Characterizing Spatial Variability of Climate-Relevant Hazards and Vulnerabilities in the New England Region of the United States

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Abstract Weather and climate have substantial effects on human health. While much is known about how morbidity and mortality are affected by moderate-to-extreme heat, poor air quality, and heavy precipitation individually, less is known about the cumulative occurrence of these climatic hazards, and the extent to which they spatially overlap with community-scale vulnerabilities. Specifically, there is interest in determining whether individuals living in places with the highest exposure to multiple health hazardous climatic conditions are also more vulnerable to having negative health outcomes. Presented here is a spatial analysis of the distribution of health-relevant climatic hazards and social vulnerabilities across the New England region of the northeastern United States. We show that the frequency of excessive heat days, heavy precipitation days, and ozone (O₃) and fine particulate matter (PM₂.₅) exceedances during the warm seasons (May–September) from 2009 to 2014 have distinct spatial distributions and are statistically significantly correlated across space with indicators of social vulnerability. We further quantify an integrated measure of the hazards and vulnerabilities to illustrate the spatial heterogeneity of overall risk, as well as to demonstrate how the choice of spatial scale influences the identification of high-risk areas. These methods are transferrable to other locations and contexts, which could be of utility not only to geographers and epidemiologists, but also to policymakers tasked with allocating public health resources to populations at greatest risk of weather- and climate-related health effects.

Plain Language Summary It is well established that extreme heat, air pollution, and heavy rain can have negative effects on public health and that certain populations are particularly susceptible to these impacts. However, little attention has been given to how the frequency of these different types of hazards are distributed across space and whether they tend to cluster in places where people are more vulnerable to their negative health effects. In this paper, we examine weather and air pollution in New England and apply a method for identifying communities that have both frequent climate-related hazards and particularly vulnerable populations. Our applications are transferrable and expandable to other locations and hazards of interest, and they are of use both to researchers and decision-makers aiming to assess and reduce weather- and climate-related risks to public health.

1. Introduction

Meteorological events affect human health in a variety of direct and indirect ways, including through exposure to temperature extremes, degraded air quality, water- and vector-borne diseases, and extreme weather events, among others (U.S. Global Change Research Program, 2016). Although much is known about the health effects of each of these events individually, less consideration has been given to how these occurrences are spatially distributed; some places experience different types, frequencies, and magnitudes of meteorological events than others. Moreover, community-scale determinants of negative health outcomes also vary across space (e.g., Flanagan et al., 2011; Reid et al., 2009, 2012). Understanding not only which places are exposed to more frequent and intense meteorological, climate-relevant hazards (hereafter “climatic hazards” or simply “hazards”) but also the extent to which the individuals living in those places are vulnerable is critical to guiding spatially explicit health assessments for multiple climatic events.

Here we focus on the impacts on human health from excessive heat, air pollution, and heavy rainfall, all of which are linked to negative health outcomes, are spatially differential, and are affected by long-term
climatic conditions. There is very strong epidemiologic evidence linking moderate-to-extreme heat to a higher risk of morbidity (Bobb et al., 2014; Buckley & Richardson, 2012; Hansel et al., 2016; Kingsley et al., 2016) and mortality (Anderson & Bell, 2011; Bobb et al., 2014; Gasparrini, Guo, Hashizume, Kinney, et al., 2015; Knowlton et al., 2009; Medina-Ramon & Schwartz, 2007), with spatially dependent relationships arising from location-specific heat mortality associations (Gasparrini, Guo, Hashizume, Lavigne, et al., 2015). There is similarly clear and consistent evidence that air pollution is harmful to human health (Cohen et al., 2005; Hoek et al., 2013; Shah et al., 2013), though the distribution of individual pollutants (and hence the populations affected) varies substantially. In particular, ambient fine particulate matter (PM$_{2.5}$) is often found in and around urban areas, while tropospheric ozone (O$_3$) can reach harmful levels on more homogeneous, regional scales (Jacob, 1999). Finally, although the relationship is less firmly established, there is evidence that heavy rainfall events are associated with higher rates of morbidity as a result of the potential effluence of nutrients, pollutants, and microbial organisms into recreational waters and drinking water supplies that fosters growth of pathogens (U.S. Global Change Research Program, 2016). For example, an analysis by Curriero et al. (2001) estimated that 68% of waterborne disease outbreaks in the United States between 1948 and 1994 were preceded by 80th-percentile rainfall events, suggesting that even less-than-extreme amounts of precipitation can prompt significant health consequences.

In the studies referenced above, the health effects of these hazards have been assessed individually; however, populations are often exposed to multiple hazards in a given year, and the extent to which these hazards overlap across space has not been analyzed. Although natural hazards generally have distinct impacts, there is nonetheless value in identifying locations threatened by frequent occurrence of multiple disparate hazards, particularly as a means for targeted interventions (Dilley et al., 2005). Despite methodological challenges, such multihazard frameworks have been employed in a variety of disaster risk management contexts (see Kappes et al., 2012 for a review). We posit here that a multihazard framework similarly has utility in the realm of public health, since identifying spatial clusters of multiple hazards may enable greater efficiency in the allocation of limited public health resources available for climate change adaptation.

