ASSOCIATING SEVERE THUNDERSTORM WARNINGS WITH DEMOGRAPHIC AND LANDSCAPE VARIABLES: A GEOGRAPHICALLY WEIGHTED REGRESSION-BASED MAPPING OF FORECAST BIAS

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ASSOCIATING SEVERE THUNDERSTORM WARNINGS WITH DEMOGRAPHIC AND LANDSCAPE VARIABLES: A GEOGRAPHICALLY WEIGHTED REGRESSION-BASED MAPPING OF FORECAST BIAS

THESIS

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Arts in the Department of Geography at the University of Kentucky

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2014
Severe thunderstorm warnings (SVTs) are released by meteorologists in the local forecast offices of the National Weather Service (NWS). These warnings are issued with the intent of alerting areas in the path of severe thunderstorms that human and property risk are elevated, and that appropriate precautionary measures should be taken. However, studies have shown that the spatial distribution of severe storm warnings demonstrates bias. Greater numbers of severe thunderstorm warnings sometimes are issued where population is denser. By contrast, less populated areas may be underwarned. To investigate the spatial patterns of these biases for the central and southeastern United States, geographically weighted regression was implemented on a set of demographic and land cover descriptors to ascertain their patterns of spatial association with counts of National Weather Service severe thunderstorm warnings. GWR was performed for each of our independent variables (total population, median income, and percent impervious land cover) and for all three of these variables as a group. Global $R^2$ values indicate that each individual variable as well as all three collectively explain approximately 60% of the geographical variation in severe thunderstorm warning counts. Local $R^2$ increased in the vicinity of several urban regions, notably Atlanta, Washington, D.C., St. Louis, and Nashville. However, the independent variables did not exhibit the same spatial patterning of $R^2$. Some cities had high local $R^2$ for all variables. Other cities exhibited high local $R^2$ for only one or two of these independent variables. Median income had the highest local $R^2$ values overall. Standardized residuals confirmed significant differences among several NWS forecast offices in the number and pattern of severe thunderstorm warnings. Overall,
approximately half of the influences on the distribution of severe thunderstorm warnings across the study area are related to underlying land cover and demographics. Future studies may find it productive to investigate the extent to which the spatial bias mapped in this study is an artifact of forecast culture, background thunderstorm regime, or a product of urban anthropogenic weather modification.

KEYWORDS: Forecast Bias, Urban Climatology, Weather and Climate, GIS, Remote Sensing
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INTRODUCTION

The National Weather Service (NWS) is responsible for issuing several different types of atmospheric and weather-related warnings. Severe thunderstorm warnings (SVTs) are issued when convective outbreaks are capable of producing hail with diameter of one inch or greater, and/or winds at speeds of 58 mph or greater (NWS 2009). Warnings are issued to inform the public of where a severe storm is occurring or imminent. Accurate warnings are essential for alerting affected areas that human and property risk are elevated, and that appropriate precautions should be taken. Severe thunderstorm warnings are released by meteorologists in local Weather Forecast Offices (WFOs) of the NWS. There are 116 WFOs in the United States, each being responsible for its own County Warning Area (CWA). CWAs generally are composed of several counties and have an average area of 75,000 km². Staff at WFOs rely on Doppler radar and computer algorithms to delineate areas of severe thunderstorm risk (NOAA 2005). Visual observations and data reported by trained storm spotters, the general public, and weather station personnel may be used as supplemental information to determine whether a severe warning is necessary.

Although institutional standards guide much of the warning process, spatial biases in the issuance of SVTs have been documented (Dobur 2005, Aguirre et al. 1994, Brooks et al. 2003, Barrett 2008, Barrett 2012). While physical factors such as regional atmospheric patterns and local topography certainly impact severe weather patterns, non-meteorological factors play substantial roles in patterns of warning issuance. Literature on the topic widely recognizes a population bias in the spatial distribution of severe thunderstorm warnings, wherein more heavily populated areas receive significantly more warnings than sparsely populated areas. This paper investigates spatial patterns of these biases for the central and southeastern United States. We seek to understand how a set of demographic and land cover descriptors are associated with changes in the spatial distribution of severe thunderstorm warnings. Geographically-weighted regression is employed to map the relationship between severe thunderstorm warning counts and population density, land cover, and income. Examination of global and local explanatory variance, residuals, and regression coefficients is used to detail the non-meteorological factors associated with severe thunderstorm warning issuance.

Bias in the issuance of severe weather warnings

Demographic and land cover biases. One factor recognized to influence the issuance of a severe thunderstorm warning by a WFO is nature of the area to be impacted.
Knowledge of the underlying distribution of population density across a forecast area may make a forecaster more or less likely to release a warning. Population density and the number of SVTs were shown to be positively correlated in the CWA serving the Atlanta region (Dobur 2005). Forecasters may also become conditioned to warn one area over another based on their perception of how likely it is that a field observation will confirm severe status. Forecasters can become accustomed to higher population areas reporting greater numbers of marginally severe storms (storms which just meet the lower thresholds of warning criteria) than less populated areas. Consequently, forecasters may overlook borderline severe storms in areas that would be less likely to report them in the first place (Dobur 2005). Anbarci et al. (2008) found that both the NWS and private weather forecasting companies produce forecasts of significantly higher accuracy for areas with greater market extent, which for these purposes can be defined as areas having more people and more economic resources. These authors also pointed out that, while the NWS does not produce forecasts for profit like private companies, it does rely on support from citizens and politicians to maximize funding received from the government. This factor may induce forecasters to prioritize urban areas over rural ones. In this light, population bias may serve as a loose proxy for economic bias.

