



The stationarity bias in research on the environmental determinants of health

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ABSTRACT

An implicit assumption often made in research on the environmental determinants of health is that the relationships between environmental factors and their health effects are stable over space and time. This is the assumption of stationarity. The health impacts of environmental factors, however, may vary not only over space and time but also over the value ranges of the environmental factors under investigation. Few studies to date have examined how often the stationarity assumption is violated and when violated, to what extent findings might be misleading. Using selected studies as examples, this paper explores how the stationarity assumption can lead to misleading conclusions about health-environment relationships that may in turn have serious health consequences or policy implications. It encourages researchers to embrace nonstationarity and recognize its meaning because it helps direct our attention to the ignored factors or processes that may enhance our understanding of the phenomena under investigation.

1. Introduction

An implicit assumption often made in research on the environmental determinants of health is that the relationships between environmental factors and their health effects are stable over space and time. This is the assumption of stationarity. As indicated by recent studies, however, the health impacts of environmental factors may vary not only over space and time but also over the value ranges of the environmental factors under investigation (Tran et al., 2019; Zhang et al., 2020). But few studies to date have examined how often the stationarity assumption is violated and when violated, to what extent findings might be misleading. As a result, how the stationarity assumption may have affected our understanding of health-environment relationships is far from clear to date.

Further, the stationarity assumption may also influence what findings are considered valuable in the publication process. This can happen when authors, journal editors, and manuscript reviewers do not recognize the meaning and importance of non-stationarity. As a result, studies that did not observe global relationships that hold for entire study areas, study periods, or value ranges of environmental factors may be considered unsuitable for publication (despite observing local relationships for different parts of the study areas, study periods, or value ranges of environmental factors). Because of this tendency to ignore the significance and meaning of nonstationary local relationships and to

recognize the importance of only global relationships (which is an attitudinal issue that may be called the *stationarity bias*), researchers may not seek to publish this kind of works, and even when attempted, editors and reviewers may tend to reject them as not valuable contributions. Over time, the absence of publications that observe only local relationships but not global relationships may lead to the false impression that environmental factors always operate globally. In this manner, the stationarity bias may lead to a publication bias (which is a statistical bias that can happen when manuscripts that observed global relationships have a much higher chance of being published than those that did not) (see Nieuwenhuis, 2016), although whether the bias is serious or can be observed is unclear because many studies may observe both global and local relationships at the same time and get published (when compared to those that only observed local relationships).

However, ignoring the meaning and implications of nonstationarity could still seriously undermine our understanding of the health impacts of environmental factors (Kwan, 2018). It is thus crucial to understand what nonstationarity is and detect its existence in research on the environmental determinants of health because ignoring it may lead to misleading conclusions. This paper seeks to heighten the awareness of authors, journal editors, and manuscript reviewers of the tendency of not recognizing the meaning and importance of studies that observed only nonstationary relationships. It highlights the stationarity bias as an attitudinal issue (a lack of recognition). It focuses on describing three

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types of nonstationarity that can be encountered in research on the health impacts of environmental factors using a limited number of selected studies as examples: spatial nonstationarity, temporal nonstationarity, and value-range nonstationarity. Further, the paper seeks to highlight how nonstationarity may confound research results and what implications they may have for effective health policy interventions. The primary purpose of the paper is to use the selected studies as examples to illustrate the potential impacts of the stationarity bias on our understanding of research findings and intervention measures, not to provide an in-depth discussion of the studies, a systematic review, or a meta-analysis. Further, as mentioned above, how the stationarity assumption may have affected our understanding of health-environment relationships is far from clear to date. The paper is thus an initial attempt to draw the attention of researchers, journal editors, and manuscript reviewers to the stationarity bias and its potential implications for the generation of reliable knowledge and intervention policies. The emphasis is more on increasing awareness than on proposing or describing methods for capturing and addressing nonstationarity (because, as described in this article, methods for this purpose already exist, especially for addressing spatial nonstationarity, and the problem is more the lack of awareness of the stationarity bias than a lack of methods).