But applying multihazard frameworks in a way that facilitates impacts assessments first requires an integration with the underlying vulnerabilities of the populations affected by the hazards (Cutter et al., 2000). The term “vulnerability” has taken on myriad definitions depending on the context and discipline (Cutter et al., 2003; Dow, 1992); in practice, vulnerability is generally invoked to reflect how the impacts of a particular hazard differ depending on the characteristics of the people exposed to it (e.g., Ahmadalipour & Moradkhani, 2018; Cutter et al., 2000; Räsänen et al., 2016; Reid et al., 2009; Vicente-Serrano et al., 2012). In particular, Jurgilevich et al. (2017) note that studies assessing the impacts of natural hazards increasingly conceptualize vulnerability following the risk framework put forth by the Intergovernmental Panel on Climate Change (IPCC; Cardona et al., 2012). In contrast to earlier, more encompassing characterizations of vulnerability (e.g., Adger, 2006; Schneider et al., 2007), the IPCC framework decouples “exposure” (i.e., entities that are affected by hazards, such as people or infrastructure) from vulnerability (i.e., traits that make harm more likely, such as poverty, social isolation, or lack of mobility; Cardona et al., 2012). This latter definition aligns more closely with the concept of social vulnerability as place-based, contextual conditions that affect both preparedness for, and ability to respond to, environmental hazards (Cutter et al., 2000; Emrich & Cutter, 2011).

Recent works have integrated these concepts to assess the interaction between meteorological hazards and vulnerabilities, albeit not with emphases on comprehensive health applications (e.g., Binita et al., 2015; Depietri et al. (2018); Emrich & Cutter, 2011; Monterroso & Conde, 2015). The geographical and environmental health literatures are lacking a comprehensive analysis integrating multiple, health-relevant meteorological hazards and vulnerabilities for the purpose of identifying localized areas and populations at greatest risk of cumulative climate-related health effects at multiple scales.

In this paper, we present an analysis quantifying and visualizing the spatial distribution of potentially health hazardous meteorological risks. Using the New England region of the United States as an example, we demonstrate how multiple hazards can be quantitatively combined with vulnerability data to identify the areas at greatest risk of being exposed to climatic health hazards. Specific questions guiding this inquiry are as follows: (1) What is the spatial distribution of health-relevant meteorological hazards across New
England, to what extent do they overlap, and to what extent do they cluster?; (2) what is the distribution of social vulnerability indicators in this region, to what extent do they cluster, and to what extent do they overlap with hazards?; and (3) are vulnerable populations more exposed to hazards compared to less vulnerable populations (i.e., can we characterize a spatial gradient in risk)? To answer these questions, we will display maps of the distributions of climatic hazards and vulnerabilities, calculate the spatial correlations between them, introduce a "climatic risk index" that facilitates identification of communities that both more frequently experience these hazards and are more vulnerable to them, and explore the role of spatial scale in identifying areas of risk.

2. Materials and Methods

2.1. Definitions and Conceptual Framework

2.1.1. Case Study: New England Region (United States)

We focused our analysis to a regional scale to highlight finer spatial variability of risks. We selected New England (Figure 1), the northeastern region of the United States comprised of the states of Connecticut (CT), Rhode Island (RI), Massachusetts (MA), Vermont (VT), New Hampshire (NH), and Maine (ME). Focusing on this area has practical and conceptual benefits, including the ability to limit the scope of potential climatic hazards.

2.1.2. Risk Framework

We followed the conceptualization of “risk” as defined by the IPCC Special Report on Managing the Risks of Extreme Events (Intergovernmental Panel on Climate Change [IPCC], 2012). In this framework, a hazard is an event that has the potential to cause tangible, deleterious impacts on social elements, an exposure is someone or something that has the potential to be harmed or damaged by a hazard, and a vulnerability is any...
condition that makes harmful effects on particular exposures more likely; the intersection of these three components is the overall risk (Cardona et al., 2012; Lavell et al., 2012). We apply this framework here in the context of climatic health impacts: a hazard is a meteorological event that has the potential to cause human morbidity or mortality, an exposure is a census tract population based on the 2010 Census, and a vulnerability is a community-scale socioeconomic or demographic characteristic that makes illness or death from a hazard more likely.

2.1.3. Defining Hazards

We limited the scope of our analysis to New England hazards that could occur anywhere within the area of interest, that is, included only atmospheric hazards; can be quantified probabilistically on a daily timescale, that is, excluded long-term and/or extremely rare hazards; and are likely to be affected by climate change with reasonable confidence. We defined health-relevant meteorological hazards as either present (above a hazard-specific, health-relevant threshold) or absent on each day during the warm season (May–September): (1) “Excessive heat days” are days with maximum heat indices greater than or equal to 95 °F (35 °C); (2) “heavy rainfall days” are days with liquid water equivalent precipitation greater than or equal to 1 inch (2.54 cm); (3) “O₃ exceedances” are days with 8-hr O₃ maxima greater than or equal to 70 ppb; and (4) “PM₂·₅ exceedances” are days with 24-hr mean PM₂·₅ concentrations greater than or equal to 35 μg/m³. The heat index threshold is based on the guideline criteria for issuance of heat advisories by the National Weather Service (NWS) for the region (National Weather Service, n.d.; Wellenius et al., 2017), the threshold for heavy precipitation was informed by the implicit characterization of a heavy rainfall day for the northeast in the Third National Climate Assessment (Kunkel et al., 2014), and the air quality thresholds are based on U.S. National Ambient Air Quality Standards, which are codified by the Clean Air Act.