Demographic biases can be associated not only with forecaster awareness of higher population densities, but also with the reality that larger numbers of people imply greater likelihood of severe weather phenomena being spotted, reported, and employed to issue a warning. Spotter networks are often sparse in rural areas, so many events may go unreported. Similarly, tornado warnings are skewed toward populated areas where they can be verified on the ground (Aguirre et al 1994, Brooks et al. 2003). Elsner et al. (2013) confirmed the presence of a weakening population bias in tornado reports in the central plains of the US between 2002 and 2011, but speculate that this could be attributable to an increase in storm chaser presence in the region. Some urban counties in Texas have been shown to have more SVT events than rural counties (Barrett, 2008). A wide range of studies have noted the increase over time of severe weather reports and attributed it in part to consistent growth in population density (Ray et al. 2002, Dobur 2005). Paulikas (2013) found that the increasing frequency of severe wind and hail reports is linked to historic population growth patterns in the Atlanta metropolitan area.

A final factor contributing to SVT demographic bias is the location of forecast offices and radar sites. WFOs and radar sites frequently are situated just west or southwest of densely populated areas. This arrangement enhances the likelihood that radar will detect severe weather before it reaches the populated area, due to prevailing westerly winds (Fine 2007). These locations are also filled with trained staff watching for signs of severe thunderstorms, using equipment whose specialized purpose is to detect the weather system. At the very least, these factors make the more populated areas “high confidence points” in terms of accurate and verified reports (Ray et al. 2002). However, it may be difficult to disentangle this bias from bias driven by forecasters’ perceptions of storm impact on an area.
**Local forecasting and severe weather culture.** WFOs are urged continually by the NWS to reduce the number of false alarms they issue for severe weather to avoid a high false alarm ratio (FAR). A warning is considered a false alarm if wind speed and hail size criteria are either unmet or unverified following issuance of the warning. The FAR for a WFO is equal to the fraction of false or unverified warnings to the total number of warnings issued. Repeatedly issuing false alarms is viewed as potentially dangerous because of the desensitization it may engender within the warned population (Barnes et al. 2007). Over-issuing warnings has also been shown to have negative economic impacts on affected areas (Sutter and Erikson 2010), which puts additional pressure on WFOs to produce accurate forecasts and warnings. Given these operational factors, the influence of the recent track record of verified versus unverified warnings at a WFO may be reflected in an office’s tendency to issue or not issue a severe weather warning. In addition, data collection practices and capabilities can differ from one WFO to the next and may also influence the decision to issue a warning (Hales 1993).

Barrett (2008) used visual and statistical analyses to describe the relationship of severe thunderstorm warnings and severe thunderstorm reports with population density and distance from the issuing WFO. He compared the patterns of SVTs both between and within CWAs for a large portion of central Texas. His study period spanned 20 years, from 1986 to 2005, and included a period of technological transition from Doppler WSR-74 and WSR-57 to NEXRAD, which added many improvements to the previously used radar networks. Barrett placed CWAs into one of 5 groups (2 urban and 3 rural), statistically defined by population density. He used linear regression to find relationships between warnings and reports, and population and distance from the WFO.

Statistical results showed low levels of significance, potentially because the study did not employ a spatially explicit regression methodology (only linear regression was used.) However, findings still evidenced a population bias for the whole of the study area, and within almost all of the individual CWAs. Barrett (2008) suggests a cause of this could be that forecasters are much more likely to issue a warning for an area if numerous reports of severe weather are received, but might be more prone to rely on radar and algorithms, and possibly not issue a warning if very few reports are received. Variations in the extent of population bias were seen among CWAs, and were accounted for by variations in county population density. Distance from WFO was shown to correlate negatively with both quantity and accuracy of warnings issued as well. There were, however, anomalous areas in which county population and county area failed to account for warning counts. In one small, sparsely populated county, Barrett attributed relatively high warning counts to the presence of two television stations with weather departments. Physiographic features, socioeconomic factors, the presence of interstate highways, and collective memory of historical weather disasters are also cited as agents prompting additional anomalies in the results.

Barrett (2012) examined not only severe thunderstorm warnings, but tornado warnings as well. Examining patterns of SVTs over a 14-year period (1996-2010), Barrett
identified several warning hot spots among NWS WFOs. Jackson, MS; Nashville, TN; and Columbia, SC stood out for the number of severe thunderstorms warnings issued. He also found a significant relationship between warnings and population, although this could vary according to whether the warnings were issued for individual storms or at a level that encompassed an entire county. Directional bias was also documented in this dissertation.WARNings were issued in a preferential direction, often upwind of a major city. Although Barrett used spatially referenced data and relied heavily on statistical techniques for interpretation of results, he did not use methods that accounted for the spatial nature of the variables. Barrett also delved into some of the more cultural aspects of warning issuance by reporting how some CWAs in his study received awards for excellence in severe weather-related service, while others were given more punitive recognition for undesired forecast practices, and relates these considerations to the outcomes of his study. His findings are echoed in the recommendations of Lindell and Brooks (2013) who stressed that there should be more study of forecasters’ decision-making processes among NWS regions, office, and between individual forecasters.

Systematic analysis of multiple social factors is beyond the scope of this study. However, it is important to bear in mind the diverse contextual and experiential factors that influence how forecasters, spotters, and the general public respond to severe weather events and warnings (Morss and Ralph 2007; Pennell 2009; Schmidlin 2009). The means by which local WFO culture and/or bias may make themselves evident in this thesis is through an examination of the spatial patterns of SVTs. We also concentrate on the evidence for spatial bias that may arise with issuance, and not in the post-event verification process.

