Dissertation Proposal

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Contents

1 Introduction

1.1 Urban systems and public health

Approximately 55% of the global population lives in urban areas with this number expected to increase to two-thirds by 2050 (United Nations, Department of Economic and Social Affairs, and Population Division 2019). Urbanization is accompanied by a suite of surface modifications that effect the surface-energy balance, hydrological flows, and the availability of vegetation, creating distinct and varied microclimates (Pickett et al. 2001). These modifications vary spatially, creating uneven landscapes of environmental externalities and benefits as well as infrastructure access. These spatial variations in turn affect and are effected by demographics and are often distinct along income and racial lines (Heynen, Perkins, and Roy 2006). Systematic inequalities arise from zoning practices and disinvestment and have a long historical legacy (Wolch, Byrne, and Newell 2014). These three subsystems–meteorological, physical, and social–are highly interdependent with complex feedbacks, and interact in complex ways characterized by non-linear dynamics and thresholding behaviors, operating across a variety of spatial and temporal scales (Liu, Dietz, Carpenter, Alberti, et al. 2007; Liu, Dietz, Carpenter, Folke, et al. 2007; McPhearson et al. 2016). Understanding the interactions of these subsystems is crucial to understanding cities as coupled human-natural systems, which is itself crucial to understanding the spatial variability of public health in urban areas.

Urban systems are complex and incorporate disparate elements usually siloed within separate disciplines (Bai et al. 2018). It is inefficient to study human and natural systems separately when attempting to undestand their interactions (Liu, Dietz, Carpenter, Folke, et al. 2007). Likewise, research is usually done in the abstract, without a focused eye to solving real-world problems. Research should provide usable solutions (Liu, Dietz, Carpenter, Folke, et al. 2007; McPhearson et al. 2016). Addressing these problems successfully involves transdisciplinary work that can examine urban systems as intersections of social, physical, environmental, and atmospheric systems (Bai et al. 2018; McPhearson et al. 2016). Understanding urban systems is a critical first step in understanding how they may respond to climate change (Bai et al. 2018). If risk can be understood quanititatively it can be projected under different climate change scenarios (McMichael 2012). Measures of public health can be used as an outcome for modelling these coupled human and natural systems.

Public health can be defined as the health of entire populations, from neighborhoods to cities to countries and on (Trochim et al. 2006). As the world becomes increasingly urban, understanding the dynamics of public health in urban environments and how they interact with climate, the environment, and society becomes increasingly important. Public health requires transdisciplinary approaches to modelling the complex systems that interact to produce variabilities in outcomes (Trochim et al. 2006). Understanding the structural variability of public health across these domains can allow for better public policies (McPhearson et al. 2016).

1.2 Weather and public health

It is intuitive to understand that weather has an effect on human health. Besides disasters like floods and tornadoes, everyday meteorological conditions effect health as well. Extremes of heat and cold can exacerbate existing conditions and effect cardiovascular and respiratory function and may lead to increased mortality (Ferreira Braga, Zanobetti, and Schwartz 2001; Soneja et al. 2016). Heat also facilitates the formation of ground-level ozone and precipitation and wind effect the severity of allergen concentrations. Atmospheric pressure and humidity likewise have effects on human health. These effects often occur at a temporal lag. Not only do atmospheric condictions affect public health, but they do so differentially across social groups (Liu, Dietz, Carpenter, Folke, et al. 2007).

Ayres-Sampaio et al. (2014) found that hospital admissions due to asthma were positively related to high levels of NO_2, low NDVI, and high temperatures, however, they examined each of these variables independently in simple linear regressions. Temperature, NO_2, NDVI, and relative humidity are not independent of each other and in fact the authors used altitude to calculate both the air temperature and NO_2 estimates. Land use was also used in the NO_2 estimates, one type of which is vegetated which would likely be highly correlated with NDVI. Furthermore, they used six year seasonal averages of these variables. Babin et al. (2007) found a positive relationship between O_3 and pediatric asthma but their dataset spanned only three years.

1.3 Urban infrastructure and environment

Urban infrastructure and environment vary spatially within the urban context and are likely to produce variabilities in health based on proximity to features. Highways and railways are major sources of pollution as are power plants and other large electrical facilities. Greenspace is known to reduce land surface temperature just as impervious surfaces are known to increase it. Villeneuve et al. (2012) found that there was an inverse relationship between greenspace and mortality. Urban trees contribute to improved air quality by reducing air pollution concentrations (Nowak, Crane, and Stevens 2006). Urban core areas are effected by the urban heat island where the increased percentage of impervious surfaces elevates temperatures. Age and material of housing stock are also likely to impact the health of residents.

1.4 Social determinants of health

It is well known that large disparities of health outcomes exist across socio-economic spectra, with minorities and the poor having the worst outcomes. These social determinants of health also vary spatially often along with the physical determinants of health present in the urban system. It is essential to understand how the social determinants interact with the climatic and physical systems to produce variabilities in public health vulnerability in order to prioritize the distribution of resources. Babin et al. (2007) found a logarithmic relationship between pediatric asthma-related emergency departmnet visits and the percentage of children living below the poverty level but this data was aggregated to the zip code level.