We chose to consider only warm season hazards because the threshold for health hazardous extreme cold temperatures is not clearly defined and the NWS issuance of a cold weather advisory is dependent on wind velocity, which was not available in our data set. Similarly, since only liquid water equivalent precipitation amounts are available year-round in this data set, we could not discern between rain and snow and hence could not assess the frequency of heavy rainfall days during the winter with reasonable confidence. In addition, we did not account for temporal contiguity of hazard days (e.g., a 3-day heat wave was counted the same as three individual, nonconsecutive excessive heat days) because of the marginality of the additional epidemiologic impact (Gasparrini & Armstrong, 2011). Finally, although there is a latitudinal temperature gradient throughout New England that could affect the relationship between heat and health effects, we used a consistent, absolute threshold for the heat index of 95 °F because: (1) Recent changes to the regional NWS offices’ issuance of heat advisories suggest an epidemiologically relevant threshold at 95 °F (National Weather Service, n.d.); (2) the frequency of days with heat index greater than 95 °F does not follow a solely latitudinal pattern (see Figure 2b in section 3.1), owing to the numerous other determinants of excessive heat, including elevation and land use; and (3) varying the thresholds would have created arbitrary boundaries of elevated risk that are not informed by epidemiologic evidence.

Figure 2. The distribution of the proportion of warm season (May–September, MJJAS) days from 2009 to 2014 with at least one potentially health hazardous threshold exceedance (a), the distribution of the proportions of days for each individual hazard (b–e), and a hot spot analysis of the proportion of days with at least one hazard (f). Shading is by 10 groups delineated by Jenks natural breaks for each plot, with the lowest values in blue and the highest values in red. The hot spot analysis indicates that there is statistically significant clustering of high proportions (“hot spots,” red) of any hazard days in southern and central CT through southwestern MA, and of low proportions (“cold spots,” blue) throughout the northern states of Vermont (VT), New Hampshire (NH), and Maine (ME) (f). Background mapping provided by ArcWorld and ArcWorld Supplement from Esri®.
2.1.4. Assessment of Spatial Scale
We quantified and visualized the distribution of climatic risk at the regional, state, and local levels, standardizing the risk values based on the census tracts within the administrative boundaries we identified. Doing so allowed us to illustrate how the choice of scale affects the pattern of risk indices. For the local level, we assessed the Boston, MA, area as a case study example and included the towns and cities within the Metro Mayors Climate Preparedness Taskforce within the Metropolitan Mayors Coalition (MMC, composed of the MA towns and cities of Boston, Cambridge, Braintree, Quincy, Brookline, Newton, Somerville, Arlington, Medford, Melrose, Malden, Everett, Revere, Chelsea, and Winthrop, Metropolitan Area Planning Council (MAPC), 2018). Although this excludes parts of the Boston Metropolitan Statistical Area as defined by the U.S. Census, it reflects an existing policy-relevant administrative boundary and hence is more directly relevant to the potential applications of this study.

2.2. Data
2.2.1. Meteorological Data
We obtained temperature and precipitation data for 1 May to 30 September for the years 2009–2014 from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) gridded data set (Daly et al., 2008; Daly et al., 2015; PRISM Climate Group, 2017), which provides daily estimates of precipitation (millimeter liquid equivalent); minimum, maximum, and mean ambient temperature (°C); mean dew point temperature (°C); and minimum and maximum vapor pressure deficit (hPa) on a continuous surface with a spatial resolution of 4-km horizontal grid spacing. We derived additional health-relevant metrics from these raw data, including relative humidity and heat index (a measure of apparent temperature that accounts for the role of humidity in perceptions of heat, Anderson et al., 2013), as described in section 2.3, and validated against observations from weather stations elsewhere (Spangler et al., 2018).

2.2.2. Air Quality Data
Measurements of PM$_{2.5}$ and O$_3$ were provided by the Fused Air Quality Surfaces using Downscaling model from Environmental Protection Agency (EPA) (2018). This model combines observed, point-based air quality monitor data with an atmospheric chemical transport model, CMAQ, to resolve air quality across the entire contiguous United States at the spatial unit of individual census tracts (EPA, 2016). We used the point estimates for daily mean PM$_{2.5}$ and 8-hr maximum O$_3$ from the Fused Air Quality Surfaces using Downscaling for the warm seasons of 2009–2014, the period with the most complete air quality data available for New England.

2.2.3. Social Vulnerability Data
The Centers for Disease Control and Prevention (CDC) provides a Social Vulnerability Index (SVI) product, which is an amalgamated measure of variables that are correlated with health disparities, including socioeconomic status (SES), age, unemployment, minority status, housing characteristics, and other indicators (Centers for Disease Control and Prevention, 2015). We used the census tract level 2010 SVI data set, since it incorporates the 2010 Census and American Community Survey data that fall within the time period of interest. The SVI data are given as either national or state percentiles, where greater values represent more vulnerable populations. In addition to the overall SVI, four thematic subindicators are provided: (1) Theme 1—socioeconomic status (including income, education, poverty, and unemployment); (2) Theme 2—household composition (age and single parenthood); (3) Theme 3—race, ethnicity, and language (population proportions of individuals who identify as being part of racial or ethnic minority groups or who have limited English language proficiency); and (4) Theme 4—housing and transportation (crowding, housing structures, group quarters, and access to personal vehicle). The SVI is calculated by rank ordering population proportions of each of the sociodemographic variables into percentiles (relative to all of the United States in the national data set or to each individual state in the respective state-level data sets), summing applicable variable percentiles within each of the four themes (as well as across all variables for the overall SVI), and then rank ordering again to a final percentile (see Flanagan et al., 2011, for full methodology and explanation of included variables). Consistent with the recommendation of CDC, we used the national percentiles for the multistate analyses and the state-specific percentiles for analyses on individual states. For the local analysis, we manually calculated metropolitan SVI values for the Boston MMC towns consistent with the data set methodology (Flanagan et al., 2011).
2.3. Data Preparation