**METHODS**

To characterize this bias, we posed these two questions: 1) *Does the spatial pattern of SVT warnings reflect bias related to WFO boundaries?* and 2) *Do demographic variables and land cover vary in their capacity to explain the number of severe weather warnings?* If there is a bias, one would expect that variability in WFO office, population, income, and land cover could explain some of the variation in SVT counts. To examine these relationships in a spatially explicit manner, geographically-weighted regression (GWR) was employed. GWR allowed for the modeling of how independent variables from the US Census and from the 2006 National Land Cover Dataset (NLCD 2006) explained the geographic variability in severe thunderstorm warning counts among selected WFOs across the central-southern US (Table 1).

The geographic extent of our study spanned thirteen states in their entirety, and portions of seven additional states (Figure 1). The study area is located primarily in the U.S. Southeast and Ohio Valley National Climatic Data Center-designated regions of the U.S., but partially extends into the South, Upper Midwest, and Northeast climate regions as well (NOAA 2014). In general, the study area increases in the number of supercell...
<table>
<thead>
<tr>
<th>Office Code</th>
<th>Forecast Office</th>
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<tr>
<td>BMX</td>
<td>Birmingham, AL</td>
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<tr>
<td>HUN</td>
<td>Huntsville, AL</td>
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<tr>
<td>MOB</td>
<td>Mobile, AL/Pensacola, FL</td>
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<td>JAX</td>
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<td>TBW</td>
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<tr>
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Table 1: Weather Forecast Office abbreviations and cities where offices are located.
Figure 1: Study region.
thunderstorms in the more central, inland locations, while sea breeze and coastal convective processes limit large severe thunderstorm development along the coast.

Data descriptions

NWS Weather Forecast Office County Warning Areas (CWA). These are the areas administered by each of the National Weather Service’s Weather Forecast Offices (Figure 2) These are also the geographic units at which WFOs are evaluated on specific aspects (accuracy, timeliness, etc.) of performance.

Severe thunderstorm warnings. NWS severe weather warning shapefiles are available from an archive maintained by Iowa State University’s Iowa Environmental Mesonet. These polygons show the bounded areas of all severe thunderstorm warnings issued by the NWS for the United States (Figure 3). Among other attributes, this dataset displays the WFO issuing each warning, the type of warning, the area in square kilometers of each warning, and the time of warning issuance and expiration. My polygons include the initial warning polygons, as well as subsequent polygons representing the movement and extension of these initial polygons up through warning expiration.

The severe warning polygon data also include each warning’s classification as either polygon or county-based. Prior to 2007, WFOs issued SVT warnings for county areas, since each WFO was comprised of a multi-county region. Since 2007, SVT warnings can also be issued using a storm-based, polygon approach. The outlines of warnings can now be customized to polygons that corresponded to storm structure in Doppler radar rather than to the boundaries of the county or counties in which the storm is developing. The storm-based warning approach, as opposed to the previously employed county-based system, was implemented to identify more specific areas of meteorological or hydrometeorological threats during severe weather events. The approach was meant to improve warning accuracy and to avoid issuing warnings for areas not directly threatened by severe weather. Our data begins in January 2007 and ends in December of 2012.

Land cover. The 2006 National Land Cover Dataset (NLCD 2006) provided a land cover classification scheme for the coterminous United States. NLCD 2006 is derived from imagery captured by the Enhanced Thematic Mapper + (ETM+) sensor on board Landsat 7. This dataset, in raster format, is produced at a 30 meter spatial resolution. Each pixel in this dataset is classified into one of 16 classes, 4 of which are developed, and 14 of which are natural or agricultural (Fry et al. 2011). Synchronous with the development of NLCD 2006, a percent imperviousness dataset was produced at the same scale from the same imagery. Threshold values for imperviousness are developed open space (imperviousness < 20%), low-intensity developed (imperviousness from 20 - 49%), medium intensity developed (imperviousness from 50 - 79%), and high-intensity developed (imperviousness > 79%).
Figure 2: County warning areas (CWAs). The three-letter abbreviation for each forecast office is shown, along with the cities where offices are located.
Figure 3: Severe thunderstorm warning polygons for 2012.
For our geographically weighted regressions to work, the independent variables needed to have a relatively continuous distribution across our study area. NLCD 2006 land cover classes proved too discontinuous, even with alternate classifications, to represent our study area in a smooth enough way. Percent impervious cover, with values theoretically ranging from 0 to 100, allowed for a more continuous distribution of data across the study area. Thus, percent imperviousness was a more optimal independent variable to include in our regressions than land cover classes. Percent imperviousness serves as a land development index alongside which SVT counts can be examined for spatial bias. Bias in SVT counts related to percent imperviousness may indicate that land use/land cover are influential in forecaster decision-making. Percent imperviousness could also serve as a proxy, expressed at a different scale, for population and economic biases.

**Demographic data.** Total population and median income at the level of census tracts were downloaded as a geodatabase from the American Community Survey, obtained via the United States Census Bureau's American Fact Finder. The American Community Survey (ACS) is an ongoing national survey distributed to randomly selected households and is used to produce period estimates of numerous demographic variables. ACS 5-year estimates in this study are for the years 2007-2011. Prior to database assembly census data were joined to tract shapefiles.

