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A Decade Review of Disease Surveillance Research Trends in the International Journal of Health Geographics (2009 to 2018)

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Abstract
The field of health geographics is rapidly growing in its methods and epistemologies. This is a review of the open-source journal *International Journal of Health Geographics*, and the trends in disease surveillance over ten years (2009-2018). Drawing from research review methodologies, we wrote a Python script to quantify research trends within the field of geographic disease surveillance, finding many articles focusing on population health, techniques of GIS, qualitative techniques, and geospatial technology for health monitoring. This was foundational in conducting an in-depth qualitative lexical analysis of article content and epistemologies. Overall, we concluded that over the time period, the Journal has become progressively more epistemologically nuanced through innovative geospatial methodologies. We believe that the inclusion of broader ontologies of sex, gender, race, and obesity could and should eventually be accommodated by ongoing increased rigor in geographic health methodologies and data collection practices.

Keywords: Bibliometrics, Meta-Analysis, Disease Surveillance, Gender Affirmation, Biomedical Research, Health Geography, Data Reliability

Preamble
As part of qualifying examinations in geography for the PhD in Earth and Environmental Sciences at the CUNY Graduate Center, we were tasked with a 10-year review of an influential peer-reviewed journal. Because we have research interests in geographic information science (GISc), demography, and geographies of health, we chose the *International Journal of Health Geographics*. What we learned from engaging in this review was how to identify gaps within a body of texts that are in conversation with one another and why those gaps are important to identify. Firstly, the identification of the gap is to ensure you are engaging in original research and eliminating research redundancy and research funding redundancy. But more importantly, identifying research gaps and journal debates is essential "to determine how the evidence falls short…in order to maximally inform researchers, policy makers, and funders on the types of questions that need to be addressed and the types of studies needed to address these questions," (Robinson et al. 2013).

Introduction
International Journal of Health Geographics (IJHG) is an open access journal distributed by BioMed Central that is dedicated to understanding the relationships between population heath, healthcare systems, social and physical environments, and places. Research themes cover a wide

spectrum of population health, geographic information systems (GIS) techniques, qualitative techniques, and geospatial technology used in health and healthcare research ("BioMed Central" 2020). By limiting its scope to data-driven, human health-related geography research, a collection of insight into a wide range of environmental health concerns from a cohesive epistemological standpoint is produced—strong qualitative deduction from quantitative comparisons within and between spatial units.

A lexical analysis of the journal found that the evolving understanding of environmental space has triggered a broadening range of spatial analysis of health (Pérez et al. 2016). Research within is primarily invested in remedying a network of environments with conditions that are not conducive to maintaining good health and the grander causes of these conditions. Themes in the journal from 2009-2018 include geographic information systems science (GISc) for targeted intervention, stretching new methods to future research, bi- or multi-objective modeling where multiple feature outputs are analyzed simultaneously, multiscalar analysis, census/government-affiliated dataset usage, data reliability/suitability evaluation, and normative semantics of gender/sex[1] and obesity.

Particular attention is paid to subjectivity in the research: both in 1) subjective interpretation of data and 2) the conditions to which people represented in the data are subject. Mapping and data visualization in IJHG represents quantified spatial relationships that have been modeled with underlying qualitative factors, capturing quantitative and qualitative patterns of incidence (Kandwal et al. 2010). Interpersonal contact, animal interfaces, physical activity levels, and food environment become understood as more than just biological issues when placed within socioeconomic or socioecological contexts, including use of local ecological knowledge (LEK) (Hacker et al. 2013, 9; Hernández et al. 2013).

Quantitative Meta-Analysis

First, for the years 2009-2018, we classified articles into different research categories in order to identify research trends. This research classification framework is adapted from various articles that provide a review of certain research topics, like GIS capabilities in epidemiology (Nykiforuk and Flaman 2011; Clarke, McLafferty, and Tempalski 1996), and research goal-specific study approaches for Dengue fever (Louis et al. 2014). The research classification framework consists of 5 steps:

1) Identify research categories
2) Search for number of articles of each research category
3) Determine the dominant research categories
4) Explore the most dominant research category in detail
5) Rank diseases based on number of articles published

[1] IJHG follows Sex and Gender Equity in Research (SAGER) guidelines, which recommend critical analysis of (biological) sex and (psychosocial) gender as important interconnected determinants of health and well-being (Heidari et al. 2016)