We derived surfaces of daily maximum heat index from the raw data using R (R Core Team, 2017) and the weathermetrics package, which calculates heat index following the algorithm used by the U.S. National Weather Service and described elsewhere (Anderson et al., 2013). Calculation of heat index requires ambient temperature and either dew point temperature or relative humidity as inputs, neither of which are reported directly by PRISM. Instead, we followed the approach of Daly et al. (2015) for estimating minimum relative humidity ($RH_{min}$), which is assumed to occur at the time of $T_{max}$ from temperature and vapor pressure deficit (VPD) as shown in equation (1) (where $T_{max}$ is in °C and $VPD_{max}$ is in Pa). Daily maximum heat index ($HI_{max}$) was then calculated using $T_{max}$ and $RH_{min}$ as inputs.

$$RH_{min} = 100 \cdot \frac{610.94 \cdot e^{(\frac{17.435 \cdot T_{max}}{243.126 + T_{max}})}}{610.94 \cdot e^{(\frac{17.435 \cdot T_{min}}{243.126 + T_{min}})}} - VPD_{max}$$ (1)

We joined the PRISM data to individual census tracts by matching the PRISM grid cell value geographically to the 2010 population centroids provided by the U.S. Census Bureau (2015), in order to best approximate the actual exposure of individuals in each tract. In cases where the population centroid latitude and longitude coordinates were missing or erroneous (51 out of 3370, 1.51%), the geographic centroids were used instead. For the SVI data, tracts missing any of the four thematic SVI values were dropped (14 out of 3,370, 0.42%).

2.3.1. Calculating Probability of Health Hazardous Days

We counted the number of days in which at least one of the potentially health hazardous thresholds was exceeded (i.e., a “health hazardous day”) for every census tract between 1 May and 30 September for the years 2009 through 2014 for New England. These counts were then divided by the total number of days in the period (918 days) to give the probability of each tract being exposed to at least one hazard on any given warm season day. This proportion is referenced throughout with phrasing such as “all hazards” and “probability of any hazard”. To aid interpretation, we also calculated the mean number of days per warm season by dividing the total number of days over the period by the number of years (six).

2.3.2. Spatial Associations

To quantify the degree of spatial dependence for each variable, we calculated the global Moran’s I (Moran, 1950) and accompanying $p$ value using the Spatial Autocorrelation tool in ArcGIS 10.4.1 (copyright © Esri: Redlands, California, United States), with row standardization and contiguity edges corners (i.e., “queen contiguity”) on the census tracts with at least one contiguous neighbor (excluded 4 out of 3,356 tracts). The Moran’s I statistic ranges from $-1$ to 1 and is used to determine whether the data are randomly distributed across space (values near 0), spatially clustered across the entire domain (values near 1), or systematically dispersed (values near $-1$). This is a first step in characterizing the spatial distribution of risk, since a lack of spatial heterogeneity in the inputs would imply that risk is either not spatially differential or driven by only one of the risk components (hence rendering an integrative calculation of risk redundant). We additionally calculated the $L$ index (Lee, 2001) to quantify the association between the various hazards and vulnerabilities across space. In contrast to traditional measures of association (e.g., Pearson correlation coefficients), the $L$ index is spatially explicit and combines the point-to-point associations of a Pearson correlation with the characterization of clustering of the global Moran’s I, both of which are of interest here. The $L$ index ranges from $-1$ to 1, with zero meaning no association between the variables, larger positive values indicating positive point-to-point associations and greater clustering, and larger negative values indicating inverse point-to-point associations and greater clustering. We calculated the $L$ index and accompanying $p$ value using the spdep package in R (Bivand & Wong, 2018). We used a $p$ value threshold of 0.05 for statistical significance in both the global Moran’s I and $L$ index.

2.3.3. Hot Spot Analyses

We calculated the Getis-Ord Gi* statistic (Getis & Ord, 1992) to determine whether, and to what extent, climatic hazards and social vulnerabilities have patterns of clustering throughout the region. We identified these clusters using the “Hot Spot Analysis (Getis-Ord Gi*)” tool in ArcGIS with neighbor settings of “contiguity edges corners” (i.e., queen contiguity) and Euclidean distance. This tool identifies areas in which the values are anomalously high or low relative to the region as a whole and, additionally, have neighbors with similarly high or low values (Getis & Ord, 1992). The result is a surface of “hot spots” of groups of census
tracts with anomalously high, contiguous hazards or vulnerabilities, “cold spots” of anomalously low, contiguous hazards or vulnerabilities, and neither hot nor cold spots, where there is not enough evidence to reject the null hypothesis that the pattern reflects what would be expected from a spatially random distribution. The definition of “high” and “low” values is determined by a z score and varies depending on the distribution of the variable of interest; the equation used to calculate the G\textsuperscript{I*} is provided by Getis and Ord (1992).

The hot spot analyses were conducted on both the probability of all hazards and on the overall SVI. The results were subset to hot and cold spots that were statistically significant at the 99% confidence level in order to reduce the potential for false positives and ensure more robust results. We then conducted two-tailed Welch’s t tests (Welch, 1938) to assess whether the characteristics of census tracts in hot and cold spots differed significantly. For example, for a hot spot analysis on overall SVI, the mean probabilities of hazards were compared between the high-vulnerability and low-vulnerability clusters. The reverse was also tested: for the hazards hot spot analysis, the mean SVI values in the hazard hot and cold spots were compared. While similar to the traditional Student’s t test, the Welch’s t test is more robust to differences in sample sizes and variances (Skovlund & Fenstad, 2000). We used a p value of 0.05 as the threshold for statistical significance in the t tests.

