Comparing Weather-Related Hazards and their Effects on Population Change in the United States, 1980–2012

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Abstract

Environmental determinists predict that people move away from places experiencing frequent and costly weather hazards, yet mounting hazard-related losses are largely attributed to growing numbers of people living in harms' way (Pielke et al. 2008). To investigate how people adapt to or remain vulnerable to weather hazards, we must first understand the relationship between weather hazards, associated losses, and population change. In our analysis, we investigate whether the five costliest types of weather hazards and the losses resulting from them are associated with subsequent population change in U.S. counties between 1980 and 2012. We evaluate these relationships using a spatial-temporal database that includes information on all U.S. counties that experienced a weather hazard during this time. The structure of the database allows for more generalizable conclusions by accounting for heterogeneity in current and past weather events and losses and past population trends. Our research departs from previous social science research that treats hazard losses as equivalent. We investigate this assumption and find that hazard events and losses from some types of hazards (hurricanes and droughts) produce more population change than others (floods, hail and tornadoes), although some counties are more vulnerable to these hazard-related population changes than others. This place-based heterogeneity in response to hazards justifies further inquiry

into how counties' environment, infrastructure, economy, and demography make some places more or less vulnerable to weather hazards.

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Scientific warnings that climate-related extremes will increasingly impact ecosystems and social systems have focused scholarly attention on social and demographic responses to weather-related hazards, particularly the migration response (IPCC 2014). In the past scientists have taken an environmentally determinist view which argues that populations living in an area susceptible to extreme climate events will out-migrate (e.g. Myers 2002). Recent demographic research shows that out-migration after destructive weather hazards is selective (Elliott 2014; Logan, et al. 2016; Shumway, et al. 2014) and depends on demographic trends and current and past weather events and related losses (Fussell et al. 2017). These advances in knowledge about the population effects of weather hazards demand more investigation into sources of heterogeneity in weather hazard impacts in order to better understand why some people and places are more vulnerable to weather hazards than others.

Are weather hazards equivalent in their effects on population change?

Much of the existing research on social vulnerability to environmental hazards operationalizes hazard impacts with estimates of total property and crop losses due to all hazards using data made easily available through the Spatial Hazards Events and Losses Database for the United States (SHELDUS) (HVRI 2015) (e.g. Ash, et al. 2013; Boruff, et al. 2005; Elliott 2014; Schultz and Elliott 2013). SHELDUS makes all hazards equivalent in terms of the dollar amounts lost, while distinguishing between crop losses and property losses. However, within the category of property losses it combines different types of losses. Losses include major and minor damage to residential homes, commercial properties, tree removal, downed power lines, private and commercial vehicles, road and highway infrastructure, fences, levees, and retaining walls. Some of these losses are private, while others are public; some prevent residence in a home, while others involve losses that are nuisances but not major disruptions to residents' lives. Currently, loss data disaggregated by damage type are not available, preventing us from directly examining the effect of specific types of hazard-related losses on population change. However, different types of hazards produce different types of losses. In the current analysis, we take advantage of the different modes of impact of specific weather hazards to investigate how much each contributes to county-level population change.

Since weather-related hazards are unpredictable in their timing and intensity, they produce spatially uneven losses in each year across U.S. counties. Over the course of a decade, however, the cumulative loss pattern reveals spatial regularities in the distribution of hazards. Figure 1 shows the total cumulative property and crop losses in a decade (1998-2007) due to all weather related hazards (Panel A) and the five costliest hazards: hurricanes and tropical storms (Panel B); flooding (Panel C); droughts (Panel D); tornadoes (Panel E); and hail (Panel F). Two things are notable in Figure 1. First, weather-related hazards differ in their spatial distributions. Aggregating hazard losses over a decade (Panel A) obscures much of the heterogeneity in the spatial distribution of specific hazards that is evident in the distribution of specific hazard losses (Panels B to

F). Second, weather-related hazards differ starkly in total losses. Hurricanes and tropical storms accounted for two-thirds of hazard-related losses during this time ($266.2 billion US$2014), while flooding-related losses were only a tenth of total losses, drought-related losses were about 6.5 percent, tornado-related losses were 4.9 percent, and hail-related losses were 4.4 percent. While we are not able to observe the types of losses that occur in each of these events, we can speculate that the difference in cumulative losses is likely due to the greater destructive power and scale of hurricanes, tropical storms, and floods relative to the other hazards. Droughts are spatially extensive, but less destructive with nearly all losses being crop-related. Tornadoes are highly destructive and spatially focused, often occurring at a sub-county level, resulting in smaller cumulative losses. Hail is also spatially focused but less destructive, causing minor damage to trees, vehicles, and buildings.

FIGURE 1

Total Cumulative Property and Crop Losses in a Decade (1998–2007) Due to All Weather-Related Hazards (A) And The Five Costliest Hazards (B–F)

[Insert Figure 1 about here]

This heterogeneity within hazards leads us to hypothesize that some, but not all, hazards will be associated with county-level population change. This is supported by a growing literature on the population impacts of hurricanes, but we know less about the potential population impacts of other types of hazards. However, consistent with the finding that hurricanes may produce more population change in particular types of places, we further hypothesize that the effect of hazard losses on future population growth will depend on county-level characteristics, with some types of hazard events being more consequential in some types of counties than others. Because our research is the first we know of to explore the heterogeneity of hazard impacts on population, we refrain from more specific hypotheses about the direction or magnitude of effects for other specific hazards in specific types of counties.

Data and Methods

Data

To obtain the spatial and temporal variability in population trends and weather hazard events and losses necessary to accomplish our research objectives, we integrated county level annual population estimates from the US Census Bureau (2016) with the Spatial Hazard Events and Losses Database for the United States (SHELDUS) (HVRI 2015). For the measures of population change we included annual, county-level estimates from 1970 through 2012. Intercensal estimates were used for the 1990s and 2000s, while postcensal techniques were used for the 1970s, 1980s, and 2010s. We did not include intercensal estimates for the 1960s because they were produced with methods that are inconsistent with later estimates. Our population change dataset treats county-year as the unit of analysis and measures annual population size for each county-year.

The SHELDUS dataset measures annual county-level fatalities, injuries, property, and crop losses associated with eighteen types of natural hazard events in the United States from January 1960 to December 2014. SHELDUS combines data from twenty-three sources though most come from the National Centers for Environmental Information data products. The loss estimates are obtained from emergency managers, U.S. Geological Survey, U.S. Army Corps of Engineers, power utility companies, and newspaper articles. These amounts refer to losses associated with damage to private property, including structures, objects, and vegetation, as well as public infrastructure and facilities. Damages or loss amounts are distributed evenly between counties in a multi-county event. As in the population data, the unit of analysis is a county-year. The population and hazard event data files were merged using ArcGIS geo-referenced county-year FIPS codes and county boundary files to produce a spatial-temporal database of county-years for each hazard type. We adjusted county boundaries to 2010 boundaries.[i] From the SHELDUS database we selected only weather-related hazards, which include avalanches, coastal storms, droughts, floods, fog, hail storms, heat waves, hurricanes/tropical storms, landslides, lightning storms, severe thunderstorms, tornadoes, wind, and winter weather as our first cut of the data. We focused on these because we expect to see more of these types of events as climate change progresses. This excludes wildfires, earthquakes, tsunamis/seiches, and volcanic eruptions, none of which are directly attributable to climate change since wildfires are typically started by human activity and geologic activity is not climate-related. After identifying the costliest types of hazards, we created separate databases for each hazard type. Each database is comprised of every year of data for a county that was ever impacted by a hazard type in at least one of the years between 1970 and 2009. These county-year databases allow us to separately assess the impact of each hazard type on subsequent population growth from 1980 to 2012.

