Title: Perceived differences in the (re)production of environmental deprivation between sub-populations: a study combining citizens' perceptions with remote-sensed and administrative data

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Highlights:

"City as a whole" concept to estimate accumulation of environmental experiences

Subjective (self-rated) data with objective (spatial) data to estimate deprivation

Urban residents and aged >= 30: high environmental deprivation across the whole city

Females, low income, indoor workers: high environmental deprivation across urban area

Perceived environmental deprivation driven by social behaviors of local population

Abstract

Environmental deprivation significantly influences urban livability. Previous studies applied spatial data to evaluate environmental deprivation across various neighborhoods, and the identified deprived areas can be directly used in urban planning as areas that need to be addressed. However, perceptions of oneself regarding the local urban environment can influence sense of wellbeing, mental health, and social behavior of this individual; and any adverse feelings from the subjective environmental status can further influence perceived environmental deprivation. This perceived environmental deprivation can be different from the estimation of "objective" environmental deprivation, and perception itself can vary among subpopulations. Absence of consideration of variation in perceived environmental deprivation can lead to a failure of sustainable planning to support all oppressed people affected by urban development. Therefore, we combined citizens' perceptions with remote-sensed and administrative data to characterize perceived environmental deprivation among subpopulations, based on a questionnaire with ranks of specific environmental issues under a "city as a whole" concept. Generally, perceived environmental deprivation among subpopulations was driven by different facts. Based on the spatial comparison, self-identified urban residents and people aged >= 30 have faced higher environmental deprivation across the whole city than self-identified rural residents and younger ages. Females, lower income population, and indoor workers have faced with higher environmental deprivation across urban areas than males and higher income population and outdoor workers. These implied that perceived environmental deprivation may be driven by social behaviors of individuals because of social inequality, while planning protocols should be targeted to specific populations to provide comprehensive community support and equity.

Keywords: environmental perception; environmental deprivation; demographic difference; spatial analytics; built environment

Introduction

Deprivation is a key concept of community planning since it can reflect the lack of a specific goods considered to be a necessity in a society. For example, previous studies have found that social and material deprivation across neighborhoods could influence the health risk and social care (Bell & Hayes, 2012; Chau et al., 2014; Pampalon et al., 2012). In term to the impact from social environment, a neighborhood with environmental deprivation can also result in an area with a lack of acceptable environmental quality as well as low quality of livability. Therefore, previous studies have developed objective-based spatial datasets to quantify the environmental deprivation across various neighborhoods (Krstic et al., 2017; Pearce et al., 2010). Such spatially-explicit approaches also facilitate detailed mapping and comparative studies of environmental quality across urban landscapes, through which deprived neighborhoods can be identified for planning and hazard reduction (Fernández & Wu, 2018; Ho et al., 2015; Ho et al., 2017; Krstic et al, 2017), and to develop place-specific protocols for improving health and wellbeing.

However, subjective perceptions of one's local urban environment can significantly influence sense of wellbeing, mental health, and social behavior (Carrus et al., 2015; Tost & Meyer-Lindenberg, 2015). Adverse feelings from the subjective environmental experiences can influence the perception of environmental deprivation of a person. The perceived (and subjective) environmental deprivation can be different from the estimation of "objective" environmental deprivation estimated based on actual environmental quality indicators (i.e. observed by monitoring stations or field measurement (Saelens et al., 2003). At the same time, perception of environmental deprivation and actual environmental quality indicators can be directly or indirectly associated. Therefore, a growing body of research explores environmental features and their roles in the (re)production of deprivation as experienced by individuals (e.g., Galea et al. 2005), underscoring the importance of perception in the lived experience of deprivation (Carlijn et al. 2010). In details, this (re)production of deprivation is a visualization of environmental experiences of oneself, considering how the ontology of "place" and "space" are connected to "self-identity" and "sense of community" of a person. According to Stets and Burke (2000), "self-identity" can be referred to the perception of a person, in term of how he/she define his role in a society or community, while McMillan and Chavis (1986) defined that “sense of community” can be expressed as the perception of how a person matters to the other people in the society, based on shared belief that their needs can be fulfilled when they can build up the society together. Since both self-identity and sense of community are linked to social engagement and psychological response of a person, it becomes two keys that can influence environmental perception and behavior among a subpopulation. Thus, protocols for urban planning should consider locals’ perceptions of their geographical settings, in addition to the traditional approaches in which quantitative “hard” data are prioritized.

More importantly, metrics of subjective (or perceived) environmental deprivation may differ significantly from objective environmental metrics such as air pollution (Saelens et al., 2003), although a certain degree of agreement should be expected. Perceived deprivation is more important for urban planning because of its linkage with self-identity and sense of community, as environmental perception itself reflects the experiential realities of the citizenry, given that the best form of urban design may be quantified by a combination of experiential and quantified indicators. However, objective metrics have the advantage of providing a lower-cost and more statistically stable proxy for analyzing environmental deprivation, particularly given the rapid nascence of free remote-sensed imagery, open data, and volunteered geographic information. A mixed-methods approach drawing upon both subjective and objective measures can therefore be deployed to improve accuracy, reliability, and cost-effectiveness, thereby providing urban planners and demographers with a data-driven basis upon which to inform theoretical-based decision-making processes. As a result, several studies have mapped subjective understanding of urban environmental quality across neighborhoods, including the use of a questionnaire-based index based on perception of local citizens (Nichol et al., 2008; Wong et al., 2017). However, the degree to which subjective and objective measures of environmental deprivation has been sparsely studied, yet constitutes an important crux for data validation and deprivation modelling.

In brief, differing perceptions of environmental deprivation can be a result of their adaptations to an adverse environment (Chui et al., 2018). For example, people who work outdoors may have a higher tolerance for adverse environmental conditions than an office worker, as they become conditioned through repeated exposure. The difference in perception may also be linked to differences in psychological and social resilience, contingent in part on social behaviors, lifestyle, and socioeconomic factors (Yu et al., 2018).

Theoretical analyses of environmental deprivation have highlighted the importance of community-specific social and political/structural factors in the production and reproduction of perceived/experienced deprivation (Nettle, 2017). Accordingly, local contextual information is indispensable to the development of a holistic analysis and policy responses. To integrate the diverse and disparate datasets required to inform such a location-specific analysis, geographical information systems (GIS) provide a suitable framework and toolset. GIS comprises approaches and software for handling a wide variety of spatial data. For example, GIS have been used to analyse satellite-derived datasets for assessing environmental quality (Aminipouri et al., 2016; Chi and Ho, 2018; Han et al., 2014). Combining with a mixed-methods analysis to understand the perceptions of environmental deprivation of each sub-population, it is expected that mapping the potential areas with higher and lower environmental deprivations will also reflect the environmental adaptation and perception among different populations.

This study follows by seeking to measure, map, and differentiate perceived factors through which environmental deprivation is (re)produced in Hong Kong. Specifically, we depart from a traditional geospatial approach by focusing on residents' perceptions of city-wide drivers of deprivation, rather than focusing on neighbourhood-level factors. Using a short-form questionnaire developed based on a "city as a whole" concept, we collect locals' opinions about what environmental variables contribute to deprivation in Hong Kong. Specifically, this "city as a whole" concept is defined based on the accumulation of environmental experiences and perceptions in different spatial and temporal dimensions of oneself in the entire city. Based on the questionnaire, we use factor analyses to evaluate the environmental issues that may potentially influence the perceptions among different populations, develop empirical indices of perceived environmental deprivation for each sub-population in the study, and compare differences of perceived environmental deprivation between sub-populations, both quantitatively and cartographically.

Data and Methods

Study Area & Endemic Risk Factors

Hong Kong is a sub-tropical city with a high population density. Based on the 2017 Edition of the "Population and Household Statistics analysed by District Council District", population density in Hong Kong is approximately 6,700 persons/km^2, with some areas up to 56,000 persons/km^2. Restricted by land use policy, appropriately 70% of Hong Kong is categorized as "country park", with the majority of inhabitants living next to the Victoria Harbor in Kowloon and Hong Kong Island, or within the "New Town". Due to the concentration of population in these areas, there is a lack of open space and greenspace within urban areas, which in combination with high population density, has been associated with elevated mortality rates (Wang et al., 2017) and depression (Ho et al., 2017) among elderly sub-populations in Hong Kong. Additionally, extreme summer heat is a significant environmental stressor, which is becoming increasingly frequent due to climate change (Aflaki et al., 2017). More acutely, severe anthropogenic air pollution from vehicular traffic and impact of regional climate can be strongly associated with adverse effects (e.g. lung diseases) in Hong Kong (Chen et al., 2017; Power et al., 2011; Ho et al., 2018; Lee et al, 2017; Shi et al., 2018). There is also evidence that urban heat can lead to increases in air pollution levels including negative effects on ground-level ozone (Xie et al., 2016), potentially constituting a compounding negative effect on human health. Anthropogenic heat and light pollution as well as traffic-related pollution (which is related to noise) in Hong Kong's urban areas may also play a role through reduced sleep quality (Pun et al., 2014).