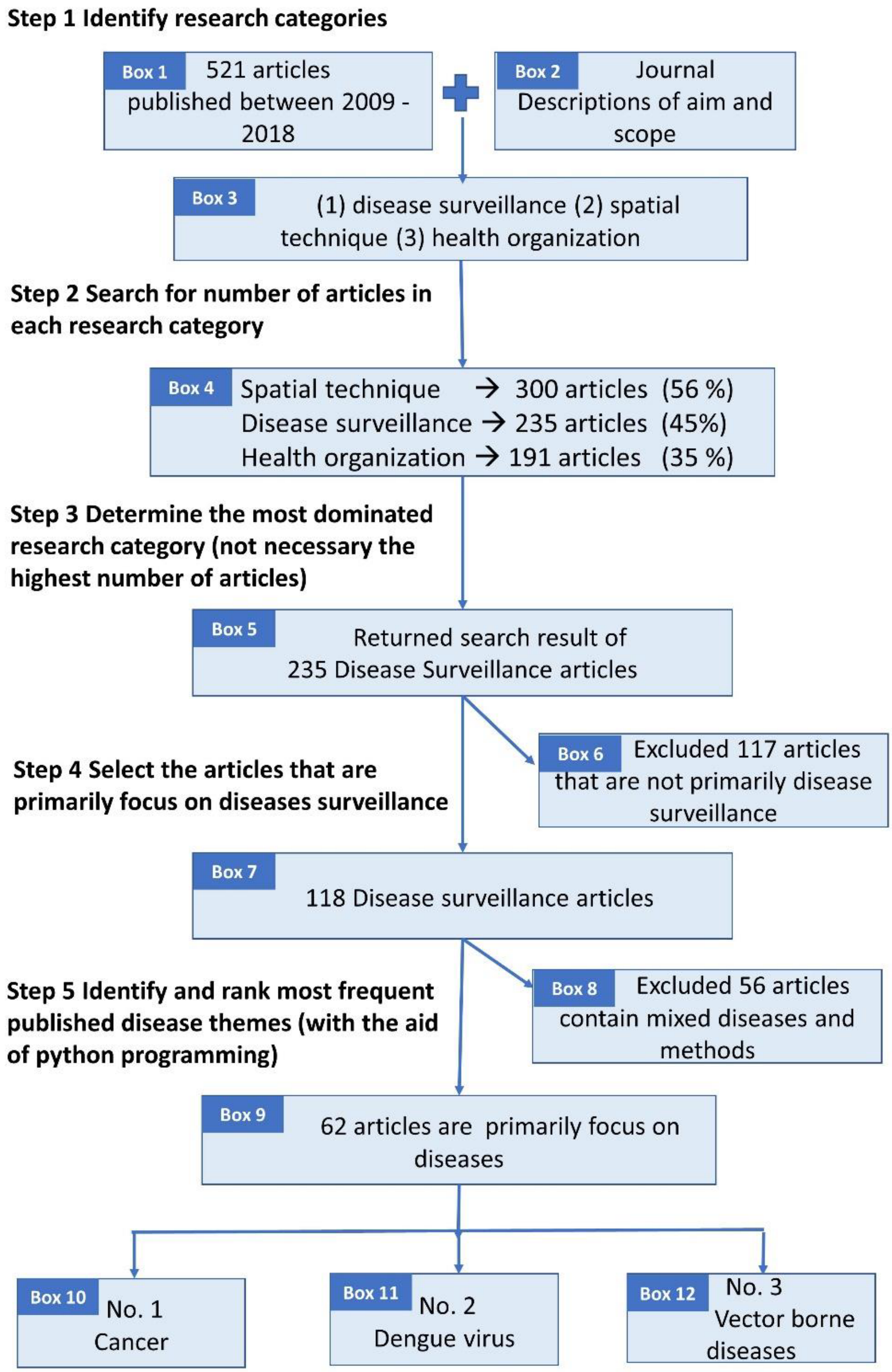

Figure 1:Series of steps to identify research trend and the most published disease. Source: PW

Figure 1 comprises of twelve boxes. Each box is labeled by numbers, such as box 1, box 2, etc. Boxes represent either number of articles or result from completing a preceding step. In step 1, IJHG's official descriptions of research aims and scope (Figure 1, box 2) and articles published in the past three years (precisely 123 articles out of 521 articles in box 1) were used to define research categories. Two important criteria for defining research categories are that definition of a research category should be broad and the definition of each research category must not overlap each other.

Three research categories were identified (Figure 1, box 3):

1) Disease surveillance research: research that performs multi tasks to monitor a disease, such as mapping and modeling

2) Spatial technique research: research that proposes new spatial or quantitative techniques or modifying existing ones

3) Health organization research: research that focuses on health institutions, healthcare systems, and health communities in the aspects of management, governance, and planning services.

After defining research categories, we searched for the number of articles of each research category by using IJHG's internal search engine (Figure 1, step 2) using categories shown in box 3 as a search keyword. For example, "disease surveillance" was used as a search keyword for disease surveillance research category. This was repeated for all other research categories: "spatial techniques" and "health organizations". Of 521 articles, 300 articles (56%) are spatial techniques. 235 articles (45%) are disease surveillance, and 191 articles (35%) are health organizations (figure 1, box 4).

Of course, summing percentages in box 4 yields more than 100% (> 521 articles) because some articles fall under more than one research category. Although the spatial technique research category has the highest percentage (56%), many of these spatial technique articles should be labeled in the disease surveillance category. Every disease surveillance project uses spatial techniques to monitor a disease. Only articles that provide theoretical explanations are considered spatial techniques research category. In short, disease surveillance and spatial technique are two related categories, in which the spatial technique can be perceived as a sub-topic of disease surveillance.

Findings

The 235 disease surveillance articles returned from the website search term "Disease Surveillance" (Figure 1, box 5) are not all purely disease surveillance research. Although all 235 articles study diseases, some have research goals that rather focus on a disease management or governance perspective.

For example, Mao et al. (2012) studied influenza pattern in the U.S., but the goal of the research is to assess the economic impact from the disease rather than monitor the spreading of the influenza. Another example is Chu et al. (2013), who studied dengue transmission, but the research goal is to locate areas for insecticide spraying. Both are excluded from disease surveillance (Mao et al. 2012; Chu, Chan, and Jao 2013). Another 117 similar articles are also excluded from the discussion (from box 5 to box 6).[2]

There are 52 articles focusing on both diseases and evaluating spatial methods (from box 7 to box 8) that are excluded. Hence, there are 62 articles remaining that focus primarily on diseases (from box 7 to box 9) as the final article samples. The diseases studied in these 62 articles were summarized and ranked. Boxes 10, 11, and 12 (figure 1) are the top three most published diseases, which are cancers, dengue virus, and vector borne diseases. The complete disease ranking result is shown in Table 1, below.

Table 1: Rank of disease surveillance articles that focus on disease surveillance published 2009-2018.