Our databases provide an important corrective to previous approaches to how populations respond to hazard impacts. Analyses that focus on population impacts of a single hazard event in a specific place commit two errors that threaten the generalizability of their findings: (1) they select only the most damaging and costly events and thereby neglect the full range of events, and (2) they ignore the cumulative impacts of previous hazard events, a source of unobserved heterogeneity. By using data from a long period of time and for the entire set of counties that have ever experienced a specific type of event during the period under study we address both concerns.

We addressed these sources of unobserved heterogeneity by measuring all hazard events and placing the effect of a single hazard event in the context of past hazard events, hazard-related losses, and past population growth. We observed hazard events and losses for the years 1970 to 2009 and population data from 1970 to 2012. We then constructed decadal measures of cumulative hazard events and losses. A decade is long enough to remove much of the random element of hazard occurrence and capture secular trends. The measures of cumulative hazard events and hazard losses sum those annual quantities over the previous 10 years. The past population trend is defined by a 10-year compound average population growth rate: $CAPGR = \left(\frac{pop_t}{pop_{t-10}}\right)^{\left(\frac{1}{11}\right)} - 1$, where *pop* is the county population in a given county-year, and *t* is the reference year. Therefore, our analysis begins in 1980, the first year in which we have 10 years of past hazard and population data. We measure future population growth as a three-year compound average annual population growth rate: $CAPGR = \left(\frac{pop_{t+3}}{pop_t}\right)^{\left(\frac{1}{4}\right)} - 1$, where *pop* is the county population in a county-year, *t*, and *t* is the reference year. We chose three years as a time frame because it allows for the possibility of population recovery and growth (or loss) after a hazard event. We also included a measure of county population density, defined as the population per square mile. Based on our decision to measure future growth in three-year intervals and data availability, we end our analysis in 2012.

Methods

Our hypothesis is that the effect of current and cumulative weather-related hazard events and losses on population change in the next three years will differ by type of weather event and county type. To test this, we estimate a random effects linear regression that takes a reduced form, evaluating the marginal impacts of each type of hazard on future population change, controlling for past population trends. We used this model in previous research investigating the effect of hurricanes and tropical storms on population change (Fussell et al. 2017). We assume that while political, social, and economic conditions and trends also influence future population growth, their influence is gauged by past population growth. Past population growth captures a large portion of this unobserved heterogeneity. To further address the issue of unobserved heterogeneity between counties we analyze our county-year data with a random effects generalized least squares regression estimation model (STATA xtreg re):

$$y_{it} = x'_{it}\,(\beta_{it}+h_i) + (\alpha_{it} + u_i) + \varepsilon_{it},$$

This random effects estimator is a matrix weighted average of the fixed-effects (within) and the between effects, where y_{it} is the outcome, the prospective three-year compound annual growth rate from time *t*, for every county *i* in year *t*; x'_{it} is a vector of county-year factors that vary across time and counties and β_{it} is the between effects parameter.[ii] The coefficients are interpreted as the average effect of a county-year factor on the future population growth rate, *ceteris paribus*.[iii] Since the data come from all U.S. counties that have experienced hurricanes between 1970 and 2012, our data constitute the entire population (not a sample) of county-years, and we report tests of statistical significance as an indication of the meaningfulness of the estimated coefficients (e.g., how different they are from zero).

Controls for county-level population density and growth trends in the model

Our models include controls for county-level population density and growth trends since our past research has shown that the population effects of weather hazards, specifically hurricanes and tropical storms, depends on these population characteristics. To illustrate the spatial distributions of our population measures we show population density, past population growth, and future population growth using 2008 as a reference year (see Figure 2). Population density (Panel A) shows densities are higher on average in the eastern United States and the West Coast compared to counties ranging from the Western mountains through the arid mid-West. Panel B shows past population trends for county-year 2008, referencing the prior decade, 1998–2007. During this period, counties in the east and west grew the fastest, while many counties throughout the middle of the country declined by more than 10 percent. Overall, most counties evince little change, registering less than 2 percent growth or decline. Panel C shows future population growth for county-year 2008, referencing change from 2008 to 2011. This shows that prospective population growth rates across U.S. counties are mostly inclining. Even for counties with declining past population growth rates, the forward projection appears to be one of little to slow growth with very few counties showing rates of decline greater than 2 percent. In additional analyses (not shown), we find that while past population growth rates and future population growth are relatively stable, variance around these annual means has been decreasing with each year. In contrast, means for population density have also been stable, but variance has been increasing with each year. This is an additional source of heterogeneity that we account for with our model.

FIGURE 2

Variability In Population Density (A), Historic Population Trends (B), and Future Growth For Counties in Reference Year 2008 (C)

[Insert Figure 2 about here]

Delving further into our investigation of differences between counties over time, we examined differences in future population growth between high and low density counties and counties with past inclining and declining growth rates (analysis not shown). We found that counties with declining past population trends, especially low density counties, tend to have higher rates of future growth, especially when past declines were large. In contrast, counties with inclining past population trends, especially high density counties, tend to have higher rates of future growth, especially when past inclines were large. Because these underlying population trends are so different, an analysis of the complete spatial-temporal database is likely to obscure the effects of hurricanes. To more cleanly expose population trends after a hurricane, we subset our data into four categories of counties: high (density >= 1,000) and low (density < 1,000) density and inclining (CAPGR>0) and declining (CAPGR<=0) past growth trends. We use these subsets in our multivariate random effects regression analysis in our analyses.

In the analysis section, we discuss the descriptive statistics for our datasets. We then present the results of our regression analysis to test our hypothesis that the effect of a weather hazard in a given year on future population growth differs by hazard type. In the final section we summarize our findings and their implications for future research on weather-related hazards and population change.

Analysis

Descriptive statistics for the spatial-temporal database and subsets

Distinguishing counties by past growth trends (CAPGR) and population density is a simple way to discern the heterogeneity of current year and cumulative hazard events and losses (see Tables 1 through 5). Rather than discussing the statistics for each of the weather hazards, we highlight several patterns. In every hazard-specific database, the vast majority of county-years were for counties with low population densities, and, of these, most had declining past growth trends. Of the remaining county-years for counties with high population densities, the majority had declining past growth. Only a very small percentage of all county-years were contributed by high density counties with inclining past growth trends. These unequal group sizes mean the low density, declining growth counties have an undue weight in any regression analysis, which is why we treat them separately in the regression analysis.