2. Spatial nonstationarity

Past studies have observed three types of nonstationarity that can confound the results of studies on the environmental determinants of health: spatial nonstationarity, temporal nonstationarity (which is encountered only in longitudinal studies), and value-range nonstationarity (which occurs when the health impacts of environmental factors vary over the value ranges of the environmental factors under investigation). Spatial nonstationarity exists when the health-environment relationship being examined varies across geographic areas (Siordia et al., 2012). When spatial nonstationarity is present, model coefficients vary spatially, and the results of global models that do not take such spatial variations into account may be misleading (Brundson et al., 1996). An important reason for the existence of spatial nonstationarity is that certain health-environment relationships are influenced or mediated by one or more spatially varying variables not included in the models. For example, the cooling effect of vegetation may vary across space because it is potentially influenced by factors that can significantly affect vegetation growth (e.g., climate or irrigation) but are not considered in the model. For instance, using geographically weighted regression (GWR), a study in New Jersey found that the association between racial minorities and toxic air releases varies over space because such association is mediated by high poverty rates, which vary from place to place (Mennis and Jordan, 2005). In this study, the adjusted R^2 of the global regression models range from 0.25 to 0.33, while the local R^2 or the GWR models range from 0.04 to 0.94, indicating that the GWR models capture a wider range of associations than the global models. The standardized regression coefficients for the variable of the percentage of black population for the global models range from -0.028 to -0.057 , while those for the GWR models range from 0.066 to 0.136, indicating that only the local models found positive associations between higher percentages of black population and higher levels of toxic air releases (while the global models observed counter-intuitive negative relationships between black populations and toxic air releases).

Another study observed that the effects of weather (temperature, wind speed, and precipitation) on people's cycling trips for leisure and commuting vary across space in Rotterdam as a result of varying urban density in different areas (Helbich et al., 2014). This study compared the results obtained from global multivariate logistic regression (LR) models and two types of local models that take spatial nonstationarity into account: autologistic regressions (ALRs) and geographically weighted logit models (GWLM). Using the corrected Akaike information criterion (AIC)

to evaluate model performance, the study found that the local models better capture the associations between weather and people's cycling behavior than the global models (where the AIC of the best-performing global model is 2339, while the AIC of the best-performing local model is 1512). The paper concluded that the effects of weather on people's cycling behaviors vary across space (e.g., between the more densely settled central areas of Rotterdam and the surrounding lower-density areas). Further, the results also reveal differences between leisure and commute trips, where leisure trips tend to be more sensitive to weather and have more noticeable spatial patterns.

The patterns of spatial nonstationarity can be complex. For instance, past studies on the spatial nonstationarity in health-environment relationships yielded a remarkable observation: the health effects of an environmental factor can be positive in some areas but negative in others (e.g., Li and Kim, 2020; Su et al., 2012). For example, using a global ordinary least squares (OLS) regression model and a geographically weighted regression (GWR) model, Siordia et al. (2012) found that although the global OLS model observed a positive association between diabetes and poverty in the U.S., the GWR model observed that the relationship between diabetes and poverty not only varies across geographic areas but also deviates from the "classical" global relationship: poverty is not always positively associated with diabetes, it fluctuates from negative to positive; in some areas, an increase in poverty is associated with a decrease in the prevalence of diabetes. In another study, Wang et al. (2018) investigated the effects of various environmental factors on people's leisure-time physical inactivity in the U.S. using a global OLS model and two local spatial regression models: a spatial lag model (SLM) and a geographically weighted regression (GWR) model. Based on the Akaike information criterion (AIC), the study found that the two local models have better explanatory power than the OLS model: SLM (AIC = 14,745; pseudo $R^2 = 0.744$), GWR (AIC = 13,415; $R^2 = 0.856$), and OLS (AIC = 16,063; $R^2 = 0.608$). It observed that the association between tree canopy coverage and people's leisure-time physical inactivity in the U.S. has a complex pattern: positive in some counties, negative in some others, and no association in the remaining counties, depending on geographic location. These complex spatially nonstationary relationships can help focus researchers' attention on the effects of environmental factors at different geographic areas or regions that are not included in their models. For example, as reported in Wang et al. (2018), it is mainly in western states like Nevada and Arizona that tree canopy coverage has negative associations with people's leisure-time physical inactivity. This means that more tree canopy coverage tends to make people more active in these semiarid or desert areas where trees and green spaces are very limited, while trees and green spaces may not have the same (or as much) physical activity promoting effect in areas with less arid climates.