Rank	**Number of Articles per Category**	**Disease/ disease agent/health condition/environmental condition**	**Number of articles (2nd column multiplied by 3rd column)**
1	15	Cancers	15 Articles × 1 Category= 25 Articles
2	11	Dengue Virus	11 Articles × 1 Category= 11 Articles
3	6	Vector Borne Diseases	6 Articles × 1 Category= 6 Articles
4	5	Malaria	5 Articles × 1 Category= 5 Articles
5	4	Influenza, Mosquito	4 Articles × 2 Categories= 8 Articles
6	3	West Nile Virus, Infant Low Birthweight, Obesity	3 Articles × 4 Categories= 12 Articles
7	2	HIV, Diarrhea	2 Articles × 2 Categories= 4 Articles
8	1	Cardiovascular Disease, Cryptosporidiosis, Chikungunya, Diabetes, Heatwave, Lyme Disease, Legionellosis, Noise, Particulate Matter (PM), Polio, Tuberculosis (TB), Sexually Transmitted Disease (STD)	1 Article × 12 Categories= 12 Articles
			Total= 62 Articles

As seen in Table 1, cancers and dengue are the top two surveilled diseases. They contrast in the sense that one is non-communicable, and the latter is communicable through vector agents. Of all the articles in Table 1, disease surveillance research in general involve three generic tasks: 1) mapping, 2) risk analysis, and 3) modeling.

[2] There are 118 articles remaining (box 7), An additional spreadsheet file shows this in more detail [see Additional file 1]

Disease Mapping

Disease mapping is a fundamental task in disease surveillance research. Maps are a powerful way of telling the story of a health problem because well-made maps are generally easy to understand and display a lot of information very quickly (Ebener et al. 2015). Disease surveillance research data for mapping come from various sources, such as geocoded addresses, GPS data, and satellite imagery. For example, 27,301 dengue fever cases were geocoded before mapping the disease incident in Columbia (Martínez-Bello, López-Quílez, and Prieto 2017). Similarly, 98,849 household locations were georeferenced to analyze country bug infestation in urban areas of Arequipa, Peru (Delgado et al. 2013). GPS has also been used to map disease transmission at various scales (Chang et al. 2009; Qi and Du 2013)

Maps that are created for disease surveillance research are meant to display disease locations, distribution, pattern, area at risk, and socioeconomic and environmental factors contributed to spreading of diseases. Frequently, after map visualization, researchers try to seek disease clustering and hotspot locations (concentrated locations of high quantities of disease incidents) to better understand disease concentration (Louis et al. 2014; Kronenfeld and Wong 2017; Duczmal et al. 2011).

Disease cluster detection can be performed at one point in time or over a period of time. There are two main types of cluster detection methods: global methods and local methods. Which clustering detection methods to use – global or local – depends on the decision of researchers. For example, *tuberculosis bacillus* (TB) death clustering of people with HIV in Africa of each year, between 1991 to 2006, was detected using Global Moran's I (Uthman et al. 2009). Local Moran's I was also used to detect clusters of a single West Nile Virus incident in the U.S. (Sugumaran, Larson, and DeGroote 2009). On the other hand, influenza clusters in Japan were detected over time from 1999-2009, using weighted standard distance techniques (Shobugawa et al. 2012).

Disease hotspot locations are usually locations where high values of disease incident are surrounded by much lower values. Similar to cluster detection, the disease hotspot detection can be done at a particular point in time or over a period of time (Chen et al. 2016). Cuadros et al. (2018) used a set of spatial techniques, particularly local indicator of spatial association (LISA), to detect hotspots of HIV incidents in South Africa and Tanzania. Hotspot locations are areas that public health department or health official need to pay particular attention for the purpose of disease prevention (Louis et al. 2014). Once both cluster and hotspot locations are confirmed, a researcher may proceed to perform risk analysis.

Risk Analysis

Hongoh et al. (2011) emphasize that risk analysis seeks to understand locations where risk occurs and how different locations have different risk levels. In their dengue fever risk mapping research, Louis et al. (2014) stated that there are four purposes of risk analysis: describing the risk, validating the risk, predicting the risk, and warning the risk. Risks are often associated with hostile environments that facilitate disease growth. For instance, high temperature facilitates the spreading of vector diseases, such as dengue, zika, chikungunya, malaria, and yellow fever (Ducheyne et al. 2018; Hagenlocher et al. 2013; Carbajo, Cardo, and Vezzani 2012). Note that a hostile physical environment is not the only reason that makes population vulnerable to disease risk. Certain demographic and socioeconomic conditions also contribute to risk and disease vulnerability. For instance, the elderly and youth demographic characteristics are vulnerable populations to dengue disease. Certain socioeconomic conditions such as poor housing condition, low formal education, and employment, also make population even more vulnerable to the dengue disease (Louis et al., 2014).

Furthermore, some risk analysis techniques require that disease incidents or disease rates are known throughout the study area. However, in reality, research data are often collected at sample locations and extrapolated to represent a larger area. Hence, it is common that risk analysis relies on interpolation techniques to estimate disease rates and incidents at non-sample locations. For example, Kriging is one of the most widely used interpolation techniques. Cuadros et al. (2018) used Kriging interpolation to compute continuous HIV disease prevalence surface in South Africa and Tanzania and then assess the HIV population at risk. The benefit of risk analysis is that it helps indicate targeted areas for public health programs to tackle the disease problem (Hongoh et al., 2011).