TABLE 1-5

Population Trends and Hazard Events and Losses for All Counties Ever Experiencing a Hazard Event

[Insert Tables 1-5 about here]

Turning to the population variables, we see similar patterns across each of the databases. Illustrating the principle of regression to the mean, counties with declining 10-year growth trends tend to experience growth in the next three years, regardless of population density. Counties with inclining 10-year growth trends tend to experience population loss in the next three years, regardless of population density. With growth trends tend to be similar in each of the hazard-specific databases, county-years in the databases for drought and flood events tend to have lower population densities than those in the other hazard event databases.

The hazard variables also have similar patterns across each of the databases. Hazard-related losses per capita in the current year and in the past decade tend to be greater in low density counties in all five databases. Hazard-related losses in these low density counties are spread across fewer residents. The number of current year and past decade hazard events are very close to average, regardless of the population density or growth trend. This is to be expected since the occurrence of a weather-related hazard events is not influenced by the population characteristics of a place.

Multivariate random effects regression analysis

To test our hypothesis that the effect of weather hazards differs by hazard and county type, we estimate random effects linear regression models for each subset of county-years in each hazard specific database (Tables 6 and 7). To facilitate interpretation of the equations, we summarize the statistical significance, direction, and size of effect for each of the independent hazard events and losses variables for each hazard database (Table 8). The summary table makes evident that hazard events and related losses only have large and significant effects in two types of events and that these effects are mainly evident in two types of counties. This is general confirmatory evidence for our hypothesis that weather hazard effects on population are not consistent and that the effect of hazards on population depends on the type of county.

TABLES 6-8

Random Effects Linear Regression for Three-Year Prospective Population Growth Rate among Counties with Declining or Inclining Growth Trends and High or Low Population Densities

[Insert Tables 6-8 about here]

First, we find that hurricanes and tropical storms, the very destructive events that were hypothesized to be most consequential for population change, have distinct impacts on the four types of counties (Table 8; Figure 3). In county-years with inclining population growth and high population densities, on average, a greater number of hurricane events in the past decade strongly depresses future population growth and higher current year hurricane-related losses slightly depress future growth. However, in these same types of counties, a larger amount of past hurricane-related losses increases future growth, on average. This effect is so large that it may cancel out the negative effects of current losses and cumulative events. Other types of counties also experience small positive effects of higher amounts of past hurricane-related losses on future population growth. Both current and cumulative hurricanes and hurricane-related losses encourage future population growth in declining, low density counties. But these effects, while statistically significant, are small.

FIGURES 3-4

Prediction of Future Population Growth Given Covariate Values Based on Results from Regression Models

[Insert Figure 3-4 about here]

Second, we find that the effect of drought is statistically significant and large in low density counties with declining populations, and to a lesser extent in low density counties with inclining populations (Table 8; Figure 4). Low density counties tend to have natural resource based economies, so the effect of drought-related losses on future population growth likely operates through changes in livelihoods. In both types of low density counties, current drought-related losses diminish future population growth regardless of their growth trend, while greater levels of past drought-related losses suppress future growth in growing counties. In contrast, in both types of low density counties, a higher number of past drought events have small but positive effects on future population growth and a current drought has a small positive effect on population growth in counties with inclining population growth. A higher number of past droughts may have contributed to converting the economy from an agricultural to an environmental amenity-based economy.

Finally, we do not find evidence that other weather-related hazard events and losses affect future population growth. We find only trivial effects of floods, hail, and tornadoes in low density county-years. These effects are so small, and they are based on the large number of low density county-years that constitute the bulk of the databases, that we hesitate to say they are important for future population change in any meaningful way.

Conclusion

In this paper we make a novel contribution to the demographic literature on weather hazards and population change in the United States by investigating heterogeneity in hazard effects on population change. To do this, we constructed a spatial-temporal databases of U.S. counties from 1980 to 2012 with population measures and current year, and cumulative measures of weather events and related losses. We modeled hazard events and losses separately for the five costliest types of hazards, in order to control for the variable spatial and temporal distribution, mode of impact, and the value of associated losses of each of these weather-related hazards. Our measures differentiated between long- and short-term effects to estimate more precisely how hurricanes influence future population trends. Our models differentiated the counties according to past population growth trends and population density, and used a reduced form, random effects linear regression model to control for the effect of county-level population characteristics and unobserved county characteristics.

We find support for our hypothesis that the some, but not all, weather-related hazards will be associated with county-level population change, but that their effects will differ between different types of counties. We find that hurricanes and tropical storms have the strongest effects in high density, growing counties: a greater number of hurricane events and greater current year losses suppress future population growth, while a greater amount of cumulative hurricane-related losses in the past decade strongly increase population growth. In other types of counties, past hurricane-related losses have a small but significant positive effect on future growth. We also find that droughts affect future population growth in low-density counties, whether they have experienced inclining or declining growth trends. A greater level of past and current drought-related losses are associated with lower growth, especially in counties with inclining past growth. These drought-related losses impact the livelihoods of agricultural workers, encouraging out-migration. On the other hand, counties experiencing droughts may still attract new residents seeking dry, warm climates. We find that a higher numbers of past droughts and a current drought are associated with small increases in population growth.

As we expected, not all hazards produce population change: we find no sizable effect of floods, hail, or tornadoes on population change. There may be several reasons for this finding. Floods and tornadoes are certainly destructive, but they may occur at a sub-county geographic scale that is too small for our database to detect. Furthermore, mobility related to these types of events may occur within counties, resulting in no change in the population. Homeowners and flood insurance may also mitigate the impacts of these hazards, allowing residents to remain in place. Infrastructure may also protect people against some of these weather hazards, so that hazard-related costs are mainly associated with repairing public roads, bridges, retaining walls, fences, and other parts of the built environment. All of these mitigation measures prevent hazards from becoming the types of events that displace people, or whose threat discourages people from settling in hazard-prone places. The lack of population change associated with hazards should not be surprising in the U.S. because of a long history of public and private investment in hazard mitigation measures and insurance against hazards.

Our analysis has several limitations. First, measures of county-level demographic, economic, and environmental characteristics would have been preferable to a simple measure of past population trends and population density, but they were not consistently available in all county-years. During this period, county boundaries changed, and counties' demographic, economic, and political characteristics have changed in ways that were difficult to measure consistently across time and space. To make the project tractable and demonstrate the value of proceeding in this line of inquiry we used simple metrics and a model that takes into account this unobserved heterogeneity. Second, our multivariate analysis did not take account of the spatial relationships between counties. While a spatial regression analysis is planned, in this analysis we sought to explore new measures and their use in a multivariate regression framework. Nevertheless, our systematic approach to spatial-temporal data show that hurricanes have heterogeneous impacts on counties, and that their impact depends on past population change and population density, explaining some of the inconsistencies in the growing field of research on weather-related hazards and population change.