Similarly, Huang et al. (2020) observed the same kind of complex patterns in the relationship between green spaces and COVID-19 transmission risk in Hong Kong. The study examined the relationship between various built-environment factors (e.g., building density, green space density) and COVID-19 risk using global Poisson regression (GPR) models and geographically weighted Poisson regression (GWPR) models. It found spatially nonstationary relationships between the built-environment factors and COVID-19 risk. For instance, green space is negatively associated with COVID-19 risk in dense urban areas, while the relationship between green space and COVID-19 risk is positive in low-density suburban areas. Again, complex spatially nonstationary relationships like this may help focus researchers' attention to other relevant factors that vary over geographic areas. In Hong Kong, for instance, the density of pubs, restaurants, and shopping malls is high in dense urban areas, where more green space may lower COVID-19 risk (perhaps through reducing the density of high-risk venues and the amount of risky human interactions). However, more green space in low-density suburban areas increases COVID-19 risk because the green spaces in low-density suburban areas in Hong Kong include many country parks that attracted a large number of people to undertake

outdoor activities (e.g., hiking or picnicking) during the lockdowns, which may increase human interactions and the potential contact with infected persons).

Thus, even when a global health-environment relationship is not observed for the entire study area, it does not mean that important and meaningful local relationships do not exist for different parts of the study area (e.g., they may be positive in some areas, negative in others, and yet no relationships exist for the rest of the study area). Note that spatial nonstationarity can be a common issue in studies that cover large geographic areas (e.g., the U.S. or China) because geographic or environmental factors may vary considerably across large areas. For instance, Wang et al. (2018) observed that different climates in different regions of the U.S. influence the effects of tree canopy coverage on people's leisure-time physical inactivity (e.g., tree canopy coverage reduces people's inactivity only in areas with semiarid and desert climates).

3. Temporal nonstationarity

The second type of nonstationarity is temporal nonstationarity, where the health effect of an environmental factor changes over time. A common form of temporal nonstationarity is the periodic changes (e.g., seasonal changes) in health-environment relationships over time. This kind of nonstationarity is often observed in the spread of infectious and vector-borne disease (e.g., influenza and dengue fever), whose spread is influenced by climatic factors with strong seasonality such as temperature or rainfall (Fisman 2007; Ewing et al., 2016; Cazelles et al., 2018). Another form of temporal nonstationarity in health-environment relationships stems from social cycles such as school terms and religious holidays (e.g., Easter and Christmas) (Cazelles and Hales, 2006). Social cycles influence the health effects of environmental factors through changes in the patterns and intensity of human interactions over time. There are now methods for addressing this type of relatively regular and predictable temporal nonstationarity in time series data, such as removing the temporal trends by detrending, implementing seasonal adjustments, or using Bayesian methods (Cazelles and Hales, 2006).

But other types of temporal nonstationarity are more difficult to address. One happens during pandemics such as COVID-19, as people's behaviors change over time in response to changes in perceived infection risk and government control measures (e.g., stay-at-home orders, travel restrictions, and quarantine requirements). As people travel less, conduct fewer out-of-home activities, and participate in fewer social gatherings, the influence of certain environmental factors (e.g., high-risk areas or venues) on disease transmission may decline (Xiong et al., 2020; Huang and Kwan, 2021; Kan et al., 2021). For instance, using longitudinal models and county-level data, a study on the COVID-19 pandemic in the U.S. observed that people's mobility declined in the early stage of the pandemic (March–April 2020) in response to mobility restriction measures (Kim and Kwan, 2021). However, after this early stage, people's mobility quickly bounced back to the usual levels, perhaps due to "quarantine fatigue" (people became tired of staying at home and thus resumed their normal travel despite continued mobility restrictions and the COVID-19 pandemic becoming more serious) (Kim and Kwan, 2021). Similar patterns of changes in people's mobility in response to government COVID-19 control measures were also observed in England, where mobility levels first declined drastically and then gradually returned to normal (Lee et al., 2021).

