PIRES, J. (2015). Measuring the sustainability of urban water services. Environmental Science & Policy. Vol. 54, pp. 142-151.

MOLINOS - SENANTE, M.; MARQUES, R.; PÉREZ, F; GÓMEZ, T.; SALA-GARRIDO, R.; CABALLERO, R. (2016). Assessing the sustainability of water companies: A synthetic indicator approach. Ecological Indicators. Vol. 61, Part 2, pp. 577-587.

Reply: We have added the references suggested by the reviewer 1 (Line 97), and have changed the reference styles based on the guidelines of the Science of the Total Environment.

Replies to Reviewer 2

Comment 1: The study developed and validated a methodology for measuring environmental vulnerability using both quantitative and qualitative data. Lines 116-119: Please add a reference substantiating the statement that using land use regression is "a technique commonly used for air pollution mapping in public health studies."

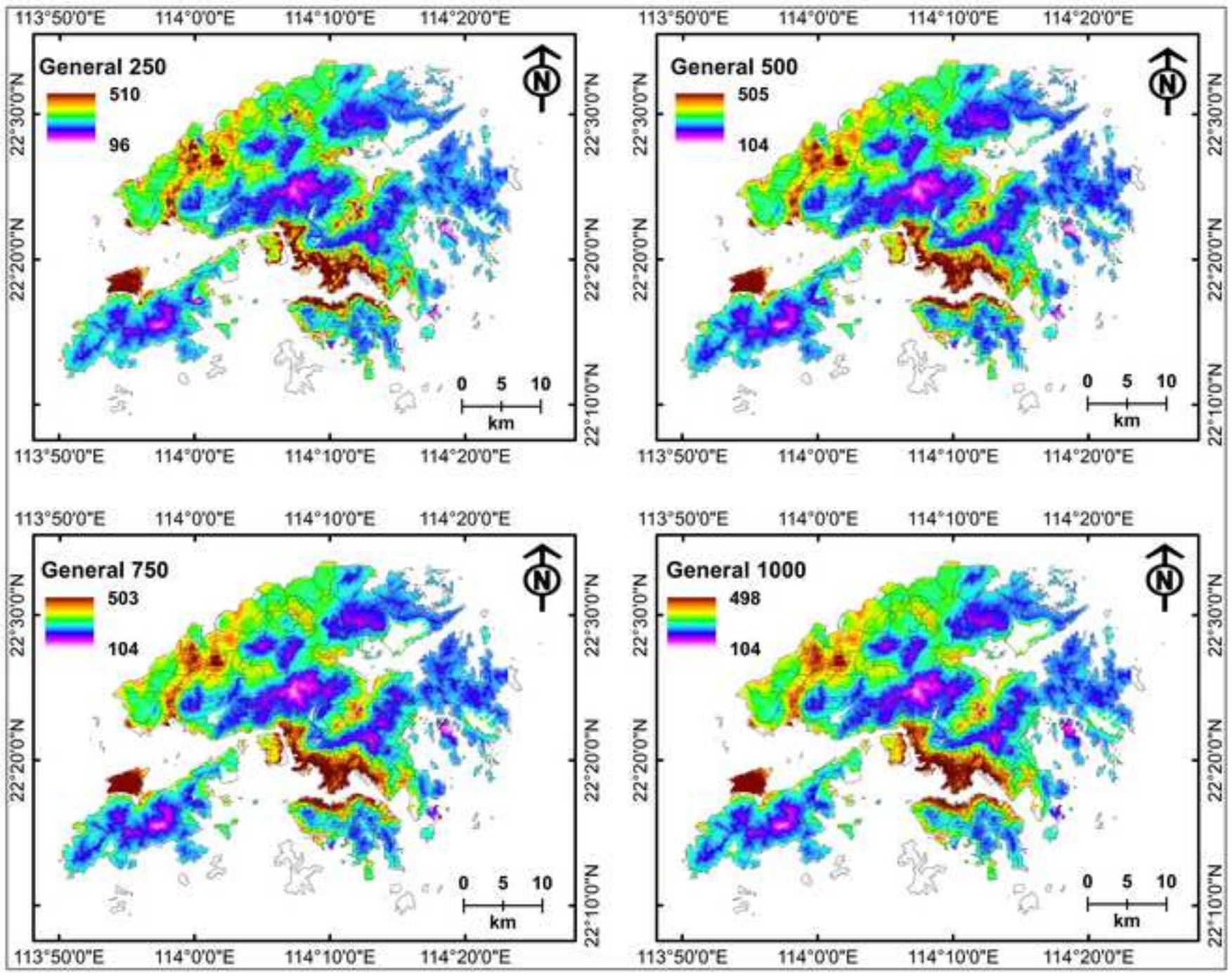
Reply: We have added the references for the statement above and is now stated in Line 124.

Comment 2: Please reference the Tables and Figures in the Results section. It is currently difficult to cross reference the results as laid out in the text with the results in the tables and figures at the end of the paper.

Reply: Thanks for the suggestion. We have checked and added all in-text references for tables and figures in the result's section, and all in-text references are now highlighted in yellow. (e.g. Line 260, Line 286)

Comment 3: Add titles to the Tables and Figures.

Reply: Thanks for you the comments. Titles of tables and figures have been added to the captions according to the suggestion of reviewer 2.