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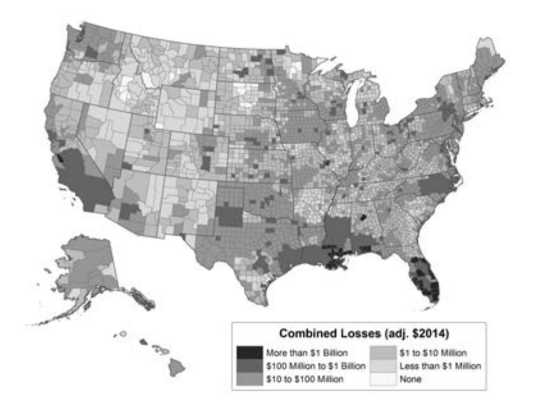
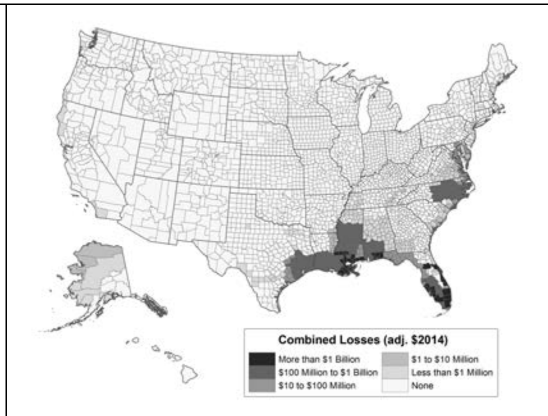
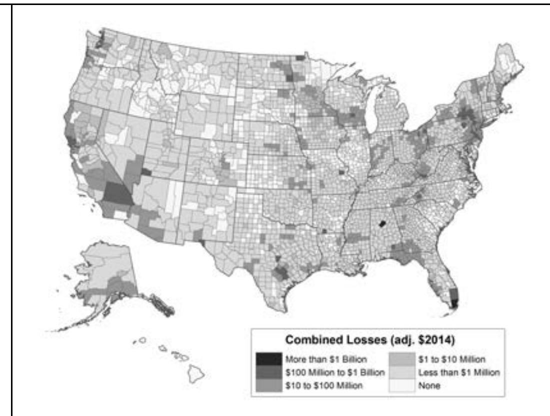
Figure 1. Total cumulative property and crop losses in a decade (1998-2007) due to A) All weather-related hazards, and B-F) The five costliest hazards