**Database assembly.** The geographic extent of the 36 CWAs served as the template to clip SVT polygons and data for percent impervious cover, total population, and median income. All data were joined to a fishnet grid composed of 20 x 20 km cells, which is the size determined optimal in an earlier pilot study. Each grid cell contained the number of SVTs issued over the six years of the study, the percent impervious surface total population, and median income. Because the NLCD is in units of 30 x 30 meters, block statistics were employed in ArcGIS to upscale the data to 20 x 20 km. In other words, individual pixel values designating the percent impervious surface over a given 30 x 30 meter area were disaggregated as areal measures, summed, and then converted into percent cover for the larger 20 x 20 km grid size used for analyses. No interpolation or smoothing algorithms were used. (Figure 4).

Total population for an individual 20 x 20 km grid cell was determined by taking the sum of population values for each census tract centroid falling within a cell. Median income within each grid cell was determined by taking the average of the centroids for each of the tracts that fell within a grid cell. However, due to the various shapes and sizes of the census tracts, not all grid cells were assigned demographic data. There were some cells in which no census tract centroids fell. These grid cells were assigned population and income values of census tract centroid nearest them (Figures 5 and 6).

Grid cell polygons from around the coastal fringe of the study area were manually selected out to minimize bias in land cover and demographic variables. This also minimized any edge effects in the SVT data along the coast. Buffering our data by
Figure 4: Percent impervious cover. All grid cells are 20 x 20 km.
Figure 5: Total population. Grid cells with the five highest total population counts are in Chicago (1,696,189 and 1,303,332), Miami (914,739 and 889,696), and Washington, D.C. (787,323).
Figure 6: Average median income. The seven grid cells with the highest values are located in D.C. and range from $110,000-$136,575. The next two highest values are in Jacksonville and Atlanta, with values of $108,560 and $102,202, respectively.
selecting only grid cells at some uniform distance inland was considered. However, because there are several large cities right along the coast that could contribute meaningful information in our analyses, manual deselection of grid cells was the preferable method. All pre-processing and analyses were performed in ArcGIS Version 10.1. Data were integrated into a USA Contiguous Lambert conformal conic projection.

**Geographically weighted regression (GWR).** A modeling technique representative of spatial nonstationarity in data relationships is essential to this study. I use geographically weighted regression because it captures the stationary trend in the global relationship between a dependent and independent variable. It also captures departures from this global relationship. These departures reflect local non-stationarity in the relationship between the dependent and independent variable. In this way, GWR is capable of summarizing a global relationship as well as highlighting ‘hot spots’ in spatially varying relationships. GWR was introduced by Brundson et al. (1996) as a regression technique in which the nature of the model varies across space to accommodate spatially structured data. A major advantage of GWR over previous methods is its ability to estimate parameters over actual geographic space, as opposed to space dictated solely by the values of variables. The technique fits a regression model to each point of observation, and lends itself to map-based visualization of results. Since its introduction, GWR has been employed throughout the social and physical sciences to model various spatially structured processes and phenomena.

GWR improves upon ordinary least squares (OLS) regression in that it accounts for the violation of independence that spatially distributed data manifest. In Equation 1, $y_i = \text{the } i^{th} \text{ observation of the dependent variable, } a_{ik} = \text{the value of the } k^{th} \text{ parameter at location } i, x_{ik} = \text{the } i^{th} \text{ observation of the } k^{th} \text{ independent variable, and } \epsilon_i = \text{independent, normally distributed error terms with zero means.}$

\[
y_i = a_{i0} + \sum_{k=1,m} a_{ik}x_{ik} + \epsilon_i
\]

GWR requires specification of several parameters that relate to the spatial nature of the data. Bandwidth is the dimension or area under which the relationship between the dependent and independent variable is spatially assessed. The shape and extent of the bandwidth is dependent on user input for the particular bandwidth method and kernel type. The Akaike Information Criterion (AICc) method is often used to select the appropriate bandwidth. This method minimizes the AICc, a value representing divergence between observed and fitted values in the regression. AICc automatically determines the optimal bandwidth that produces the best predictions. In addition, AICc values are useful for comparing explanatory power between models that have the same dependent variable, but different explanatory variables. The goal of a GWR model is to minimize the AICc value, so the explanatory variable with the lowest divergence value can be assumed to explain more variance than the others. Another specification, the kernel value, is used to produce geographic weighting in the GWR model for each
observation based on values and distances to nearby observations. A fixed kernel is appropriate when the data appear to be somewhat regularly positioned across the study area, with little to no clustering, as is the case in our gridded data.

In terms of output, quantification of explanatory variance over the entire study area is summarized in the global $R^2$ for the GWR regression model. GWR also calculates an indicator of the extent the explanatory power of this global model varies locally, in a quantity known as the local $R^2$. Mapping the distribution of the local $R^2$ is a powerful way to assess how a regression model responds to underlying heterogeneity in independent variables. In this study, it provides an indication of how well SVT warning counts can be explained by the underlying changes in land cover and demographic variables. A high local $R^2$ indicates that the underlying pattern of the independent variable is more strongly associated with SVT counts for a given area. One may infer that if a location has a high local $R^2$ compared to its surroundings, SVT warnings are preferentially issued for storms that track across it or originate near it.

GWR also produces standardized residuals. Inspection of standardized residual distribution can be used to provide information about whether factors still remain which are unaccounted for by the model. If standardized residuals are clustered it can indicate that another factor or variable is shaping the distribution of the dependent variable. In this study, clustering of standardized residuals was used to identify NWS forecast offices that have anomalous patterns of SVT issuance. Clustering of exceptionally high or low standardized residuals falling within the boundaries of a forecast office would indicate that its forecast practices and/or the thunderstorm regime fall outside of what can be predicted from a more global model. In other words, it indicates that NWS forecast office location should be considered when modeling SVT warnings.