***Highlights (for review : 3 to 5 bullet points (maximum 85 characters including spaces per bullet point)**

- Combined subjective and objective environmental measures for vulnerability index
- Evaluated subjective environmental vulnerability index with mortality data
- Vulnerability Index was highly associated with mental related mortality
- Cardiorespiratory and digestive deaths were associated with vulnerability index

1 **Abstract**

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

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

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

22

23 **Keywords:** environmental vulnerability; environmental measures; environmental cognition;

24 community health; spatial analytics; deprivation index

25

26 **Introduction**

27 Neighborhood-based environmental impact is a major factor that can influence community
28 health risk across a city. Previous studies have demonstrated significant impacts from intra-urban
29 air pollution on morbidity and mortality (Ho et al., 2018a); as well as the influence of spatial
30 variations in extreme heat on short-term health risk (Beyer et al., 2014; Ho et al., 2017; Krstic et
31 al., 2017). In addition, the lack of greenspace and higher urban density are the community factors
32 that can modify the health risk of vulnerable populations (Wheeler et al., 2015; Wong et al.,
33 2017).

34 In order to evaluate environmental impacts on local health, previous studies have commonly
35 applied a cross-sectional analysis or a case-series analysis along with objective environmental
36 data to estimate potential environmental influences on health risk (Hondula, et al., 2012; Woo et
37 al., 2017). The objective environmental data are mainly derived from spatial buffers of the
38 environmental dataset, without linkage to, or inclusion of human perception associated with the
39 environmental experiences. There are also several environmental vulnerability indices derived
40 based on objective environmental data for health risk estimation and prevention (Rugel et al.,
41 2017). These studies aim to develop a more comprehensive framework for identifying
42 neighborhoods with potentially higher health risk, as protocols for community planning.

43 The aforementioned studies have advocated the use of objective environmental data for
44 public health analyses. However, recent studies have indicated that subjective feelings about a
45 community by a person can play an important role in influencing his/her health status. For
46 example, subjective social scores can identify the neighborhood vulnerability (Wong et al., 2008),
47 and such scores have been found to have significant relationships to actual health risk. In

48 addition, several subjective neighborhood scores have been defined for measuring deprivation of
49 a built environment (Saelens et al., 2003), and some studies have found that these subjective
50 scores were useful in long-term health prediction.

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

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

66 Here we applied a systematic approach to analyze subjective environmental vulnerability
67 among urban population, and evaluated the potential use of a subjective environmental
68 vulnerability index for community health planning. The specific objectives of this study include to
69 1) collect information on subjective environmental vulnerability among an urban population

70 based on an online cohort; 2) evaluate the weight and importance of each subjective
71 environmental vulnerability item with factor analysis; 3) develop a subjective environmental
72 vulnerability index based on the results of factor analysis; 4) map the intra-urban subjective
73 environmental vulnerability based on the developed index; and 5) evaluate the potential use of
74 this spatial index for analyzing long-term health impacts, with using a case-series analysis to
75 estimate associations between the index and cause-specific mortality. The results of this study
76 can be used to improve public health surveillance by locating high-risk areas for community
77 planning. The identification of high-risk areas can also be useful to improve the environmental
78 dimension of sustainability (Marques et al. 2015; Molinos-Senante et al., 2016).

79

80 **Data and Methods**

81 *Online Cohort Data*

82 An online cohort with 120 subjects from Hong Kong was examined in this study. This cohort
83 was approved by the Human Subjects Ethics Sub-committee of The Hong Kong Polytechnic
84 University (Reference Number: HSEARS20180124002). All data of this cohort were collected
85 between Feb 14, 2018 and Mar 13, 2018, including the demographic information about each
86 subject, and an 8-item survey for rating the subjective environmental statuses that can influence
87 environmental vulnerability. The followings are specific questions of the 8-item survey: 1) “do you
88 think traffic-related air pollution is a serious environmental problem?”, 2) “do you think
89 regional-based air pollution is a serious environmental problem?”, 3) “do you think light pollution
90 is a serious environmental problem?”, 4) “do you think lack of vegetation or greenspace is a
91 serious environmental problem?”, 5) “do you think high city/building density is a serious

92 environmental problem?”, 6) “do you think summer heat is a serious environmental problem?”, 7)
93 “do you think lack of open space or parks is a serious environmental problem?”, and 8) “do you
94 think anthropogenic heat is a serious environmental problem?”. Each subject ranked the
95 questions in five-scales, in which “1” indicates the “least serious” and “5” indicates the “most
96 serious”. The selection of these eight items was based on a literature search, given that all items
97 were associated with adverse health effects (Chepesiuk et al., 2009).

98

99 *Spatial Data*

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

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

106 To demonstrate the regional air pollution within the city, a map of fine particulate matter
107 (PM_{2.5}) map at 500 m resolution, derived from 142 cloud-free Moderate Resolution Imaging
108 Spectroradiometer (MODIS) Aerosol Optical Depth (AOD) datasets between 2007 and 2009, was
109 used (Ho et al., 2018b). This PM_{2.5} map was estimated based on the algorithm from Bilal et al.
110 (2017), which was proven to be promising for local use over Hong Kong (R = 0.78).

111 Light pollution was demonstrated based on a radiance dataset retrieved from a 2015
112 nighttime Visible Infrared Imaging Radiometer Suite (VIIRS) with 750 m resolution. VIIRS image
113 was acquired from the National Oceanic and Atmospheric Administration (NOAA) and can

114 represent the typical nighttime light scenario across Hong Kong. The light pollution map and the
115 regional air pollution map were masked by the land boundary and non-water areas of Hong Kong
116 for further modelling.