1.5 Current limitations

While there are many calls for transdisciplinary and systems-based approaches to studying urban areas, few studies have actually attempted to answer the complex questions posed by urban systems. In particular, public health studies in this vein are even fewer. While some studies attempt to understand the variability of public health vulnerability in relation to heat and the built environment, the data are too aggregated to get a sense of the actually spatial dependency of these relationships. Likewise, many studies look at heat-related mortality, however, these counts are not only low enough to be statistically problematic, the mortality coding is problematic as well. Few, if any, studies incorporate atmospheric, physical, and social systems.

The long-standing paradigm for studying urban systems was to conceptualize them as human systems superimposed upon natural systems. It has become clear that a more accurate model is that of coupled and natural systems which explicitly characterize the multidirectional and dynamic interactions between these systems. The modelling of coupled and human natural systems requires statistical techniques that unite data across spatial and temporal scales and can derive meaning over many levels of uncertainty. Improving these techniques will be key to predicting the effects of climate change on public health. Understading how human and natural systems are coupled requires modeling the couplings across spatial and temporal scales (Liu, Dietz, Carpenter, Folke, et al. 2007).

1.6 Research questions

How do social determinants of health interact with climate and urban infrastructure and environment to produce variabilities in public health outcomes?

2 Data

Studying the interactions of urban systems and the relationship with public health requires both an outcome and an instance. The proposed research seeks to explore and describe pediatric asthma in the Kansas City metropolitan area as an example of the variability of public health and how that relates to the spatial and temporal variabilites and interactions of atmospheric conditions, enviromental characteristics, and social factors.

Asthma is a chronic inflammatory disease that is associated with a collection of symptoms that produce breathing difficulties (Won et al. 2016). Asthma has been variously shown to be effected by air pressure, temperature, thunderstorms, allergens, and air pollution (Won et al. 2016; Soneja et al. 2016). Asthma occurrence has been shown to be higher in individuals living close to highways and railways and other high traffic density areas. Asthma is associate with social factors as well and occurrence also tends to be higher in people of color and among the urban poor (Won et al. 2016). However, few studies examine the synchronicities between these factors.

2.1 Study area

The Kansas City metropolitan area as delineated by the United States Census Bureau is located at 39.0398°N latitude and 94.5949°W longitude and spans two states and six counties: Johnson and Wyandotte Counties in Kansas, and Platte, Clay, Cass, and Jackson Counties in Missouri. The Köppen climate classification is humid subtropical (Cfa), with rainfall year round, averaging 964mm annually. The annual temperature average is 12.8°C, with a maximum average high of 26.1°C in July and a minimum average low of -2°C in January (https://en.climate-data.org/location/715044). The Kansas City metro area exhibits characteristic patterns of urban sprawl, which is generally defined as "geographic expansion over large areas, low-density land use, low land-use mix, low connectivity, and heavy reliance on automobiles relative to other modes of travel" (Stone, Hess, and Frumkin 2010) showing a 55 percent increase in built area between 1972 and 2001 (Ji 2008). The Kansas City metro area had an estimated population of 2,142,419 in 2018, a 5 percent increase from 2000. An estimated 24.2% of the population are under the age of 18. 73.9% of the population under the age of 18 are identified as white alone, 7.4% as black alone, 0.3% as American Indian alone, 3.2% as asian alone, 0.4% as native Hawaiian alone, and 2.6% as some other race alone. 6.9% of the population identify as two or more races and 11.7% identify as hispanic or latino of any race. In 2018, 5.1% of children under the age of 18 lived in households with income below the poverty level and 7.6% lived in households receiving some kind of public assistance. 31.4% live in single parent households (https://data.census.gov/cedsci).

2.2 Pediatric asthma

KC Health CORE is a collaborative initiative between Children's Mercy Hospital and the Center for Economic Information at the University of Missouri, Kansas City created to investigate the geographic disparity of pediatric health outcomes. This analysis will use pediatric asthma data from 2001-2012 geocoded to street centerlines based on the patients' home address at the time of admission. Although the dataset contains information on the years 1999 and 2001, the observations seem inconsistent with the remaining years. There is a good possibility that this is due to differences in data procedures those years will not be considered. The data come from a retrospective collection of pediatric asthma encounters within the Children's Mercy Hospital network. In this instance children ages 2-18 are considered. The original medical records were formatted according to Table 1.

The data were further classified into three severity levels with one being the lowest and 3 being the highest according to the International Classification of Diseases, 9$^{\text{th}}$ revision diagnoses codes (ICD-9) and the patient class. The patient class records both the location and the type of treatment received by the patient–e.g. controlled vs. acute care, inpatient vs. outpatient, etc. See Kane (2020) for more details.