To draw out the statistical significance of the spatial patterning of standardized residuals, Moran's I calculations were performed on the standardized residuals of each independent variable to determine the degree of spatial autocorrelation. This quantifies the degree the standardized residuals are randomly distributed, clustered, or evenly dispersed. When the Z score or p-value indicates statistical significance, a positive Moran's I index value indicates tendency toward clustering while a negative Moran's I index value indicates tendency toward dispersion.

GWR produces local regression coefficients that can track how a single independent variable can shift in the direction of its association with the dependent variable across the study area. In this study, positive coefficients indicate an increase in SVT counts relative to the independent variable beyond that not accounted for in the global model. SVT counts need to be increased beyond the modeling of their stationary distribution to match the observed data. Negative coefficients indicate a downweighting of SVT counts relative to the independent variable beyond that not accounted for in the global model. However, the complexity that allows GWR to elaborately illustrate spatial relationships also engenders less certainty in interpretation of coefficients. This spatial dependency in
coefficient values renders it impossible to directly compare coefficients in one location with those in another location due to the lack of a universal base model (Charlton and Fotheringham 2009). Currently, GWR ignores that the local models must relate to a global reference model in order to express the local parameters as variation around their global counterparts. (Wheeler and Tiefelsdorf 2005). It is with less conviction, given the flaws inherent to GWR, and the particularly large region being studied, that we can make definitive statements about relationships from one locale to another based on GWR coefficients.

RESULTS
A total of 220,928 severe thunderstorm warnings occurred over the six year duration of our data. The total absolute number of SVT counts per CWA showed an increase in the center of the study area, with SVT counts per CWA falling off toward the ocean coasts and toward more northern CWAs (Figure 7). The top 5 CWAs in terms of the absolute number of warning counts and the states in which they were chiefly centered were Jackson, Mississippi (JAN), Memphis (MEG), Greenville-Spartanburg (GSP), Peachtree City/Atlanta (FFC), and Blacksburg (RNK). The five CWAs with lowest SVT counts were Melbourne (MLB), Tampa (TBW), Miami (MFL), Newport/Morehead City (MHX), and Wilmington (ILM). When SVT counts were standardized by area, however, the top five CWAs were Charleston (CHS), Jackson, Kentucky (JKL), Greenville-Spartanburg (GSP), Baltimore/Washington D.C. (LWX), and Blacksburg (RNK). The lowest five were Tampa (TBW), Miami (MFL), Melbourne (MLB), Davenport/Quad Cities (DVN), and New Orleans/Baton Rouge (LIX) (Figure 8). Gridded counts of individual SVT polygons identified CWAs with unusually high counts confined to their boundaries (Figure 9). These included RNK in Virginia; LWX in Maryland and Virginia; CAE in South Carolina; CHS in South Carolina and Georgia; RAH in North Carolina; MRX, MEG, and OHX in Tennessee; HUN and BMX in Alabama; JAN in Mississippi; and LSX in Missouri. Edge effects are notably present in the CWAs around the Carolinas (CHS, GSP, CAE, RAH), and north into Virginia and Maryland (RNK and LWX). High SVT counts were also dispersed around some major urban areas. The major cities that exhibited a strong propensity for high SVT counts (versus high counts throughout the surrounding CWA) were St. Louis, Nashville, and Washington, D.C. The two largest metropolitan areas, Chicago and Atlanta, had low SVT counts.

The average size of SVT polygons was 1439 ± 929 km². Size of polygons did not exhibit any regional pattern or association with CWAs (Figure 10). However, in some cases, average polygon warning area was nearly double that of other areas. Part of this is related to the number of county-based versus storm-based warnings in a CWA. Counties are still the most frequent level at which SVTs are issued (Figure 11). Of the total of SVTs issued across the study area, 73% were issued at the county level, even though the storm-based method has been available since 2007.
Figure 7: Total severe thunderstorm warning count per CWA. Natural breaks classification.
Figure 8: Total severe thunderstorm warnings, standardized by CWA area in km. Natural breaks classification.
Figure 9: Severe thunderstorm warning count per grid cell, 2007-2012.
County warning area boundaries
Average SVT polygon area (km²)

Figure 10: Average size (km²) of severe thunderstorm warning polygons (county-based and storm-based). Defined intervals of 400 km².
Figure 11: Percentage county-based warnings out of total.
**GWR model performance and global $R^2$.** It is standard to perform OLS before GWR to gauge how the spatial structure of the data impacts regression relationships. Population, median income, percent imperviousness, and the regression with all three variables combined had consistently low $R^2$ values in OLS. GWR produced significantly better regression results (Table 2). Global $R^2$ for each individual independent variable accounted for approximately 55% of the explanatory variance in SVT counts. When all three variables were included in a single regression equation, explained global variance decreased slightly to 50% (adjusted $R^2$). AICc values, consistent with $R^2$ results, indicated a uniformity in model performance. This was not unexpected, as all of the independent variables are likely correlated. However, the individual local spatial patterns comprising these global models exhibited considerable as a function of independent variables, forecast offices, and cities and developed corridors.

