EXTREME WEATHER EVENTS AND RURAL-URBAN MIGRATION

by

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THESIS ABSTRACT

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In numerous regions around the globe, climate change can be expected to change the pattern of severe weather events. Migration flows have been systematically larger the higher the proportion of the population in urban areas in the destination county relative to the origin county. Richer models demonstrate that the effects of a number of different types of extreme weather events (i.e. flooding, heat waves, and wildfires) in the origin county on county-to-county migration flows are statistically significantly greater when the destination county is more urbanized compared to the origin county. The effect of the number of fatalities from flooding and heat waves in the origin county on migration flows is also amplified when the destination county is more urbanized. Thus it appears that even in a developed country like the U.S. extreme weather events still exacerbate rural-to-urban migration flows.

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For any errors or inadequacies that may remain in this work, of course, the responsibility is entirely my own.

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CHAPTER I

INTRODUCTION

In numerous regions around the globe, climate change can be expected to change the pattern of severe weather events. The nature of future changes in these patterns can be difficult to predict, but it is instructive to consider some of the potential consequences of extreme weather on household migration decisions based on past events. Tacoli (2009) rightly points out that extreme weather event will cause increasing levels of mobility but it is very difficult to predict exactly how climate change will impact migration. One reason for this could be the lack of comprehensive data on migration flows especially for countries like Bangladesh which is very much prone to natural disasters.

Casual empiricism in some developing countries (e.g. Bangladesh) suggests that increasing rates of weather-related disasters have the effect of driving rural dwellers off the land and into urbanized areas. This displacement puts considerable strain on society's resources. Unfortunately, detailed migration and weather data for Bangladesh are not available. Hence, we examine county-to-county migration decisions in the U.S., treating various types of extreme weather events as random exogenous shocks to the affected communities and economies.

I am particularly interested in whether rural-to-urban migration flows are altered systematically in the wake of extreme weather events. My data for the U.S. suggest that this is the case. I plan to explore a variety of specifications for a panel of over half a million annual U.S. county-to-county flows over a period of five years (2006-2010). The reason I was interested in this research is to provide appropriate information for policy responses at the local level. I was originally interested to study migration pattern in Bangladesh but due to lack of data I am focusing on US counties instead.

Literature Review

Black, Adger et al. (2011) in their article “The effect of environmental change on human migration” discusses a new framework for understanding the effect of environmental changes on migration. To these researchers it is surprising how academic discussions about environmental change have been, until recently, almost completely silent on the role of migration. It is instructive that recent debates on climate change and migration have tended to focus on migration as a problem or threat. For example, a common theme in much media, policy and campaign group discourse on climate change is that future environmental change will lead to the displacement of millions of people as ‘‘environmental refugees’’ or ‘‘environmental migrants’’. A paper presented at the AAAS in January 2011 prompted media reports repeating earlier projections of ‘50 million environmental refugees by 2020’ (Black, Adger et al. 2011). Despite a number of bold claims, however, the evidence base in this field is both varied and patchy, with an absence of coherent frameworks for thinking about, and testing hypotheses on, environmental change and migration.

The article goes on to describe the following five drivers of migration: Economic drivers include employment opportunities and income differentials between places. Political drivers cover not only conflict, security, discrimination and persecution, but also the political drivers of public or corporate policy over, for example, land ownership or enforced relocation. Demographic drivers include the size and structure of populations in source areas, together with the prevalence of diseases that affect morbidity and mortality. Social drivers include familial or cultural expectations, the search for educational opportunities, and cultural practices over, for example, inheritance or marriage. The environmental drivers of migration are exposure to hazard and availability of ecosystem services. The five drivers rarely act in isolation, and the interaction of the five drivers determines the details of movement (Black, Adger et al. 2011).

Black’s list rightly points out a range of future environmental changes that have the potential to influence the drivers of migration, with the most significant and extensive being global climate change, land degradation and the degradation of coastal and marine ecosystems. Each of these types of change is likely to impact migration both directly, as well as indirectly, through impacts on other drivers.

This study focuses specifically on the effects of climate change on migration. According to Black, Adger et al. (2011), global climate change driven by increases in the concentration of greenhouse gases in the atmosphere primarily manifests itself in changes to weather patterns at a place and an increase in sea level, due to the thermal expansion of sea water and inputs from melting land ice.

While the above article on environmental migration examines the drivers of mobility and also tries to identify locations that are affected by environmental change, it does not pay much attention to where people move in response to environmental changes. The destination is important for the findings in this thesis since I am interested in understanding whether migration flows are statistically significantly greater when the destination county is more urbanized. Findlay (2011) argues that much can be learned from applying established knowledge from the migration research literature to the specifics of environmental mobility. Migration destinations of environmental movers are examined in two different contexts. First, research is reported relating to the migration destinations of populations affected by drought and food insecurity. Second, Europe is studied as a destination region for migration flows. The paper concludes that, in place of estimates of the number of environmental migrants, a more productive focus of research would be to achieve deeper understanding of the destinations selected by current environmental migrants, and to appreciate why immobility is as great a problem as movement to new locations for those concerned with climate adaptation planning.

Gottschang (1987) presents a statistical introduction to migration. This is important for my research because I will be using regression-like methods in my research. Interestingly, the article finds that the regression coefficients of the disaster variables for the North China Plain and Manchuria are generally consistent with the common sense assumption that life-threatening events reduce the desirability of an area in the eyes of potential migrants. The article concludes that undoubtedly major disasters on the North China Plain and in Manchuria affected the decision of migrants. It goes on to explain that “the largest recorded wave of migration prior to the twentieth century took place in the late 1870s, when the great North China drought and famine of 1876-79 caused the deaths of some 9 million people”.

Hunter (2005) summarizes classic migration theories of potential use in the exploration of environmental context within migration research and also examines migration in association with natural hazards. An important point she made in the article is the social variation in vulnerability to natural hazards (which might be useful in interpreting our results). People who are in the low end of the socio-economic spectrum are most vulnerable to natural hazards and are also less likely to be equipped for rebuilding. Hence they are forced to live on marginal land outside urban areas or places that are prone to a natural disaster.

Another interesting point was about the displacement of millions of people as a result of natural disasters in this article using examples of China and Bangladesh. As a result of flood in 1994, mass migration to urban areas took place in China. In Bangladesh natural calamities also “push” migrant from rural to urban areas and as a result there has been an increase in the number of beggars and people looking for work in towns and cities.

Using American Housing survey, Hunter also finds that people migrating due to natural disasters are older and tend to be female headed households and are characterized by lower income and educational levels. Hence the less socio-economically advantaged people are most likely to migrate following a natural disaster because they do not have enough assets in order to rebuild. On the other hand, households with more assets are more likely to rebuild because the amount of extreme-weather related damages is less, due to their ability to undertake protective or mitigation measures.

According to Tacoli (2009), extreme weather events such as floods and hurricanes often force people to leave their homes and move to other places but those who migrate are often extremely vulnerable. An interesting point in this article is that displaced people tend to return as soon as possible in order to reconstruct their homes and livelihoods. An important factor mentioned in the article that has an impact on out-migration from an origin county is access to government and non government support system. A very good example is that of hurricane Katrina when mass migration never occurred. This can be attributed to the rapid humanitarian response by different groups to support the affected victims.

According to Krishnamurthy (2012), the increased likelihood of climate-related disasters is likely to increase the vulnerability of exposed populations. The article reviews recent discussions on the relationships between extreme weather events and migration (both voluntary and forced) and suggests that, if adequately planned, relocation strategies can be an effective adaptation strategy. The article argues that some forms of migration might be adaptive, while others (especially forced and involuntary migration) may indicate failure to adapt. In this context, the article also examines the policy discourse surrounding the links between disasters and migration, highlighting the crucial role of governance structures in facilitating the creation of international and national institutions to help cope with disaster risk.

According to Warner, Hamza et al. (2010), when people are faced with severe environmental degradation they have one of three options: (1) stay and adapt to mitigate the effects; (2) stay, do nothing and accept a lower quality of life; or (3) leave the affected area. The process of movement and migration is usually subject to a complex set of push and pull forces, where push forces relate to the source area while pull factors relate to the destination. These forces are in constant flux, as much as environmental change, and interact with socio-economic and political conditions including state or government decision making powers, which can tip the balance at any point by either denying movement or the right to settle elsewhere. Warner, Hamza et al. (2010) focus on how environmental change and environmental hazards contribute to the migration by exploring the mechanisms through which vulnerability and migration are linked via livelihoods, relocation policies, and other factors. The paper begins by outlining important definitions of what is environmentally induced migration. The paper also considers the question of whether migration is a process that reduces or increases vulnerability. The paper draws on literatures in many disciplines including ecology, environment, and climate change; the sociology of migration; the anthropology of displacement; and economics.

Research Area

Global climate change driven by increases in the concentration of greenhouse gases in the atmosphere primarily manifests itself in changes to weather patterns, both across time and space, and an increase in sea level, due to the thermal expansion of sea water and inputs from melting land ice in polar regions and at high elevations. The goal of this thesis is to determine how severe weather events possibly induced by climate change affect migration responses in the entire United States. We try to outline a conceptual model of migration decision making in the face of hazards using evidence from county to county migration data and some appropriate statistical approaches. For migration, we use information about the addresses of tax-filers, matched across years. We try to follow the movement of people from one county to another between one tax year and the next tax year. We try to understand how different types of extreme weather affect flows between potentially about10 million county pairs. . (There are roughly 3100 U.S. counties, leading to 3100 x 3100 county pairs, counting each direction between any pair as a separate flow.)