2.3.4. Calculating Risk

We sought to quantify a climatic risk index for the study region that numerically incorporates both the probability of hazards occurring and the degree of social vulnerability among the census tract exposures (implicitly included in our quantification of the hazards as being either present or absent for every day at every population centroid). We used the minimum-maximum standardization approach (Jain et al., 2005) to get the all-hazard probability and national overall SVI data on comparable scales from −1 to 1 (equation (2)). In contrast to other standardization techniques (e.g., calculating z scores), the minimum-maximum standardization retains the underlying distribution of the data and hence is nonparametric. This method has been successfully employed in other risk contexts (e.g., Bjarnadottir et al., 2011).

\[
y_i^* = \frac{(x_i - x_{\text{min}}) \cdot (y_{\text{max}}^* - y_{\text{min}}^*)}{x_{\text{max}} - x_{\text{min}}} + y_{\text{min}}^*
\]

Here \(y_i^*\) is the minimum-maximum standardized value for each \(i\)th census tract, \(x_i\) is the value for the variable of interest in census tract \(i\), \(x_{\text{min}}\) (\(x_{\text{max}}\)) is the minimum (maximum) value for the variable of interest across the entire domain, and \(y_{\text{min}}^*\) (\(y_{\text{max}}^*\)) is the user-defined lower (upper) bound of the standardized index. We used bounds of −1 and 1 in our analysis (with −1 being the lowest risk, 1 being the highest risk, and 0 being an approximate “average” or “baseline” risk) and assumed that the relative contributions to the climatic risk index are equal between the hazards and vulnerabilities.

To combine these standardized values into an overall risk index, we averaged the two numbers; the resultant index is highest for census tracts that have values closer to 1 for both the hazards and vulnerabilities, and it is lowest in places closer to −1 in both metrics. Indices with smaller absolute magnitude occur either when both standardized values are close to zero, or when the hazards and vulnerabilities are similar in magnitude but have opposite signs (e.g., high proportion of hazard days but low SVI and vice versa).

3. Results

3.1. Distributions of Hazards

The frequency of all climatic hazards during May through September over the period 2009–2014 shows strong spatial dependence across New England, with the highest values seen in southern and central CT through southwestern MA (Figure 2a). The individual hazards show markedly different spatial distributions, however: excessive heat days are relatively frequent not only in central CT but also in the greater Boston, MA, area and southeastern MA (Figure 2b). Heavy precipitation days show much greater heterogeneity across the region, with high probabilities occurring in parts of every state (Figure 2c). Ozone exceedances, by contrast, have a strong latitudinal gradient with the highest frequency of days in southern CT and areas adjacent to New York City to the southwest (Figure 2d). The incidence of PM\(_{2.5}\) exceedances is negligible for the New England region (Figure 2e) and therefore is omitted from much of the remaining discussion. Statistically significant clustering of regionally high values (hot spots) of all hazards can be seen...
throughout southern and central CT through part of southwestern MA, while significant clustering of regionally low values (cold spots) are seen throughout nearly all of northern New England (Figure 2f). All of the hazard variables have very high and statistically significant global Moran’s I values (data not shown), suggesting very strong spatial clustering: values ranged from 0.84 (p value <0.0001) for heavy rainfall days to 0.99 (p value <0.0001) for ozone exceedances.

3.2. Distribution of Vulnerabilities

On average, New England has lower levels of the Social Vulnerability Index compared to the United States as a whole, although the SVI range spans approximately the entire spectrum (0.1st percentile through 99.91st percentile); the median value of the SVI in the study region is 30.7, indicating that half of the census tracts of New England have social vulnerabilities in the lowest one third of the nation, and only 12.2% are in the highest quintile of vulnerability nationally. Nonetheless, there is substantial spatial variation in social vulnerability across the region (Figure 3a). Overall, the census tracts with the greatest SVI values occur in or around the larger metropolitan areas, including neighborhoods in Boston, MA; Providence, RI; and Hartford, CT.

However, substantially different patterns emerge when looking at the types of vulnerabilities contributing to the total SVI. Although the socio-economic component of the SVI (Theme 1) shows high values in many of the urban areas, there are also pockets of this vulnerability in many of the rural parts of New England (Figure 3b). Similarly, both the household composition (Theme 2) and housing and transportation (Theme 4) components of the SVI appear to have less clustering, with high values seen throughout many rural and urban parts of the region (Figures 3c and 3e). By contrast, the race, ethnicity, and language component (Theme 3) of the SVI appears to be highly concentrated in urban parts of central CT; Providence, RI; and the greater Boston, MA area (Figure 3d). Statistically significant clustering of high overall SVI is found in many urban and suburban parts of central CT; the Boston, MA metropolitan area; and around Providence, RI (Figure 3f). Statistically significant clusters of regionally low values of overall SVI are found in western CT, eastern MA, and throughout VT and NH. Similar to the hazards data, all of the vulnerability metrics have positive, statistically significant global Moran’s I values (albeit of lower magnitude than the hazards), reflecting clustering throughout the region: the global Moran’s I values range from 0.31 (p value <0.0001) for the housing and transportation component (Theme 4) of SVI to 0.74 for the race, ethnicity, and language component (Theme 3).

3.3. Intersection of Hazards and Vulnerabilities

Our conceptual framework defines risk as the intersection of hazards, exposures (implicitly incorporated into our calculation of hazards), and vulnerabilities. As a prerequisite to characterizing the overall risk, we show here how the previously described hazard and vulnerability metrics intersect.