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

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

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

133

134 *Data for Community Health Applications*

135 In order to examine the relationship between subjective environmental vulnerability and

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

143 In order to minimize any potential bias in the modelling, daily information on temperature and
144 air pollution were retrieved and used in this study. Hourly temperature data were obtained from
145 the weather station located at headquarters of the Hong Kong Observatory and were averaged to
146 a daily basis. Air pollution data used in this study are as follows: particulate matters (PM₁₀),
147 nitrogen oxides (NO_x), ground-level ozone (O₃), and sulfur dioxide (SO₂). These air pollution data
148 were the average of daily air quality information from seven air monitoring stations (Central
149 Western, Sham Shui Po, Sha Tin, Tai Po, Tsuen Wan, Kwai Chung, and Tap Mun) operated by the
150 Hong Kong Environmental Protection Department. These stations covered both urban and rural
151 areas of Hong Kong.

152

153 *Development of Subjective Environmental Vulnerability Index*

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

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

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

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

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

180 boundary of Hong Kong.

181

182 *Case-Series Analysis*

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

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

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

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

203

$$\begin{aligned} \text{Case } (1,0) \sim & \beta_0 + \beta_1(\text{Vulnerability}) + \beta_2\text{Unemployed } (1,0) + \beta_4(\text{Age}) \\ & + \beta_5(\text{Gender } (1,0)) + \beta_6(\text{Hot Day } (1,0)) + \beta_7(\text{Cold Day } (1,0)) \\ & + \beta_8(\text{High PM}_{10} \text{ Day } (1,0)) + \beta_9(\text{High NO}_x \text{ Day } (1,0)) \\ & + \beta_{10}(\text{High O}_3 \text{ day } (1,0)) + \beta_{11}(\text{High SO}_2 \text{ day } (1,0)) + \beta_{12}(\text{DOW}) \\ & + \beta_{13}(\text{Month}) \end{aligned}$$

204

205 where *Case (1,0)* is a binary variable indicating whether the decedents were died from a
206 corresponding specific cause-of-death; *Vulnerability* is the average value of the subjective
207 environmental vulnerability index of each TPU; *Age* is a continuing variable indicating the age of
208 death; *Gender (1,0)* is a binary variable indicating gender of a decedent, with male as “1” and
209 female as “0”; and *Unemployed (1,0)* is a binary variable indicating employment status, in which
210 decedents classified as “economically inactive” were “1” and others were “0”. In addition, *Hot*
211 *Day (1,0)* represents the date of death with temperature $\geq 95^{\text{th}}$ percentile between 2007 and
212 2014, while *Cold Day (1,0)* indicates that date of death with temperature $\leq 5^{\text{th}}$ percentile. *High*
213 *PM₁₀ Day (1,0)*, *High NO_x Day (1,0)*, *High O₃ Day (1,0)*, and *High SO₂ Day (1,0)* were binary
214 variables indicating the date of death with PM₁₀, NO_x, O₃, or SO₂ $\geq 95^{\text{th}}$ percentile.

215 *Age*, *Gender (1,0)*, *Unemployed (1,0)*, *Hot Day (1,0)*, *Cold Day (1,0)*, *High PM₁₀ Day (1,0)*,
216 *High NO₂ Day (1,0)* and *High O₃ Day (1,0)* were the confounders of this study, together with a
217 category variable of *DOW* indicating the day of week for controlling the weekday/weekend effect
218 and a category variable of *Month* indicating seasonal effects.

219 In this study, we repeated the test for four versions of the subjective environmental
220 vulnerability index individually, in order to evaluate whether each version of the vulnerability
221 index can be used for predicting long-term health impacts. For each test, each “case” group was
222 compared with the “control” group, separately. The odds ratio (OR) and the 95% confidence
223 interval (CI) were reported from each model to determine the association between the subjective
224 environmental vulnerability index and each type of cause-specific mortality. Based on each
225 regression, the OR was used to evaluate the difference between two mortality groups in a
226 10-units increment in the subjective environmental vulnerability index.

227

228 **Results**

229 *Data Summary*

230 In general, the online cohort had a balanced sample size and included subjects with a
231 dynamic demographic profile. Of the subjects, 40.8% were male and 59.2% were females; and
232 46.7% were younger than 30 years old while 53.3% were aged 30 or above. In addition, 51.7%
233 had lower income (monthly income \leq HKD\$20,000), and 48.3% had higher income. Noted that
234 the cutoff of HKD\$20,000 is approximately to USD\$2,500. A total of 68.3% declared themselves
235 as urban residents, while 31.7% of them declared as sub-rural or rural residents. There were also
236 25.0% who declared themselves as outdoor workers or manual labors and 75.0% as indoor
237 workers.

238 Based on the raw score (1 to 5) retrieved from the online cohort (Table 1), traffic-related air
239 pollution was the factor that most of the subjects generally weighted the highest. The average
240 score for the question of “do you think traffic-related air pollution is a serious environmental

241 problem?” was 4.13 out of 5, with a standard deviation of 0.89. It was followed by the influence
242 of high building density. For the question of “do you think high city/building density is a serious
243 environmental problem”, the average score was 4.11 with a standard deviation of 1.00. In
244 contrast, subjects from the online cohort generally weighed vegetation amount and availability of
245 open space lower than other factors. The average score for the question “do you think lack of
246 open space or park is a serious environmental problem” was 3.53 out of 5, with a standard
247 deviation of 1.00, and the average score for “do you think lack of vegetation or greenspace is a
248 serious environmental problem” was 3.68 out of 5 with a standard deviation of 1.03. Since
249 standard deviations of scores retrieved from all factors were generally large, this suggested that
250 simply using the average of raw scores to determine the importance of each factor may not be
251 appropriate.

252 To evaluate the use of the subjective environmental vulnerability index for
253 neighborhood-level health estimation, 259,514 decedents between 2007 and 2014 from the
254 mortality dataset were examined in this study. Of these, there were 60,004 decedents from
255 cardiovascular mortality, 63,357 decedents from respiratory mortality, 5,521 decedents from
256 mortality associated with mental and behavioral disorders, 2,252 decedents from mortality
257 associated with diseases of nervous systems, 15,404 decedents from mortality associated with
258 diseases of the genitourinary system, 11,161 decedents from mortality associated with diseases
259 of the digestive system, and 98,247 decedents from cancer-related mortality. There were also
260 3,568 accidental decedents used as controls in the case-series analyses.