Interestingly, a study of the COVID-19 pandemic in Hong Kong observed how changes in government control measures over time influenced the temporal distributions of different spatial clusters of COVID-19 cases (Kan et al., 2021). Using space-time scan statistics to identify the space-time clusters of COVID-19 cases, the study observed that the implementation of travel restrictions and quarantine requirements on travelers from Mainland China in early February 2020 led to a significant drop in the clusters of imported cases. As many overseas Hong Kong residents and students returned to Hong Kong since early

March due to the deterioration of the pandemic in Europe and other regions of the world, the Hong Kong Government implemented a series of quarantine requirements on travelers from many foreign countries (e.g., Italy, France, Germany, and Japan). Further, seeing that the number of imported cases increased sharply from mid-March despite the quarantine requirements on all travelers arriving at Hong Kong, the government implemented criminal prosecution and compulsory confined quarantine on quarantine breakers, banned any group gatherings of more than 4 persons in any public place, and required all karaoke lounges, nightclubs, and mahjong venues to be temporarily closed. These control measures led to a steady decline in the clusters of local cases in April 2020.

As these two examples indicate, the mutual influences among COVID-19 risk, people's behaviors and government interventions change over time in a highly complex manner. Ignoring this kind of temporal nonstationarity arising from the changes in people's behaviors or government intervention measures may lead to misleading conclusions about the influences of various environmental factors on the spread of COVID-19. It may also lead to ineffective intervention policies, because restricting people's mobility to control the pandemic may be effective only for a short period in the early stage of the pandemic, as Kim and Kwan (2021) concluded.

Another type of temporal nonstationarity that is difficult to address arises from major changes at different stages of people's life courses. Here, the health effects of environmental factors may change over time due to changes in people's residential neighborhoods, workplaces, and locations of daily activities (Pearce et al., 2016). As a result of these changes, people may have different daily mobility patterns or socio-economic environments that can drastically change their exposures to and the health impacts of different environmental factors (Kwan, 2012). While longitudinal and lifecourse approaches can take into account this kind of temporal nonstationarity to a certain extent, the detailed data (e.g., residential history and daily mobility patterns) needed to address it may not be available or may have serious limitations (Freeman et al., 2020; Jia et al., 2020).

4. Value-range nonstationarity

The third type of nonstationarity is value-range nonstationarity, where the relationship between an environmental factor and its health effects changes, sometimes considerably, over the observed value range of the environmental factor. This kind of nonstationarity may take various forms, one of which occurs when a health-environment relationship changes after the environmental factor reaches a certain value (i.e., the threshold). This phenomenon is referred to as the threshold effect (Tran et al., 2019; Zhang et al., 2020). There are two kinds of thresholds, depending on where they occur along the value range of an environmental factor. Some environmental factors have to reach certain minimum levels in order to have any health impact. For others, a given change in their values after exceeding the threshold may lead to no further change or a dramatic change in the direction or size of its health effects; the former case is the result of reaching a maximal response beyond which further increase in the exposure to the environmental factor will have no additional health impact.

The patterns of value-range nonstationarity can also be complex: the health effects of an environmental factor may be positive or negative or significant or not significant for different value ranges. For instance, Zhang et al. (2020) examined the effects of four bus micro-environmental factors on passengers' momentary mood: noise, temperature, relative humidity, and passenger load (using 10–25 separate linear models to cover the entire value ranges). The study observed nonstationary health-environment relationships that vary in a complex manner. For example, the effect of noise on passengers' momentary mood is not significant in the first 11 models that cover the noise range of 54–78 dB. However, the effect becomes negative, significant, and stronger as the noise level increases beyond the 12th model (65–79 dB).

(Note that the separate models used in the study cover slightly overlapping ranges of the environmental factors using moving windows.)

In the same study, the changes in the relationship between relative humidity and passengers' momentary mood are even more dramatic (Zhang et al., 2020). Relative humidity (RH) has a positive effect on passengers' momentary mood from the 11th to the 17th models (RH = 41–62%). For the 18th and 19th models (RH = 48–64%), the relationship becomes very weak and insignificant. For the 20th and 21st models (RH = 50–66%), the relationship turns significant again but becomes negative. Thus, the relationship between relative humidity and passengers' momentary mood is first significant and positive, then insignificant, and finally significant and negative.

As the study shows, the patterns of value-range nonstationarity can be complex. The health effect of an environmental factor can be positive or negative and can be significant or not significant over different value ranges of the environmental factor. Thus, because of value-range nonstationarity, even when a health-environment relationship is not observed globally (i.e., for the entire value range of the environment factor), it does not mean that significant and meaningful relationships do not exist locally for different sections of the value range. These complex patterns in the health effects of environmental factors cannot be detected using global linear models or non-threshold models. But even when they can be addressed with threshold or nonlinear models (e.g., Zhao et al., 2019; Zhang et al., 2021), the complex patterns of value-range nonstationarity still need to be deciphered carefully in order to obtain a nuanced understanding of the health-environment relationship in question (i.e., why the health-environment relationship changes in a particular way, and what factors explain such changes).