2.3 Atmospheric data

Atmospheric data include both station and satellite observations. The spatial variation of meteorological data will be assessed using remotely-sensed data including land surface temperature (LST) and other variables to be determined based on availability. LST from the Moderate Resolution Imaging Spectroradiometer (MODIS) are available daily at 1 km spatial resolution, with two passovers during daylight—once in the morning and once in the afternoon—and two during the nighttime. Cloud cover produces low-quality images so the 8-day composite images may be a suitable alternative depending on the desired temporal resolution. This data can be accessed and manipulated using the Google Earth Engine analysis platform (https://

Table 1: Structure of the original pediatric asthma data records submitted by CMH to UMKC-CEI.

Category	Attributes
Diagnosis	Date of admission ICD-9 code Event account number Patient medical record number (MRN) Patient residential address
Demographics	Birthdate Sex Race Ethnicity
Visit characteristics	Payment type Patient class

earthengine.google.com/). Derived variables may include: LST anomolies relative to the mean and the diurnal temperature range.

Station data were retrieved from the NOAA National Centers for Environmental Information for the Kansas City Downtown Airport, MO, US. The station is located at 39.1208°N, 94.5969°W. Daily precipitation totals, maximum temperature, and minimum temperature were retrieved for all dates between 1900-01-01 and 2019-10-19. Daily average wind speed, direction of fastest 2-minute wind, and direction of fastest 5-minute wind were retrieved for the years 2000-2012. Daily maximum 8-hour ozone concentration and daily mean PM2.5 concentration were retrieved from the EPA for the JFK Community Center in Kansas City, KS, US, located at 39.117219°N, 94.635605°W for the years 2000-2012. These data represent the daily temporal variability of atmospheric conditions for the entire study area although there is certainly unaccounted for spatial variability. Derived variables may include: daily percentile values, number of days in a row that values exceed a predetermined threshold value (e.g. 95th percentile high temperature days to indicate a heat wave), diurnal rangess, and seasonal trends.

2.4 Environmental data

Land cover data comes from the Mid-America Regional Council (MARC) created the Natural Resources Inventory (NRI) map of Greater Kansas City with an object-based classification, using SPOT data from May, June, and August of 2012 as well as ancillary data (LiDAR, hydrography, parcels/zoning class, transportation centerlines, streamlines, and floodplains). The resulting land cover map has an estimated accuracy of 83 - 91% for the Level I classifications of impervious, barren, vegetated, and water. Impervious comprises buildings and other impervious surfaces, barren comprises land with 0 - 10% vegetated fraction, vegetated comprises land with 10-100% vegetated fraction, and water comprises water features. The spatial resolution of the NRI landcover map is 2.5 m and the extent is the 4,423 square miles that comprise the 9 county Kansas City metropolitan area (Mid-America Regional Council and Applied Ecological Services 2013). An alternative or complementary land cover dataset is the National Land Cover Dataset (NLCD) produced by the United States Geological Survey (USGS), a 30 m resolution land cover map, including percent of impervious surface, based on Landsat imagery (http://www.mrlc.gov). A more specifically urban-oriented classification system is comprised of local climate zones (LCZs), "regions of uniform surface cover, structure, material, and human activity that span hundreds of meters to several kilometers in horizontal scale" (Stewart and Oke 2012). The scheme delineates 17 separate LCZs, each with a distinct temperature regime originating from a relatively homogenous collection of surface properties, primarily the density and height of roughness objects o(Stewart and Oke 2012).

Additionally, spatial features from the built environment will be acquired for the study area, including, but not limited to: street and highway network, rail network, and power infrastructure. Traffic density data will also be acquired if possible. Derived variables may include density of or proximity to infrastructure networks or greenspace.

2.5 Social determinants of health data

There are two primary levels of social determinants of health for this study: individual and community. Each observation of pediatric asthma is coded for sex, race, age, ethnicity, and payment type—specifically Medicaid or other state coverage, private insurance, or self pay. Community-level characteristics come from the United States Census (https://data.census.gov/cedsci/). Variables include the percent of minority residents, percent of households below the poverty level, and the percent of owner-occupied households. While the block group is the highest resolution of census geography for which this information is available, the unit of analysis will likely be the census tract due to the geographic sparsity of daily pediatric asthma observations. The census tract is roughly equivalent to a neighborhood and the associated data provide an appropriate proxy for community structure.

3 Preliminary analysis

Basic relationships between variables calculated at the census tract level for the summer (June, July, August) of 2010 (Figs. 1, 2, 3, 4, 5, 6). LST is the median MODIS pixel value in degrees Celsius, asthma rate is the number of pediatric asthma cases per number of children, the percent minority is the percent of total residents who are non white, and the mean percent impervious is the mean NLCD percent impervious pixel value all calculate at the census tract geography.

4 Limitations of simple modeling techniques

- Missing data—cloud cover, etc.
- Trying to combine qualitative and quantitative data types.
- Spatial and temporal granularity
  - (census tracts dividing the city; days, weeks, months, years)
  - levels of detail
- collinearity

These issues are interesting as well as problematic.