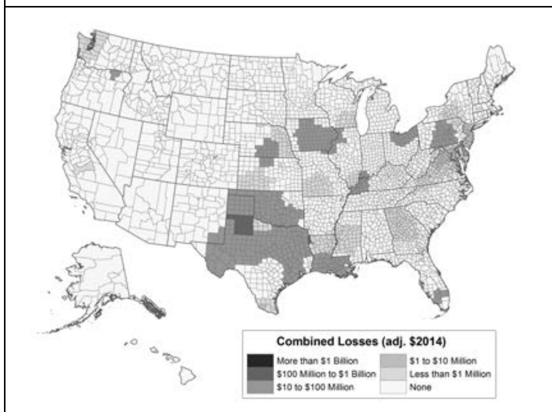
Panel A. All hazards



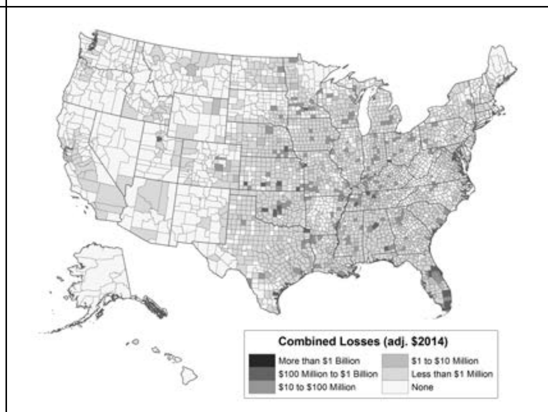
Panel B. Hurricanes and tropical storms



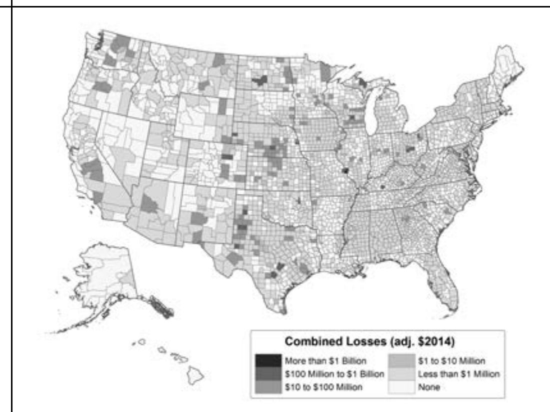
Panel C. Flooding



Panel D. Drought

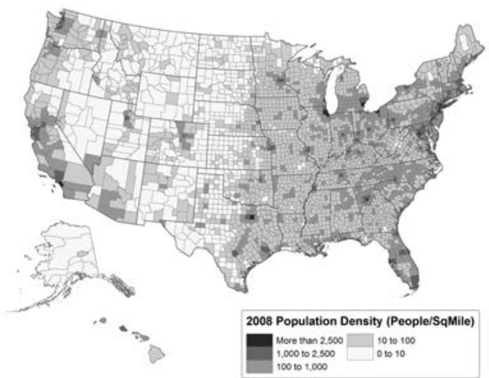


Panel E. Tornadoes

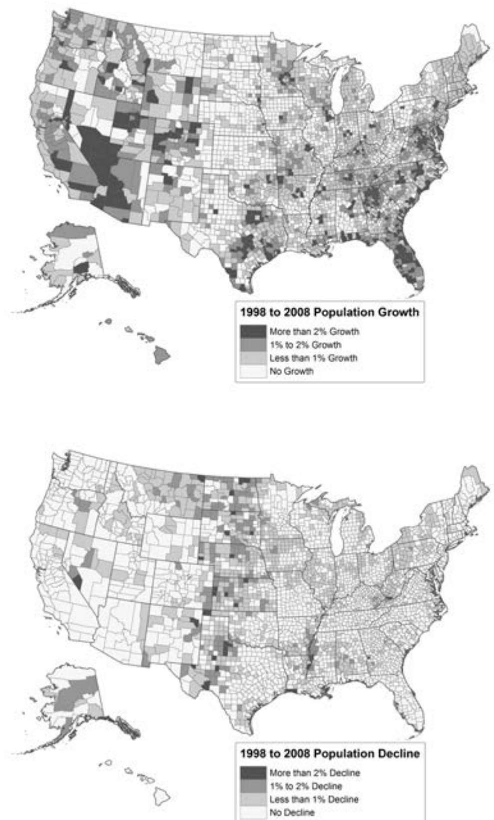


Panel F. Hail

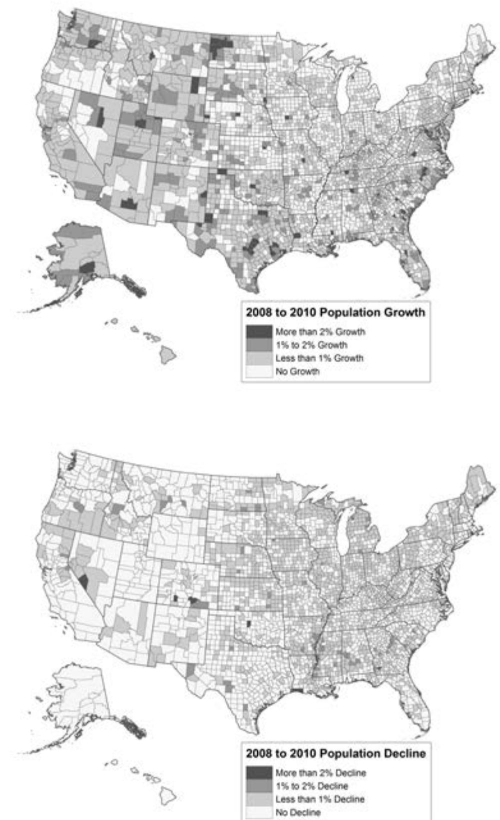
Figure 2. Variability in A) Population density, B) Historic population trends, and C) Future population trends for counties based on reference year 2008



Panel A. Population density 2008



Panel B. Historic Population trends: 1998 to 2008



Panel C. Future Population trends: 2008 to 2010

Figure 3: Prediction of future population growth given covariate values based on results from regression models

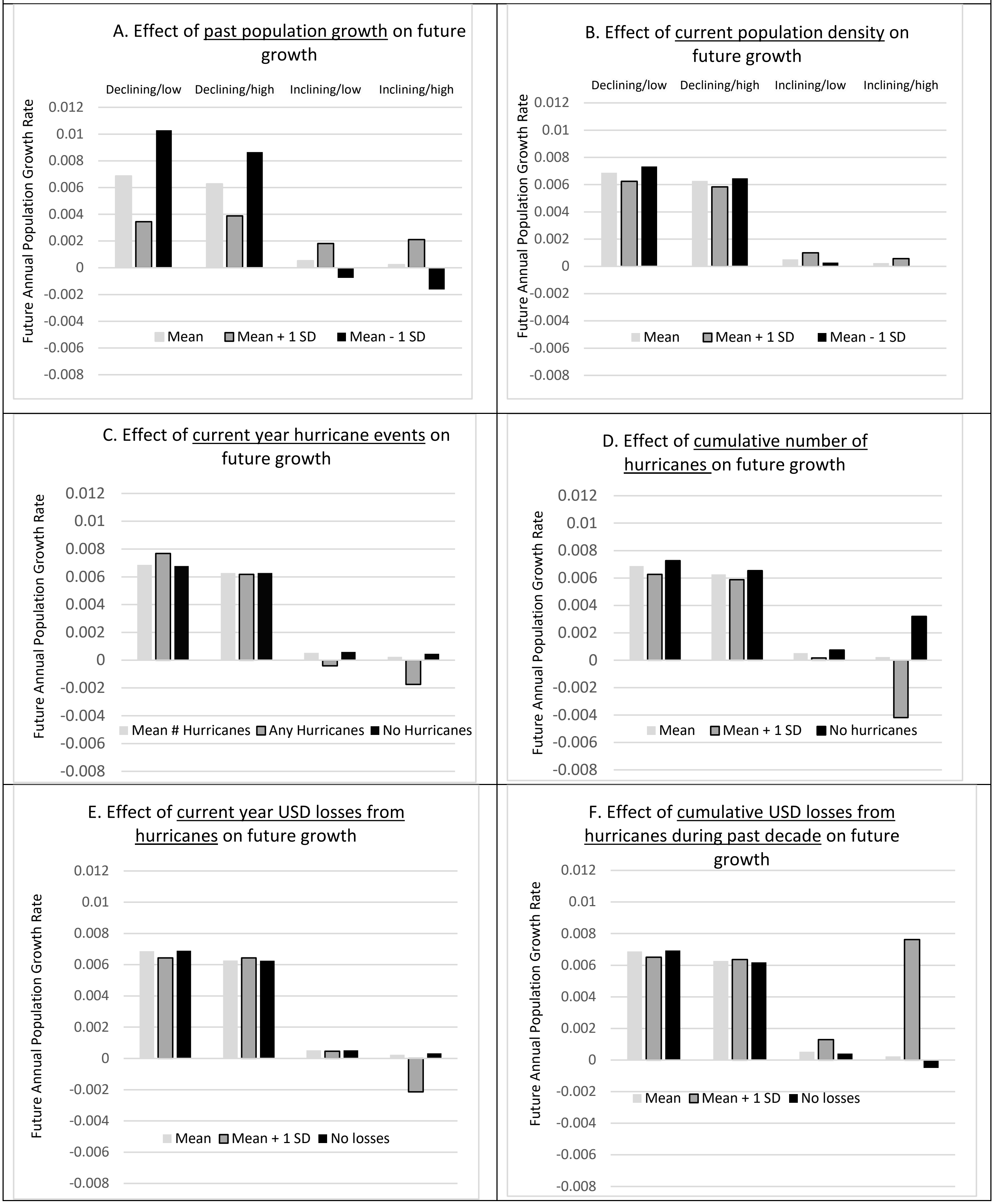


Figure 4: Prediction of future population growth given covariate values based on results from regression models