Cohort Data

This study evaluates perceived environmental deprivation among sub-populations based on an online cohort of Hong Kong residents. Study approval was obtained through the Human Subjects Ethics Sub-committee of The Hong Kong Polytechnic University (No: HSEARS 2018 01 24 002). Adult participants were recruited online via email, Facebook, WhatsApp, and an online forum, and asked to complete an online survey about their perception of the overall urban environment in Hong Kong. A total of 120 participants completed the survey between Feb 14 and Mar 13, 2018. The information related to environmental perception from this survey was evaluated and validated by a previous study (Ho et al., 2019), based on a mortality dataset (2007 – 2014) of Hong Kong with 259,514 decedents.

Participants provided their age, sex, monthly income, self-identified locations of residence (urban, subrural, rural), and type of work (outdoor work, manual labor, others), which were subsequently used to categorize participants into sub-populations (as described below). All subjects also completed a set of 8 Likert-scale questions (Table 1) about the relative importance of literature-derived factors contributing to environmental deprivation. Specifically, Likert-scale has commonly been used to measure self-rated mental health, wellbeing and deprivation (Cuijpers et al., 2009; de Craen et al., 2003). In details, each subject rated each question with on a scale of one to five, whereby lower values corresponded to that variable having lesser perceived importance in the (re)production of environmental deprivation in Hong Kong, and higher values to greater perceived importance. In order to capture a broader understanding of the study area, all questions referred to perceptions of environmental deprivation across the whole of Hong Kong, rather than participants' specific places of residence or work.

Spatial Datasets

In addition to the online survey, we analyzed eight geospatial datasets to map factors related to environmental deprivation among sub-populations across Hong Kong.

A high-accuracy black carbon (BC) map with 10-meter spatial resolution (Barrett et al., 2018; Lee et al., 2017) was used to map the geographical variability of traffic-related air pollution. 142 cloud-free Moderate Resolution Imaging Spectroradiometer (MODIS) Aerosol Optical Depth (AOD) datasets with 500-meter resolution were used to estimate the spatial variability of fine particulate matter ($PM_{2.5}$) from 2007 to 2009. Based on the Hong Kong-specific method developed by Bilal et al. (2017), we averaged the AOD datasets and converted the result to a $PM_{2.5}$ map of the study area.

To measure and map nighttime light pollution we used a cloudless 2015 satellite image from the Visible Infrared Imaging Radiometer Suite (VIIRS) with 750-meter resolution. The VIIRS radiance map was then used to represent nighttime light exposure.

Open spaces were measured using a vector-based land use map from the year 2012, which we then converted to a raster dataset with 10-meter resolution. A vegetation cover dataset with 10-meter resolution was derived from 2015 and 2016 SPOT satellite images (Wong et al., 2017; Ho et al, 2018b).

In order to represent urban building density across Hong Kong, an urban sky view factor (SVF) map from Yang et al. (2015) was acquired. In brief, SVF represents the proportion of the total sky that is not occluded by objects (e.g., trees and buildings) and is therefore viewable from an observer on the ground (Hodul et al., 2016). The selected SVF dataset was derived by Zakšek et al. (2011), who used airborne LiDAR data and a building map of Hong Kong. Higher SVF values indicate areas with more visible sky and lower building density.

Spatial variability of summer heat was estimated with a land use regression (Shi et al., 2017), based on urban morphometric data and local weather data. Anthropogenic heat data were calculated from two satellite-derived datasets as an indicator of the annually averaged daytime anthropogenic heat flux across Hong Kong (Wong et al., 2015).

Spatial Data Pre-processing

Due to potential error stemming from spatial uncertainty, in which the aggregation of data from originally different resolutions/scales may induce error (Cebrecos et al., 2018), we used the Focal Statistics toolbox in ArcGIS to conduct a pixel-by-pixel spatial averaging, using a 250-meter search radius. This technique generalizes the scaling effect from multiscale data sources (e.g. 10m resolution vs 700m resolution), while producing a spatially smoothed result useful for evaluating environmental deprivation at the neighborhood-scale.

Before the application of focal statistics, all spatial datasets were resampled to a 10-meter resolution. Where necessary, pixel values were rescaled (standardized) from 0 to 100, so that higher values correspond to poorer environmental quality or deprivation. SVF was standardized by a multiplicative factor of 100. Focal statistics were then applied accordingly to produce the following standardized datasets for subsequent statistical analysis: average regional air pollution (in 250-meter radius); average traffic-related air pollution (in 250-meter radius); average light pollution (in 250-meter radius); percentage of vegetation cover (in 250-meter radius); average sky view factor (in 250-meter radius); average summer temperature (in 250-meter radius); percentage of open space (in 250-meter radius); and average anthropogenic heat (in 250-meter radius).

To estimate environmental deprivation across neighborhoods, higher values of all datasets should hypothetically indicate areas with lower environment quality. However, standardized datasets of percentage of vegetation cover, average sky view factor and percentage of open space were the datasets with high values indicating better environment. Therefore, the following equation were applied to these standardized datasets: *100 – pixel*, for the conversion of these datasets to spatial parameters hypothetically associated with poorer environment as follows: percentage of non-vegetation cover, high. All standardized datasets were further clipped by the land boundary of Hong Kong.

Factor Analyses and Environmental Deprivation Mapping

Following the conceptual framework of a previous study that measured the overall environmental deprivation among general population in Hong Kong (Ho et al., 2019), factor analyses were applied to construct a series of empirically-derived indices for measuring environmental deprivation based on the spatial datasets and the survey results. Varimax rotation (based on the first two factors) was applied to estimate factor loadings for perceived environmental deprivation among each sub-population, with the use of the “XLSTAT” software.

The factor loadings were used to summarize the major factors and potential hidden factors associated with perceptions of environmental deprivation among each sub-population. The following pairs of sub-populations were categorized and compared: Male vs. Female; Age < 30 years old vs. Age >= 30 years old; monthly income <= HKD \$20,000 vs. monthly income > HKD \$20,000); self-identified urban resident vs. self-identified subrural/rural resident; outdoor/manual labor vs. not-outdoor/manual labor. These categories were selected based on heuristically-derived commonalities of social behaviors, lifestyle, socioeconomic status, and psychological resilience, reflecting the greatest expected between-group differences of environmental resilience and adaptation (Chan et al., 2012).

As shown in Figure 1, each of the ten sub-populations were separately processed to produce different raster layers, each of which represents the spatial distribution of a given sub-population's perceived environmental deprivation in Hong Kong. This was achieved by separately running a factor analysis for each sub-population, where the input variables are their responses for each of the 8 deprivation variables. The top two factor loadings (channels) from each sub-population's factor analysis were selected, and their sum (channel D1 + D2) was assigned as the weight for each of the 8 variables. This resulted in ten separate empirical deprivation indices, each specific to a sub-population.

For each resulting sub-population's index, its combined factor loadings (D1 + D2) for each variable were then multiplied by that variable's corresponding preprocessed spatial dataset (via raster multiplication) and summed to produce a final weighted raster layer for each sub-population, based on a spatial multi criteria analysis (SMCA) documented in previous studies (Ho et al., 2015; Ho et al., 2018c; Ho et al., 2019). For each sub-population pair (e.g., males vs. females, indoor vs. outdoor workers), one of their deprivation raster layers was subtracted from the other, resulting in a *difference* raster, indicating the spatial distribution of differences between each sub-population's perceived environmental deprivation. All raster arithmetic was completed on a pixel-by-pixel basis without smoothing, and the results were mapped.

Additionally, the 10 deprivation indices specific to each sub-population were mapped and further overlaid with land use types in the study area, categorized as: urban residential areas; commercial/industrial areas; rural residential areas. Note that urban residential areas were compiled with the following land use types: private residential areas (housing units owned privately) and public residential areas (i.e., government owned subsidized housing units). The average pixel value (and standard deviation) was calculated for each land use type, for each index, and reported as a table below.