"Environmental processes arise from interactions of various processes. These interactions are often occurring at various scales in space and time. Although it is often convenient to simplify such systems either by ignoring the multivariate interaction, or by assuming spatial/temporal stationarity, linearity, and Gaussianity, it is increasingly the case that the scientific questions of interest are becoming sufficiently complex that one can no longer justify such assumptions." (Wikle 2003). "these data are often of differing spatial and temporal support, orientation, and alignment, relative to the process of interest" (Wikle 2003) "the environment encompasses many different interacting processes. It follows that one of the biggest challenges and growth areas in environmental statistics will be concerned with linking the many processes contributing to specific environmental questions of concern" (Wikle 2003).

"THere are varying intervals of time between human-nature interactions and their ecological and socioeconomic effects." (Liu, Dietz, Carpenter, Folke, et al. 2007)

"Studying CHANs requires a new paradigm that emphasizes hierarchical couplings of natural and human sysems across organizational, spatial, and temporal scales." (Liu, Dietz, Carpenter, Folke, et al. 2007)

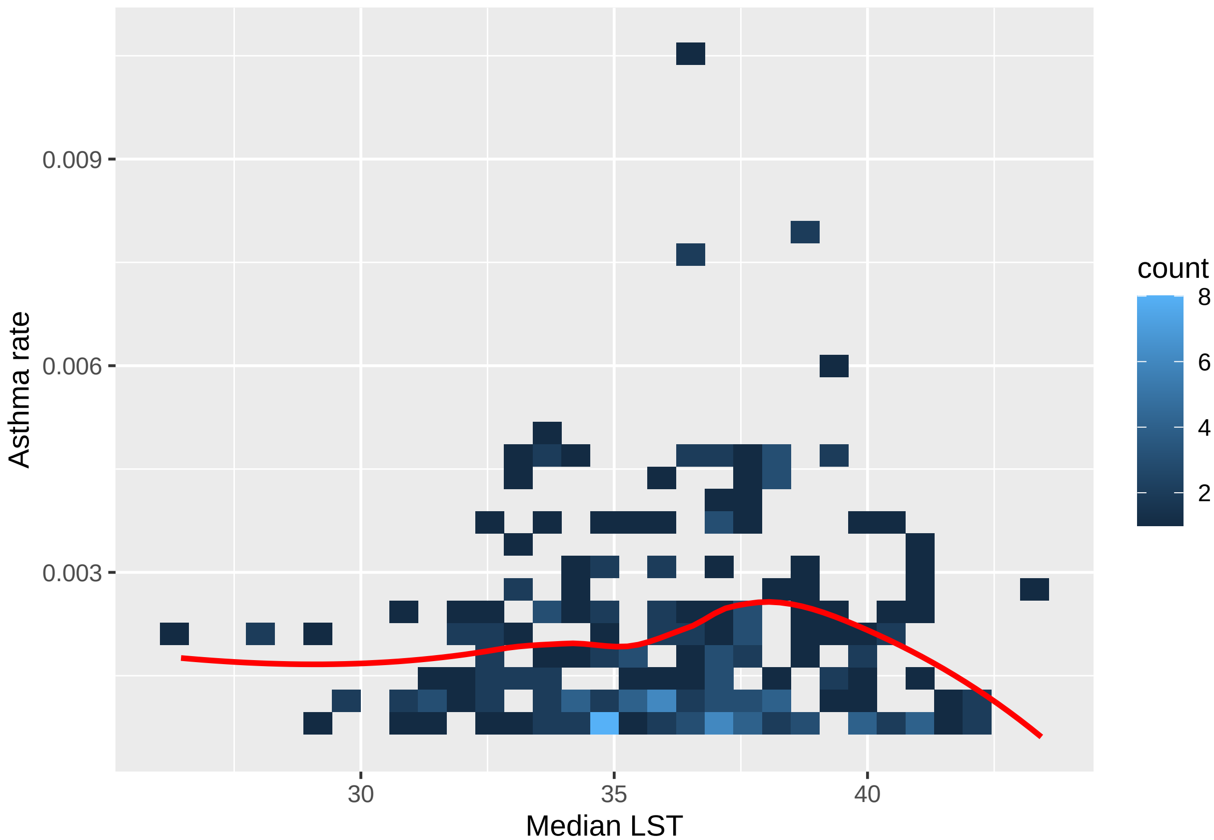

Figure 1: Daily pediatric asthma count by median daily LST

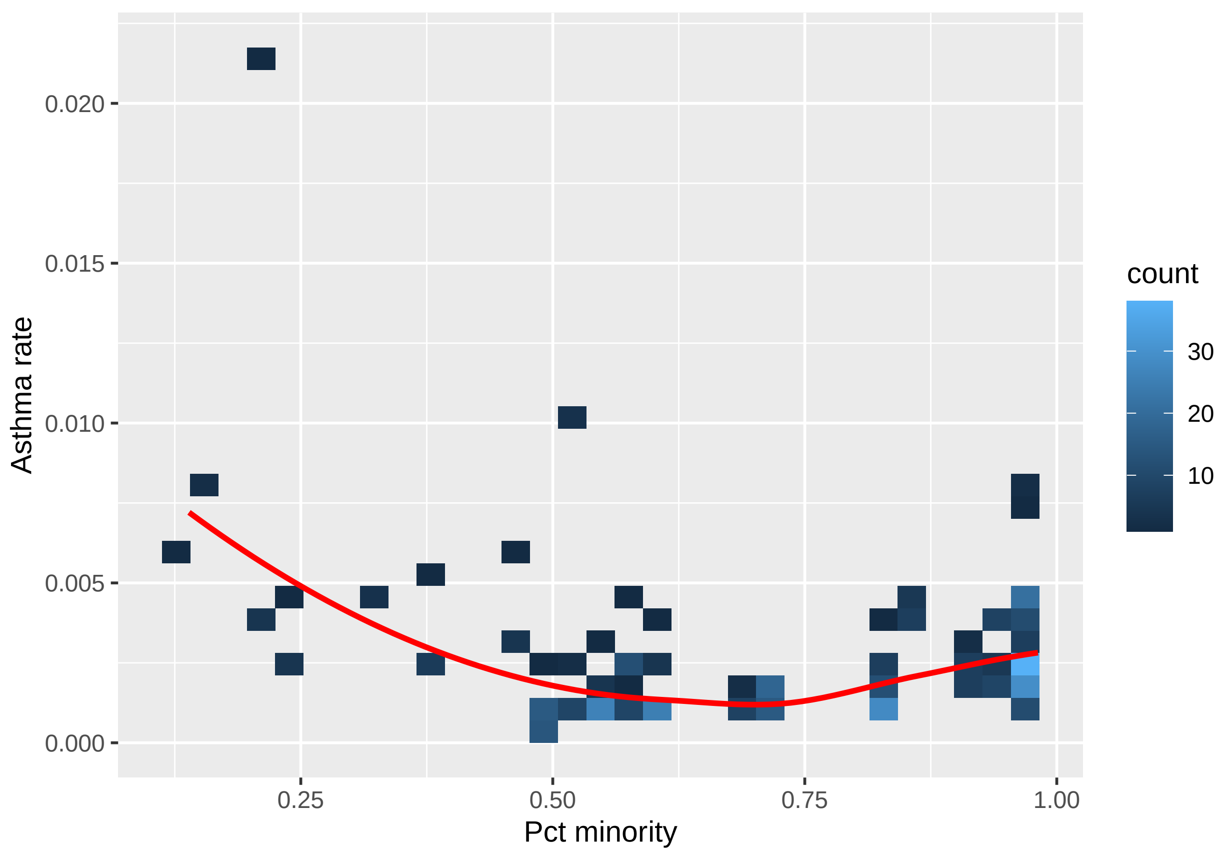

Figure 2: Daily pediatric asthma count by percent minority

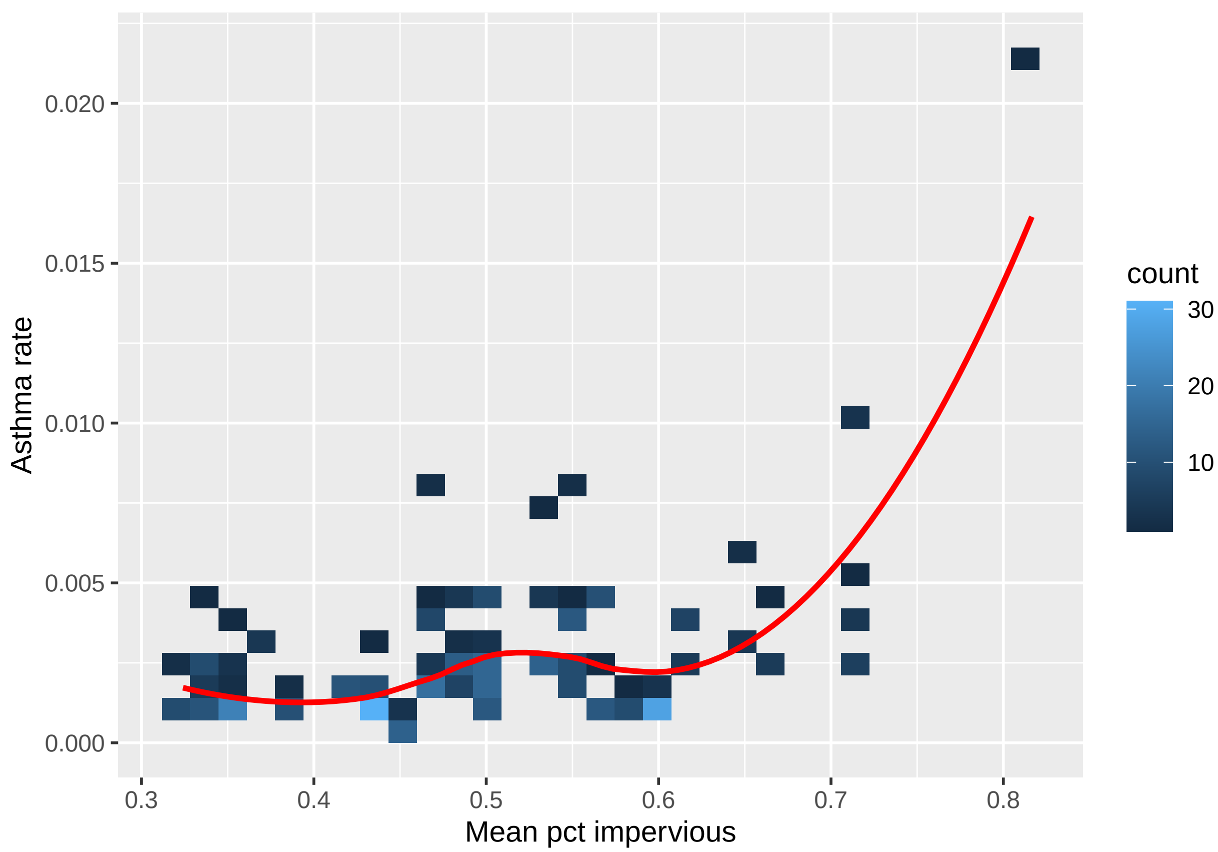

Figure 3: Daily pediatric asthma count by mean percent impervious land cover

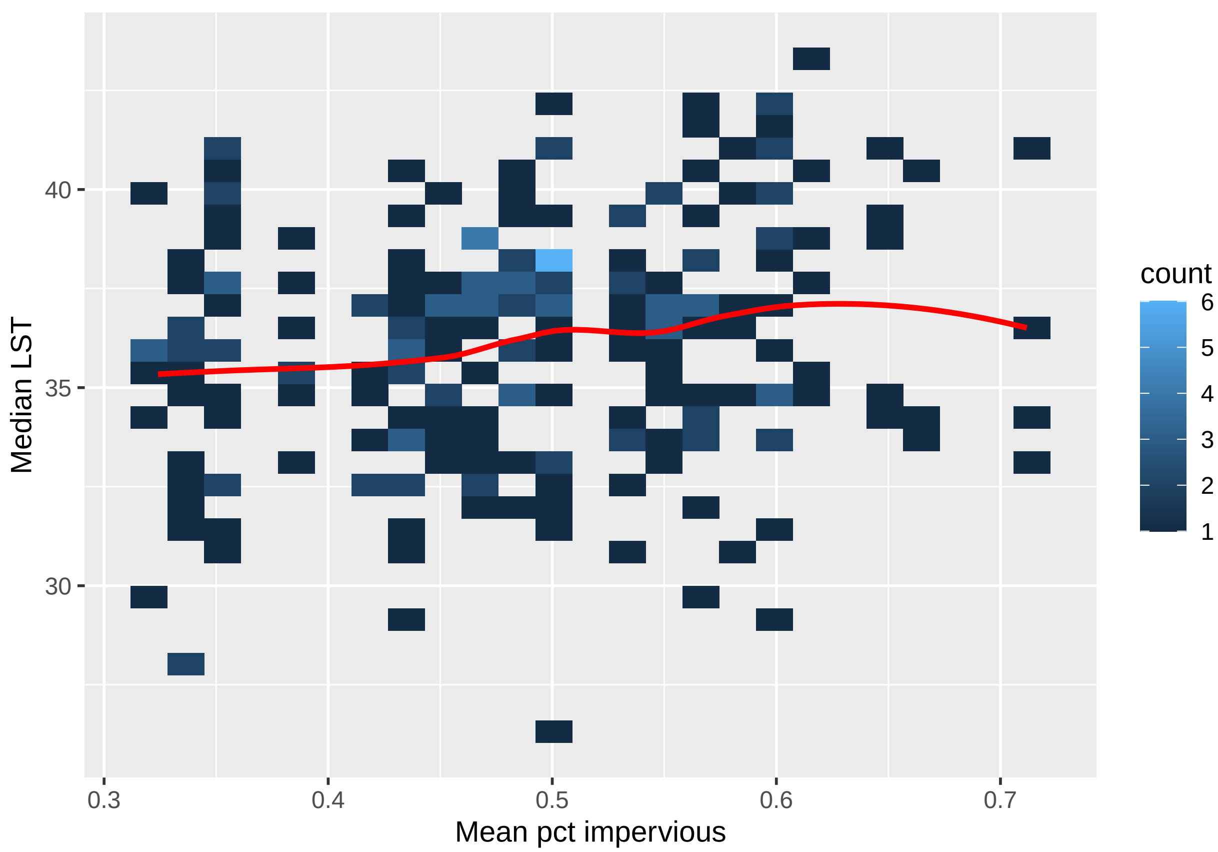

Figure 4: Daily median LST by mean percent impervious land cover

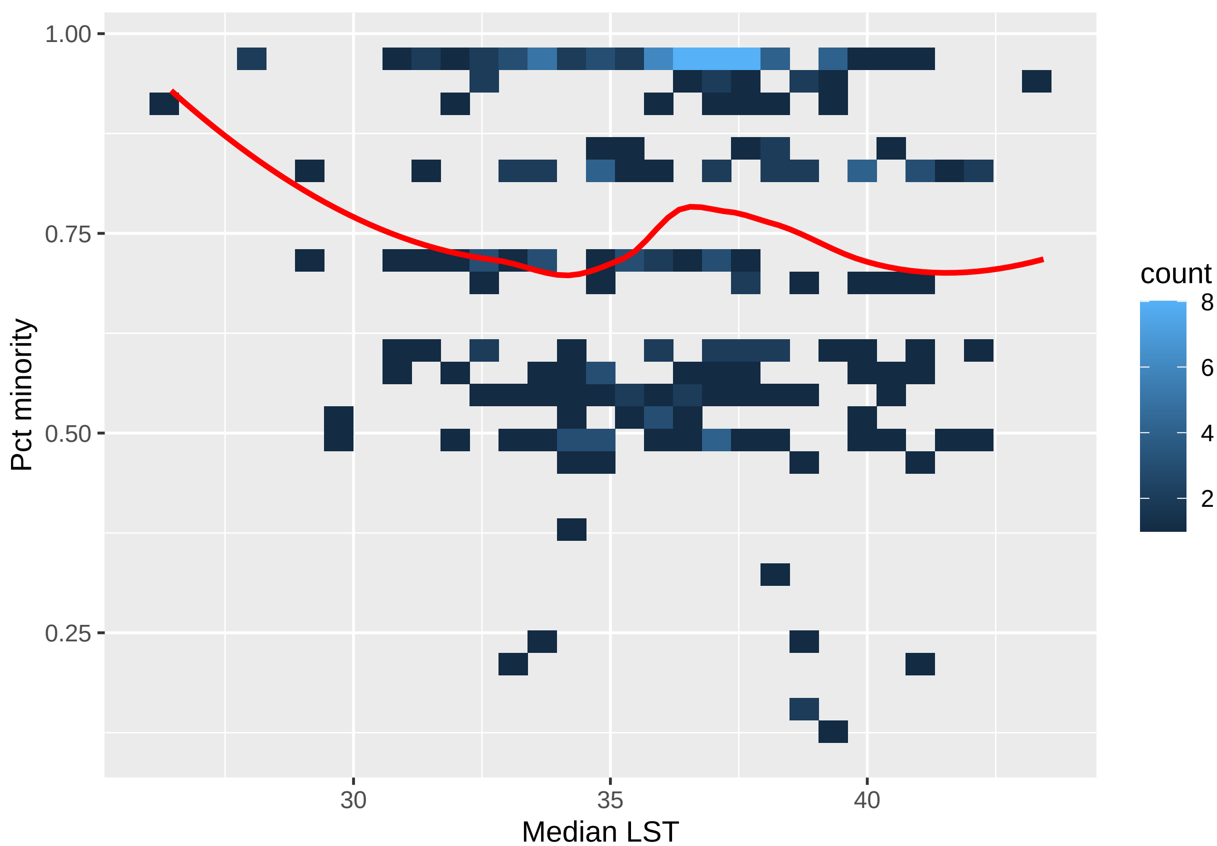

Figure 5: Percent minority by daily median LST

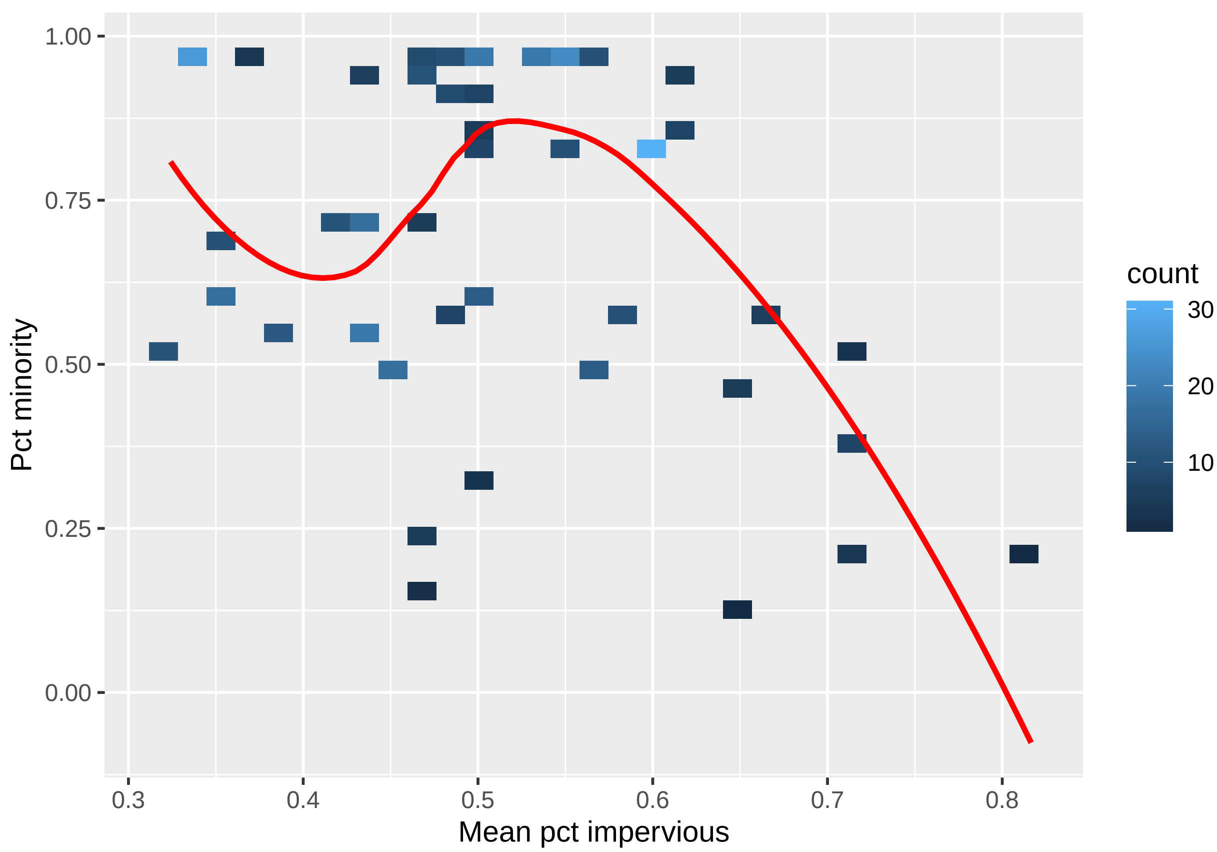

Figure 6: Percent minority by mean impervious land cover

"It is important to note that there was no expectation of high correlations with the environmental variables because the exacerbation of asthma symptoms depends on several other external factors (e.g., indoor pollution, viral infections) and host factors (e.g., genetics)" (Ayres-Sampaio et al. 2014)