261

262 *Subjective Environmental Vulnerability Index*

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

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

$$\begin{aligned} Vulnerability = & 0.646 \times Traffic + 0.840 \times Regional + 0.432 \times Light + 0.919 \\ & \times LowVeg + 0.979 \times BuildingDensity + 0.836 \times SummerHeat + 1.018 \\ & \times LowOpenSpace + 0.907 \times AnthroHeat \end{aligned}$$

280 where *Vulnerability* is the final score of the subjective environmental vulnerability index;
281 *Traffic* is the normalized traffic-related air pollution scored from 0 to 100; *Regional* is the

282 normalized regional air pollution scored from 0 to 100; *Light* is the normalized light pollution
283 scored from 0 to 100; *LowVeg* is the inversed percentage of vegetation coverage scored from 0 to
284 100; *BuildingDensity* is the inversed percentage of sky view scored from 0 to 100; *SummerHeat* is
285 the normalized values of summer air temperature scored from 0 to 100; *LowOpenSpace* is the
286 inversed percentage of open space scored from 0 to 100; and *AnthroHeat* is the normalized
287 values of anthropogenic heat scored from 0 to 100.

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

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

299

300 *Validation with case-series analysis*

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

303 The most significant cause-specific mortality that can be estimated based on subjective

304 environmental vulnerability index is the mortality associated with mental and behavioral
305 disorders. Compared with accidental deaths, the decedents with mental and behavioral disorders
306 generally resided in neighborhoods with higher subjective environmental vulnerability. The
307 results are consistent with four versions of the subjective environmental vulnerability index. In
308 10-units increase of subjective environmental vulnerability index, OR from the average of the 250
309 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
310 from the average of the 750 m map is 1.022 [1.011, 1.034], and OR from the average of the 1000
311 m map is 1.022 [1.011, 1.034], while controlling for gender, age, short-term weather, short-term
312 air pollution, weekday/weekend and seasonal effects.

313 The second significant cause-specific mortality is cardiovascular mortality, and followed by
314 respiratory mortality as third. In 10-units increase of subjective environmental vulnerability index,
315 OR for the comparison between cardiovascular mortality and accidental deaths from the average
316 of the 250 m map is 1.011 [1.004, 1.019], controlling for gender, age, short-term weather,
317 short-term air pollution, weekday/weekend and seasonal effects. In addition, OR from the
318 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
319 [1.005, 1.020], and OR from the average of the 1000 m map is 1.013 [1.006, 1.021].

320 Based on the comparison between respiratory mortality and accidental deaths, in 10-units
321 increase of subjective environmental vulnerability index, the ORs from average of 250 m, 500 m,
322 750 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
323 1.010 [1.002, 1.018], respectively.

324 In addition, we found a low but significant result showing that deaths from diseases of the
325 digestive system are 0.9% to 1.0% more likely to reside in a neighborhood with higher subjective

326 environmental vulnerability, when compared with accidental deaths. Based on the case-series
327 analysis, we did not find any significant spatial difference between the following decedents and
328 accidental deaths: cancer deaths, deaths from mortality associated with nervous diseases, and
329 deaths from mortality associated with genitourinary diseases.

330

331 **Discussion**

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

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

348 In addition, our results indicate that subjective environmental vulnerability does not
349 influence all types of diseases, but has the highest association with mental impairment, and
350 secondarily with cardiorespiratory and digestive diseases. These results imply that subjective
351 environmental vulnerability is very likely to influence mental health issues, or to affect chronic
352 diseases indirectly controlled by the mental status of a person. Specifically, cardiovascular and
353 respiratory diseases are likely related to physical activities and walkability, while previous studies
354 have demonstrated that environmental conditions can influence attitudes and practices of
355 physical activities and walkability of a person (Handy et al., 2002). Therefore, a person with
356 long-term expose to an environment causing negative cognitions can accumulate a significant
357 adverse effect on their cardiorespiratory health. There is also literature indicating the effects of
358 low environmental quality on the diet and metabolism of a person (Ghosh et al., 2018; Yang et al.,
359 2017), in which adverse environmental cognition may increase such negative effects on local
360 population, resulting in increased prevalence of digestive diseases. It is notable that
361 approximately 99.0% of decedents with mental and behavioral disorders in this analytic dataset
362 were people who died from dementia. This result implies environmental conditions can directly
363 influence people with dementia through cognitive functions, and can directly influence this
364 population through the interaction between adverse environmental cognitions, depression, frailty,
365 physical activities, walkability, and other chronic diseases. Indeed, recent literature has indicated
366 that air pollution and environmental changes can be factors contributing to dementia (Cioffi et al.,
367 2007; Chen et al., 2017).

368 Based on our study, the following protocols are suggested to reduce adverse effects on
369 community health through using the subjective environmental vulnerability index: 1) locating

370 neighborhoods with higher subjective environmental vulnerability with the use of our index; 2)
371 establishment of more community support for the local population, especially for people with
372 chronic diseases associated with subjective environmental vulnerability, for the improvement of
373 their quality of life and health status; 3) to deliver health education to vulnerable people, in order
374 to improve their health status through enhancing their knowledge, attitude and practice for
375 mitigating environmental risk; and 4) to improve the environmental quality of high-risk
376 neighborhoods through community planning (e.g. urban greenery) and environmental
377 monitoring (e.g. local warning system and air quality monitoring stations). These actions should
378 be undertaken immediately, and evaluated every three to five years, in order to maintain the
379 effectiveness of healthcare and risk mitigation.