Results

Data Summary

The demographic composition of survey participants is summarized in Table 2. When divided into sub-populations, differences between participants' perceived importance of each variable in the (re)production of environmental deprivation were observed, as shown in Table 3, where higher numbers correspond to greater importance of a given variable. All eight variables had a mean perceived deprivation score greater than the Likert-scale midpoint (>2.5), indicating that were all perceived to be important contributors to environmental deprivation. Participants rated traffic-related air pollution slightly higher than the other variables, with a mean score of 4.13 out of 5. Building density was the second highest rated variable, and vegetation and open space received the lowest overall scores. Significant differences of means and variance were identified between sub-populations' responses (One-way ANOVA F=4.98, df=7, p<0.001).

The subsequent factor analysis identified key combinations of variables perceived to be important in the (re)production of environmental deprivation, as shown in Table 4. The first factor for all participants comprised three major environmental deprivation variables identified by all participants: anthropogenic heat, regional air pollution, and summer heat. High building density and traffic-related air pollution were also perceived in the initial survey to be important facets of environmental deprivation in Hong Kong, while a lack of vegetation and open space were perceived to be less important in the (re)production of environmental deprivation.

Sub-Populations' Perceptions of Environmental Deprivation

Sex

The first factor (D1) for males primarily emphasized the built environment's importance in deprivation, with the highest factor loadings for high building density, lack of vegetation, and lack of open space. The second male factor (D2) was dominated by summer heat. The primary female factor also had stronger contributions from the built environment, while the second factor primarily comprised anthropogenic heat, air pollution, and light pollution. The differences between male and female participants' perceptions were minor, with some difference observed between their ratings for traffic pollution, light pollution, and summer heat.

Age

Among participants aged < 30 years, the first factors that contribute to the perceptions of environmental deprivation were anthropogenic heat, regional air pollution, and light pollution. In addition, summer heat, traffic-related air pollution, and higher building density were considered important issues. In contrast, lack of open space and vegetation were not among the leading factors chosen by the younger participants, although they did emerge in the second factor (D2) as being an important component of environmental deprivation.

In comparison with the younger participants, persons aged >= 30 considered the built environment (lack of open space, lack of vegetation, high building density) to be more important causes of environmental deprivation, with summer heat being the predominant variable for the second factor.

Income

Traffic-related air pollution, anthropogenic heat, and regional air pollution were three major environmental issues among the lower income sub-population. A lack of vegetation and open space were leading concerns for their second factor.

Participants with a higher income identified lack of open space, lack of vegetation, higher building density, light pollution, and traffic-related air pollution as key drivers of deprivation in Hong Kong. Summer heat and regional air pollution were the major hidden factors emerging in D2.

Home Location

Overall, the self-identified urban sub-population had concerns primarily about the lack of vegetation and open space, as well as high building density. The other environmental issues were comparatively lower in the first factor. The second factor loadings highlighted anthropogenic heat, regional air pollution, and summer heat as dominant variables associated with environmental deprivation.

Participants who self-identified as living in rural and subrural areas had less concern about a lack of vegetation and open space, rather pointing towards higher building density and regional air pollution. The hidden factors emerging in the second factor loadings were traffic-related air pollution and light pollution.

Workplace Setting

The results indicated that people who were outdoor workers had serious concerns about deprivation associated with the built environment (lack of open space, high building density, and lack of vegetation cover). Traffic-related air pollution was another, albeit less important, variable identified in the analysis. The second factor (D2) highlighted light pollution for this sub-population.

Curiously, participants who worked indoors had an even higher concern about a lack of vegetation, in addition to lesser concerns about a lack of open space. The secondary factor comprised similar proportions from all of the deprivation variables (high building density, light pollution, traffic-related air pollution, regional air pollution, summer heat, anthropogenic heat) except for a lack of vegetation and open spaces.

Spatial Differences in Perceived Environmental Deprivation

All sub-populations' perceived environmental deprivation scores were high in urban areas, indicating a broad agreement that the concentration of these variables in urban areas correspond to worse living conditions. In some cases, urban areas had deprivation scores four to five times higher than the rural areas.

Figures 2 – 6 indicated the territory-wide difference of perceived environmental derivation among sub-populations. When summarized by land use types (table 5), female participants' deprivation index indicated a much stronger adverse perception of environmental deprivation in urban areas than males, with a mean score 8.71 points higher. The contrast was even stronger for commercial and industrial areas, in which the female index was an average of 16.95 points higher than the male index. This difference was much smaller in rural residential areas, in which females only averagely scored 3.03 higher. Compared to people aged < 30, the older aged population's index was higher across the entire study area (figure 3), with particularly high scores in urban areas, due to their emphasis of the built environment's importance in (re)producing deprivation. In rural areas, the difference between age groups was smaller.

In urban areas, the lower income sub-population's index scores were consistently higher than those of their higher-earning counterparts (figure 4), with particularly notable differences in the perception of deprivation in commercial and industrial areas. These differences were smaller in rural areas, although the lower-income index scores were still slightly higher overall. self-identified Urban residents' index scores were higher across the entire study area than self-identified subrural/rural residents, except in a few uninhabited remote areas (figure 5). These differences were strong in both commercial/industrial areas and urban residential areas. There was also a strong disparity in perceived environmental deprivation indices between outdoor and indoor workers (figure 6). In brief, indoor workers' scores were much higher in urban areas, while outdoor workers, including manual laborers, scored perceivable higher in rural areas.

Discussion

Implications for Perceived Environmental Deprivation

In this study, a "city as a whole" concept was applied to characterize perceptions of environmental deprivation among different populations, and to map perceived deprivation using remote-sensed imagery and administrative datasets. This “city as a whole” concept is defined based on the accumulation of environmental experiences and perceptions in different spatial and temporal dimensions of oneself in the entire city. The results indicate that sub-populations had differing perceptions of which features constituted important issues for environmental deprivation, and the use of factor analysis uncovered underlying thematic areas comprising multiple variables (e.g., the built environment). By mapping these results and comparing to land use categories, geographical differences in sub-populations’ perceived drivers of environmental deprivation were observed. Specifically, different subpopulations had their own beliefs on environmental issues associated with higher risk, resulting in an entirely different perception of environmental deprivation across districts.

In summary, we observed that self-identified urban residents and people aged 30 years or older had a higher perception of environmental deprivation across the city than self-identified rural residents and younger populations. Females, lower income residents, and indoor workers may experience higher environmental deprivation across urban areas than males, higher income residents, and outdoor workers. These were interesting findings, since these would explain their social behaviors (e.g. spatial mobility, daily activities) in relation to perceived environmental deprivation. Further research might interrogate these disparities to uncover potentially explanatory social, economic, and political processes at play. Differences between self-identified urban and rural residents’ perceptions of deprivation may be explained by their relative exposures to the variables comprising their respective dominant factors.

For self-identified urban residents, high mobility of these individuals across the “city” can be resulted in a negative perception of the city, since they may have experienced with adverse environmental issues frequently, which further increase their psychological burden(s). For example, self-identified urban residents likely have more exposure to the built environment variables and atmospheric variables that act as stressors (e.g., building density and heat), thereby becoming more adapted to these stressors than their rural counterparts. At the same time, they did not have a residential environment with high environmental quality compared to the "rural residents", and this may reduce their ability to relieve any negative feelings from adverse environment. Therefore, these self-identified urban residents had a strong perception that local environment of this city has been highly deprived. Specifically, a lack of vegetation was more strongly scored by self-identified urban residents than rural, suggesting that the importance of green spaces is more strongly appreciated in their absence. In fact, people living in historical urbanized areas have much less chance experiencing greenery than subrural/rural population in Hong Kong, due to their daily activities for work and social behaviors as well as high-density settings of this compact city. Such high-density settings can also increase the prevalence of depression among older people (Ho et al., 2017b). These results implied that urban residents were the oppressed population of the adverse environment, and they need much higher social and environmental justices for the enhancement of livability.

Age may also represent a degree of cumulative exposure, such that a relatively greater amount of time experienced by the older sub-population includes a greater total amount of time exposed to features associated with deprivation. However, older residents did not have successful adaptations because they indicated higher scores overall than their younger counterparts. This is linked to the adaptation theory posed above because successful adaptation would only happen when there is not an occurrence of accumulation of negative perceptions higher than the level of resilience. As a result, if someone constantly experienced social and environmental event, this can induce adverse effects on emotions and perception.