CHAPTER II

DATA AND METHODOLOGY

A regression-like methods and geographical information systems (GIS) was used to produce tables and maps to describe and explain county to county migration in response to a disaster. For this research, we used two main data sets:

1. The Statistics of Income (SOI) division of the Internal Revenue Service (IRS) from which we got our migration information based on tax returns.
2. SHELDUS (Spatial Hazards Events and Losses Database for the United States) is a county-level hazard data set for the U.S. for 18 different natural hazard events types and for each event the database includes the beginning date, location (county and state), property losses, crop losses, injuries, and fatalities that affected each county. (SHELDUS website). We also used all of the county-level data on all events including drought, flooding, hail, heat, hurricane, severe storm, tornado, wildfire, wind, and winter weather. We collected these data directly from the SHELDUS website.

IRS Migration Data Limitations

The Statistics of Income (SOI) Tax Stats files provided by the U.S. Internal Revenue Service are the source for our county-to-county migration data. In this study, one of the major limitations is that the flow of migrants between any pair of counties is censored if the number of tax returns is less than ten. In cases like this, the flows are aggregated with a total for a larger origin or destination area. Hence for our study, we focus on county pairs that display “significant flows” in each year of our data set. We do not attempt to explain any minor flows that might occur. This reduces the size of our county pairs from 60 million to 500,000 observations.[1]

[1] For most origin counties, there are several destination counties with substantial flows (typically most nearby counties and a handful of major population centers at greater distances. However, in any given tax year, it should not be expected that more than ten households will move to every single one of the other 3100+ counties in the U.S., many of which are distant and rural.

At this point an obvious concern could be whether this censoring means that we are missing big chunks of the country inn our analysis. This is answered by our map in Fig 1 in Appendix B that shows the spatial pattern of origin counties. The map one on the right is for the period 2005 to 2010 and one on the left is for 2007. We also made similar maps for different individual years as well as aggregated years and from all we get pretty much the same counties each time. These maps demonstrate that while there are many missing potential destination counties for each individual origin county, we aren't leaving whole swaths of the country out of the analysis. There are some significant flows from every county.

Basic Formula and Its Interpretations

We start with a simple equation for gravitational attraction A:

$$A = g\, m_1 m_2 / d^2$$

where arguments include the mass of each object and the distance between them and parameter g is a gravitational constant. Gravitational attraction model have been used in the past to explain migration. We adapt the simplest gravity model to explain migration as a function of the populations of the origin and destination counties, and the distance between the county centroids. We include a random error term ε and now our basic formula to explain migration between county i and county j in year t is given by:

$$migration_{ijt} = g\left[X_{ijt}\right]\frac{\left(Pop_i\right)^{\beta_1}\left(Pop_j\right)^{\beta_2}}{\left(distance_{ij}\right)^{2\beta_3}}\exp\left(\varepsilon_{ijt}\right)$$

The parameters β_1, β_2 and β_3 are all equal to one in the standard gravitational formula, but we will allow them to take on whatever values the data imply and test whether $\beta_1 = \beta_2 = \beta_3 = 1$ can be rejected statistically. In order to produce a convenient additively separable error variable, we take logs of both sides and our basic formula then looks like the following equation:

$$\begin{aligned}\log\left(migration_{ijt}\right) &= \log\left(g\left[X_{ijt}\right]\right)\\ &+ \beta_1\log\left(Pop_i\right) + \beta_2\log\left(Pop_j\right) - 2\beta_3\log\left(distance_{ij}\right) + \varepsilon_{ijt}\end{aligned}$$

We will model the first term, $\log(g[X_{ijt}])$, as a function of set of variables that measures different types of weather hazards in origin county i in year t, $weather_{kit}$, where $k=$floods, droughts, hailstorms, heat waves, hurricanes, severe storms, tornadoes, wildfires, wind storms and winter weather. We will also allow the derivatives of $\log\left(migration_{ijt}\right)$ with respect to each of these measures of weather hazards to depend upon than indicator for whether the destination county is relatively more urbanized than the origin county: $1(UrbanizationDifference)_{ij}$. Finally, to account for unobserved heterogeneity at the state level, we include fixed effects for each origin state and fixed effects for each destination state, as well as year fixed effects:

$$\log\left(migration_{ijt}\right)=\left\{\begin{array}{l}\beta_0+\beta_4\left[1(UrbanizationDifference)_{ij}\right]\\ +\sum_{k=1}^{10}\beta_{4k}weather_{kit}\\ +\sum_{k=1}^{10}\beta_{5k}1(UrbanizationDifference)_{ij}\times weather_{kit}\\ +\beta_6 stateFE_i+\beta_7 stateFE_j+\beta_8 yearFE_t\end{array}\right\}$$
$$+\beta_1\log\left(Pop_i\right)+\beta_2\log\left(Pop_j\right)-2\beta_3\log\left(distance_{ij}\right)+\varepsilon_{ijt}$$

Collecting terms and adding other control variables shown to affect migration flows in

other studies, this equation can be written as:

$$\log\left(migration_{ijt}\right)=\left\{\begin{array}{l}\left[\beta_0+\beta_4 1(UrbanizationDifference)_{ij}\right]\\ +\sum_{k=1}^{10}\left[\beta_{4k}+\beta_{5k}1(UrbanizationDifference)_{ij}\right]weather_{kit}\\ +\beta_6 stateFE_i+\beta_7 stateFE_j+\beta_8 yearFE_t+\beta_9 OtherControls_{it}\end{array}\right\}$$
$$+\beta_1\log\left(Pop_i\right)+\beta_2\log\left(Pop_j\right)-2\beta_3\log\left(distance_{ij}\right)+\varepsilon_{ijt}$$

The model is set up so that both weather and the relatively more rural-to-urban (versus relatively urban-to-rural) direction in which migration occurring will affect migration flows. The baseline level of migration applies to the urban to rural flows. A differential effect is added for flows that are relatively more rural to urban. For this paper, we do not care as much about whether the baseline level of migration on average, after controlling for all heterogeneity (including weather events) is larger or smaller from urban to rural flows (β_0) or for rural to urban flows ($\beta_0 + \beta_4$). Our main concern is the effect of weather on migration and whether these effects are different between urban to rural and rural to urban. And that is answered by this coefficient β_{5k} which will tell us whether the effect of weather on migration is different for urban-to-rural flows (β_{4k}) than it is for rural-to-urban flows ($\beta_{5k} + \beta_{5k}$). If the coefficient(s) β_{5k} is greater than zero, then extreme weather events of type *k* produce greater migration from rural to urban counties than vice-versa.

CHAPTER III

VISUAL REPRESENTATION OF RAW DATA

Figures 3 through 13 in Appendix B consist of a series of maps that show the heterogeneity in spatial pattern of each type of extreme weather over our six-year sample. The maps depict weather events for 2006 through 2011. We focus on ten different kinds of hazards, namely floods, droughts, hail, heat waves, hurricanes, severe storms, tornadoes, wildfires, high winds and finally severe winter weather. From all these, we see that the pattern of events is not the same every year. The key insight is that there is a lot of independent variations across time and space in these different weather events. To identify the independent effects of each type of weather event, we need to have our variable of interest move differently than other variables we are also controlling for. We include all the origin and destination state fixed effects, so there is nothing about state-level unobserved heterogeneity that will be confounded with weather effects. Likewise, the time fixed effects mean that there is no unobserved heterogeneity, common across all counties but differing across years, that might be confounded with the effects of weather patterns. These maps show that the patterns are substantially different across space and different across time and this variation will help us to identify the effects of just weather.

Figure14 shows migration by county and by year. The maps illustrate migration per capita and the variable that we used is net flows (outflow minus inflows). The net flows are all relative to the population of the county in 2000. The red counties are the ones which are losing population while the blue counties are the ones which are gaining population. Notice that in these maps there is also considerable heterogeneity over time and space. In these maps, we see more people moving out of parts of east coast and mid west and settling in the west coast in the year 2005. This trend is maintained for the years 2006 and 2007 until recession hit in 2008. After 2008, we see people moving out of west coast as well and we see maximum migration in 2010.

There is a real temptation to compare the migration maps to the maps that show the occurrence of hazards in different years. But this is really difficult to do because we have too many maps. Instead, we undertake regression analyses to see whether there was more outmigration from the counties which experienced severe weather events than from elsewhere and more so in the rural to urban direction than from urban to rural.

Migration Flows and Marginal Distribution of Migrants

Table 1 in Appendix A shows the annual county to county migration flows. Note that we are concerned with the second flow measure, which are the total exemptions meaning (roughly) the total number of migrating persons (rather than households). These figures show that on average, the numbers of migrants across counties don't change very much over time.

The histogram in Figure 2 (Appendix B) shows the marginal distribution of the dependent variable (the logarithm of exemptions). It is obvious from this graph that the censoring of data at 10 *households* does not seem to produce a marked truncation of the distribution of the logarithm of the number of exemptions. We are losing the bottom tail of this distribution, likely including a huge number of zero flows (so we may not actually be losing much of the mass of the distribution). We do appear to be covering the mode of the distribution. The data in Figure 2 reflect the roughly half-million flows used in our analyses (out of a potential 60 million county pairs over six years).

Results and Discussions

Table 2(Appendix A) shows our simplest model that explains whether the flow from rural to urban is different according to whether there are any extreme weather events of each type in the origin county. Referring to the estimating specification given above, the coefficients are all β_{5k} that give the difference in the effect of extreme weather on migration for rural-to-urban flows (versus urban-to-rural). If the coefficients are positive that would imply that the extreme weather causes greater rural-to-urban migration. Take the example of heat wave; we can say from the table that if there is at least one, there will be 11% higher migration for rural to urban than urban to rural. In the case of hurricanes, it is 7% higher and so on.