Disease Modeling

Some disease research attempts to predict and simulate disease incidents through disease modeling. Carbajo et al. (2012) classified two modeling approaches based on the studies of dengue disease: 1) theoretical modeling and 2) empirical modeling. Theoretical modeling considers all variables that are part of disease transmission and try to predict the disease incidents, whereas empirical modeling attempts to seek disease distribution based on actual disease incident data and environmental variables (Carbajo, Cardo, and Vezzani 2012). Wen, Hsu, and Hu (2018) used a theoretical modeling approach, creating three different statistical models to predict human mobility and dengue disease distribution. In contrast, Chan et al. (2015) used an empirical modeling approach to forecast dengue fever based on dengue incidents in Kaohsiung City, Taiwan.

Different regression techniques are often used in modeling to quantify the relationships between disease and disease related variables. For example Poisson modeling is used for studying ambient air quality and cardiovascular disease (Yoo, Brown, and Eum 2018). Amoah et al. (2018) also used Poisson geostatistical modeling to study malaria in Africa. Although both studies are Passion regression based, Yoo et al. (2018) and Amoah et al. (2018) have very different modeling outputs, implying that disease modeling provides lots of opportunities for improving and modifying exiting techniques.

Disease Surveillance in Cancer Research

After discussing common tasks of disease surveillance research, based on table 1, cancer is the next most prominently featured disease. When considering cancers by gender, the most popular study of gendered cancers are breast cancer, for women, (Mandal et al. 2009; Tian et al. 2010; Bauer et al. 2013; Lemke et al. 2015; Klassen et al. 2015; Tatalovich et al. 2015) and prostate cancer, for men (Hinrichsen et al. 2009; Mandal et al. 2009; P. Goovaerts and Xiao 2011) respectively. Other frequently studied cancers are colorectal cancer (Henry et al., 2009; Mobley et al., 2010) and lung cancers (Lemke et al. 2013) for both of those genders. Some studies examine multiple types of cancer (lung, breast, prostate, female genital system, colorectal cancers) in one publication (Philips et al. 2011; Mandal et al. 2009).

Cancer research usually begins with mapping cancer incidents and other variables related to cancers to understand their spatial distribution. For example, Tatalovich et al. (2015) mapped late-stage breast cancer (LSBC) incidents in “females” aged 40 and older from 2006 to 2010 in eight U.S. states[3]. The LSBC incident mapping then allows Tatalovich et al. (2015) to examine the differences of LSBC incident rates among the eight states with respect to different social factors and ethnic groups. Goovaerts and Xiao (2011) also started their research of late-stage prostate cancer diagnosis in the "male" population across 67 Florida counties from 1981-2007 by mapping the disease incidents. Then, they explained temporal difference between race and types of areas (urban versus rural areas) (Goovaerts and Xiao, 2011).

There are no specific cancer clustering detection methods that dominate the research. Cluster detection methods are case-specific. Hinrichsen et al. (2009) used three different global spatial clustering detection methods—1) Cuzick-Edward's k-NN, 2) Moran's I, and 3) Tango's Maximized Excess Events Test (MEET)—to identify high prostate cancer incident areas in Maryland, whereas Mandal et al. (2009) used only one method—local Getis-Ord Gi*—to detect clusters of female breast cancer and male prostate cancer of all counties in the U.S..

In cancer research hotspot analysis often performs after cluster detection. For example, Hinrichsen et al. (2009) look for cancer hotspot for different cancer stages in order to understand cancer spatial distribution of different stages after the confirmation of cancer clustering. Mandal et al. (2009) identify the difference of cancer pattern between female breast cancer and male prostate cancer across the U.S. first and then performed hotspot analysis.

To better explain cancer incidents, researchers often examine the relationships between cancer incidents and demographic, socioeconomic, and physical environmental factors through regression techniques. Multiple demographic characteristics are often included in cancer research. For instance, Henry, Niu, and Boscoe (2009) examined age and gender to help explain colorectal cancer survival. "Race and ethnicity" is a popular demographic factor used in many cancer researches. For instance, Tian et al. (2010) examined the relative and absolute racial disparities of breast cancer mortality among different ethnic groups. Goovaerts and Xiao (2011), and Ruktanonchai et al. (2014) also focused on race.

There are a wide range of socioeconomic variables used in cancer research, ranging from common variables, such as employment status, income level, to less common variables, such as phone ownership (Phillips et al., 2011). Cancer studies often examine multiple socioeconomic variables rather than one single variable. Interestingly, some cancer research associate socioeconomic variables with health behaviors, such as Mobley et al (2010) studied cancer in population that practice cancer prevention through endoscopic screening. Klassen et al. (2015) also studied the relationship between women with breast cancers and smoking behavior of women across different ethnic groups, and social classes.

For physical environmental factors, cancer research tends to relate physical environmental factors to risk exposures. The techniques used on physical environmental factors also involve interpolation and modeling. For example, Goria et al. (2009) performed risk analysis of population residing around municipal solid waste incinerators, in which they might be exposed to toxic chemical miasma.

Hendryx et al. (2012) examined mortality from cancer and non-cancer of population that lived near polluted water discharge locations. Interestingly, Bauer et al. (2013) studied the correlation between exposure to highly illuminated nightlights and breast cancer using lung cancer as a reference.

[3] New Jersey, Georgia, Kentucky, Louisiana, California, Utah, Iowa, New Mexico

Our disease ranking in Table 1 has two implications. First, the top-ranking diseases, such as cancer and dengue virus, indicate high demands that such diseases need to be understood most urgently. Conducting research on the most published diseases would certainly provide research community with more information for disease prevention and mitigation planning. Second, diseases that are at the bottom of the ranking can imply that these diseases are understudied and there are needs for further research to be done. There is a high demand for research and plenty of disease surveillance research opportunities to offer for both studying a disease and inventing new disease surveillance techniques.