Due to the change in social lives and possibly also the decrease in health statuses, subpopulation with age >= 30 has an accumulation of negative socio-environmental experiences for decades and this may have been higher than their level of resilience. Particularly, it has been a debate in Hong Kong regarding increasing numbers of migrants and impacts of regional air pollution, due to rapid urban development in mainland China. One expects that through an excessive amount of total cumulative exposure, these older populations would not be resilient or adapted to the built environment and atmospheric stressors. In addition, this effect is hard to be alterable. Once emotions and perception of a person were dropped below the threshold of psychological resilience, it is not easy to be recovered by “adaptation” (Marshall & Stokes, 2014). Therefore, this older population has higher perception of environmental deprivation, in comparison with those younger ages.

For the difference between indoor and outdoor workers, it could be a result caused by difference in self-experiences. The workplace setting sub-populations (indoor and outdoor workers) may reflect a proxy for workplace location, in that indoor workplaces are more likely to be concentrated in commercial areas than outdoor workplaces (e.g. construction sites). Specifically, indoor workers had higher opportunities to experience with adverse environmental experiences in urban areas, and they may have less negative experiences in outdoor environment. Therefore, they gave a higher rank of the adverse environmental issues related to urban areas than outdoor workers or manual workers because the indoor workers would perceivably recognize rural areas as a better environment than those outdoor workers who had been constantly suffered from outdoor environmental exposures. As a result, indoor workers had high factor loadings for built environment variables in the factor analysis. Variables more likely to be experienced outdoors had very low factor loadings (e.g. heat and air/light pollution). In contrast, outdoor workers’ perceived deprivation had a higher factor loading for traffic-related air pollution, but similar values for built environment variables.

The largest between-group differences in factor loadings were observed for income. Based on the map, low income population has a much stronger negative perception on the urban environment (Figure 4). This partially because the persons with lower income generally put a stronger hope regarding a better environment across rural area, since compact environment across urban area for was not only a place associated with negative geophysical environment, but also the location representing their lower socioeconomic status and possible lower quality in daily lives. This mixed feeling may result in a strong perception that the living environment in urban areas has been deprived, therefore, this environment has to be changed. In comparison, higher income population perhaps had more alternatives in social behaviors to improve their quality of life, therefore, their negative feelings to urban areas were relatively generalized. Specifically, the low-income subpopulation’s responses were dominated by atmospheric variables (e.g. heat and air pollution), compared to the higher-income group, whose factor loadings indicated much greater concern about the built environment. This was true for both factors (D1 and D2), underscoring the relative importance of the built environment to this sub-population, as well as indicating a high level of within-group agreement about which variables were most serious. A concentration of residential areas with low socioeconomic status and low environmental quality in urban areas (e.g. Sham Shui Po) may explain the low-income sub-population’s high perceived environmental deprivation scores in the urban areas.

Finally, the difference in females and males could be a result caused by the difference in social behaviors. It is well recognized that females generally have more appreciations to participate in social activities within high-density urban environment than males, while males are more active to participate in outdoor activities. In addition, females are often to be caregivers of frail individuals with problems for outdoor activities (Stone et al., 1987). These result in a higher perceived environmental deprivation of rural area from females than males.

Based on the results above, a multiple-level community plan should be developed to enhance the environmental perception among all populations. Specifically, we should include the following elements in the planning protocols to enhance the environmental perception among self-identified urban populations: improvement of environmental quality, reduction of building density, and increase of urban greenery. To enhance the environmental perception among older people, it is necessary to include both improvement of environmental quality and social support (e.g. increase of social cohesion) in order to increase the community resilience across the neighborhoods. For supporting the indoor workers, it is necessary to apply the plan of “garden city” to re-design the commercial areas, in order alter their negative perceptions of workplace, while supporting the outdoor workers should be based on education, in order to improve the preparedness for environmental risk prevention so that they would have less health burdens from adverse environment. To enhance the environmental perception of low-income population, it is necessary to not only improve the environmental quality across their residential neighborhood, but also to enhance their social identity and sense of community so that they can have stronger positive place attachment (Allacci & Magder, 2013). This is because local issues may affect perception of environmental deprivation of low-income population given their orientation and geographic range of activities. Specifically, social, economic, environmental inequities are pre-existed among this low-income population. Therefore, enhancing environmental conditions and reducing deprivation may contribute to positive place attachment, social capital and cohesion (Fu, 2018), so that low-income population can socially support each other even they may be facing with multiple inequities. Finally, supporting the difference in gender needs to integrate with community engagement, so that they can explore the different sides of the city to enhance environmental perception.

Limitations and Future Directions

In this study, the "city as a whole" concept should not be compared with the data-driven purpose from real-time location-based analysis, since these two approaches represent entirely different frameworks. For the "city as a whole" concept, we hereby define it as an "all-inclusive" framework, because this framework hypothesizes population in a megacity should be highly mobilized, and the population has been experienced with multiple environmental conditions in different date/time and locations. Therefore, their perceptions, especially those pertaining to environmental deprivation, should be from the accumulation of experiences in different spatial and temporal dimensions. The perceptions of environmental deprivation from the accumulation of experiences should also be a fixed image of environmental understanding, and is not easily altered by any spatiotemporal change.

In contrast, data-driven purpose from real-time location-based analysis is an "all-exclusive" framework. It assumes that inception and interruption of perceptions from environment can be occurred in a real-time manner, in which any interpretation of environmental deprivation can be a result in a particular time under a specific location. Therefore, instead of theoretically hypothesizing environmental deprivation as a component of the accumulation of environmental perceptions, real-time location-based analysis aims to stratify the results by maximizing the spatio-temporal dynamics of data modelling (Song et al., 2019). Results from such real-time analysis are expected to be differ significantly from the interpretation based on the “city as a whole” model.

Based on the statements above, we argue that both methods have their own advantages, since they represent two different components of perceptions of environmental deprivation. A follow-up study can seek to estimate location-specific perceptions of deprivation based on real-time spatiotemporal analysis. This future research utilizing real-time analysis should be conducted with location-based approaches (such as mobile apps), and should require very detailed ethnical consideration and institutional approval.

Finally, our study has used a relatively small sample size to compare perception of environmental deprivation among various subpopulations. Although the use of this dataset for applications of environmental perception has been validated (Ho et al., 2019), a further study with more participants as well as longitudinal data should be able to enhance the future development.

Conclusion

Results of this study highlight subjectivities contingent upon demographic and socioeconomic lines of difference between sub-populations, the distinctions between which serve to illuminate further nuances about the ways in which environmental deprivation is experienced, produced, and reproduced. We assert that this is particularly important for socioeconomically and otherwise marginalized populations, whose voices are often less prominent in discourses aimed at policymakers.

While our results may inform policy-orientated opportunities for environmental modification and/or planning purposes, we assert that more detailed and quantifiable understandings of multiple environmental deprivation are crucial prerequisite steps towards developing equitable solutions to the burdens of the built and atmospheric environment. By developing more population-specific indices of environmental deprivation and mapping the results, carefully targeted policy responses are more likely to be effective.

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Table 1 - 8 Likert-scale questions about the relative importance of literature-derived factors contributing to environmental deprivation.

Questions
1) Do you think that traffic-related air pollution is a serious environmental problem?
2) Do you think that regional-influenced air pollution is a serious environmental problem?
3) Do you think that light pollution is a serious environmental problem?
4) Do you think that lack of vegetation or greenspace is a serious environmental problem?
5) Do you think that high city/building density is a serious environmental problem?
6) Do you think that summer heat is a serious environmental problem?
7) Do you think that lack of open space or park is a serious environmental problem?
8) Do you think that anthropogenic heat is a serious environmental problem?