$L$ indices calculated between each of the hazards and vulnerabilities indicate that overall SVI is significantly and positively spatially correlated with every type of hazard, the strongest of which is with heat index ($L = 0.160$; Table 1). All of the combinations of hazards and

Figure 3. The distribution of social vulnerability throughout New England as measured by the 2010 Social Vulnerability Index (SVI; national percentiles): overall vulnerability (a), individual components of this vulnerability (b–e), and a hot spot analysis of the overall vulnerability (f). Shading is by 10 groups delineated by Jenks natural breaks for each plot, with the lowest values in blue and the highest values in red. The hot spot analysis indicates that there is statistically significant clustering of high proportions (hot spots, red) of overall SVI in urban parts of southern New England, and of low proportions (cold spots, blue) throughout the suburbs (f). Background mapping provided by ArcWorld and ArcWorld Supplement from Esri®.
vulnerabilities have statistically significant \( L \) indices (albeit some are small in absolute magnitude, as might be expected in a complex social-environmental system), with the exceptions of socioeconomic SVI with any hazard, as well as housing and transportation SVI with heavy precipitation days. Spatial correlations between all-hazards probability and each of the SVI metrics are positive (indicating clustering of covarying hazards and vulnerability), with the exception of housing and transportation SVI, which has a slightly negative \( L \) index. Race, ethnicity, and language SVI showed consistently greater, positive spatial correlations across all of the hazards identified, particularly for excessive heat.

At the regional scale, the \( t \) tests demonstrate that the areas of concentrated social vulnerability (i.e., “overall SVI hot spots”; see again Figure 3f) have statistically significantly greater probabilities of experiencing health hazardous days. At this spatial scale, for overall SVI, the difference is driven almost entirely by excessive heat days: on average, relative to the low-vulnerability clusters, census tracts in the high-vulnerability clusters experience an additional 1.03 (95% confidence interval [CI] [0.38, 1.68]) days with any hazard per warm season. These hot spots are exposed, on average, to 1.28 (95% CI [0.96, 1.59]) more excessive heat days per warm season, while the differences in mean number of days for the remaining hazards are not statistically significant (Figure 4a).

These differences are starker when considering the clusters of vulnerability by race, ethnicity, and language SVI rather than by overall SVI: on average, the difference between the mean number of warm season days in the hot and cold spots of this type of vulnerability is 6.92 days (95% CI [6.59, 7.26]) for all hazards, 3.81 days (95% CI [3.67, 3.96]) for excessive heat, 0.45 days (95% CI [0.34, 0.56]) for heavy precipitation, and 3.82 days (95% CI [3.53, 4.11]) for ozone exceedances (Figure 4b).

Finally, areas of concentrated high probability of potentially health hazardous days (i.e., “hazard hot spots”; see again Figure 2f) have statistically significantly greater mean values of social vulnerability, in terms of overall SVI; household composition SVI; and race, ethnicity, and language SVI. Specifically, comparing mean SVI values across hot and cold spots of any-hazard probability showed statistically significant differences in total SVI (10.7 percentage points [95% CI [7.7, 13.7]]) greater overall SVI in hazard hot spots); household composition SVI (9.8 percentage points [95% CI [6.5, 11.8]]) greater in hot spots); and race, ethnicity, and language SVI (43.8 percentage points [95% CI [41.6, 45.9]]) greater in hot spots) (Figure 4c). At this regional scale, we observed no statistically significant difference between either socioeconomic or housing and transportation components of the SVI between the hot and cold spots of all hazards.

### 3.4. Distribution of Climatic Risk Index

Our climatic risk index reflects a relative measure of the distribution of combined probability of all hazards and overall Social Vulnerability Index for a given area, with the goal of identifying populations that are both more frequently affected by climatic hazards and more vulnerable to having negative health outcomes. At the regional scale, the largest climatic risk indices are found in metropolitan census tracts throughout New England. Specifically, areas with the highest climatic risk indices went from southwestern CT through central CT and up to southwestern MA (Figure 5a). Providence, RI, and some areas adjacent to Boston, MA, also have particularly high climatic risk indices. By contrast, nearly all of VT, NH, and ME have average or

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| Vulnerability metric | Heat | Precipitation | \( O_3 \) | \( PM_{2.5} \) | Any hazard |
|----------------------|------|--------------|--------|--------------|------------|
| Total SVI            | 0.158** | 0.060**       | 0.060** | 0.028**      | 0.117**    |
| Socioeconomic status SVI | 0.026** | 0.041**       | -0.019* | -0.031**     | 0.002      |
| Household composition SVI | 0.061** | 0.083**       | 0.120** | -0.100**     | 0.120**    |
| Race/ethnicity/language SVI | 0.523** | 0.128**       | 0.295** | 0.158**      | 0.452**    |
| Housing/transportation SVI | 0.053** | -0.014        | -0.072* | 0.092**      | -0.030**   |

Note: Greater positive \( L \) indices reflect greater point-to-point correlation and spatial clustering. Each hazard is statistically significantly correlated with total Social Vulnerability Index (SVI), and the greatest associations are between each hazard and the race, ethnicity, and language SVI.

\(*p < 0.05. \quad **p < 0.01.\)
below-average risk indices. Overall, there appears to be a latitudinal gradient of the climatic risk index, with higher values in southern New England and lower values in the northern parts.

3.5. Choice of Scale: State- and Local-Level Analyses

Calculations of the climatic risk index and hot spot analyses are scale dependent and thus are relative to the geographic area of interest. We visualize here how the choice of scale affects the identification of higher climatic risk indices. In contrast to the regional-scale analysis, in which nearly all of the census tracts in VT, NH, and ME have negative values of the climatic risk index, the state-level values illuminate the heterogeneity of risk within each state (Figure 5b). While the same areas of high risk that were identified in the regional analysis are still indicated as high risk here (e.g., central CT and Providence, RI), additional areas of elevated risk can now be observed in central ME, southern NH, and southern VT, relative to each respective state.