While Table 2 shows a simple model, Table 3 contains a richer model to explain the magnitude of the flow differentials for rural to urban versus urban to rural in response to a disaster. In our richer model, we have diversified how we measure the impact of these weather events. The estimates in this table show the derivative of migration flows with respect to severe weather in the origin county with respect to the number of events in the origin county and with respect to total days and with respect to crop damage and so on. In other words, our simple model explained the flow from rural to urban based on whether there were any events or not. The richer model explains the flow not only based on whether there were any events but also based on the characteristics of those events. Hence when we generalize to allow for seven different ways for measuring the impacts of those events, we see that in some cases those are no longer significant because others have taken over portions of the explanatory power and there is a degree of multicollinearity between these different measures of the incidence of extreme weather events. To find out the overall derivative, each coefficient for a type of weather even is multiplied by the value of the corresponding characteristic and the terms are summed. The overall derivative of expected migration flows with respect to droughts, for example, will differ according to the characteristics of the droughts during the year in question.

Other Control Variables

Table 4 (Appendix A) shows the other determinants of migration that we controlled for in our regression models which fall into three categories:

1. *Gravity Variables*: these variables have coefficients that are consistent with the gravity model. They are not exactly a gravity model, since their estimated values are not all one, but the expected proportionality is maintained.
2. *Missing migrants*: The IRS data include counts of migrants between counties only if these migrating individuals filed tax forms in each year. People are more likely not required to file taxes if they have very low incomes or if they are retired and their only form of income was Social Security payments. Thus we included variables for the percent of the resident population 65 years and over (available for 2010) and for the percent of people of all ages in poverty, calculated across the period from 2006 to 2010, for both the origin and the destination counties associated with each flow. The expected signs on each of these variables are

negative as we expect uncensored migration flows to be smaller when these groups represent a larger proportion of either population.

3. *Economic*: The economic literature on migration suggests that employment opportunities in the destination county may be a significant determinant of migration. We capture trends in employment by using the lagged percentage growth rate in total employment for both the origin and destination counties. This coefficient for origin counties is not different from zero, but for destination counties, it is positive and significant. That suggests that people do not necessarily move because of lack of new job opportunities in the origin county, they move to get better job opportunities in the destination counties.

CHAPTER IV

CONCLUSION

Many countries are concerned about the prospect of increased rural-to-urban migration that may be induced by changes in the pattern of extreme weather events associated with climate change. In many parts of the world, however, there is a lack of migration information. This makes it difficult if not impossible to assess the pattern of migration in response to extreme weather. Thus we have focused our investigation on patterns in the United States over a six year period, using migration information from the Internal Revenue Service (IRS).

We have seen in our simple model that all of the point estimates relevant to our main hypothesis are positive, suggesting that extreme weather events tend to increase rural-to-urban migration more than urban-to-rural migration, leading to a net effect of increasing urbanization. We have also seen some statistically strong significant effects in cases of floods, heat, hurricanes, tornadoes and winter weather. We found considerable evidence that most types of extreme weather events tend to increase rural to urban migration flows (and in some cases to decrease urban-to-rural flows, or at least to increase them by a smaller amount).

We are not sure whether climate change will increase rural to urban migration through more intense disasters. But if scientists can tell us what they think will happen to, for example, floods or heat or tornadoes, the model can then simulate the migration responses by counties, states or even regions.

From our tables and maps, it seems that the trends of higher mobility linked to natural disasters are likely to continue and intensify. Underlying these trends is a growing need for the diversification of income sources.

APPENDIX A

TABLES

Table 1: Annual county-to-county migration rates, per county pair (flows>=10)

VARIABLES	(1) 2005	(2) 2006	(3) 2007	(4) 2008	(5) 2009	(6) 2010
Tax returns	87.15	87.62	86.33	86.95	86.49	87.40
(~households)	(323.5)	(327.8)	(314.9)	(316.4)	(316.4)	(327.4)
Total exemptions	166.7	167.3	163.6	162.0	160.9	163.0
(~individuals)	(636.9)	(647.5)	(611.4)	(595.7)	(597.4)	(621.2)
Observations	94,814	98,401	96,759	98,861	96,426	91,419

Table 2: Selected Key coefficients from a regression model to explain log(county to county flows)

	Any events?
1(rural to urban) x origin_floods	0.0637***
	(2.988)
1(rural to urban) x origin_drought	0.0359
	(0.898)
1(rural to urban) x origin_hail	0.0520*
	(1.780)
1(rural to urban) x origin_heat	0.112***
	(3.816)
1(rural to urban) x origin_hurricane	0.0670***
	(3.203)
1(rural to urban) x origin_sev.storm	0.0456**
	(2.152)
1(rural to urban) x origin_tornadoes	0.0528***
	(2.853)
1(rural to urban) x origin_wildfires	0.0326
	(0.571)
1(rural to urban) x origin_winds	0.0364
	(1.183)
1(rural to urban) x origin_winter	0.0340***
	(3.379)
Other variables (not reported due to similarity with Table A1	
Generalized gravity model terms	Yes
Origin county fixed effects	Yes
Destination county fixed effects	Yes
Time fixed effects	Yes
Baseline severe weather effects, all seven measures	Yes

Table 3:Differential effects of severe weather events for logarithms of rural-to-urban flows. We highlighted the figures which are negative as well as significant

Selected (key) coefficients only	Any events?	# Events	Total days	Crop damage	Property damage	Total injuries	Total deaths
1(rural to urban) x origin_floods	0.0326* (1.658)	0.0107** (2.039)	-0.00293** (-2.189)	-0.00269*** (-2.798)	0	0.00495*** (6.761)	0
1(rural to urban) x origin_drought	0	0.0164*** [a] (3.485)	0[a]	0	0	0	0
1(rural to urban) x origin_hail	0	0	0.00976* (1.805)	-0.00738** (-2.028)	0.000887* (1.693)	0	0
1(rural to urban) x origin_heat	0	0.0280* (1.838)	0	-0.00224*** (-3.654)	0	0	0.0307*** (4.243)
1(rural to urban) x origin_hurricane	0.0535** (2.438)	0	0	0	0	0.00152*** (4.401)	0.00153*** (2.789)
1(rural to urban) x origin_sev.storm	0	-0.0284*** (-3.936)	0.0311*** (4.121)	0.0906** (2.210)	0	0	0.0583* (1.743)
1(rural to urban) x origin_tornadoes	0.0395** (2.571)	0	0	0	0.00257*** (3.164)	0	-0.0183*** (-2.688)
1(rural to urban) x origin_wildfires	0	0	0	-0.0313*** (-2.840)	0.000475* (1.945)	0.0129*** (3.899)	0
1(rural to urban) x origin_winds	0	0.0709*** (3.066)	-0.0588*** (-3.085)	0	0	0	0
1(rural to urban) x origin_winter	0	0	0	0.001000*** (2.868)	0	0	0.0809*** (6.818)

Zero restrictions are not rejected by the data.

Table 4: Other components to regression model

VARIABLES	Coefficient
Log(distance between counties)	-0.869*** (-34.53)
Log(origin population, 2000)	0.419*** (38.43)
Log(dest. Population, 2000)	0.411*** (21.91)
Origin pop % 65+ (2010)	-0.0163*** (-5.703)
Origin % poverty (2005-10)	-0.000970 (-0.466)
Dest. pop % 65+ (2010)	-0.00796*** (-2.983)
Dest. % poverty (2005-10)	-0.00721*** (-6.709)
Origin: lagged employment growth	-0.0551 (-0.740)
Dest.: lagged employment growth	0.346*** (4.010)
1(rural to urban)	-0.0903*** (-3.032)