Table 2 - demographic composition of survey participants

Sub-population		Count (n)	Percent (%)
Sex	**Male**	49	40.8
	Female	71	59.2
Age	**< 30 years**	56	46.7
	≥ 30 years	64	53.3
Monthly Income	**< $20 k HKD**	62	51.7
	≥ $20 k HKD	58	48.3
Home Location	**Urban**	82	68.3
	Subrural/Rural	38	31.7
Work Setting	**Outdoor**	30	25.0
	Indoor	90	75.0

Table 3 - differences between participants' perceived importance of each variable in the (re)production of environmental deprivation

Variables	All Participants	Sub-populations									
		Sex		Age		Income		Home Location		Work Setting	
		Male	Female	< 30 years	≥ 30 years	< $20 k HKD	≥ $20 k HKD	Urban	Subrural /Rural	Outdoor	Indoor
Traffic-Related Air Pollution	4.13 (0.89)	4.17 (0.93)	4.11 (0.87)	4.16 (0.83)	4.11 (0.95)	4.16 (0.85)	4.11 (0.93)	4.16 (0.92)	4.08 (0.82)	4.27 (0.79)	4.09 (0.92)
Regional Air Pollution	3.81 (1.03)	3.92 (1.05)	3.74 (1.02)	3.73 (0.98)	3.88 (1.08)	3.76 (1.01)	3.86 (1.05)	3.77 (1.03)	3.90 (1.03)	3.97 (1.07)	3.76 (1.02)
Light Pollution	3.70 (1.06)	3.58 (1.05)	3.78 (1.06)	3.59 (1.09)	3.80 (1.03)	3.62 (1.06)	3.77 (1.06)	3.67 (1.09)	3.76 (1.00)	3.80 (0.96)	3.67 (1.09)
Lack of Vegetation	3.69 (1.04)	3.63 (1.06)	3.72 (1.02)	3.71 (1.00)	3.66 (1.07)	3.71 (0.97)	3.66 (1.10)	3.83 (0.98)	3.37 (1.10)	3.97 (1.07)	3.59 (1.02)
High Building Density	4.11 (1.00)	3.98 (1.06)	4.19 (0.96)	4.21 (0.94)	4.02 (1.05)	3.98 (1.05)	4.23 (0.95)	4.06 (1.05)	4.21 (0.91)	4.37 (0.77)	4.02 (1.06)
Summer Heat	3.73 (1.20)	3.69 (1.34)	3.76 (1.11)	3.75 (1.28)	3.72 (1.13)	3.66 (1.18)	3.81 (1.23)	3.65 (1.22)	3.92 (1.15)	4.13 (1.07)	3.60 (1.22)
Lack of Open Space	3.53 (1.00)	3.48 (0.95)	3.56 (1.03)	3.54 (0.91)	3.52 (1.07)	3.48 (1.03)	3.57 (0.97)	3.60 (1.00)	3.37 (0.97)	3.70 (0.95)	3.47 (1.01)
Anthropogenic Heat	3.84 (1.02)	3.90 (1.06)	3.81 (1.00)	3.82 (1.05)	3.86 (1.01)	3.74 (1.02)	3.94 (1.02)	3.84 (1.02)	3.84 (1.03)	4.07 (0.87)	3.77 (1.06)

Table 4 - factor analysis identified key combinations of variables perceived to be important in the (re)production of environmental deprivation

		Factor D1	Traffic-Related Air Pollution	Regional Air Pollution	Light Pollution	Lack of Vegetation	High Building Density	Summer Heat	Lack of Open Space	Anthropogenic Heat	Channel Description
		All Participants	0.412	0.635	0.393	0.080	0.462	0.594	0.259	0.650	Heat and Air Pollution
Sub-populations	**Sex**	**Male**	0.520	0.366	0.296	0.637	0.645	0.087	0.539	0.524	Built Environment
		Female	0.222	0.217	0.032	0.884	0.645	0.332	0.748	0.200	Built Environment
	Age	**< 30 years**	0.412	0.623	0.587	-0.035	0.409	0.426	0.100	0.667	Heat and Air/Light Pollution
		≥ 30 years	0.522	0.362	0.371	0.783	0.598	0.143	0.845	0.515	Built Environment and Traffic
	Income	**< $20 k HKD**	0.711	0.620	0.347	0.140	0.499	0.513	0.191	0.654	Heat and Air Pollution
		≥ $20 k HKD	0.533	0.179	0.566	0.619	0.588	0.034	0.657	0.359	Built Environment
	Home Location	**Urban**	0.277	0.214	0.090	0.896	0.608	0.366	0.710	0.253	Built Environment
		Subrural/Rural	0.093	0.666	0.108	0.377	0.790	0.552	0.557	0.388	Built Environment and Heat, but not lack of vegetation
	Work Setting	**Outdoor**	0.554	0.113	0.107	0.627	0.736	0.166	0.917	0.316	Built Environment
		Indoor	0.117	0.293	0.031	0.821	0.483	0.309	0.790	0.259	Built Environment

		Factor D2	Traffic-Related Air Pollution	Regional Air Pollution	Light Pollution	Lack of Vegetation	High Building Density	Summer Heat	Lack of Open Space	Anthropogenic Heat	Channel Description
		All Participants	0.234	0.205	0.039	0.839	0.517	0.242	0.759	0.257	Built Environment
Sub-populations	Sex	Male	-0.111	0.477	-0.133	0.110	0.344	0.936	0.392	0.491	Heat and Air Pollution
		Female	0.565	0.662	0.545	0.030	0.332	0.468	0.256	0.680	Heat and Air/Light Pollution
	Age	< 30 years	0.045	0.216	-0.169	0.614	0.480	0.392	0.782	0.165	Built Environment
		≥ 30 years	0.139	0.542	-0.005	0.172	0.442	0.878	0.208	0.473	Heat and Air Pollution
	Income	< $20 k HKD	0.134	0.286	0.007	0.872	0.550	0.350	0.785	0.315	Built Environment
		≥ $20 k HKD	-0.073	0.683	-0.070	0.140	0.289	0.799	0.386	0.518	Heat
	Home Location	Urban	0.370	0.622	0.298	0.141	0.374	0.563	0.298	0.810	Heat
		Subrural/Rural	0.744	0.227	0.593	0.232	0.101	-0.306	0.493	0.243	Traffic and Light Pollution
	Work Setting	Outdoor	0.006	0.616	0.805	-0.190	0.176	0.594	0.258	0.661	Heat and Air/Light Pollution
		Indoor	0.509	0.620	0.306	0.147	0.483	0.476	0.189	0.665	Heat and Air Pollution

		Within Sub-pop Differences	Traffic-Related Air Pollution	Regional Air Pollution	Light Pollution	Lack of Vegetation	High Building Density	Summer Heat	Lack of Open Space	Anthropogenic Heat	Key Differences between Sub-populations
	Sex	D1	0.298	0.149	0.264	0.247	0.000	0.245	0.209	0.324	Heat

Sub-populations		**D2**	0.676	0.185	0.678	0.080	0.012	0.468	0.136	0.189	Traffic and Light Pollution
	Age	**D1**	0.11	0.261	0.216	0.818	0.189	0.283	0.745	0.152	Open space and Vegetation
		D2	0.094	0.326	0.164	0.442	0.038	0.486	0.574	0.308	Open space, heat, and Vegetation
	Income	**D1**	0.178	0.441	0.219	0.479	0.089	0.479	0.466	0.295	Open space, regional air pollution, heat, and Vegetation
		D2	0.207	0.397	0.077	0.732	0.261	0.449	0.399	0.203	Vegetation
	Home Location	**D1**	0.184	0.452	0.018	0.519	0.182	0.186	0.153	0.135	Regional air pollution and Vegetation
		D2	0.374	0.395	0.295	0.091	0.273	0.869	0.195	0.567	Summer Heat
	Work Setting	**D1**	0.437	0.18	0.076	0.194	0.253	0.143	0.127	0.057	Traffic air pollution
		D2	0.503	0.004	0.499	0.337	0.307	0.118	0.069	0.004	Traffic and Light Pollution

Unitless total differences (both factors combined)		**Traffic-Related Air Pollution**	**Regional Air Pollution**	**Light Pollution**	**Lack of Vegetation**	**High Building Density**	**Summer Heat**	**Lack of Open Space**	**Anthropogenic Heat**	**Key Differences between Sub-populations**
Sub-populations	**Sex**	0.974	0.334	0.942	0.327	0.012	0.713	0.345	0.513	4.160
	Age	0.204	0.587	0.38	1.26	0.227	0.769	1.319	0.46	5.206
	Income	0.385	0.838	0.296	1.211	0.350	0.928	0.865	0.498	5.371
	Home Location	0.558	0.847	0.313	0.610	0.455	1.055	0.348	0.702	4.888

	Work Setting	0.940	0.184	0.575	0.531	0.560	0.261	0.196	0.061	3.308

Table 5 – perceived differences in the (re)production of environmental deprivation summarized by land use types