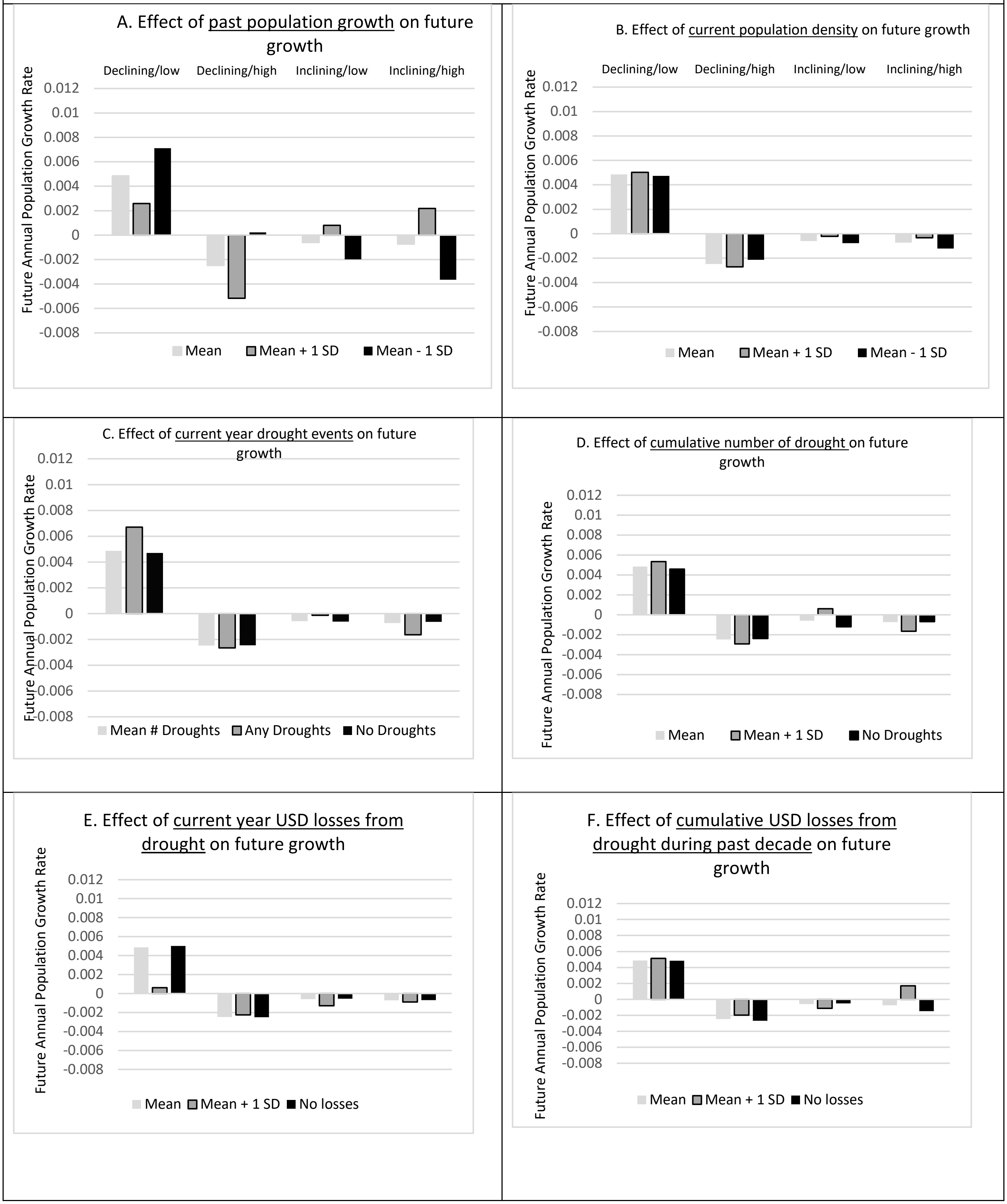


Table 1: Population Trends and Hazard Events and Losses for All Counties Ever Experiencing a Hurricane Event					
	All County-Years 1980-2009, Among Counties Ever Exposed to Hurricanes Between 1970-2009 (means (s.d.))				
	All Counties	Counties With <u>Declining</u> 10 Year Population Trend		Counties With <u>Inclining</u> 10 Year Population Trend	
		Pop Density < 1000 People/Square Mile	Pop Density >=1000 People/Square Mile	Pop Density <1000 People/Square Mile	Pop Density >=1000 People/Square Mile
N of cases	39,314	28,999	2,010	7,481	824
Population Variables					
Compound Annual Pop Growth Rate from year=t to t+3	.0061 (0.019)	.00821 (.012)	.007 (.008)	-.002 (.010)	-.001 (.012)
Compound Annual Pop Growth Rate from year=t-11 to t	-.00898 (0.0129)	-.01307 (.012)	-.01 (.009)	.005 (.006)	.005 (.006)
Population Density (people per square mile) in year t	418.785 (2503.25)	129.085 (172.023)	4156.024 (8907.199)	71.272 (137.926)	4652.892 (6951.653)
Hazard Variables (Hurricanes)					
$ Losses (million)/capita (USD 2014) in past decade	.000981 (0.008)	.00085 (.005)	.0001 (.0001)	.002 (.014)	.0003 (.003)
$ Losses (million)/capita (USD 2014) in a county-year	.00012 (.002)	.00012 (.002)	.00001 (.0002)	.0001 (.002)	.00004 (.001)
# of hurricanes in past decade	1.272 (1.979)	1.296 (2.005)	1.326 (2.007)	1.111 (1.768)	1.742 (2.601)
Any hurricane in a county-year	.091 (.287)	.094 (.292)	.105 (.307)	.073 (.260)	.101 (.301)

Table 2: Population Trends and Hazard Events and Losses for All Counties Ever Experiencing a Flood Event					
	All County-Years 1980-2009, Among Counties Ever Exposed to Flood Between 1970-2009 (means (s.d.))				
	All Counties	Counties With Declining 10 Year Population Trend		Counties With Inclining 10 Year Population Trend	
		Pop Density < 1000 People/Square Mile	Pop Density >=1000 People/Square Mile	Pop Density <1000 People/Square Mile	Pop Density >=1000 People/Square Mile
N of cases	99740	65814	2730	30038	1158
Population Variables					
Compound Annual Pop Growth Rate from year=t to t+3	.004 (.012)	.01 (.01)	.007 (.007)	-.003 (.009)	-.001 (.01)
Compound Annual Pop Growth Rate from year=t-11 to t	-.006 (.013)	-.01 (.01)	-.009 (.008)	.006 (.006)	.005 (.005)
Population Density (people per square mile) in year t	231.432 (1623.157)	103.97 (151.71)	3671.981 (7827.208)	47.354 (97.678)	4139.237 (6003.125)
Hazard Variables (Flood)					
$ Losses (million)/capita (USD 2014) in past decade	0 (.02)	.0003 (.002)	3.67 E-05 (.0001)	.001 (.003)	.0001 (.0005)
$ Losses (million)/capita (USD 2014) in a county-year	4.26 E-05 (.001)	.00003 (.001)	5.59 E -06 (.0001)	6.85 E-05 (.001)	7.89 E-06 (.0002)
# of floods in past decade	6.34 (7.87)	6.176 (7.265)	8.008 (8.343)	6.475 (8.949)	8.225 (8.986)
Any flood in a county-year	.33 (.47)	.326 (.469)	.392 (.488)	.321 (.467)	.360 (.480)