380 Although there are advantages of using neighborhood-level subjective environmental
381 vulnerability index as a tool to estimate community health risk, some limitations of our study
382 should be noted. First, environmental cognition is highly influenced by local experience and
383 cultures, thus the results of this study may not be transferrable to the other cities. Therefore, our
384 study was focused on the effectiveness of measuring subjective environmental vulnerability as a
385 tool for community health assessment, instead of defining our results from mortality analyses as
386 global/universal guidelines for community planning. Second, spatial datasets from this study
387 were synoptic datasets. These synoptic datasets hypothesized environmental vulnerability as a
388 typical scenario, but subjective environmental vulnerability may be a spatiotemporal component
389 in reality. Time-series of data may enhance the data modelling, but can also create a large
390 statistical bias from ecological fallacy, since the mobility of a person within a day cannot be
391 included in a traditional time-series dataset. In order to solve this problem, a future study using

392 mobile apps for health reporting is suggested here. This method can enhance the measurement
393 of subjective environment vulnerability, since the location-based service can help to identify the
394 actual location and time that influence the environmental cognition of an individual. However,
395 human ethics is the greatest obstacle of such application. Based on the level of ethical approval
396 that we could obtain, the approach of using synoptic dataset as typical scenario is still
397 appropriate.

398 **Conclusions**

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

405

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413

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497

498 **Captions of Figures**

499

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

501

502 **Figure 2** – Environmental vulnerability across Hong Kong mapped based on subjective

503 environmental status of all subjects from the online cohort

504

505 **Figure 3** - Odds ratio (OR) and the 95% confidence interval (CI) reported from the results of

506 250-m map to determine the association between the subjective environmental vulnerability

507 index and each type of cause-specific mortality. Based on each regression, the OR was used to

508 evaluate the difference between a cause-specific mortality and accidental mortality in a 10-units

509 increment in the subjective environmental vulnerability index.

510

511 **Figure 4** - Odds ratio (OR) and the 95% confidence interval (CI) reported from the results of

512 500-m map to determine the association between the subjective environmental vulnerability

513 index and each type of cause-specific mortality. Based on each regression, the OR was used to

514 evaluate the difference between a cause-specific mortality and accidental mortality in a 10-units

515 increment in the subjective environmental vulnerability index.

516

517 **Figure 5** - Odds ratio (OR) and the 95% confidence interval (CI) reported from the results of

518 750-m map to determine the association between the subjective environmental vulnerability

519 index and each type of cause-specific mortality. Based on each regression, the OR was used to

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

522

523 **Figure 6** - Odds ratio (OR) and the 95% confidence interval (CI) reported from the results of
524 1000-m map to determine the association between the subjective environmental vulnerability
525 index and each type of cause-specific mortality. Based on each regression, the OR was used to
526 evaluate the difference between a cause-specific mortality and accidental mortality in a 10-units
527 increment in the subjective environmental vulnerability index.