Sub-populations	Descriptions	Mean Deprivation Index Score (Standard Deviation)		
		Urban Residential	**Commercial/ Industrial**	**Rural Residential**
Sex	**Male - Female**	-8.2 (9.2)	-17.0 (10.8)	-3.0 (8.1)
Age	**Aged ≥ 30 years - aged < 30 years**	66.1 (14.0)	73.0 (14.3)	51.5 (9.7)
Income	**monthly income ≥ $20 k HKD - monthly income< $20 k HKD**	-23.0 (11.5)	-30.5 (12.4)	-12.0 (8.1)
Home Location	**Urban - rural**	73.8 (15.3)	75.3 (14.9)	57.9 (10.5)
Work Setting	**Indoor - Outdoor**	15.6 (16.1)	20.9 (17.1)	-1.5 (11.4)

Captions of figures

Figure 1 – Flow chart (conceptual framework) of this empirical study

Figure 2 – perceived differences in the (re)production of environmental deprivation between males and females

Figure 3 – perceived differences in the (re)production of environmental deprivation between aged >=30 and ages < 30

Figure 4 – perceived differences in the (re)production of environmental deprivation between higher and lower income populations

Figure 5 – perceived differences in the (re)production of environmental deprivation between self-identified urban and rural residents

Figure 6 – perceived differences in the (re)production of environmental deprivation between indoor and outdoor workers

Captions of appendix figures

Appendix figure 1 – Study Site (Hong Kong)

Figure 1

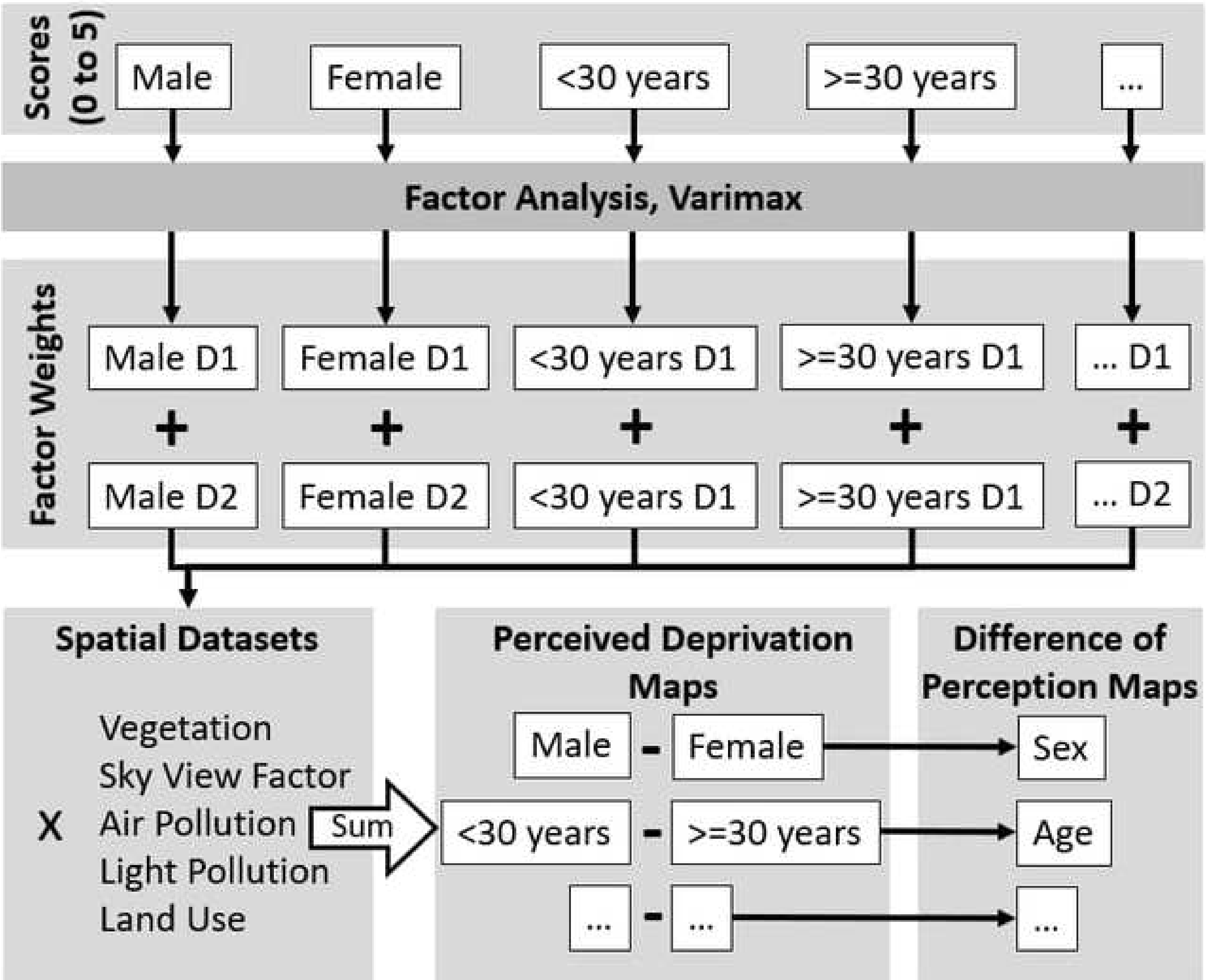
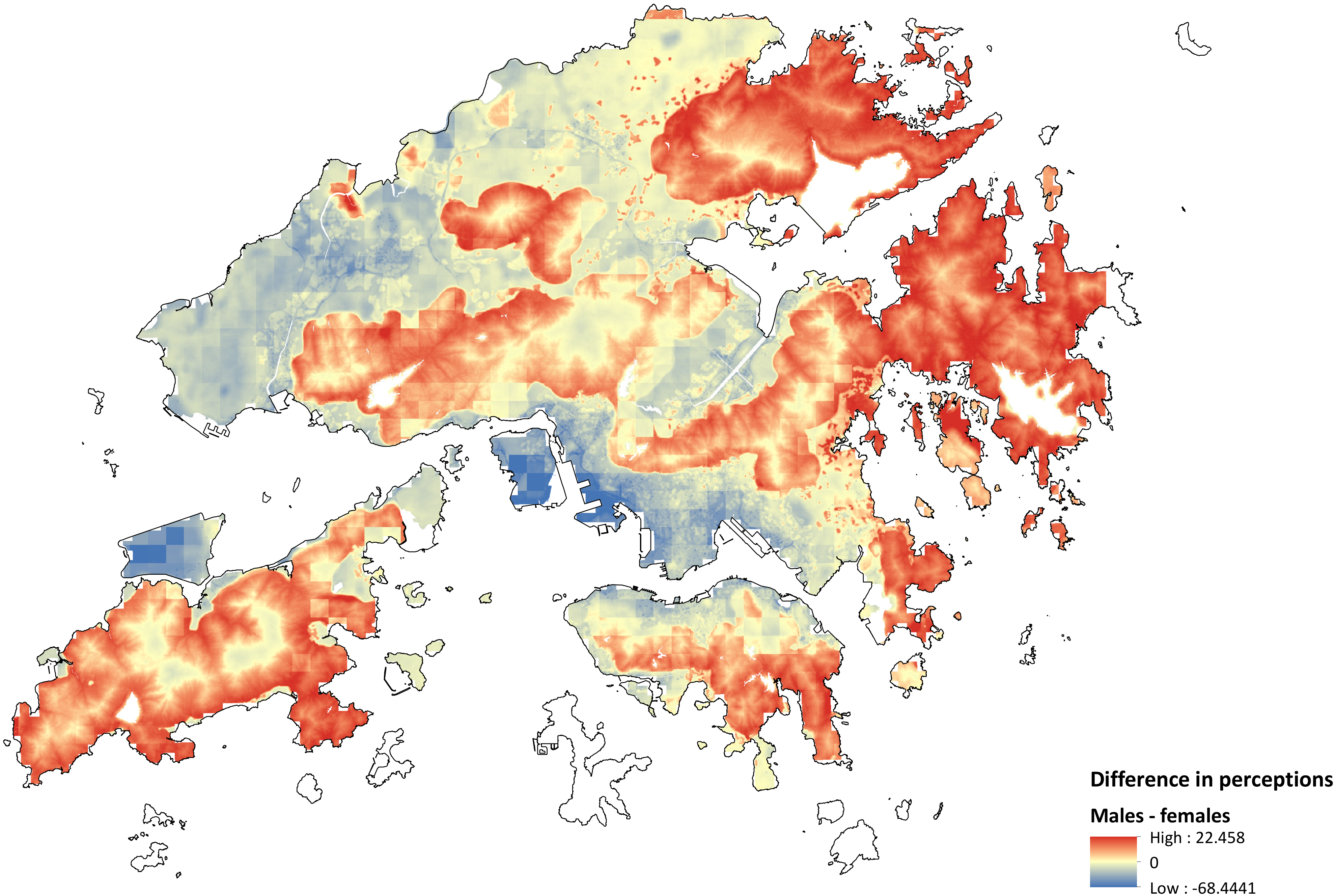
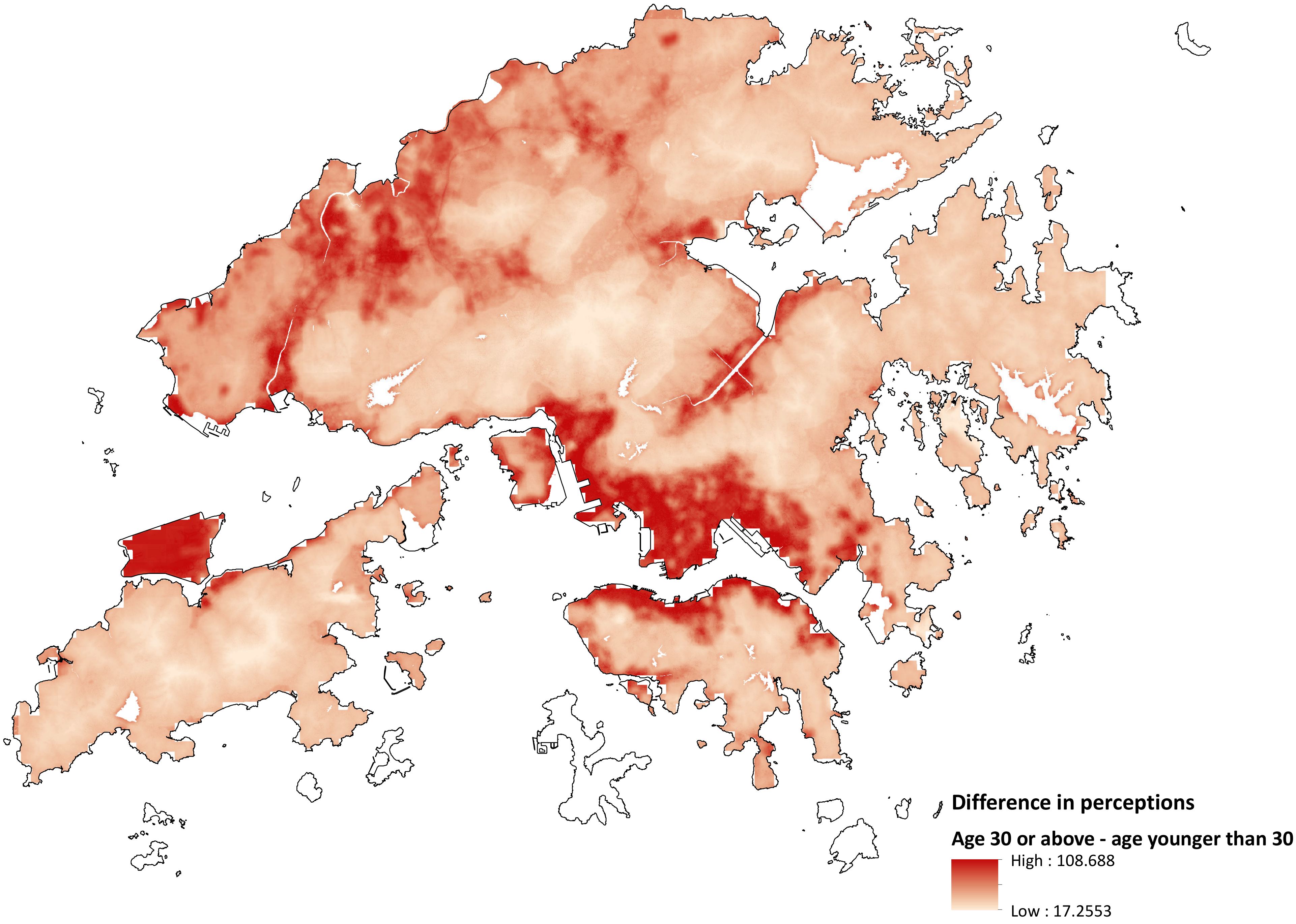