Trends in Targeted Intervention and Health Risk Behaviors (HRB)

Identifying candidates for targeted intervention involves proposing strategies for environmental health concerns such as treating patients (healthcare provision), slowing the spread of disease (ill-health prevention), and/or remediating any sociospatial landscape component that indicates or is linked to poor health outcomes[4]. The goal is to decrease exposure to hazards in order to increase good health at the scale of the community, (Drackley, Newbold, and Taylor 2011; Dutey-Magni and Moon 2016, 16; Hacker et al. 2013, 9; Mavoa et al. 2011, 2; Santos, Chor, and Werneck 2010; Zhang et al. 2013; Zhou and Li 2018).

HRBs are often attributed to socioeconomic and political factors. Environments determined to foster HRBs are targeted for intervention. Predicated on the idea that poor environmental conditions promote behaviors that lead to increased risk of ill health, IJHG identifies the condition(s) and prescribes improvement of those conditions to reduce HRB. Disability and poverty, especially within elderly populations, motivates many researchers to propose modification to the built environment for decreasing access and functional limitations, and sedentary lifestyles (Etman et al. 2016; Vallée and Chauvin 2012). Sedentary lifestyle HRBs are also linked to poverty and the associated lack of recreational time-space for vulnerable groups (i.e. youth populations) (Grigsby-Toussaint, Chi, and Fiese 2011; Marzi, Demetriou, and Reimers 2018).

Poor perception of the environment is specifically found to increase multiple HRBS, including sedentary lifestyle (Boulos and Yang 2013; Marzi, Demetriou, and Reimers 2018; Wang et al. 2019; Zhou and Li 2018), intake of harmful substances (Spilkova, Dzúrova, and Pitonak 2014), unsafe sex practices (Westercamp et al. 2010), and failure to seek or continue medical treatment. For example, past difficulties in hospitals leads to poor perception of the hospital environment, which is linked to failure to seek medical treatment, which is in turn linked with poor community health outcomes. Bad experiences have far higher impact on failure to seek medical treatment than Euclidian distance to facilities, at least in countries with socialized health care (Cavalieri 2013; Vallée and Chauvin 2012; Spilkova, Dzúrova, and Pitonak 2014).

Discrimination on the basis of gender/sex, race, sexuality, HIV-status, or other stigmatized social statuses may be linked to an increased risk of poor experiences in hospitals and alienation from the formal healthcare system (Kandwal et al. 2010). So, people living in the sociospatial margins are at greater risk of ill health. As such, the relegation of poor people to live in the socio-geographic margins is violent and deadly. In fact, even referring to the issue as

[4] The term "health outcomes" is used as opposed to "health" because this journal is largely looking at population data at the scale of the community as opposed to the scale of the body. The field of health geographics, as distinct from health care, is primarily concerned with manipulation of the environment as opposed to individual health treatment plans.

"social" is less apt than referring to it as "political," especially if we need to avoid placing blame on the people living within the clusters.

National Context for Healthcare Analysis

Failure to seek or continue formal health care is attributed to varying socioeconomic obstacles between countries. Compared with western Europe, failure to seek health services functions contrarily in the United States, which uses primary care provider-led health care (PHC-led) systems, where individuals are likely to be impeded by a lack of health insurance or confusion about how their particular insurance works. In European countries with socialized health care, lack of vehicle ownership (a distinct indicator of poverty), especially in remote or rural areas, is the prime obstruction to health care access (Comber, Brunsdon, and Radburn 2011).

PHC-led systems have high impedance to health care access because navigating the PHC-led health care landscape is expressly more complicated, (Lin, Wan, Sheets, Gong, & Davies, 2018, p. 6)[5]. Hypothetically, if one has a suspected tumor in the United Kingdom, they can often go straight to an oncologist for cancer testing and diagnosis. Mapped, this is a three-point process (home-oncologist-home). In the PHC-led system, one's HMO will require a patient to see their primary physician, who will decide whether or not to refer them to a radiologist, who will send results back to the primary physician, who then will decide whether or not to refer to them to an oncologist—a nine-point process. In this case, there is a higher likelihood of the patient dying prematurely or dropping out of the testing/diagnosis/treatment process, especially in patients who have limited mobility in time-space (Hossain and Laditka 2009, 3; Mobley et al. 2006).

Mobile Technologies and Time-Space

Healthcare provision planning and emergency service planning are highly contingent on understanding human navigation of the environment. One digital method to measuring people's movements is the rendering of Precision Information Environments (PIEs), as described in "Crowdsourcing, Citizen Sensing and Sensor Web Technologies For Public And Environmental Health Surveillance And Crisis Management," (Boulos et al. 2011), which is the most accessed article in IJHG's history. PIEs…

> "aim at providing tailored access (i) to information from multiple data streams/sensors, and (ii) to analysis, simulation, decision support, and collaboration/communication capabilities. PIEs achieve this through novel interactions that adapt to the varying users (e.g., first responders, policy makers and the public) and phases of emergency management (from planning to response, recovery and mitigation) in distributed situation room and field settings," (Boulos et al. 2011, 3).

These data environments can be sourced from multiple mobile devices, like mobile phones or stand-alone GPS devices attached to bikes.

The budding popularity is likely due to mobile gaming's ability to fill in technology barriers to data aggregation cited in many IJHG projects, (Browne, Goldstein, and Rasbash, n.d.; Burgoine, Alvanides, and Lake 2013; Comber, Brunsdon, and Radburn 2011). This includes integration of sensor technologies, augmented reality (AR), virtual reality (VR), GPS, GIS,

[5] This article, *A multi-modal relative spatial access assessment approach to measure spatial accessibility to primary care providers, utilizes a* Gaussian function, which is an impedance function that adds a coefficient to account for social impedance in travel, including the particular cost of travel and the particular time it takes to travel to the facilities from different zones.