Table 3: Population Trends and Hazard Events and Losses for All Counties Ever Experiencing a Drought Event					
	All County-Years 1980-2009, Among Counties Ever Exposed to Drought Between 1970-2009 (means (s.d.))				
	All Counties	Counties With <u>Declining</u> 10 Year Population Trend		Counties With <u>Inclining</u> 10 Year Population Trend	
		Pop Density < 1000 People/Square Mile	Pop Density >=1000 People/Square Mile	Pop Density <1000 People/Square Mile	Pop Density >=1000 People/Square Mile
N of cases	59044	38297	1426	18552	769
Population Variables					
Compound Annual Pop Growth Rate from year=t to t+3	.004 (.0012)	.007 (.012)	.008 (.009)	-.003 (.009)	-.002 (.012)
Compound Annual Pop Growth Rate from year=t-11 to t	-.003 (.013)	-.012 (.011)	-.011 (.010)	.007 (.006)	.005 (.005)
Population Density (people per square mile) in year t	176.984 (619.853)	105.606 (153.795)	2174.102 (1506.273)	47.048 (95.836)	3163.045 (2632.749)
Hazard Variables (Drought)					
$ Losses (million)/capita (USD 2014) in past decade	.001 (.008)	.0003 (.002)	.00004 (.0001)	.002 (.014)	.00003 (.0001)
$ Losses (million)/capita (USD 2014) in a county-year	.0001 (.002)	.00004 (.001)	4.08E-06 (.00003)	.0002 (.003)	2.84E-06 (.00002)
# of droughts in past decade	1.257 (2.254)	1.315 (2.382)	1.525 (2.261)	1.128 (1.993)	.960 (1.159)
Any drought in a county-year	.082 (.275)	.081 (.272)	.101 (.301)	.083 (.277)	.081 (.272)

Table 4: Population Trends and Hazard Events and Losses for All Counties Ever Experiencing a Tornado Event					
	All County-Years 1980-2009, Among Counties Ever Exposed to Tornado Between 1970-2009 (means (s.d.))				
	All Counties	Counties With <u>Declining</u> 10 Year Population Trend		Counties With <u>Inclining</u> 10 Year Population Trend	
		Pop Density < 1000 People/Square Mile	Pop Density >=1000 People/Square Mile	Pop Density <1000 People/Square Mile	Pop Density >=1000 People/Square Mile
N of cases	90091	59063	2351	27807	870
Population Variables					
Compound Annual Pop Growth Rate from year=t to t+3	.004 (.011)	.007 (.011)	.007 (.007)	-.003 (.008)	-.001 (.011)
Compound Annual Pop Growth Rate from year=t-11 to t	-.006 (.013)	-.012 (.011)	-.009 (.008)	.006 (.006)	.005 (.005)
Population Density (people per square mile) in year t	199.901 (1083.391)	108.691 (152.511)	2893.781 (4835.658)	45.731 (89.741)	4039.927 (4570.182)
Hazard Variables (Tornado)					
$ Losses (million)/capita (USD 2014) in past decade	9.04 E-05 (.001)	7.06 E-05 (.0005)	.00001 (.00004)	.0001 (.002)	.00001 (.00005)
$ Losses (million)/capita (USD 2014) in a county-year	1.16 E-05 (.0004)	7.85 E-06 (.0002)	1.16 E-06 (.00001)	2.09 E-05 (.0008)	1.17 E-06 (.00001)
# of tornadoes in past decade	2.573 (3.045)	2.624 (3.111)	3.246 (5.694)	2.423 (2.544)	1.874 (2.502)
Any tornado in a county-year	.178 (.382)	.181 (0.385)	.188 (.391)	.170 (.376)	.137 (.344)

Table 5: Population Trends and Hazard Events and Losses for All Counties Ever Experiencing a Hail Event					
	All County-Years 1980-2009, Among Counties Ever Exposed to Hail Between 1970-2009 (means (s.d.))				
	All Counties	Counties With **Declining** 10 Year Population Trend		Counties With **Inclining** 10 Year Population Trend	
		Pop Density < 1000 People/Square Mile	Pop Density >=1000 People/Square Mile	Pop Density <1000 People/Square Mile	Pop Density >=1000 People/Square Mile
N of cases	95582	62575	2480	29447	1080
Population Variables					
Compound Annual Pop Growth Rate from year=t to t+3	.004 (.012)	.007 (.012)	.007 (.008)	-.003 (.009)	-.001 (.010)
Compound Annual Pop Growth Rate from year=t-11 to t	-.006 (.013)	-.012 (.011)	-.010 (.009)	.006 (.006)	.005 (.005)
Population Density (people per square mile) in year t	221.858 (1609.761)	105.964 (152.897)	3584.999 (8047.667)	47.331 (98.088)	3972.574 (6119.172)
Hazard Variables (Hail)					
$ Losses (million)/capita (USD 2014) in past decade	.0001 (.001)	.0001 (.0004)	.00002 (.0001)	.0003 (.001)	1.36 E-05 (.0001)
$ Losses (million)/capita (USD 2014) in a county-year	.00001 (.0002)	5.73 E-06 (.0001)	2.33 E-06 (.00004)	2.49 E-05 (.0003)	6.63 E-07 (1.04 E-05)
# of hail events in past decade	5.234 (8.190)	4.422 (7.269)	4.941 (11.355)	6.964 (9.409)	5.715 (6.707)
Any hail in a county-year	.225 (.417)	.204(.403)	.198 (.399)	.271 (.444)	.238 (.426)

Table 6. Random effects linear regression for three-year prospective population growth rate among counties with declining population growth trends (county-years 1980-2009 ever exposed to specific weather hazard type between 1970-2009); coefficient (se)					
	Hurricane	**Drought**	**Floods**	**Hail**	**Tornadoes**
Declining Population Growth Trends					
PANEL A (<1000 Pop/Square Mile)					
Historic CAPGR	-.285 (.007) ***	-.206 (.007)***	-.210 (.005)***	-.220 (.005)***	-.221 (.005)***
Population Density	-3.60E-06 (7.10E-07)***	1.07E-06 (7.33E-07)	-3.27 E-07 (5.81 E-07)	4.49E-07 (5.64E07)	1.78 E-07 (5.8 E-07)
Past Losses (million)/cap.	-.073 (.012) ***	.057 (.030)	.032 (.025)	.453 (.117)***	-.315 (.080)***
Current $ Losses (million)/cap.	-.213 (.021) ***	-.424 (.045)***	-.063 (.052)	.722(.319)	-.093 (.215)
Past # of disaster events	-.0003 (.00004)***	.0002 (.00002)***	-.00001 (6.37 E-06)	-.0001 (6.42E-06)***	-5.8 E-05 (1.71 e-05)**
Current disaster event	.0009 (.0002) ***	.002 (.0002)***	.0003 (.00008)***	.00003 (.0001)	-.0001 (9.43 E-05)
Constant	.004 (.0002) ***	.002 (.0002)***	.003 (.0001)***	.003 (.0001)***	.003 (.0001)***
R-Square Within (Between)	.022 (.646)	.0021 (.6941)	.002 (.654)	.002 (.651)	.002 (.688)
PANEL B (>=1000 Pop/Square Mile)					
Historic CAPGR	-.265 (.024) ***	-.269 (.028)***	-.272 (.020)***	-.298(.021)***	-.331 (.021)***
Population Density	-4.80E-08 (4.38E-08)	-1.56E-07 (2.60E-07)	-6.36 E-08 (4.01 E-08)	-4.32E-08 (3.91E-08)	-7.79 e-08 (6.12 E-08)
Past Losses (million)/cap.	.884 (.301) **	5.077 (2.712)	-2.53 (1.054)	1.50 (1.391)	-8.131 (3.434)
Current $ Losses (million)/cap.	.802 (.702)	7.413 (6.943)	-1.31 (1.474)	-1.165 (2.914)	-7.195 (10.067)
Past # of disaster events	-.0002 (.0001)	-.0002 (.0001)	-.00004 (.00002)	.00004 (.00001)**	8.71 E-05 (3.86 E-05)
Current disaster event	-.0001 (.0004)	-.0002 (.0007)	.0003 (.0002)	-.0004 (.0003)	.001 (.0003)
Constant	.004 (.0005)***	-.005 (.0008)****	.005 (.0004)***	.004 (.0004)***	.004 (.00004)***
R-Square Within (Between)	.0234 (.6204)	.022 (.516)	.021 (.614)	.022(654)	.047 (.650)