APPENDIX B

FIGURES

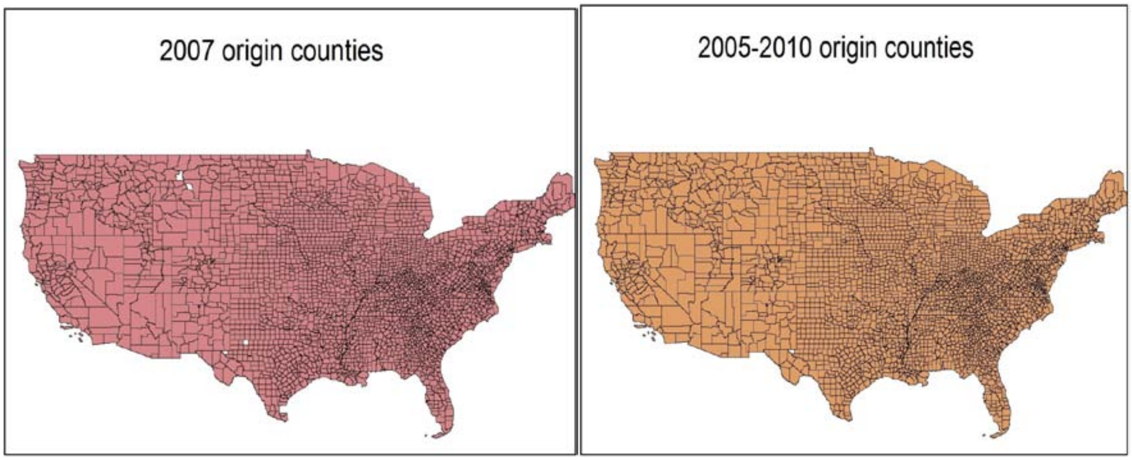

Fig 1: Origin counties covered by our study

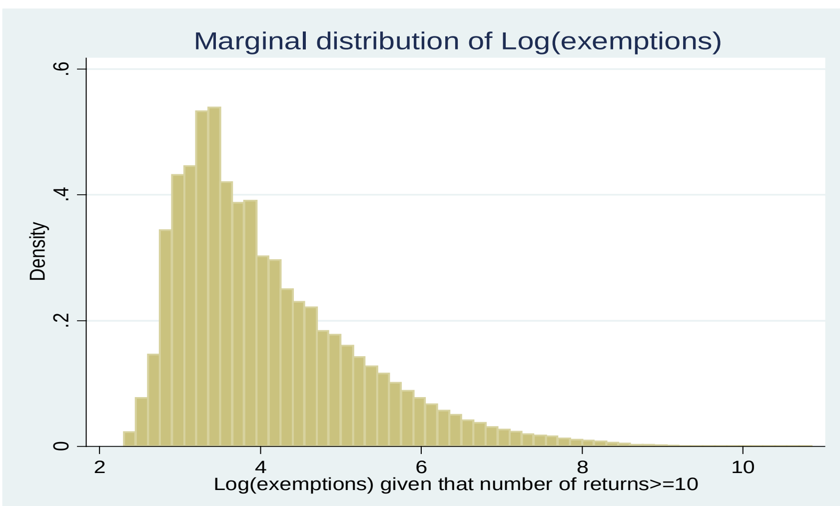

Fig 2: Histogram for 500,000 county-to-county flows over six years

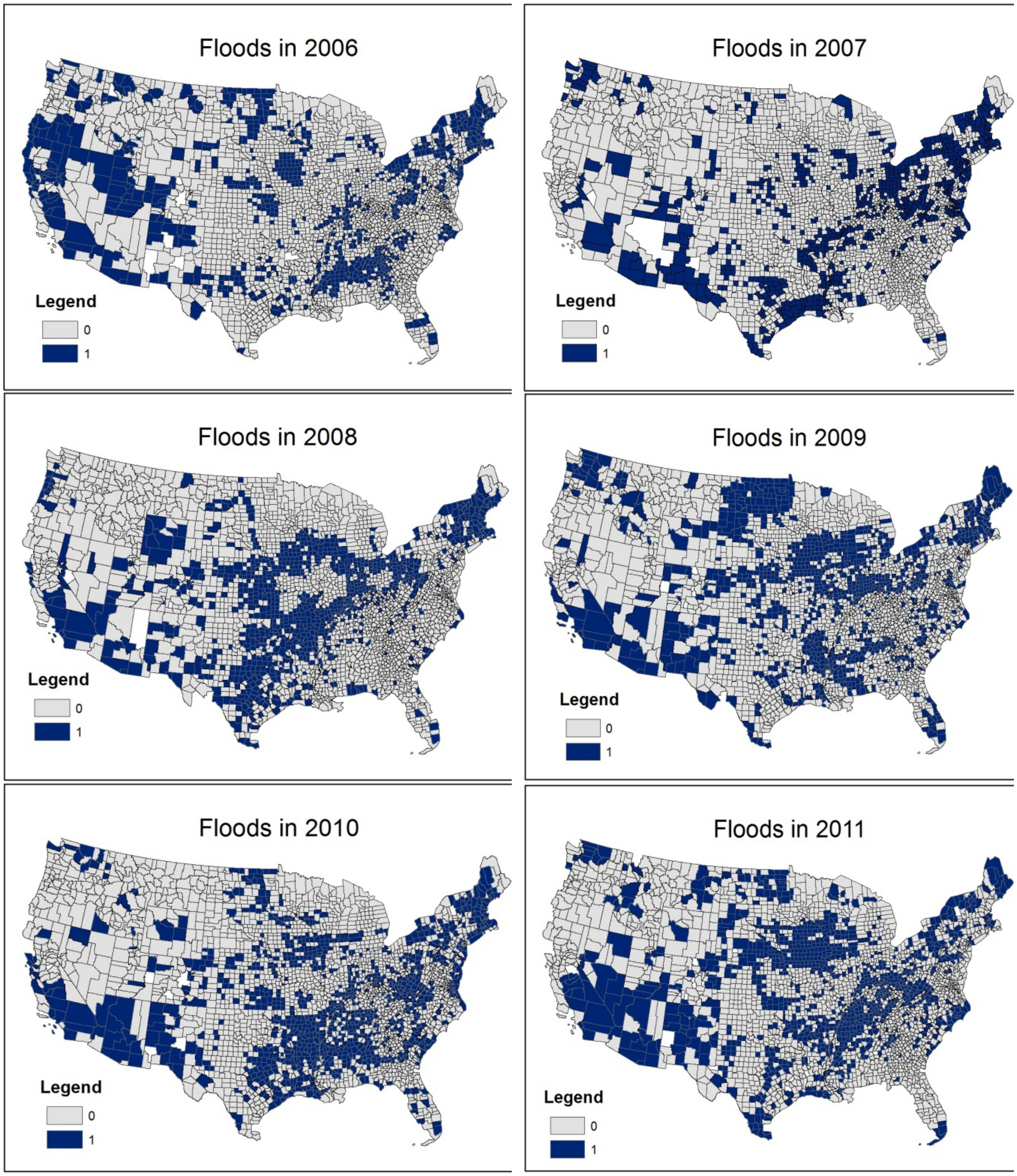

Fig 3: Spatial pattern of floods from 2006 to 2011

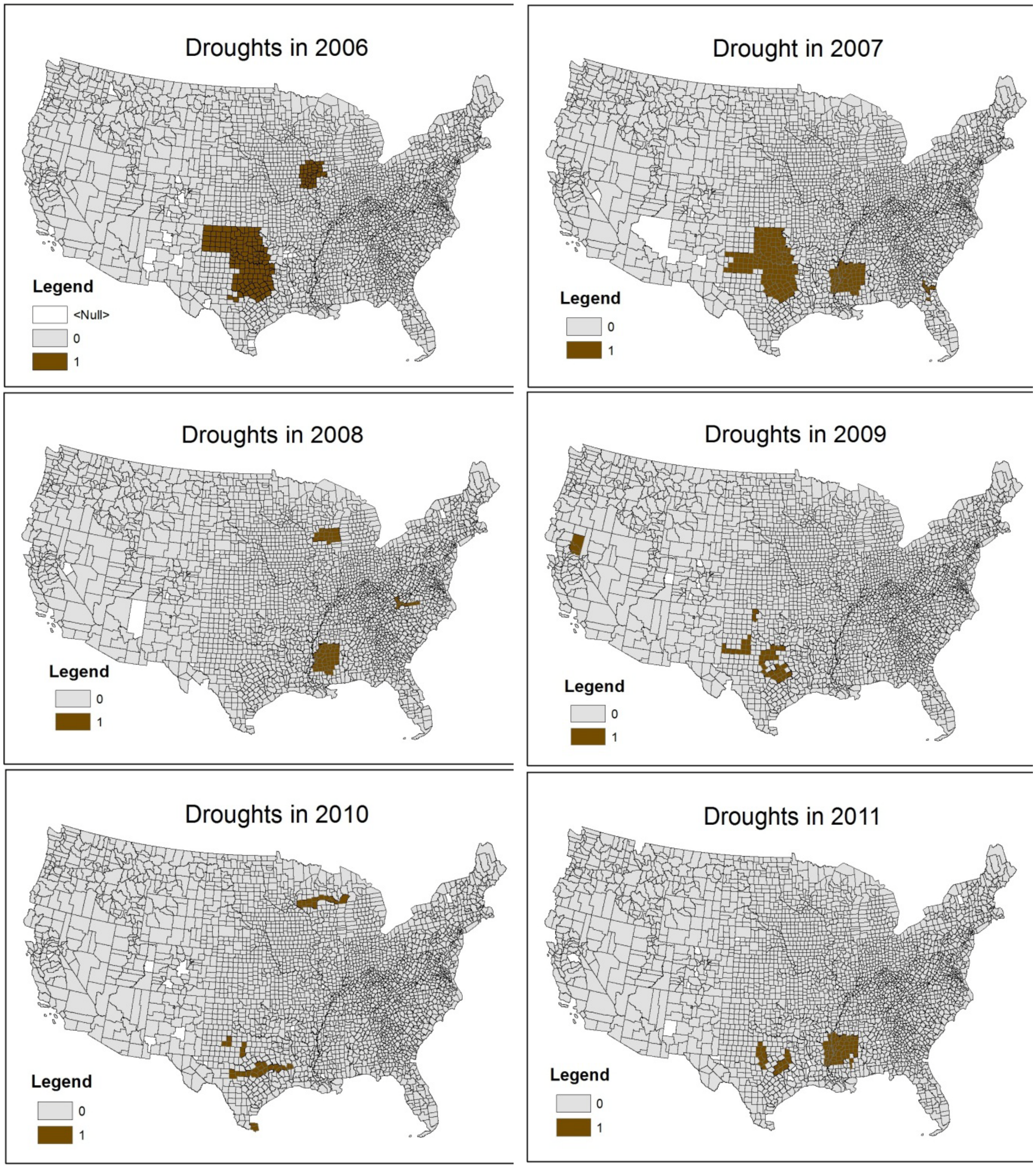

Fig 4: Spatial pattern of droughts from 2006 to 2011

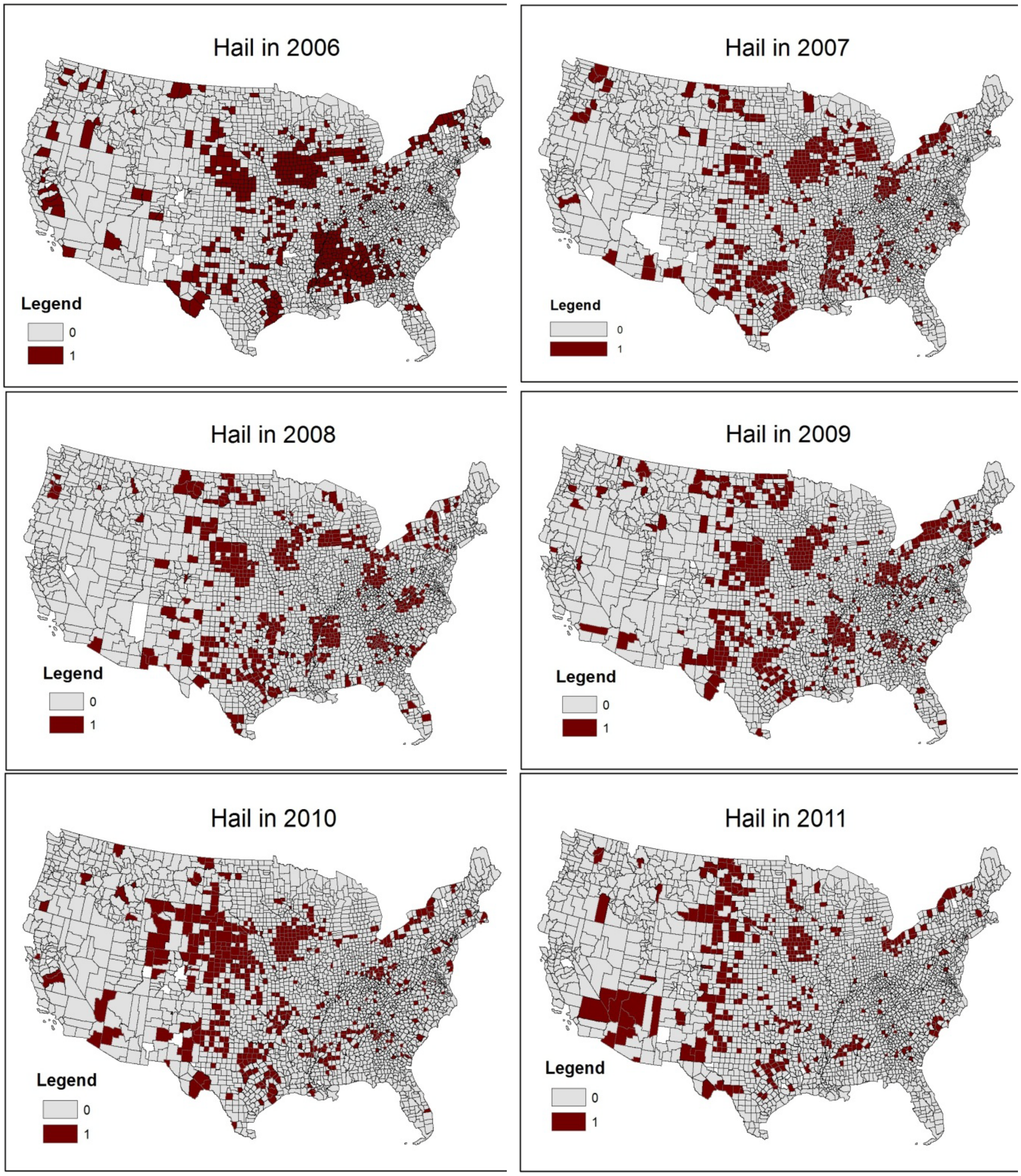

Fig 5: Spatial pattern of hail from 2006 to 2011

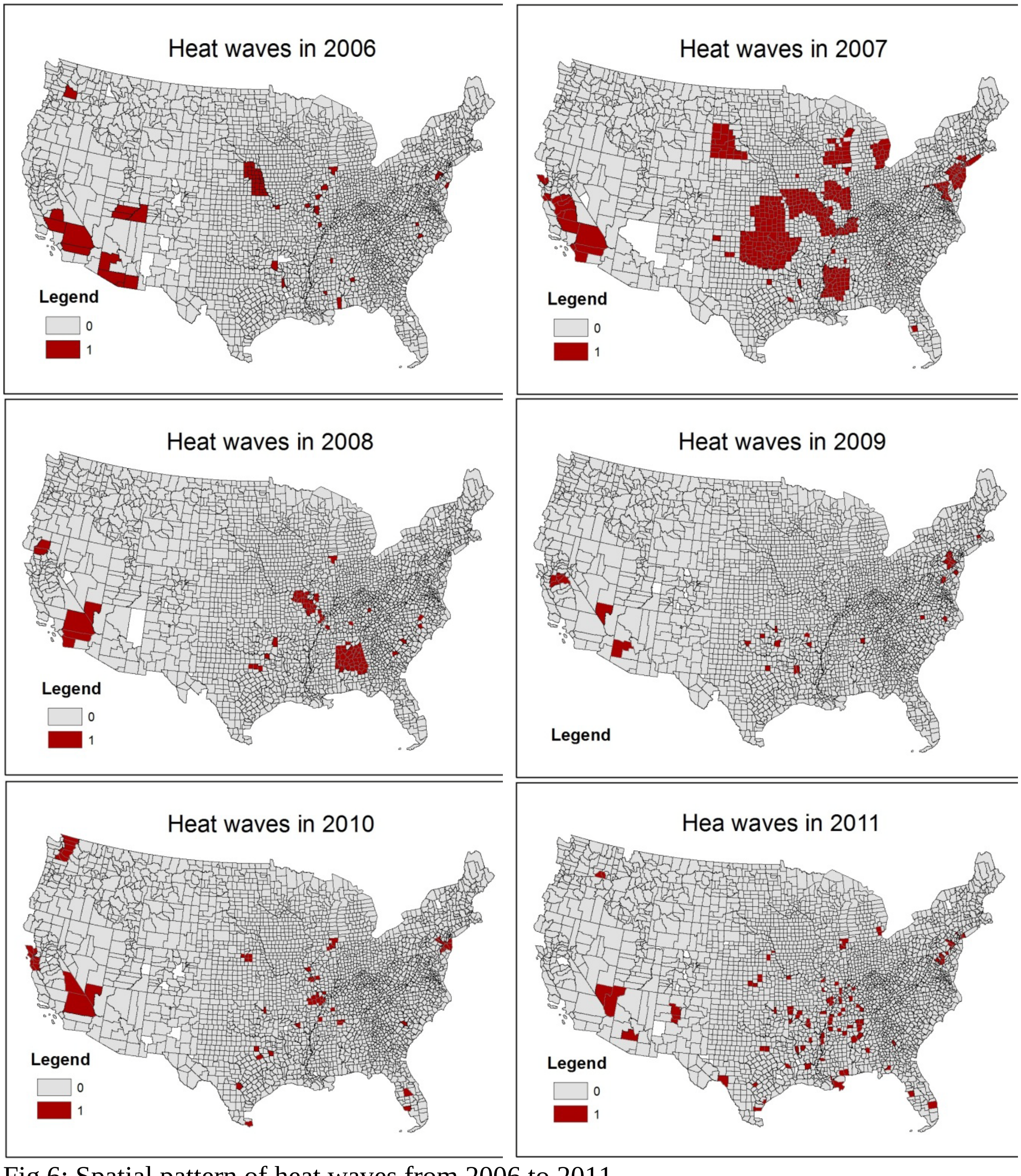

Fig 6: Spatial pattern of heat waves from 2006 to 2011

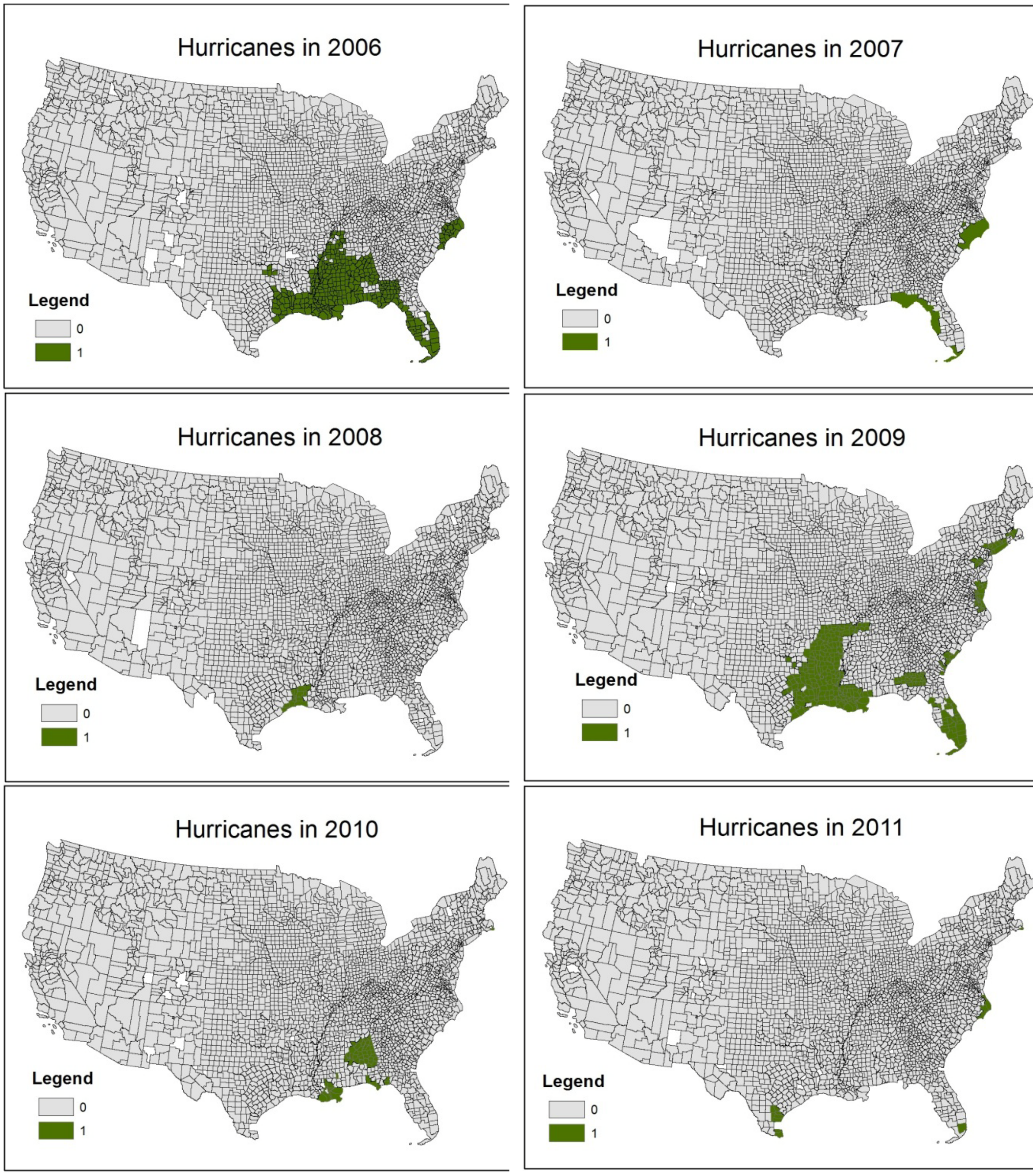

Fig 7: Spatial pattern of hurricanes from 2006 to 2011

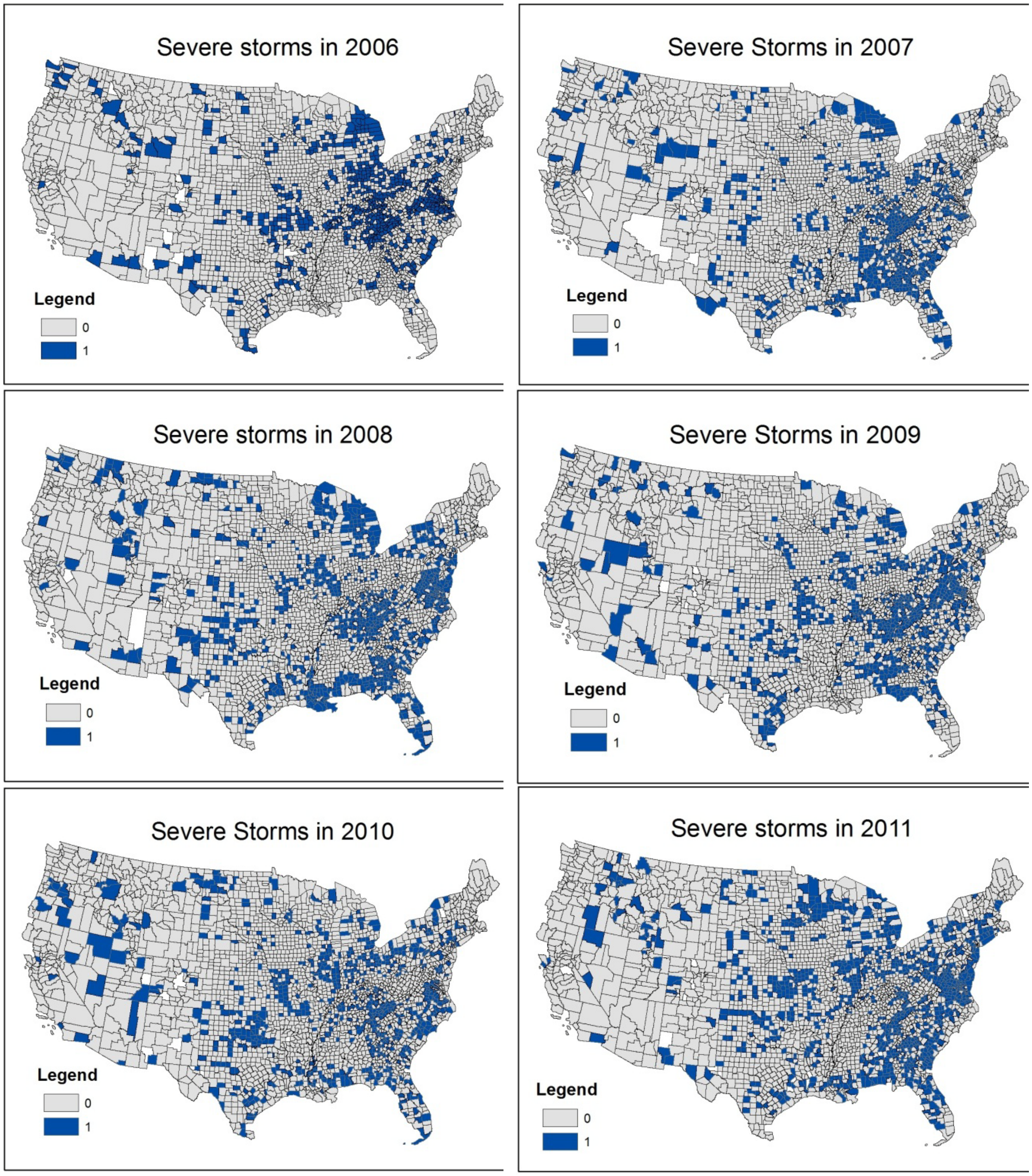

Fig 8: Spatial pattern of severe storms from 2006 to 2011

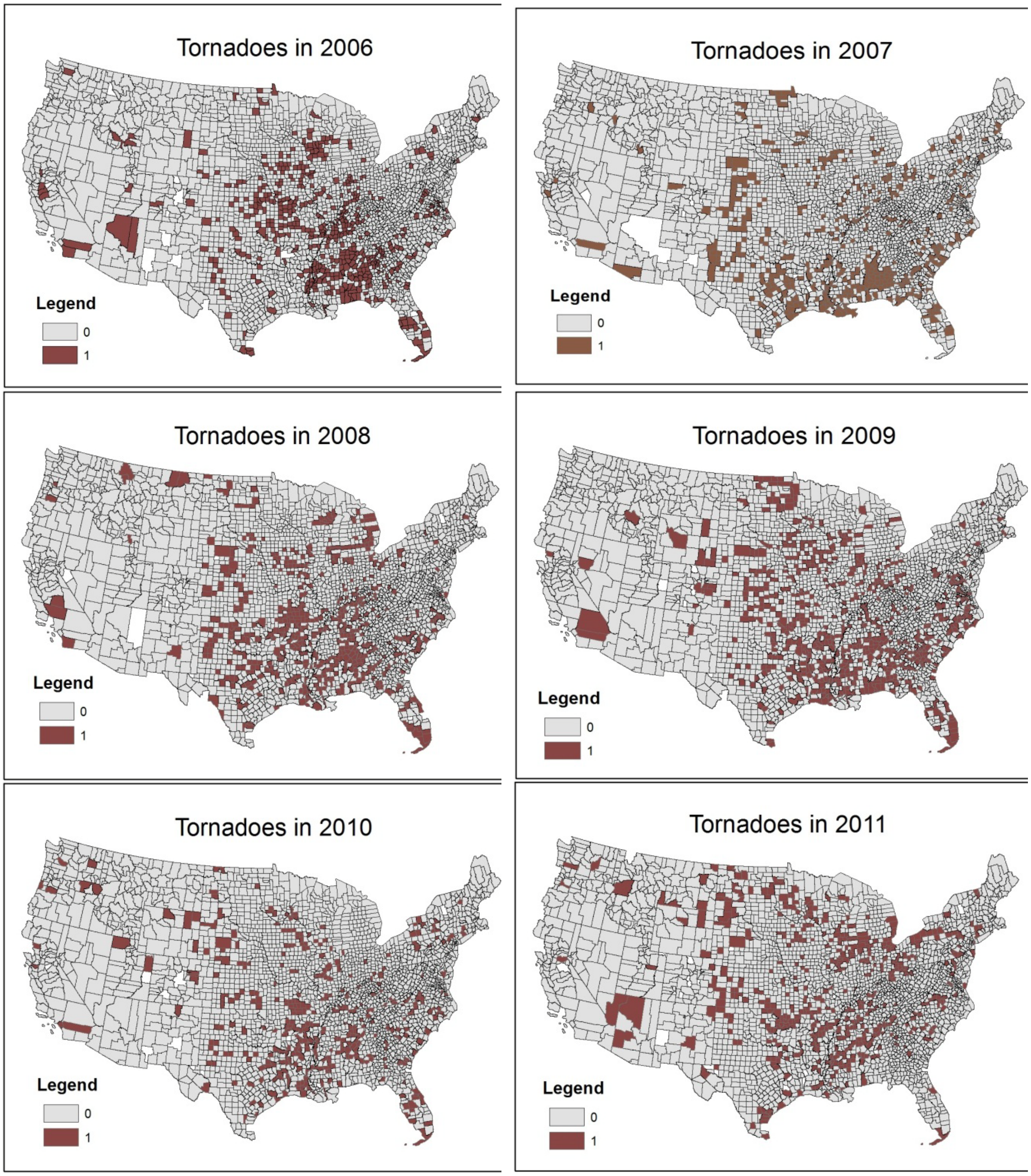

Fig 9: Spatial pattern of tornadoes from 2006 to 2011

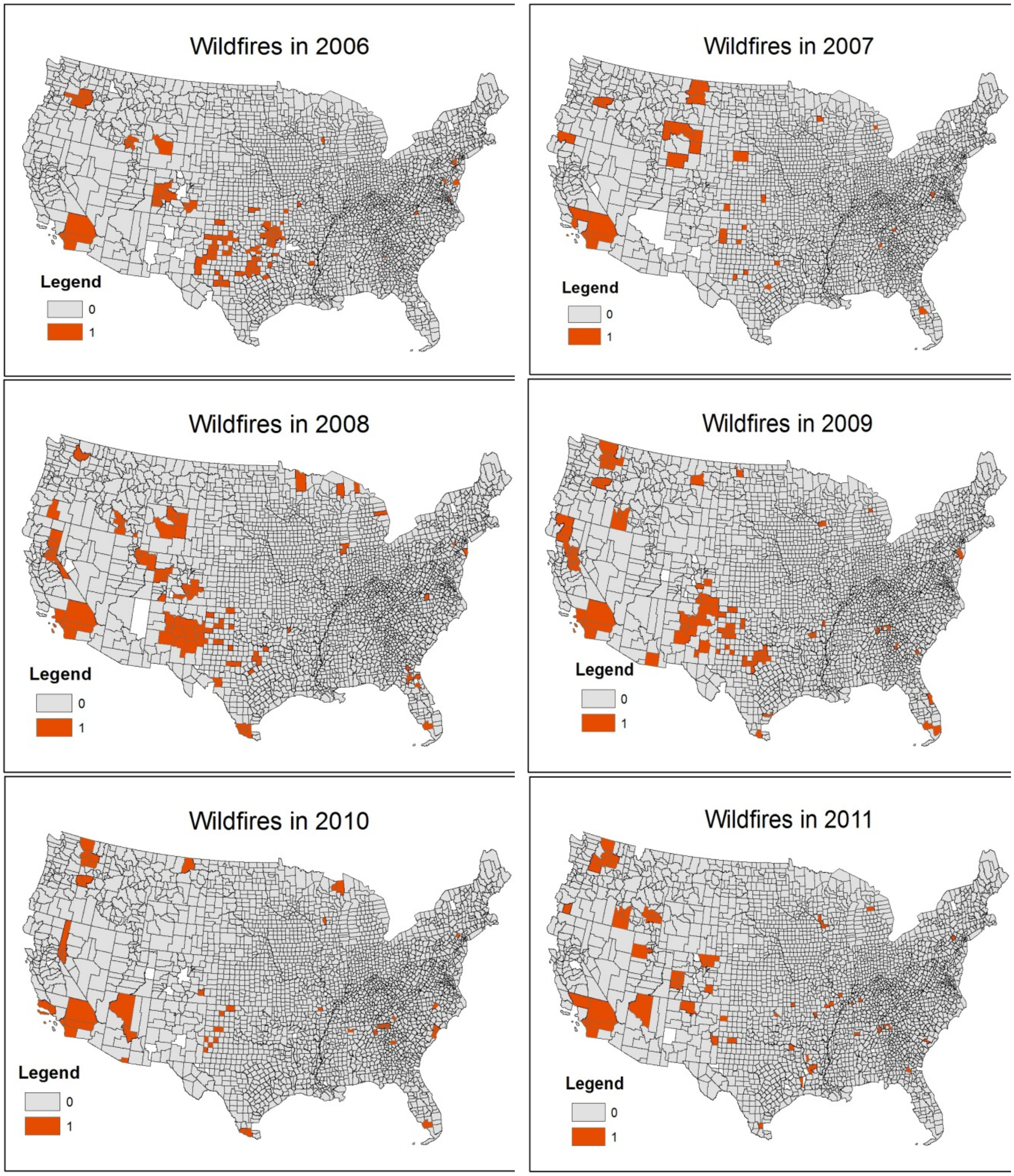

Fig 10: Spatial pattern of wildfires from 2006 to 2011

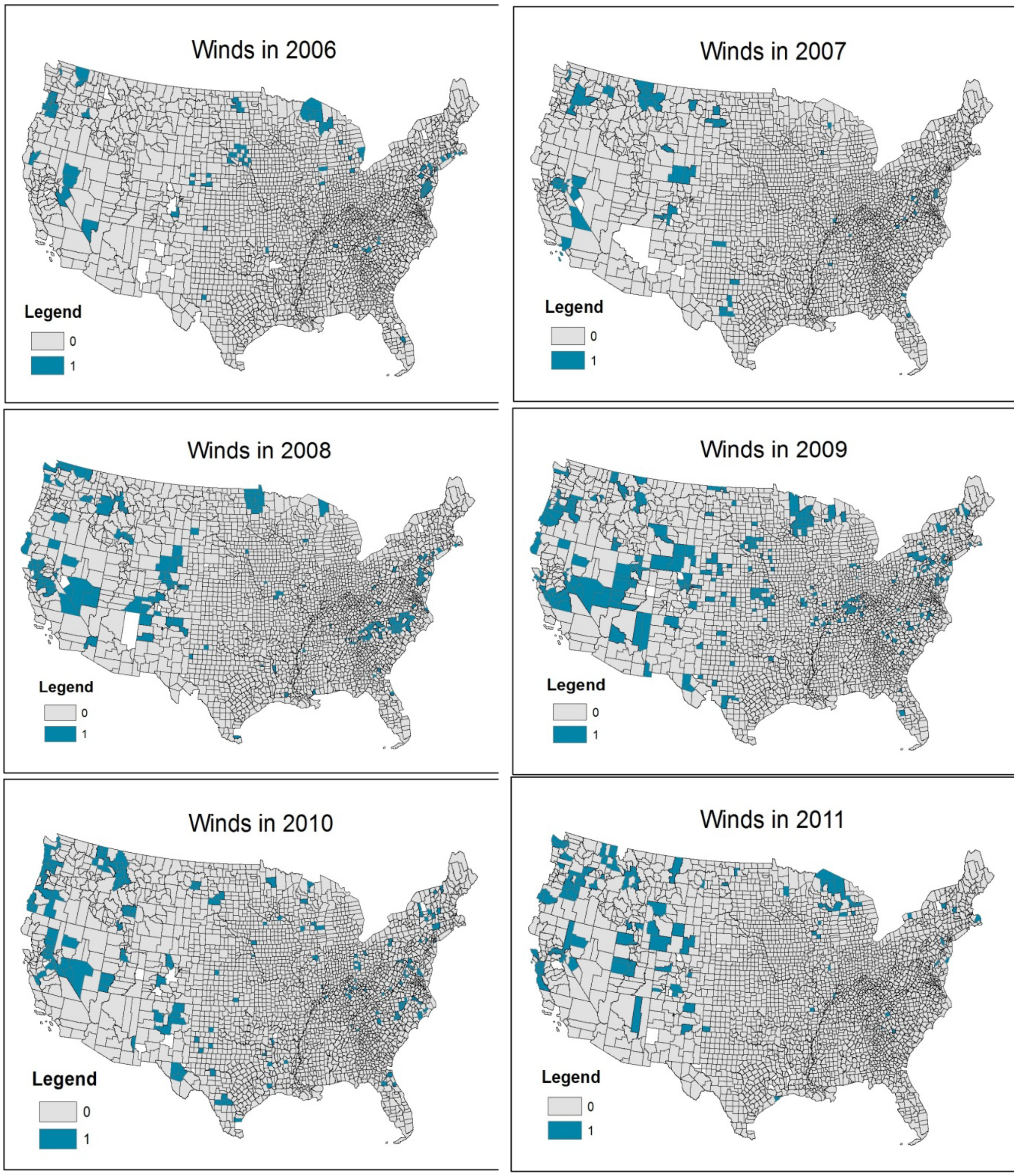