Internet connectivity, street imagery, and machine learning for novel approaches to health promotion, including getting people to increase their physical activity through gameplay (Fisher and Lassa 2017; Boulos et al. 2017; Wang et al. 2019; Wong 2017). Mobile tools that acquire dynamic data (Ray and Ebener 2008; Delamater et al. 2012; Schootman et al. 2016; Zhou and Li 2018, 2) are useful because "travel and health service access is complex, not reducible to a few static modelled outputs." These approaches "use a unique set of tools to explore this complexity, promote discussion and build understanding in order to produce better planning outcomes" (Fisher and Lassa 2017, 13). For increasing access to health care, it has the potential to measure how people navigate a landscape and locate safe and well-perceived spatial units (Boulos and Yang 2013; Boulos and Robinson 2009).

Health geographers are interested in comparing data at two or more scales or within the same timeframe in two or more locations with the hopes of uncovering environmental factors in the ecological, built, and/or social landscape that might be causal or correlated. It is important to note that although there is not always a direct or exclusive causation of illness or risky behavior, certain factors, like discrimination, dilapidation, crowding and violence, "at least exacerbate such problems" (Peters 2013c, 259).

Sex and Gender Subjectivities

Although the technology is capable of aggregating data on multiple gender subjectivities, the data itself fails to include multifaceted sex and gender data. Multivariate and bi-objective modeling can be made to accommodate a more diverse set of people if more information about the individuals are available (Gu, Wang, and McGregor 2010). Technologies become obsolete and so research methods need to be ahead of the game to avoid serious gaps in knowledge. IJHG includes articles that review and rank different technologies for best suitability (Robertson and Nelson 2010), but the question remains as to whether the data being analyzed are complex enough.

Likewise, the cultural landscape changes. Socioeconomic affairs change the circumstances and ontologies under which research is being conducted. Emergence of new viral and bacterial diseases like HIV and new forms of hepatitis and herpes, new mental health ontologies, and even an unprecedented death by "air pollution" do not fit into the current epidemic transition model, (BBC, 2019; Peters, 2013b, p. 120). Anti-binary, spectral, or prismatic paradigms of gender, sex, chromosome combinations, genitalia, and sexuality do not fit into current demographical models either and remain stigmatized.

Stigma alienates people from natural support systems. Not seeking or continuing medical treatment is, in itself, a major HRB that impacts individuals outside a cisnormative, heteronormative, or genital-normative body. Regardless of the specifics of identity, "disclosure of a [presumed] gay lifestyle can severely hamper access" to someone's natural support system, (Baez 1996, 71–72). Stigma evolves into dehumanization and oppression when those biases lead to exclusion of such groups from medical data that is used to create law and government policy, and allocate health resources.

Although data buckets can never fully characterize a person, the inclusion of more demographic categories and more options within each category may help in a process of normalization that reduces stigma and some of stigma's consequences in the medical community, especially HIV. People should be able to report their sex and gender separately, and each gender and sex category should have multiple options across the prisms of gender and sex. Placed specifically in the context of geography, studies like "Geospatial Analysis Of HIV-

Related Social Stigma," add to the existing literature on stigmatized behavior the movements of people suffering from stigma so has to use the behavioral patterns to plan improved interventions (Westercamp et al. 2010; Kandwal et al. 2010).

Including historically erased subjectivity in formal scientific health research can serve to socially destigmatize the subjectivity. Urgently, that includes mental ill-health stigma, intersex stigma, HIV stigma, and gender and sexuality stigma. This journal focuses on manipulation of the environment, so it would be an appropriate venue to start protective work on intersex or other binary non-conforming groups. This is because, in the health care landscape, instead of manipulating the landscape to accommodate a wider set of differentiated human bodies, manipulation occurs at the scale of the body.

Particularly, in order to navigate the therapeutic landscape, intersex individuals' genitals are surgically manipulated to assimilate into the narrow imaginary of genital differentiation. The surgery can be violent, particularly those who are surgically given vaginas, and happens at such a young age that intersex people do not even know they are intersex. Documents on nonconsensual genital manipulation for intersex individuals is specifically done for "better quality sexual intercourse" (Woodhouse 2004). This is rooted in a narrow heteronormative, cisnormative, genital-normative, and pregnancy-normative imaginary of sex and sexuality.

Types of Bodies Neglected in the Therapeutic Landscape

The therapeutic landscape, the realm of health geographics, and the world at large do not accommodate certain bodies, whether because of body size, intersex status, or gender nonconformity. IJHG has demonstrated vestment in subjectivity and it would be a valuable progression to increase both the depth (number of variants within each category) and breadth (number of categories) of the data collected about individuals. Self-reported data is imperfect, but it can reveal a wealth of information. In the case of data reliability, when datasets are not broad or deep enough to account for certain individuals' demographic data, people are subsumed into best-fit categories, thus are erased in the data and unaccounted for in the landscape. For example, fertility and fecundity studies only include "females" aged 14 to 49, and births to people outside those age groups are placed into the closest fit age category, erasing data on pediatric and geriatric birth (Peters 2013a).

Society is extraordinarily stratified. There is some research that has served to expose healthcare disparities at the level of race and gender, but there are several likely gaps in self-reported race and gender data, especially when there are not enough checkboxes for someone to accurately illustrate their experienced subjectivities. Articles in IJHG focus on data reliability and/or suitability, but rarely focus on data complexity. Since data aggregates are the epistemologies of health geographics, this could be remedied by the inclusion of broader ontologies of sex, gender, and race.