**Total Population.** Total population accounts for only 10% of the local variance in SVT counts across much of the study area (Figure 12). Maximum local explanatory variance associated with population ranges from 20 - 45% in the vicinity of cities. The largest proportions of SVT counts explained by population lie along a coastal area south of Washington, D.C., which extends south to Norfolk, VA. Roanoke, Indianapolis, and St. Louis all had high local $R^2$ values, as did the Atlanta-Columbus-Macon, GA corridor. Several large cities did not have high local $R^2$, notably Chicago and Nashville.

Standardized residuals for population exhibited weak but significant clustering (Moran’s I = 0.034, $z = 3.15$, $p = 0.002$). CWAs in the central east and the central west of the study area had standardized residuals > 2.5 deviations from the mean, a trend which was also visible in the SVT counts per CWA (Figures 13 and 14).

The coefficient raster surface for population confirmed sensitivity of SVT counts to underlying population trends (Figure 15). For total population, red values indicated positive coefficients and high SVT counts relative to underlying population. Blue values indicate negative coefficients and low SVT counts relative to population. The Washington, D.C. corridor, along with the Sunbelt cities running up from Mississippi, Georgia, and into the Carolinas, have positive coefficients indicating SVT counts are weighted more positively. Hotspots for positive coefficients were also observed within the St. Louis; Jackson, MS; and Memphis CWAs. These CWAs exhibited a clear ring signature with an upweighting of SVTs in association with higher population and a diminished weighting of SVTs in outer-lying areas. Negative coefficients are found in less populated areas, as is most evident in parts of Kentucky and the Georgia coastal plain.

**Median income.** Median income had higher local $R^2$ peaks, approaching 55% in a few locations (Figure 16). The Washington-Norfolk corridor had an areally extensive and high local $R^2$. A peak in local $R^2$ occurs west of Washington, D.C. that appears to correspond with the outermost high incomes that characterize the most outlying suburbs, suggesting that warnings may be preferentially issued here because of its greater
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Table 2: Geographically weighted regression results
Figure 12: Local R2 for total population. Defined intervals of 0.05.
Figure 13: Standardized residuals for total population, classified as standard deviations.
Figure 14: Standardized residuals for total population. Natural breaks classification.
Figure 15: Coefficient surface for total population.
Figure 16: Local R2 for median income. Defined intervals of 0.05.
concentration of wealth. Local R² also peaked around the WFO city of Wilmington, NC. The Asheville-Raleigh corridor saw a wide area of local R² values ranging from 20-30%. Higher local R² for the Atlanta-Macon-Columbus corridor of Georgia stretched from wealthier northern suburbs to suburban areas well south of Atlanta's urban core. Peaks in R² emerged south of Nashville and to the east of Knoxville. St. Louis also has high local R² on the upwind side of the city adjacent to higher income suburbs.

In general, the coefficients indicated a division between wealthier cities and less affluent rural areas (Figure 17). The coefficients for median income show a tendency to be positive in many of the wealthier areas that also had higher local R². Areas of low income in Kentucky, the Atlantic coastal plain, the panhandle of Florida and the regions surrounding Wilmington, NC were associated with negative coefficients. WFO bias and edge effects were more apparent in coefficient maps for St. Louis, Memphis, and Jackson.

Standard residual values associated with median income were weakly clustered across the study area (Moran’s I = 0.046, z = 4.3, p <0.001). This clustering is predominantly seen in the CWAs in the central east forecast offices, and to the west in Memphis as well. (Figures 18 and 19).

Percent impervious surface. Like the other independent variables, percent imperviousness showed areas of low R² outside of developed regions (Figure 20). Local R² increased to 20-25% in the general vicinity of cities. Only two urban regions exhibited the peak local R² values approaching 45%. The Atlanta-Macon-Columbus corridor exhibited high local R², particularly around Columbus, which is the site of Fort Benning Army Base. The Washington, D.C. corridor again stands out, along with Indianapolis and St. Louis. Storms tracking across the impervious surfaces demarcating these cities tend to have more severe thunderstorm warnings issued than the surrounding areas.

Coefficients were positive in the broad regions affiliated with one or several cities. Negative coefficients emerged outside of these developed corridors where there is less impervious surface (Figure 21). Ring patterning, in which coefficients change abruptly at the edge of CWA boundaries, was pronounced for several CWAs including JKL in Jackson, KY; JAN in Jackson, MS; and MEG in Memphis. Standardized residuals were slightly clustered for percent impervious surface (Figures 22 and 23); Moran’s I = 0.039, z = 3.6, p < 0.001). As in the other maps of standardized residuals, the more extreme residual values and clustering were associated with CWAs in the central east portion of the study area.

All three variables. GWR using all three variables produced an adjusted global R² of 0.56 indicating that the model explains more than half of the variation in storm warning counts (Figure 24). Local R² values range up to 0.60. Washington, D.C. has the highest local R² values. A large region of high local R² values lies directly west of Washington, D.C. St. Louis is surrounded by the second largest area of noticeably elevated local R²,
Figure 17: Coefficient surface for median income.
Figure 18: Standardized residuals for median income, classified as standard deviations.
Figure 19: Standardized residuals for median income. Natural breaks classification.
Figure 20: Local R2 for percent imperviousness. Defined intervals of 0.05.
Figure 21: Coefficient surface for percent imperviousness.
Figure 22: Standardized residuals for percent imperviousness, classified as standard deviations.
Figure 23: Standardized residuals for percent imperviousness. Natural breaks classification.
Figure 24: Local R2 for all three variables.
chiefly south and southeast of the city. Increases in $R^2$ form a region connecting Atlanta, Macon, and Columbus, GA. Nashville and Indianapolis show distinct elevations in $R^2$ values as well. Several major urban areas in the region including Chicago, Cleveland, and Pittsburg present little to no indication of higher local $R^2$. Much of the rural terrain between developed corridors also exhibited low local $R^2$ suggesting that these areas may be underwarmed. Another trend in local $R^2$ for this model is the lack of high values in the northernmost and southernmost parts of the study area, which likely reflects the general trend of more severe thunderstorms in the middle latitudes of this region.