Additional intrastate differences become apparent at this state-level scale. For example, the distribution of socioeconomic vulnerability varies between the states: in VT, NH, and ME, significant clustering of SES vulnerability is found in the rural, northern parts of the states, while in CT, RI, and MA, these clusters are mostly in the metropolitan areas (Figure 6a). As a result, the differences in mean hazard probabilities between the most and least socioeconomically vulnerable clusters differ in sign between the northern and southern states of New England: hot spots of SES vulnerability tend to have greater frequency of potentially health hazardous days than cold spots in the southern states but lower frequency in the northern states (Figure 6b). However, other types of vulnerability (e.g., race, ethnicity, and language SVI) do have consistent patterns across states (Figure 6c and 6d). Finally, spatial heterogeneity at the local scale can also be observed. In the MA cities and towns that make up the Boston MMC area (MAPC, 2018), the greatest climatic risk index values are observed in central and southern Boston, as well as in the northern suburbs of Malden, Medford, and parts of Somerville and Cambridge (Figure 7).

4. Discussion

4.1. Summary and Significance

We presented here a visualization of the spatial distribution of health relevant climatic hazards and social vulnerabilities across six New England states. We also offered a methodology for quantifying the covariability of these hazards and vulnerabilities and proposed a climatic risk index that can be used to identify populations at the intersection of highest probability of experiencing these hazards and the greatest vulnerability to resultant health impacts from exposure to them. Our results show that there is statistically significant spatial heterogeneity of climatic risk indices across New England, driven in large part by the incidence of excessive heat days and concentrations of social vulnerability in metropolitan areas. Finally, we showed how the choice of spatial scale informs the identification of high-risk areas, which are context and location dependent.

This analysis builds upon other works in assessing meteorological hazards and their coincidence with the spatial distribution of sociodemographic characteristics. Emrich and Cutter (2011) combined county-level markers of social vulnerability with incidence of multiple hydrometeorological
hazards in the southeastern United States, with economic damages as the outcome of interest. Similarly, Depietri et al. (2018) assessed spatial overlap between heat, flooding, and social vulnerability for New York City and found convergence in some coastal areas. Others have worked to quantify an integrative measure of this spatial heterogeneity: Monterroso and Conde (2015) developed a municipality-scale exposure index for climate change in Mexico that integrated meteorological hazards with projected climatic changes and four sociodemographic variables, Binita et al. (2015) calculated a county level “climate change vulnerability index” for the state of Georgia, and Zhou et al. (2015) demonstrated a province-scale disaster risk index in China. All of these analyses established methodological frameworks for quantifying covarying hazards and vulnerabilities to identify areas more or less prone to multiple weather- and climate-related hazards; however, none of them were explicitly tailored toward public health outcomes. By contrast, Boumans et al. (2014) provided a rigorous health impact assessment but applied this only to excessive heat in one county in Texas. While Wolf and McGregor (2013) found statistically significant clustering of heat vulnerability in London, as well as spatial concordance with the urban heat island, they too considered only extreme heat in one location. Finally, while Lung et al. (2013) and Forzieri et al. (2016, 2017) established multihazard frameworks for future life-threatening hazards in Europe related to climate change, data availability limitations precluded comprehensively assessing community-scale determinants of negative health outcomes. Our paper complements and builds upon these existing analyses by (1) applying a multihazard risk framework to present-day events and vulnerabilities that are more explicitly and acutely linked with negative health outcomes, (2) improving the quantification of risk by utilizing a nonparametric standardization technique that retains the underlying distribution of hazards and vulnerabilities, (3) demonstrating the influence of the choice of scale on identification of high-risk populations, and (4) using a spatially explicit methodology for comparing mean values of hazard incidences between clusters of highly vulnerable populations.

In comparing the frequency of hazards among clusters of vulnerable populations, we found particularly large, statistically significant disparities by the race, ethnicity, and language SVI at both the regional and state levels. Our findings suggest that New England communities with greater population proportions of individuals from racial and ethnic minority groups or with English language barriers tend to experience disproportionately more health hazardous days during the warm season. This finding concurs with vast literatures on environmental justice and environmental inequalities, which suggest that communities of low socioeconomic status or with high proportions of individuals who identify as being part of racial or ethnic minority groups are disproportionately burdened by environmental hazards (see Brulle & Pellow, 2006; Mohai et al., 2009, for reviews). The importance of this disparity of exposure is underscored by the racial

Figure 5. A comparison of the distributions of climatic risk indices based on data at the regional (a) and state (b) scales. Background mapping provided by ArcWorld and ArcWorld Supplement from Esri®.