Scores (0 to 5)
Male
Female
<30 years
>=30 years
...
Factor Analysis, Varimax
Factor Weights
Male D1
Female D1
<30 years D1
>=30 years D1
... D1
+
Male D2
Female D2
<30 years D1
>=30 years D1
... D2
Spatial Datasets
X
Vegetation
Sky View Factor
Air Pollution
Light Pollution
Land Use
Sum
Perceived Deprivation Maps
Male
-
Female
<30 years
-
>=30 years
...
-
...
Difference of Perception Maps
Sex
Age
...

Figure 2



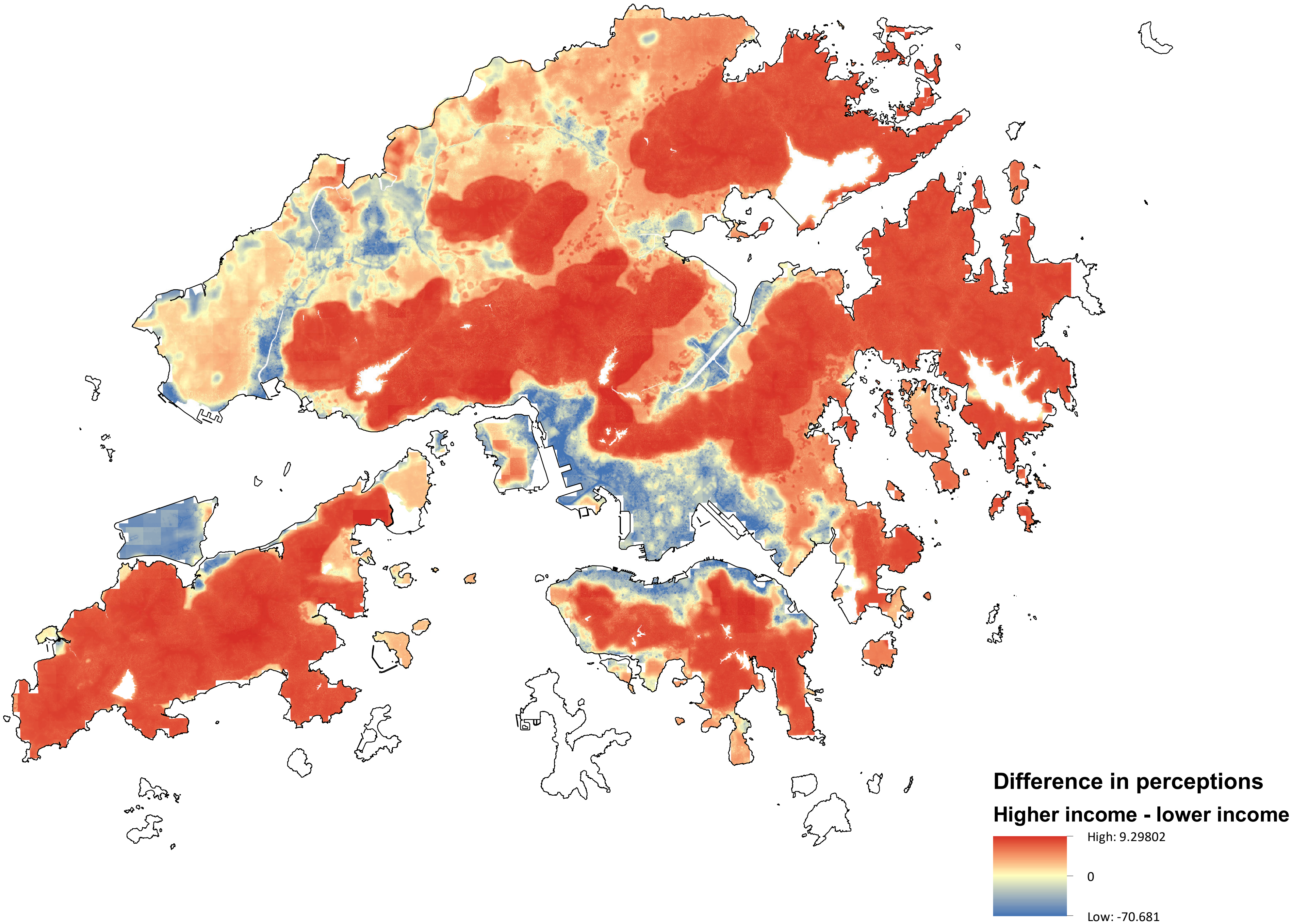
Difference in perceptions
Males - females
High : 22.458
0
Low : -68.4441