*p<.01, **p<.005, ***p<.001

Table 7. Random effects linear regression for three-year prospective population growth rate among counties with inclining population growth trends (county-years 1980-2009 ever exposed to specific weather hazard type between 1970-2009); coefficient (se)					
Inclining Population Growth Trends	**Hurricane**	**Drought**	**Floods**	**Hail**	**Tornadoes**
PANEL A (<1000 Pop/Square Mile)					
Historic CAPGR	.214 (.023) ***	.232 (.013)****	.208 (.010)***	.195 (.010)***	.205 (.011)***
Population Density	3.41E-06 (1.74E-06)	3.99 E-06 (1.82 E-06)	2.95 E-06 (1.32E-06)	3.83 E-06 (1.32-06)**	5.41 e-06 (1.48 E-06)***
Past Losses (million)/cap.	.055 (.001) ***	-.037 (.005)***	.080 (.018)***	-.145 (.053)*	.093 (.029)**
Current $ Losses (million)/cap.	-.033 (.045)	-.233 (.023)***	.099 (.043)	.228 (.153)	-.097 (.057)
Past # of disaster events	-.0002 (.00009)	.0006 (.00003)****	.00007 (6.8 E-06)***	-.00004(6.68 E-06)***	-.0001 (.00002)***
Current disaster event	-.001 (.0004) **	.0005 (.0002)	.0004 (.0001)***	-.0004 (.0001)**	.0002 (.0001)
Constant	-.0006 (.0003)	-.003 (.0002)***	-.0024 (.0002)***	-.001 (.0002)***	-.002 (.0002)***
R-Square Within (Between)	.0287 (.0003)	.046 (.065)	.032 (.125)	.023 (.06)	.026 (.088)
PANEL B (>=1000 Pop/Square Mile)					
Historic CAPGR	.312 (.090) ***	.584 (.081)***	.603 (.063)***	.717 (.066)***	.653 (.073)***
Population Density	4.71E-08 (6.92E-08)	-1.55 E-07 (1.92 E-07)	2.48 e-08 (6.3 E-08)	-3.38E-09 (6.91E-08)	-9.82 e-08 (9.84 E-08)
Past Losses (million)/cap.	2.463 (.253) ***	24.407 (9.212) *	-.212 (.671)	5.712 (4.069)	2.387 (8.047)
Current $ Losses (million)/cap.	-2.379 (.464) ***	-8.554 (32.552)	-1.15 (1.836)	38.027 (28.603)	4.60 (28.892)
Past # of disaster events	-.0017 (.0003) ***	-.0008 (.0005)	-.00008 (.00004)	-.0001 (.0001)	.0003 (.0002)
Current disaster event	-.0022 (.001)	-.001 (.002)	-.0004 (.0006)	-.001 (.0007)	-.001 (.001)
Constant	.001 (.0009)	-.004 (.001)***	-.002 (.0007)**	-.003 (.001)***	-.004 (.001)***
R-Square Within (Between)	.318 (.0053)	.214 (.009)	.161 (.165)	.194 (.24)	.191 (.308)

*p<.01, **p<.005, ***p<.001

Table 8. Summary of Random Effects Linear Regression for Three-Year Prospective Population Growth Rate among Counties with Declining or Inclining Population Growth Trends and High or Low Population Densities (County-Years 1980-2009 Ever Exposed to Hazards Between 1970-2009)

	Hurricane	Floods	Drought	Tornadoes	Tornadoes
Declining Population Growth Trends					
PANEL A (<1000 Pop/Square Mile)					
Past Losses (million)/cap.	Positive, small			Negative, trivial	Positive, trivial
Current $ Losses (million)/cap.	Positive, small		Negative, large		
Past # of disaster events	Positive, small		Positive, small	Negative, trivial	Negative, small
Current disaster event	Positive, small	Positive, trivial	Positive, large		
PANEL B (>=1000 Pop/Square Mile)					
Past Losses (million)/cap.	Positive, small				
Current $ Losses (million)/cap.					
Past # of disaster events					Positive, trivial
Current disaster event					
Inclining Population Growth Trends					
PANEL A (<1000 Pop/Square Mile)					
Past Losses (million)/cap.	Positive, small	Negative, trivial	Negative, small	Positive, trivial	
Current $ Losses (million)/cap.			Negative, small		
Past # of disaster events		Positive, trivial	Positive, small	Negative, trivial	Negative, trivial
Current disaster event		Negative, trivial			Negative, trivial
PANEL B (>=1000 Pop/Square Mile)					
Past Losses (million)/cap.	Positive, large				
Current $ Losses (million)/cap.	Negative, small				
Past # of disaster events	Negative, large				
Current disaster event					

Note: Cells with no comments are not statistically significant at the .05 level.

Notes

[i] The spatial boundary files used for our mapping and modeling were generated from the 2010 TIGER/Line Shapefile. Historical SHELDUS data has already been conflated to modern (2010) boundaries and thus requires no boundary corrections over time. The population data used in our study, the US Census Bureau county-level intercensal population estimates, are based on decadal boundaries that are anchored on boundary definitions at the end of the decade. In other words, we only had to correct for boundary issues in 1970, 1980, 1990, and 2000, not all individual years. Most county boundaries do not change. For those that have changed we use the basic, but standard, process of areal weighting, or reassigning population counts based on the proportion of the county area that changed.

[ii] h_i induces the variation of the parameters across individual counties; α_{it} is the constant; u_i is a group-specific random element, similar to ε_{it} except that for each group there is just a single draw that enters the regression identically in each period.

[iii] There is considerable debate about the appropriate application of fixed and random effects models for estimating panel data results. A recent paper by Clark and Linzer (2015) sheds light on the debate, offers guidance on choice of models, and encourages practical and theoretical assessments. We do not estimate a fixed effects model because we have theoretical and practical reasons to include county-level effects and a fixed effects model would make evaluating these effects impossible (Clark and Linzer 2015, 407). In this article, we present the results of our random effects estimation that corrects the standard errors. Furthermore, we also evaluated models with a robust correction to control for heteroskedasticity