10.1029/2018GH000179
and socioeconomic inequities that have been observed in the subsequent health outcomes from environmental hazards (see Morello-Frosch et al., 2011; Gronlund, 2014, for reviews). This analysis is particularly important in the context of continued climate change, which has the potential to influence the frequency and severity of each of the hazards assessed here. Under a high-emissions scenario, excess mortality attributable to heat waves is projected to increase for much of the eastern United States by the mid-21st century, with intracounty variability in the degrees of severity (J. Y. Wu et al., 2014). Similarly, Jacob and Winner (2009) concluded that atmospheric warming constitutes a “climate penalty” (S. L. Wu et al., 2008) on ozone, whereby decreases in tropospheric ozone concentrations from emissions reductions are partially offset by increases in atmospheric conditions that are favorable to ozone formation (i.e., high temperatures, clear skies, and stagnant air). Consequently, excess mortality from climate-attributable changes in ozone under a high-emissions scenario is projected to increase in the northeastern and Midwestern regions in 2030, with different rates of increase seen depending on the county (Fann et al.,

Figure 6. The state-level distribution of hot spots and cold spots of Theme 1 Social Vulnerability Index (SVI; socioeconomic status [a]) and Theme 3 SVI (race, ethnicity, and language [c]) throughout New England, and a comparison of the frequency of hazard days during the warm season (2009–2014) between the 99% confidence hot and cold spots within each state (b and d). On average, hazard days occurred more frequently in the clusters of high vulnerability by the socioeconomic status SVI in the southern states (Connecticut [CT], Rhode Island [RI], and Massachusetts [MA]) but less frequently in the northern states (Vermont [VT], New Hampshire [NH], and Maine [ME]). By contrast, hazard days consistently occur more frequently in the clusters of high vulnerability by the race, ethnicity, and language SVI for every state. Background mapping provided by ArcWorld and ArcWorld Supplement from Esri®.

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Although there is not yet a clear consensus on the influence of climate change on particulate matter (Dawson et al., 2014), its disproportionately high public health burden relative to ozone (Fann et al., 2012) necessitates its inclusion in comprehensive climatic health assessments. By contrast, there is confidence that heavy precipitation events in the northeast have been increasing over the twentieth century (Huang et al., 2017), and both the frequency and intensity of precipitation events are projected to increase in the northeastern United States over the next century (Schoof et al., 2010).

Finally, we showed how the identification of higher-risk areas is affected by the choice of spatial scale, suggesting that analyses of comprehensive climatic health risks should be specific to the location and question of interest. This concurs with findings from a case study in coastal France, which suggested that vulnerability in coupled human-natural systems is scale dependent (Mavromatidi et al., 2018). With this consideration in mind, our methodological framework is transferrable to other locations and contexts: the specific hazards and types of vulnerability metrics, as well as the spatial extent of interest, can be adjusted depending on the research questions of interest in a particular locale. Policymakers at all administrative scales can use this approach in their decision-making, both for short-term adaptive measures for improving public health infrastructure and for longer-term community planning and climate adaptation.

4.2. Limitations

Our analysis is a preliminary case study upon which future works can build; as such, there are several limitations. First, we considered each hazard as a dichotomous variable and therefore did not assess severity of the hazard beyond threshold exceedances. This simplification facilitates creation and interpretation of the climatic risk index but necessarily results in some loss of information about severity of hazards. However, we expect that accounting for magnitude of hazards would not substantively change the identification of high-risk locations. Second, we did not account for temporal contiguity of hazard days. For example, we considered three consecutive days of high heat (i.e., a 3-day heat wave) to have the same health impacts as three

Figure 7. The climatic risk index at the scale of the Metro Mayors Climate (MMC) Preparedness Taskforce composed of Boston and several nearby towns, outlined in bold (Boston, Cambridge, Braintree, Quincy, Brookline, Newton, Somerville, Arlington, Medford, Melrose, Malden, Everett, Revere, Chelsea, and Winthrop). Greater values (red) indicate areas that have both frequent hazards and greater social vulnerability, relative to the cities and towns included here. Background mapping provided by ArcWorld and ArcWorld Supplement from Esri®.
separate, nonsequential days of high heat. However, the additional impact arising from the duration of sustained extreme heat appears to be small relative to the cumulative impact of each individual day (Gasparrini & Armstrong, 2011). Third, we weighted all hazards and vulnerabilities equally in the calculation of the climatic risk index, which could overestimate or underestimate the actual risk to human health; additional research could apply explicit exposure-response functions to improve upon our conceptual framework.

Fourth, we used a generalized indicator of social vulnerability (the Social Vulnerability Index from CDC) based on percentiles, which may not comprehensively reflect the actual, absolute vulnerabilities of the exposed communities. Nonetheless, the broad applicability of the SVI, its utility in identifying places with relatively high social vulnerability, and the fact that it is publicly available facilitate the reproducibility of this work and its application to other research contexts. Moreover, others have noted that while specific characteristics of vulnerability can vary between hazards, several traits, such as low socioeconomic status, are generally applicable to all hazards (Cardona et al., 2012). Finally, we have assessed a relatively short time period (six warm seasons), which limits our ability to definitively characterize these hazards as reflective of the long-term climatology. In general, 30 years of data are needed to define a climate state; however, we were limited by the availability of spatially resolved air quality data. Given the relatively small geographic extent of our study, we assumed that while the absolute frequency of hazards may be influenced by internal climate variability, the relative spatial distribution of these hazards is not likely to be substantially affected by large-scale drivers of interannual variability (e.g., the El Niño–Southern Oscillation or the North Atlantic Oscillation).

5. Conclusion

Climatic hazards with the potential to affect public health are spatially heterogeneous across New England. Although indicators of social vulnerability are also heterogeneously dispersed over this area, there is statistically significant overlap between the various metrics of vulnerability and excessive heat, heavy rainfall, and regulatory exceedances of O₃ or PM₂.₅, particularly with respect to the race, ethnicity, and language SVI. The resultant distribution in the climatic risk index—a nonparametric combination of the hazards and vulnerabilities—suggests a statistically significant gradient in overall risk of exposure to potential health effects from meteorological events. The choice of spatial scale, relevant hazards, and particular types of vulnerability informs the identification of higher-risk locations and populations.

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