528

529

530

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

533

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

534

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

536

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

537

Figure 1

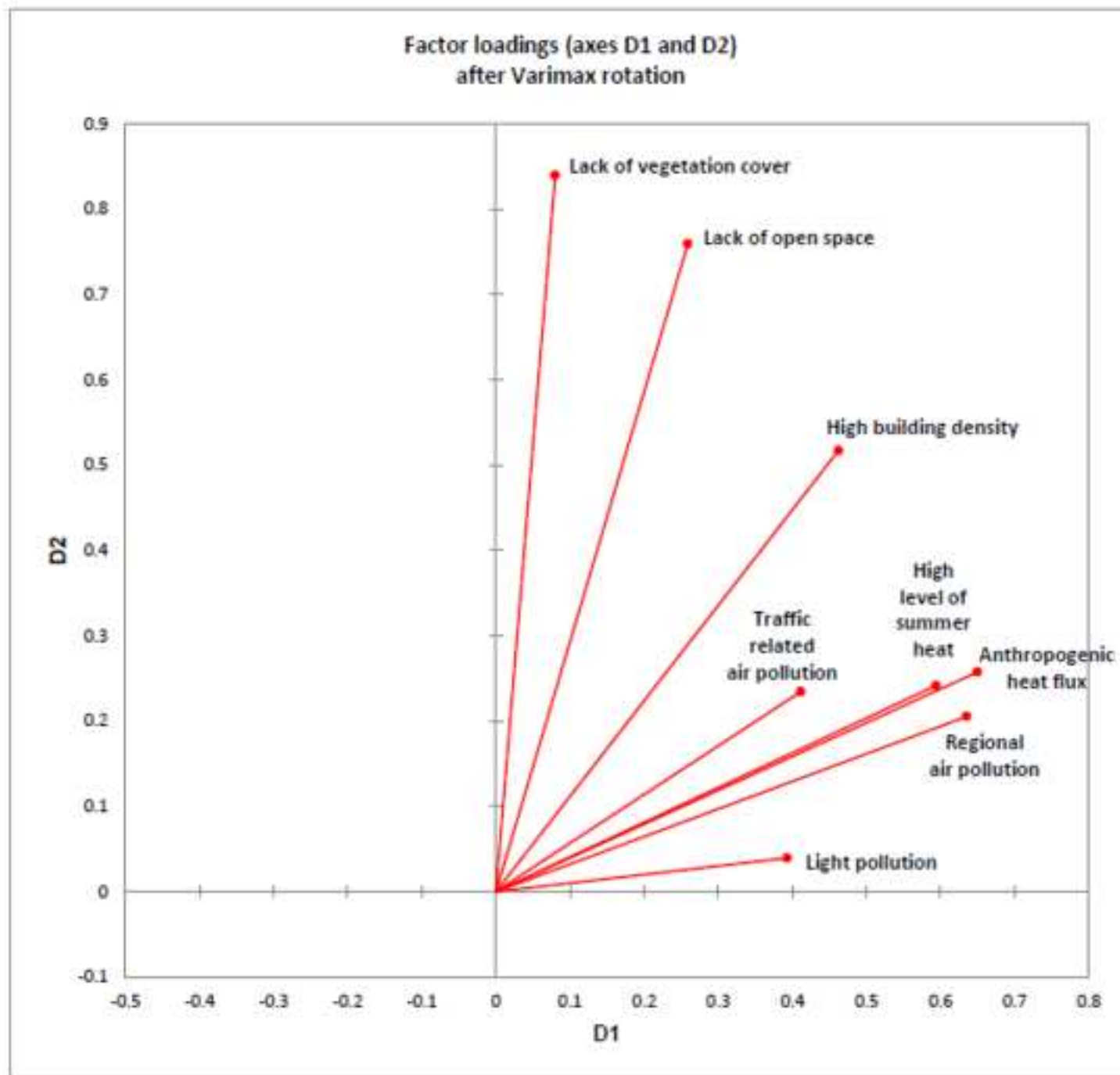


Figure 2

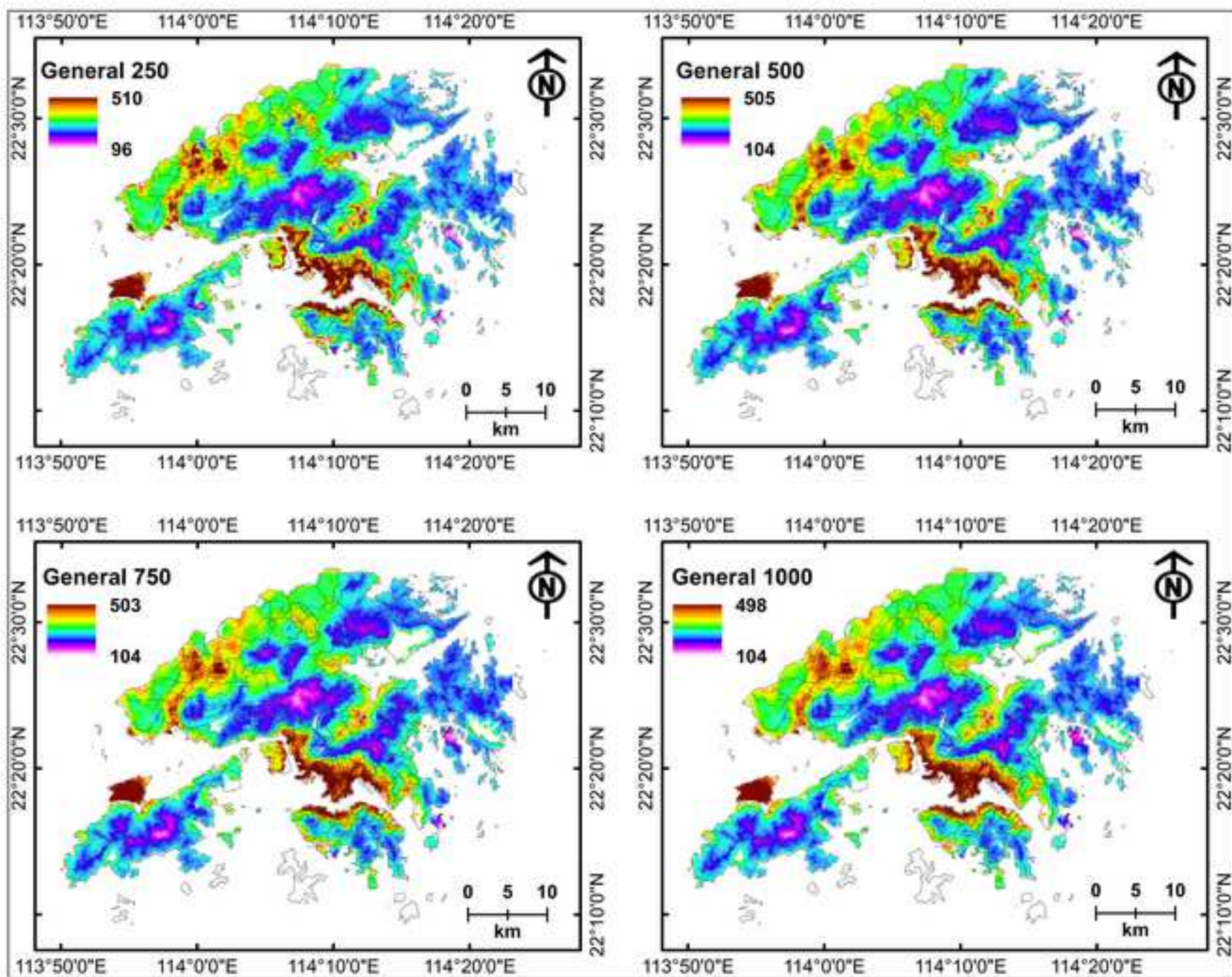