Figure 3



Difference in perceptions
Age 30 or above - age younger than 30
High : 108.688
Low : 17.2553

Figure 4



Difference in perceptions
Higher income - lower income
High: 9.29802
0
Low: -70.681

Figure 5

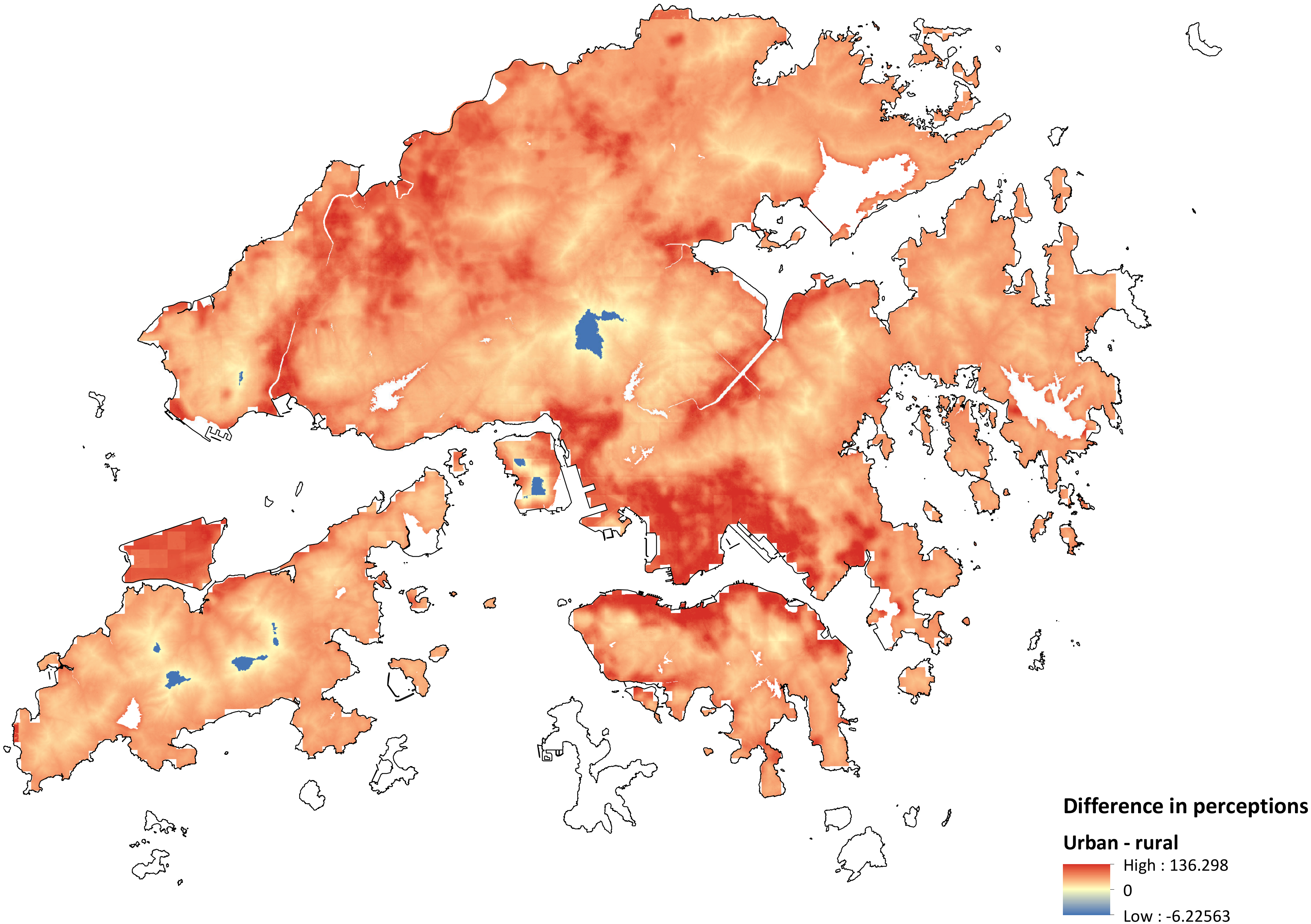
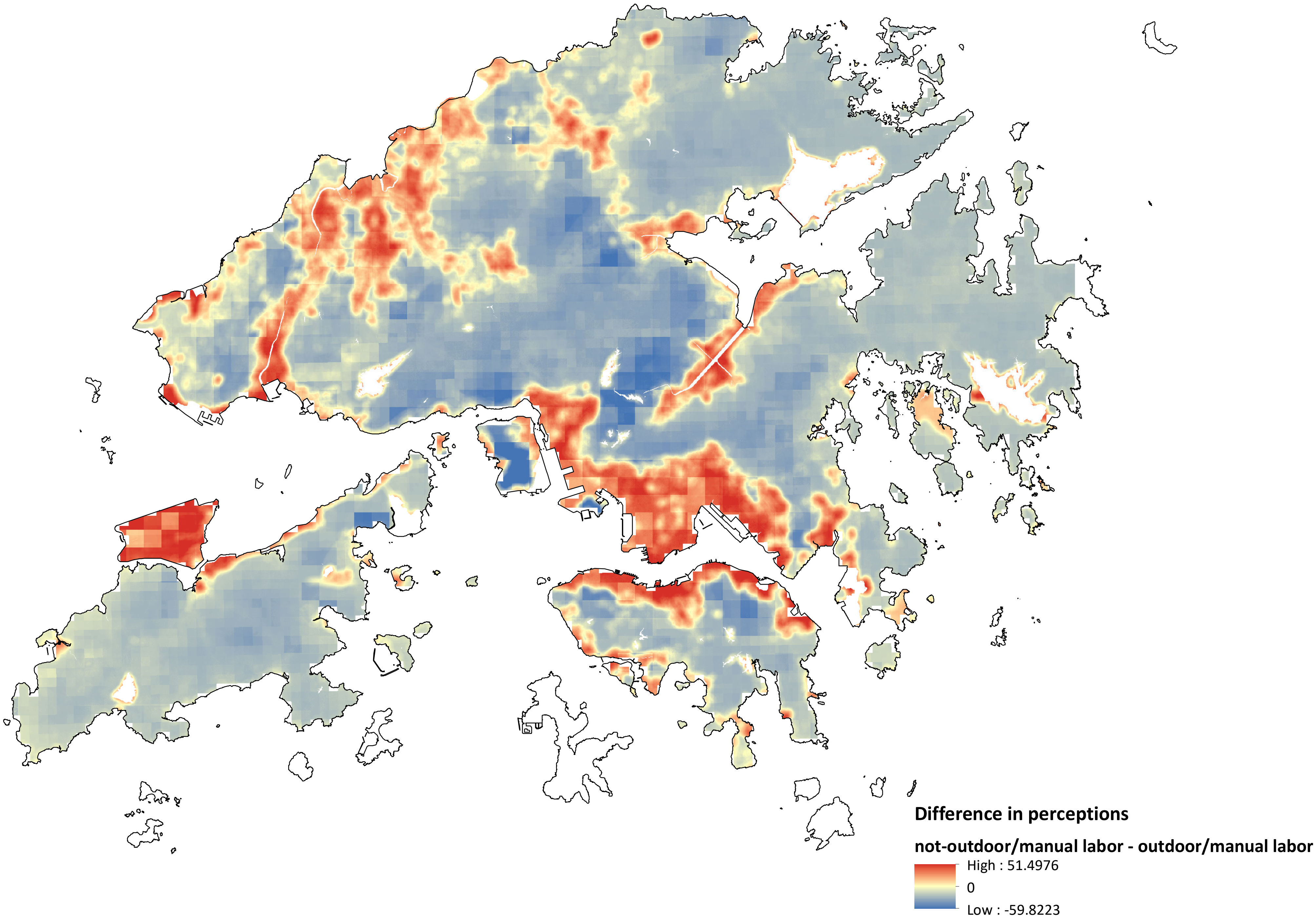

Difference in perceptions
Urban - rural
High : 136.298
0
Low : -6.22563

Figure 6


Difference in perceptions
not-outdoor/manual labor - outdoor/manual labor
High : 51.4976
0
Low : -59.8223

appendix Figure 1