**DISCUSSION**

The overall pattern of SVT counts reveals a geographical gradient characterized by fewer thunderstorms in the north, as well as adjacent to the coast. The thermodynamic environment for severe thunderstorm development is comparatively weaker in these northern and coastal areas than in central and southern parts of the study region. However, alongside this natural thunderstorm trend documented within SVT distribution, there existed a propensity for SVT counts to behave differently near CWA boundaries. SVT counts issued through forecast offices in Charleston, Columbia, Greenville, Raleigh, Blacksburg, and Washington, D.C. tended to decrease near CWA borders. The propensity for standardized residuals to cluster in these areas provides further evidence that CWA boundaries significantly relate to SVT issuance and distribution.

More than half of the variance in the distribution of SVTs could be attributed to the underlying demographic and land use template based on global $R^2$ values. The independent variables all had very similar global $R^2$ values, which could indicate some degree of multicollinearity. However, patterns of local $R^2$ for each independent variable exhibited considerable city to city variability. Cities where one variable appeared to have significant influence on SVT counts might demonstrate no substantial relationship with another variable. For example, median income had a strong relationship with SVTs in Nashville, but total population and percent impervious surface showed minimal variation. Similarly, SVTs in Wilmington, NC respond strongly to median income but not to the other two variables. The distribution of SVTs around Indianapolis was positively associated with total population and impervious surface, but the influence of median income was muted. Atlanta, Washington DC, and St. Louis were the only urban areas that exhibited consistent association with each of the three independent variables. Chicago, despite its size, did not show any significant association of SVT counts with land cover or demographics.

The locations where peak local $R^2$ occurred around some urban areas tended to shift spatially depending on which independent variable is used. St. Louis had high local $R^2$ for all three independent variables, but the spatial distribution of each local $R^2$ values was different. Imperviousness and population had peaks on the downwind, southeastern side of the city while median income peaked on the upwind, southwestern side. Similarly, the strongest association of SVTs with impervious surface, income, and
population in Atlanta developed only on the east side of a line running north to south through the city center. These differences may reflect a combination of local forecast knowledge about the distribution of income around a city. It may also reflect a propensity to issue warnings preferentially along an upwind-downwind axis in cities. Evidence of this hypothesis is seen in the local R² distribution around Nashville, which trends along a southwest to northeast (upwind to downwind) axis.

While large cities were initially thought to be the most relevant category of development to consider, the results indicated that military and governmental presence may also play a role in the issuance of SVTs. A region of elevated R² also appears northeast of Tallahassee, close to Moody Air Force Base outside of Valdosta, GA. Columbus, GA has high local R² values that may be related to its proximity to Fort Benning Army Base. The overall high local R² around Washington-Norfolk corridor suggests that forecasting stimulated by the presence of political and governmental infrastructure may occur. Wallops NASA Flight Facility at the southern tip of the Delmarva Peninsula may also be a reason for higher local R² in this area, in addition to the proximity of naval traffic associated with Norfolk, VA. To test if Washington, D.C. has high local R² because of any coastal edge effect, GWR analyses were rerun without the Delmarva Peninsula. Local R² remained elevated indicating that edge effects are not a likely source of the high local R².

The higher local R² in the vicinity of cities and city clusters is distributed across a background of low local R² values. These more rural areas may be underwarned, but underwarning is not necessarily confined to areas of lower population density. When low R² values are viewed in relation to the boundaries between CWAs, several cities stand out as potential “holes” in SVT issuance. Lexington, KY is located in a warning dead zone between the Jackson, KY and Louisville, KY WFOs. Chattanooga, TN is also located near CWA boundaries, which may downweight the likelihood of SVT issuance. A large number of smaller cities, many of which are not indicated in our maps, and a significant number of people may lie outside of preferentially warned areas detected in this study.

While results did convey how CWA jurisdictions and underlying land cover and demographic variables influence the distribution of SVT issuance, several factors may bias our attempt to model SVT issuance. Some bias associated with cities and forecast offices in this study may not necessarily be attributable to human perception. For example, this study does not take into account the way different kinds of thunderstorms may influence issuance (Guillot et al. 2008). Isolated supercell and convective line storms are most likely to be accurately forecasted as their higher radar intensities make them easier to identify as compared with pulse and non-organized storms. Their distribution is likely non-random across the study area, as the mid-South is where large tornadic supercells are more common. Information about preferential thunderstorm initiation zones and their tracks would also be useful for developing this thunderstorm climatology. Thunderstorms may preferentially develop over the Blue Ridge Mountains.
inland from Washington, D.C. and Baltimore (Ntelekos et al. 2007) thereby confounding forecast bias. However, given the spatial extent and temporal depth of our study, tracking individual thunderstorms would be methodologically challenging, and no data are readily available.