Figure 3

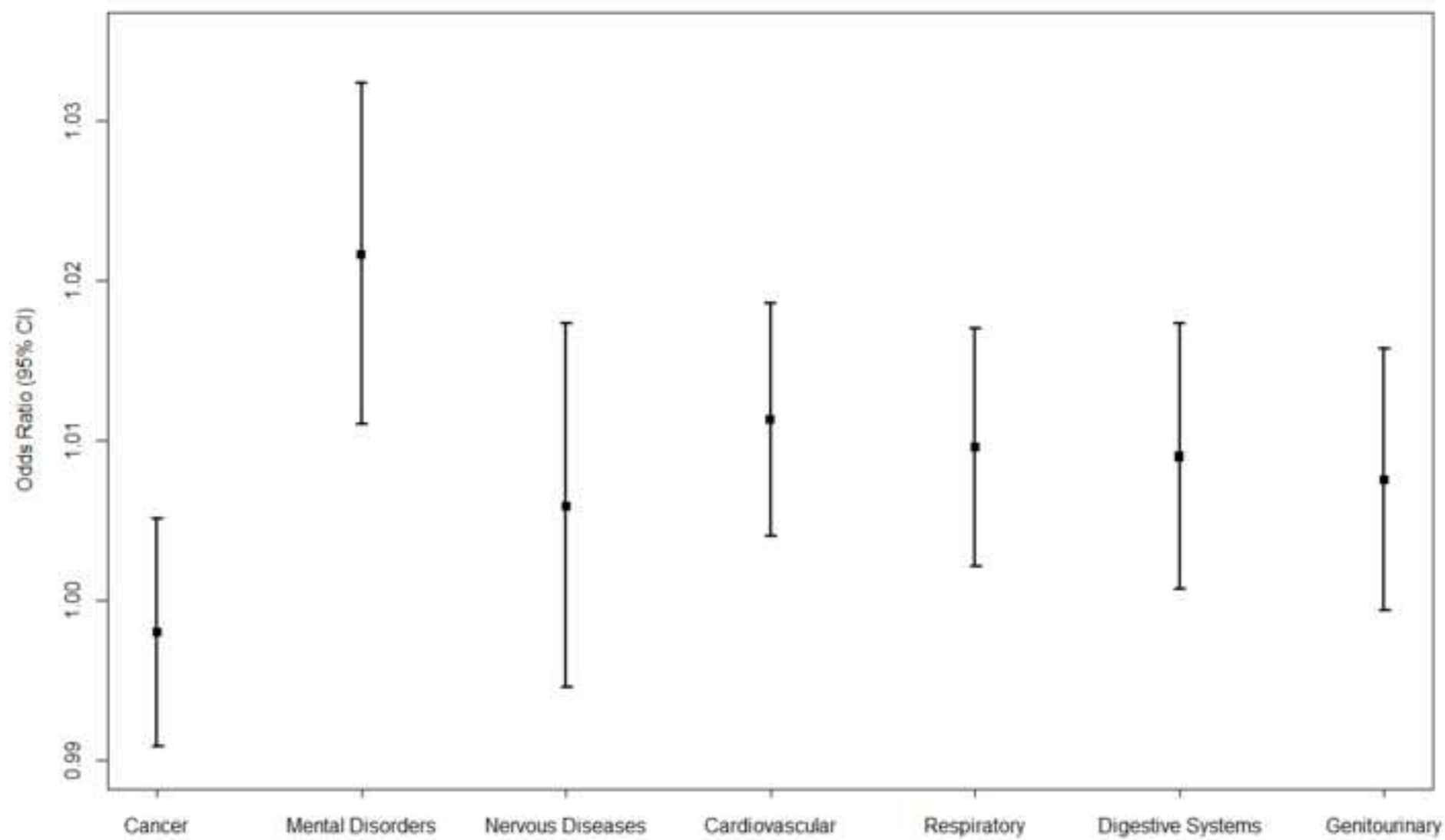


Figure 4

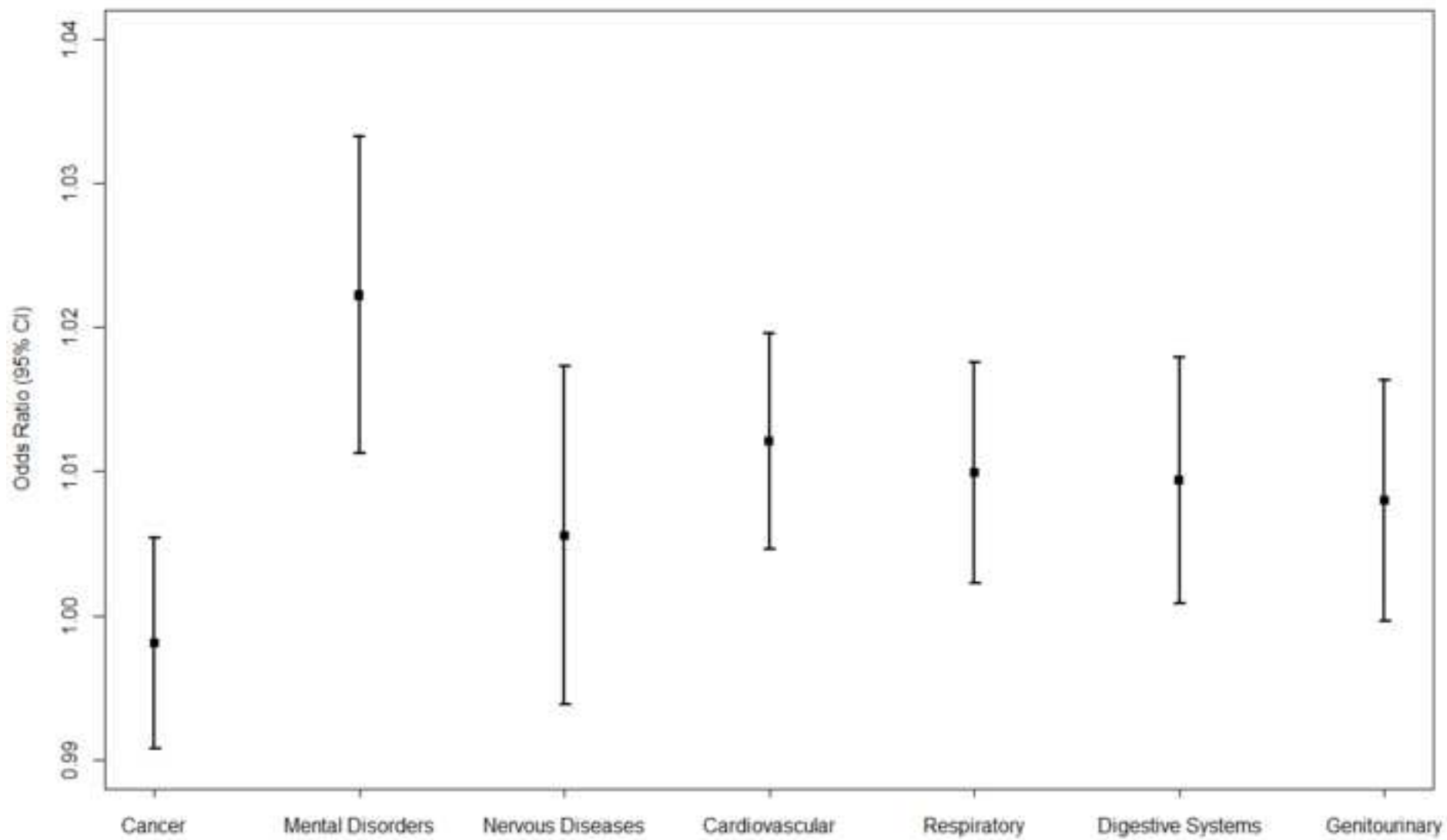


Figure 5

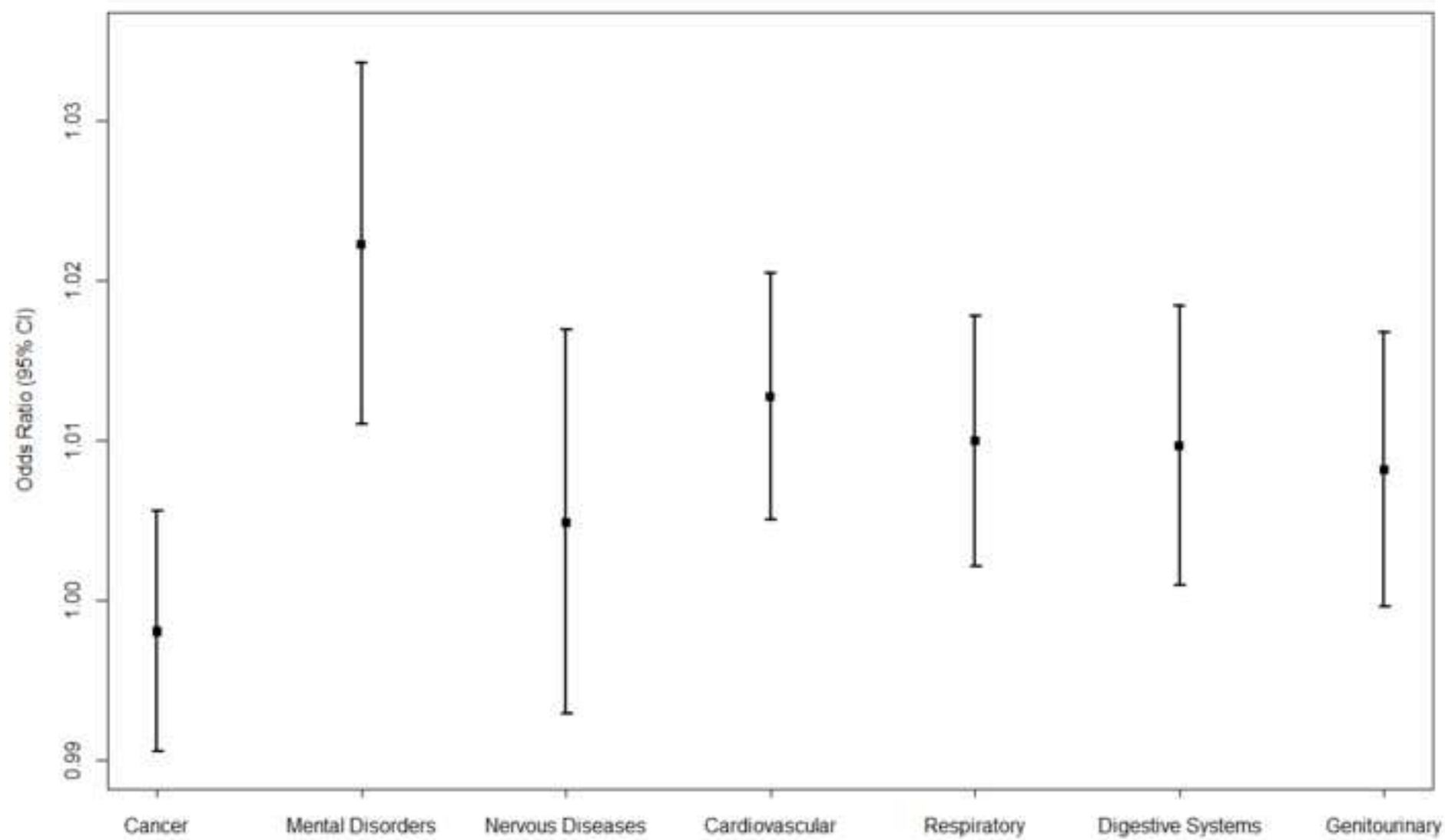


Figure 6