This prescription to remedy the data gap calls for seemingly unorthodox gender and sex data, but just like people fall into multiple ethnic and racial categories, they also fall into highly differentiated categories of sex and gender. Merely allowing someone to self-identify in both a gender option and a sex option, and adding a third+-sex and third+-gender to each category could open up an unprecedented wealth of knowledge.

Advances in the tools and methods, and the research emerging from GISc give us the capacity to analyze human health data in a way that better approaches a depiction of people that matches reality by capturing our unique subjectivities in the data[6]. IJHG already utilizes varied and sophisticated methods to better employ subjectivity to the world of health care.

If data collection is deeper and wider, more subjectivities can be formally included in the healthcare landscape, minimizing people's alienation from healthcare provision or service delivery. It would also refine geostatistics on how illnesses manifest differently for different demographics, how illnesses might manifest similarly in different demographic subsets, what social structure might exacerbate morbidity and mortality when biological processes appear to be the same.

Bi-objective modeling is used to survey demographic disparities in breast cancer, denoting a significantly lower mortality for non-Hispanic white women than other groups, (Tian, Goovaerts, Zhan, & Wilson, 2010; Tian, Wilson, & Zhan, 2011). Examinations of racial and demographic disparities in prostate cancer have been less conclusive during this time period, but the research is still gender- and sex-exclusive (Goovaerts and Xiao). However, there are likely greater barriers to gynecological health for transmasculine people, for example, which would indicate disparities in sex-linked health conditions. 33% of articles in Volumes 9-17 include the word "female," but absent entirely are "transgender," "gender non-conforming," "non-binary," "agender," and "intersex" individuals, all of whom have health needs that extend beyond the genital-sex-gender binary ontology (and are likely statistically significant). They are rendered invisible by the data and the analysis.

For example, if it is found that transgender people disproportionately die from breast cancer, what correlations are found there? Do people taking estradiol vs. testosterone hormone replacement therapy (HRT) vary in their morbidity? Outside this journal, it is found that "an increased risk of breast cancer in trans women [with HRT] compared with cisgender men and a lower risk in trans men [with HRT] compared with cisgender women," supporting an argument that cisgender and transgender individuals should be subject to the same screening and treatments (Blok et al. 2019, 1). However, what is lacking is the comparison of, say, breast or ovarian diseases in transmen and ciswomen who have not undergone HRT, where a major difference between the groups might be real and perceived safety entering facilities for obstetrics and gynecology and the HRB of simply not going, (CHCUW, 2011).

A sex binary, gender binary, and sex-gender-genital link is perpetuated by datasets that contain only "male" and "female"[7] information. Women and men as mutually exclusive patient groups is cisnormative and treated as incidental, with descriptive remarks of which "gender" may be more predisposed to an illness in that dataset, like colorectal cancer for "men," (Henry, Niu, and Boscoe 2009; Mobley et al. 2010) or regarding health conditions traditionally linked to one "sex" (e.g., pregnancy, breast cancer, prostate cancer), (Pierre Goovaerts and Xiao 2011; Tatem et al. 2014; Vieira et al. 2008). Resultantly, the concept of "women's health" refers exclusively to cisgender women of reproductive age (Tatem et al. 2014).

One limiting factor in how deep or broad data has been within this journal has been use of data from health care records and the census or other "official" datasets. While use of information from health care records, censuses, and other "official" datasets has been a limiting factor in health geographics research, private industry has been mining massive amounts of intimate personal data such that marketers eschew grouping people by demographic information

[6] There are additional critiques of privacy risks in using GIS for public health see: (Boulos, Curtis, and AbdelMalik 2009; Jung and El Emam 2014)

[7] Datasets are available for all published works.

(sex, age, location) for a "tribe"-based model[8] in which "brands can layer attitudinal and behavioral insights on top of demographic data to paint a far richer, more nuanced picture of real people" (Bakhtiari 2019). Moving away from the traditional demographic data "isn't easy, it requires major investment, first-party data and qualitative insights into the underlying thoughts, dreams, challenges and needs of both individuals and groups," (ibid). Unfortunately, there are a slew of potential privacy issues with mining people's digital data and there are seemingly far fewer resources for health care research and meta-analysis than for multi-national corporations.

Debates on a Western Model of Obesity and Ill-Health

Varying conclusions about the three-way intersection of obesity, food environment, and physical activity are also in conflict. Whereas obesity is a statistical correlative for certain ill-health outcomes, it is treated as directly causal to ill-health. An internal journal conflict is among the differing ontologies of obesogenics, wherein some scientists enforce the obesogenic environment thesis: that obesogenics are resultant of the food environment, and some conclude they are independent of the food environment, especially when evaluated outside of a western model of obesogenics.

Many researchers hypothesize a direct link between obesity and an obesogenic food environment or link physical activity to obesogenics, with a normative assumption that the food environment determines dietary intake, (Burgoine, Alvanides, and Lake 2013; Burgoine and Harrison 2013; Harrison et al. 2014; Maguire et al. 2017). There are questions surrounding whether the food environment and dietary intake are actually co-constitutive. For example, Bivoltsis et al. (2018) suggest that other analyses of spatial exposure (including 'availability' and proximity) to food outlets does not in fact result in conclusive evidence that food environment proximal to the home determines food intake.

Whereas the connection between the food environment, dietary intake, and obesogenics, "brings some needed focus to food industry and regional planning practices, which potentially assigns culpability to powerful and malignant actors," race and class subjugation are downplayed, reinforcing healthism, because those same spatial units that are "characterized as obesogenic tend to have features that, when juxtaposed to the ideal [leptogenic] environments, reveal important, unstated preferences for certain types of places and their attendant lifestyles [which] may ironically worsen wealth disparities among different environments," (Guthman 2011, 67).