Urban forms and processes have also been shown to contribute to thunderstorm activity in or around some urban areas, although there is substantial variation from city to city in the way thunderstorms are modified (Ashley et al. 2012). As land cover changes, thermodynamic mechanisms and the built environment can alter atmospheric stability in such a way as to augment convection in thunderstorms. Thunderstorms can split in the vicinity of cities and then strengthen after merging downwind. Aerosol mechanisms may also enhance the vertical development of thunderstorms by modifying how raindrops coalesce and circulate within a thunderstorm. Other authors suggest that this aerosol influence on thunderstorms and their phenomena may extend over regional scales (Bell et al. 2009; Stallins et al. 2013), even well outside of cities. Urban locations with greater spatial and temporal variability in aerosol regimes and convective processes may make the issuance of SVT warnings challenging (Petersen and Rutledge 2001).

A range of studies have established that urban land cover and air pollution may contribute to anthropogenic modification of convective events in the vicinity of Washington, D.C. and Baltimore (Ntelekos et al. 2007; Ntelekos et al. 2008; Zhang et al. 2011) as well as around areas of St. Louis, Chicago, and Cleveland (Huff and Changnon 1973). The Indianapolis region has a strong climatological effect on regional thunderstorms upwind and downwind of the city (Niyogi et al. 2011). Rozoff et al. (2003) observed that added heat from anthropogenic effects encourage deep convection downwind of St. Louis. Urban anthropogenic effects also influence weather patterns downwind (east) of Atlanta (Stallins et al. 2006; Diem 2008) and Memphis (Ashley et al. 2012). Patterns in how local $R^2$ peaks shift around a city may provide clues to delineate urban effects on thunderstorms from forecaster bias. The relatively unbiased nature of SVT counts in the north of the study area stands out with respect to greater $R^2$ variation in the south. The greater likelihood of urban thunderstorm augmentation in the humid south may be one explanation for this pattern. On the other hand, more homogenous agricultural landscapes and suburbs to the north provide a rationale for the lessened inclination to issue warnings for cities. In the south, where there still remain relatively isolated towns surrounded by more intact forests, the tendency to see a bullseye in the impact of a storm on a particular city may be more pronounced.

CONCLUSIONS

Employing GWR allowed us to assess how WFO jurisdictions, land cover, and demographic variables relate to the issuance of severe thunderstorm warnings. The spatial nature of the analysis allowed areas to be pinpointed which exhibit high degrees of bias. Several WFO offices had distinctive SVT issuance practices. There are clear associations with developed areas and increased numbers of SVT counts that stand out from their mean relationship across the study area. It is not entirely misplaced to
suggest that more than half of the variance in the issuance of SVT warnings across the lower eastern US is related to whether or not thunderstorms are moving into a populated or perhaps even wealthier region. The regions of greatest SVT response, as based on the combination of evidence mapped in this study are the Washington, D.C. area; the Asheville-Greenville-Charlotte corridor; St. Louis; Nashville; Memphis; the Atlanta-Macon-Columbus corridor; Jackson, MS; and Indianapolis. Conversely, regions to the northern interior of the study areas, including major cities like Chicago, Pittsburgh, and Cleveland did not show extensive evidence of forecaster bias.

This and other studies leave little question that bias related to population and economic resources exists in SVT distribution. Because the purpose of SVTs is to protect people and property, it could be argued that areas with more people and more resources receiving more warnings is unavoidable. In this light, bias could be seen as a natural part of warning issuance, and therefore relatively unproblematic. However, living in a place with fewer people should not be less safe than living in a place with more people. Although bias may be an inherent characteristic of SVT issuance, ensuring equitable warning practices for all NWS subjects remains vital. Furthermore, production of accurate climatological records is also partially dependent on warning issuance being minimally affected by non-meteorological factors. Discernment of how and where bias is particularly strong can allow it to be corrected in a systematic way (Elsner et al. 2013).

Several new lines of investigation originated from this research. As forementioned, to what extent is SVT issuance related to WFO practices, as opposed to anthropogenic modification of thunderstorms? The findings of this study also confirm the recent call for more behavioral research on forecasters’ judgment and decision-making processes, and the ways these processes differ across individuals and NWS regions (Lindell and Brooks 2013). For example, why do forecasters continue to release more warnings at the county level instead of at the level of individual storm polygons? Barrett’s (2012) finding that population bias is greatest in storm-based polygons suggests that the choice of which to use may reflect local forecast culture. Qualitative investigations to address these question may complement the intensively quantitative practice of forecasting.

In closing, this study allows severe weather forecasters to see over a wide geographic area how non-meteorological factors play a role in their decision-making process. The information presented here should have relevance not only to forecasters, but to the general public as well. It is important that citizens gain awareness of any forecaster bias which may give preference to particular groups of people or to particular geographic areas over others. For instance, this study presents very strong evidence that residents of Washington, D.C. may be the most thunderstorm-warned population group in the U.S., not only based on SVT issuance patterns, but also on the sensitive infrastructure that undoubtedly resides in the area. Conclusions related to the presence or absence of bias in the study region, and in all areas served by the NWS, may aid in considering the efficacy, or equitability of the basic architecture of severe warning issuance.
References


Barrett, K. M., 2008: The County Bias of Severe Thunderstorm Warnings and Severe Thunderstorm Weather Reports for the Central Texas Region, Geology, Baylor University. [Available online at http://hdl.handle.net/2104/5161.]

——, 2012: The Spatial Distribution of Contiguous United States Thunderstorm Related Short-Fuse Severe Weather Warnings, Geography, Texas State University-San Marcos. [Available online at https://digital.library.txstate.edu/handle/10877/4293.]


Diem, J. E., 2008: Detecting summer rainfall enhancement within metropolitan Atlanta,


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