5. Concluding remarks

When nonstationary health-environment relationships exist, research findings at one geographic location, time point or value range cannot be generalized globally, and as a result, it is often impossible to make simple statements that summarize the complex nonstationary relationships observed. Authors, editors, and reviewers thus need to refrain from treating simple global statements about health-environment relationships as the sole indicator of the importance of a paper's contribution. Nonstationary associations draw our attention to factors and processes that affect health-environment relationships but were not included in the analysis (note that some of these factors, like culture, may not be captured by any straightforward measures). We need to embrace nonstationarity, consider it valuable, and realize its importance because it helps direct our attention to the ignored factors or processes that may enhance our understanding of the phenomena under investigation. More importantly, the problem is often not the lack of methods for taking nonstationarity into account (as indicated by the discussion in the last three sections) but the lack of awareness of the importance and meaning of nonstationarity that leads to a disregard of the value of studies that did not observe global health-environment relationships, despite observing crucial local relationships.

The stationarity bias in research on the environmental determinants of health is an attitudinal issue resulting from ignoring the meaning and importance of spatial, temporal, or value-range nonstationarity. The stationarity assumption presumes that only global health-environment relationships for entire study areas, study periods, and value ranges of environmental factors are important. But it ignores the existence and importance of local relationships for parts of the study areas, study periods, and value ranges of environmental factors. It maintains that studies that did not observe global relationships have no meaningful findings.

The stationarity bias can lead to misleading findings of health-environment relationships that may in turn have serious health consequences or policy implications. Because few, if any, studies have examined this issue to date, it can only be explored here with some examples. For instance, in a study of the potential impact of an urban

heat island on thermally sensitive populations (i.e., people with ill-health and older adults) in Taiwan, Su et al. (2012) used geographically weighted regression (GWR) to capture the spatial nonstationarity of the relationships between several land cover types (built-up area, paddy field, and other vegetation) and the surface temperature in Tao Yuan, Taiwan. The study found significant spatial nonstationarity in these relationships and the strength of these relationships was markedly higher in the GWR models than those in the global models (the R^2 values for the global models range from 0.186 to 0.578, while the R^2 values for the GWR models range from 0.607 to 0.718). The urban heat island estimated by the GWR models was 3.17 °C while it was 2.63 °C as estimated by the global models. These results indicate that using the global models and ignoring spatial nonstationarity could lead to an underestimation of the urban heat island, which may in turn lead to a failure to recognize and adequately address the health risks of the thermally sensitive populations. Further, the study by Wang et al. (2018) in the U.S. observed negative associations between tree canopy coverage and people's leisure-time physical inactivity only in the semiarid and desert regions of the country, while tree canopy coverage has a positive association with people's leisure-time physical inactivity in 6% of U.S. counties, and there is no association in 60% of the counties. This means that increasing tree canopy coverage to reduce people's physical inactivity is likely to be effective only in the semiarid and desert regions of the country, and in 60% of the counties in the country, increasing tree canopy coverage is unlikely to have any influence on people physical inactivity. Thus, a policy that is effective in reducing people's physical inactivity in some regions may not be effective in others. The nonstationary associations between environmental variables and leisure-time physical inactivity observed in Wang et al. (2018) can help local government to develop location-specific interventions to encourage people to undertake more physical activity in different geographic areas.

Further, ignoring the temporal nonstationarity in people's response to government intervention measures may lead to the ineffective control of the spread of pandemics (e.g., restricting people's mobility to control pandemics may be effective only for a short period). Finally, the adverse health impacts of an environmental factor (e.g., temperature or noise level) may increase dramatically beyond the threshold level, and health authorities need to be aware of this kind of value-range nonstationarity and take adequate preventive measures. It is thus crucial for researchers and governments to recognize and avoid the stationarity bias, which may hinder our understanding of complex health-environment relationships and undermine the effectiveness of health intervention measures.

Declaration of competing interest

The author declares no competing financial interests.

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