Studies of the food environment take place "in predominantly western settings," to the extent that western epistemology of the food environment is erroneously "generalized to other cultural contexts," (Hanibuchi et al., p. 6). For example, Maguire's evaluation of the socioeconomic differentiations of the food environment in the UK are not applicable to socioeconomic differentiations of the food environment across Asia (Maguire et al. 2017). In non-Western settings like Aichi Prefecture, Japan, those in proximity to supermarkets had equal likelihood of high BMI compared to those near fast food restaurants, which directly contradicts similar aforementioned studies in the west (Hanibuchi et al. 2011). Many people were determined to have access to neither, and thus are underweight and likely malnourished. Similar work in Africa also indicates a challenge to the western-centric assumption that daily calorie-intake is linked to level of nutrition and that poverty, malnutrition, and hunger are directly related, (van Wesenbeeck, Keyzer, and Nubé 2009). In Ethiopia, for example, poor people still

[8] like Volvic's "tribes with shared passion points" or Netflix's "taste communities"

consume the recommended 2,000 kCal/day, but there is instead a high incidence of malnutrition. In context, the Ethiopia in this snapshot could be an eligible subject for Zapada-Caldas et al.'s biofortification targeted intervention project (2009).

Overall, the obesogenic environment thesis attributing obesogenics to a social model erroneously problematizes larger bodies, which is evidenced by ignoring factors that might make a body "skinny," (Guthman 2011, 153–56). For example, there is a lack of acknowledgement of the obesity paradox, where those who are obese are more likely to survive acute illnesses at equal or higher rates than those in the normal weight range, and at significantly higher rates than those who are underweight. Within this problem, the obesogenic environment thesis neglects the political economy of food distribution.

Conclusions

Among disease surveillance research, disease mapping, risk analysis, and disease modeling are the most common tasks that disease surveillance researchers performed. Although these three tasks are distinct, they should not be treated separately. They are in fact interconnected and this interconnection provides comprehensive descriptive and quantitative information of the disease locations through map visualization and spatial analyses. The results from the three common tasks also indicate who the population at risk are, what factors and variables contribute to the disease, and what the situation would likely to be in the future or of certain conditions were to be introduced.

IJHG's contributors are already questioning ontologies and epistemologies of obesogenics and the environment and there is already precedent for MMMC/multivariate modeling methods, so complex geographic analysis of sex and gender is possible, (Ali et al. 2007; Cavalieri 2013; Mobley et al. 2010; Sartorius and Sartorius 2013; Zhang et al. 2013). MMMC is important to capture individuals because "all people are members of multiple and overlapping social groups," within which they are both objects and agents (Katz 2001, 714).

Ease of specificity in collecting data for targeted goals using real-time user participation, high global rates of mobile data connectivity, and use of rapid data transmission from emerging technologies is an expected progression in IJHG*,* for which data reliability has been amongst the main obstructions in the varying theoretical frameworks and methods. It is also important to note that since it costs approximately $2900.00[9] to publish in IJHG, most authors may need additional or reallocated funding for their work. Volumes that have running themes (food environment, respiratory illness, etc.) tend to run in conjunction with a contemporaneous boom in grants available for research in those fields.

In the realm of health, morbidity must be evaluated at the scale of the body within specific biogenic understanding, at the scale of the environmental conditions in which the morbidity is experienced, and at the scale of the nation-state of healthcare under which the people are subsumed. The work herein seeks to describe and/or propose modification to the landscape of health and wellness through the critical use of quantitative geospatial analysis.

Overall, IJHG publishes thoughtful, timely works that point toward a mutual goal of increasing world health through environmental justice. Over the time period, the Journal has become progressively more epistemologically nuanced through innovative geospatial methodologies. We believe that the inclusion of broader ontologies of sex, gender, race, and obesity could and should eventually be accommodated by ongoing increased rigor in geographic

[9] Cost as of 2022. These funds are used to keep the journal freely and permanently accessible online.

health methodologies, but the starting point must be in the data collection phase before it is distilled down for analytical uses. Robust methodologies could open a pathway to run more in-depth data, and thus create a demand and justification for increased rigor in data collection for disease surveillance. Emerging methodological technologies have the potential to deepen epistemologies and ontologies, producing a snapshot of the health landscape that approaches a clearer picture of reality.

Abbreviations

AR: Augmented Reality
GIS: Geographic Information Systems
GISc: Geographic Information Science
GPS: The Global Positioning System
HIV: Human Immunodeficiency Virus
HMO: Health Maintenance Organization
HRB: Health Risk Behavior
HRT: Hormone Replacement Therapy
IJHG: International Journal of Health Geographics
LEK: Local Ecological Knowledge
LSBC: Late-Stage Breast Cancer
LISA: Local Indicator of Spatial Analysis
MEET: Maximized Excess Events Test
MMMC: Multiple Membership Multiple Classification
NOAA: National Oceanic and Atmospheric Administration
PHC-led: Primary Care Provider-Led Health Care
PIE: Precision Information Environment
PM: Particulate Matter
STD: Sexually Transmitted Disease
TB: Tuberculosis/*Tuberculosis Bacillus*
UK: United Kingdom
U.S.: United States
VR: Virtual Reality

Availability of Data and Materials

The Python algorithm for sorting is available from the authors on reasonable request. The spreadsheet of articles from Figure 1, Box 7 can be found in the supplementary files.

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Authors' Contributions

PW wrote the Python script, conducted the quantitative meta-analysis related to disease surveillance, and generated the research trends series. RJ conducted the meta-analysis of qualitative trends in targeted intervention, national contexts, and data-bucket inclusion and exclusion. All authors read and approved the final manuscript.

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