If there are three qualities of models that cannot all be maximized—realism, precision, and generality—our point is to maximize realism and generality. And if increasing resolution means decreasing predictability, our goal is to explore and describe an urban system comprised of atmospheric, social, and environmental subsystems that interact in complex ways, moving towards a universal methodology. This is largely uncharted territory, both technically and pragmatically, but a better understanding of these kinds of systems could go far in prioritizing resources towards those with the most need and increasing environmental justice.

5 A tentative modeling approach

Hierarchical models connect a series of conditional models with probability rules and make it possible to account for uncertainties, use first principles, and simiplify modeling specifications (Wikle 2003). Joint distributions of covariates can be separaated into a series of conditional models (Wikle 2003).

"as the level of complexity increases (or"subjective" prior information is included) the Bayesian paradigm is usually necessary" (Wikle 2003).

"hierarchical modeling provides a framework by which to simplify complicated environmental systems, so that uncertainty can be linked in a coherent fashion" (Wikle 2003).

"CHANS can be concepturalized as entities with nested hierarchies. In CHANS, people and nature interact reciprocally across diverse organizational levels. They form complex webs of interaction that are embedded in each other." (Liu, Dietz, Carpenter, Folke, et al. 2007)

An advantage of a Bayesian MCMC approach over maximum likelihood methods is that the group-level parameters are estimated in the model rather than considering them part of the error term. Not only does this provide measures of uncertainty of the random effects, it enables exploring the structure of the random effects (Bürkner 2017; Miaou, Song, and Mallick 2003). A hierarchical Bayes model would allow the modeling of spatial random effects, i.e. differences in the relationship between the covariates and pediatric asthma incidence between census tracts. Assessing the spatial variability of risk can allow for prioritazation of resources to those communities most at risk. Additionally, due to the low count of incidence per individual census tract, there is a large variability between analysis units that can make simple estimates unreliable. Poisson-based hierarchical Bayes models with spatial random effects can account for this high variance and reveal geographic patterns in the data (Miaou, Song, and Mallick 2003). These models utilize information from surrounding areas, thus borrowing strength in order to produce smoothed estimates for the individual census tracts, preserving geographic resolution while producing stable estimates (Ghosh et al. 1999; Best, Richardson, and Thomson 2005). The point values shrink towards a value defined by the distribution of all of the tracts in the hierarchical structure (Best, Richardson, and Thomson 2005). Additionally, the structured heterogeneity of spatial correlation between neighboring census tracts can be specified (Ghosh et al. 1999). The small geographical and temporal resolution produces data that is sparse by nature, posing statistical problems of observational noise corrupting the signal of interest (Best, Richardson, and Thomson 2005).

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