Fig 11: Spatial pattern of winds from 2006 to 2011

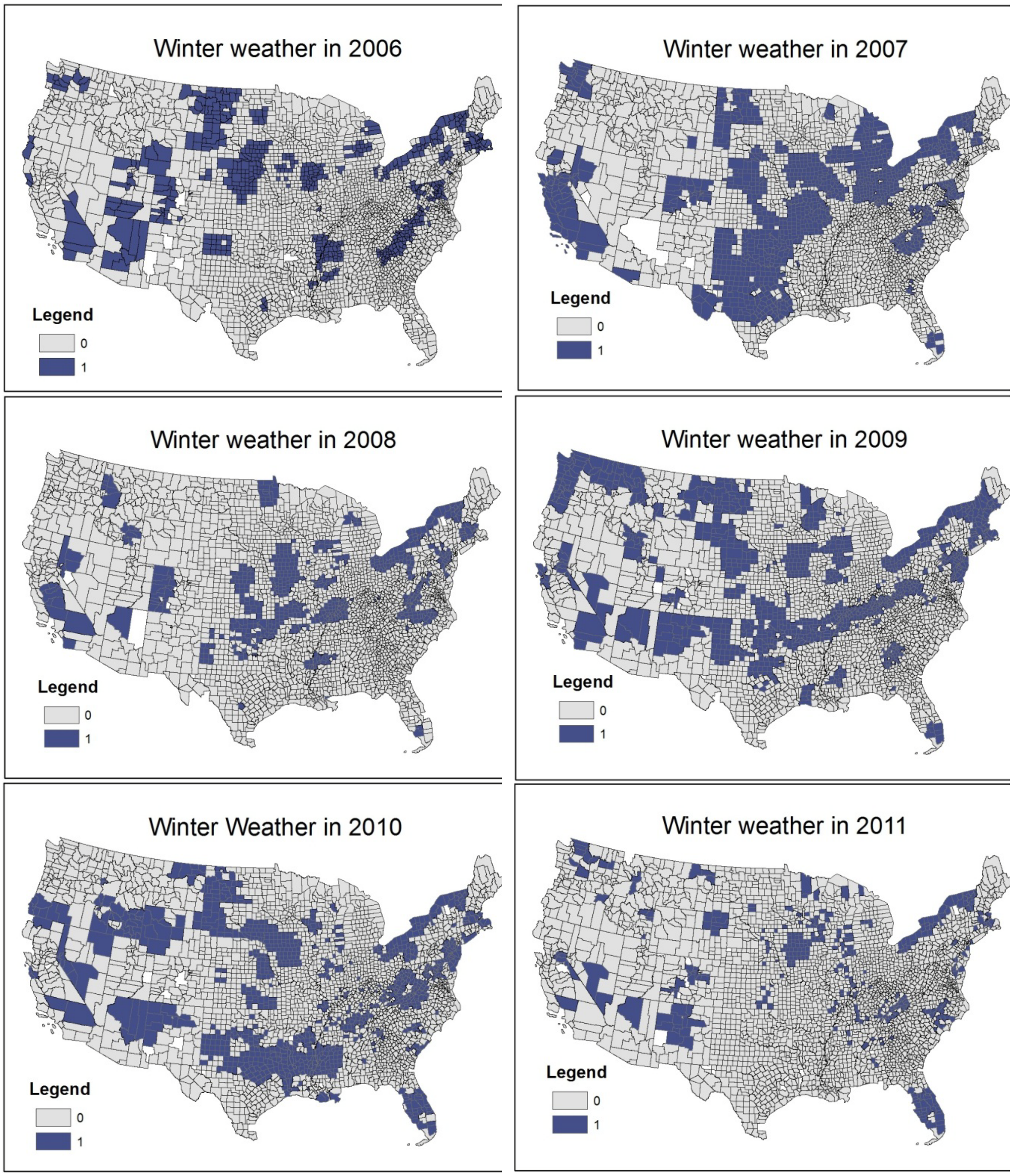

Fig 12: Spatial pattern of winter weather from 2006 to 2011

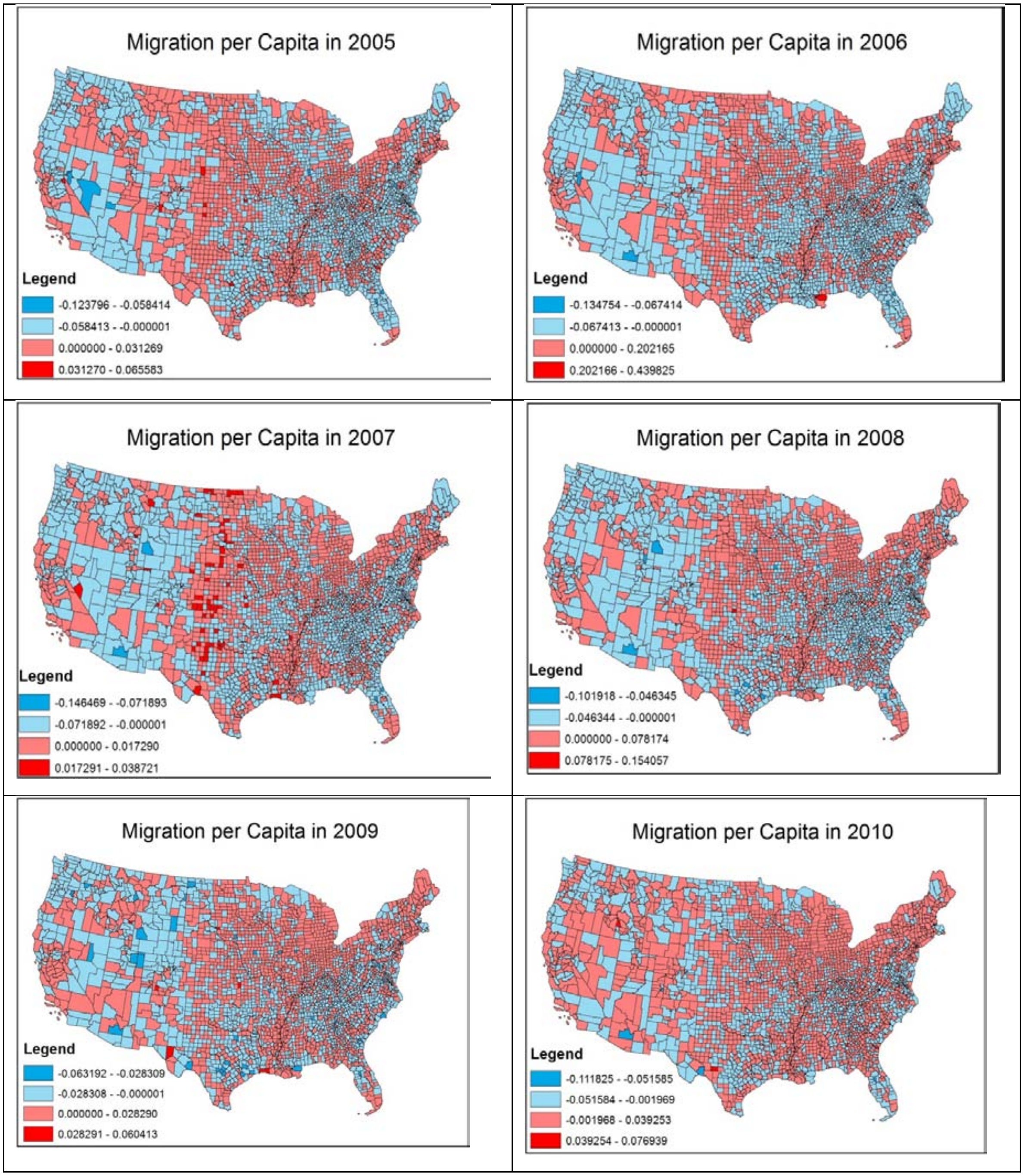

Fig 13: Migration per capita from 2005 to 2010

APPENDIX C

GIS INSTRUCTIONS

Step 1: Base Map
In ArcMap, I added counties shapefile from the zipped data file. To do this, I undertook the following steps:

1. Go to ESRI's website (http://www.esri.com/)
2. Click on "products" tab on the web page
3. Click on "Free Data" under the data section
4. Next, click on "Census 2010 TIGER/Line Data"
5. Then, click on "Download Shapefiles" in the yellow box in the left hand side corner
6. The layer type that I selected is "counties and equivalent" and then submitted
7. Save the folder in C drive
8. Unzip the data file

Step 2: Change projection if needed
From the map, it is clear that the shapefile is not projected (it has only GCS North American 1983). For spatial statistical analysis, it is usually recommended (sometimes required) that the map is projected. I changed the projection in the following ways:

1. Right-click the data frame in the table of contents and click Properties.
2. Click the Coordinate System tab on the Data Frame Properties dialog box.
3. Choose a coordinate system from the tree or click the Import button and browse to a data source that is defined with the coordinate system you want to use (I used USA Contiguous Albers Equal Area Conic)

Step 3: Add the excel file to Arcmap
To add a Microsoft Excel table to ArcMap:

1. Click the Add Data button .
2. Click the Look in drop-down arrow and navigate to the Excel workbook file (.xls).
3. Double-click the Excel workbook file.
4. Click the table you want to add to ArcMap.
5. Click Add.

   Excel tables, like other tables without associated features, only show up on the Source tab of the ArcMap table of contents.

Step 4: Convert excel table to dbase

1. Open Arc Map
2. Click on Arc Catalog
3. Open the excel file

4. We have to change the excel files from .csv to dbase. To do that, we need to export the excel file. Once we locate the excel file in Arc Catalog, right click the file and click export (to dbase single)
5. Specify the output location (this is the folder where we want to save our export excel files)
6. Name the output table (for example, 2010.dbf)
7. Leave the expression part blank
8. Click ok

Step 5: Edit excel file
After importing the excel data, ArcGIS converts the spreadsheet numeric fields to double precision or types that do not meet our needs. Hence it is necessary to create new field of desired type ("text" in out case) and calculate values into them.

1. Open Arc map
2. Open the excel file
3. Go to Table options and click "add field"
4. Name the field "CntyFIP", the type should be "text" and the length can be changed to 20.
5. A new column will appear which is named "CntyFIPS"
6. Next, Select the whole "CntyFIPS" column and right click
7. Go to field calculator and enter the equation CntyFIPS = [origin_fip]
8. Click ok
9. Now we want to add "0" to all 4 digit FIP codes. To do that, select the whole table upto the point where it is all 4 digit FIP codes
10. Right click on CntyFIPS and go to Field calculator. Once there, enter the equation, CntyFIPS = "0" + CntyFIPS. Click ok and all 4 digit codes will have a "0" before them

Step 6: Join excel table to counties

1. Open Arc Catalog
2. Add the county shapefile to Arc Map
3. Right click on the shapefile and go to "Joins and relates" and then to "Join"
4. The field in the layer that the join is based on will be "GEOID 10"
5. The table to e joined to this layer will be the excel table\
6. The field in the table that the join will be based on is "CntyFIPS"
7. We would want to keep only the matching records for joining options
8. Click ok

Step 7: Labeling

1. Right click on the new joined layer
2. Go to “properties” and change the layer name in the General tab (to for example, Fl_2010)
3. Next, go to “Symbology” and click “Unique values” under categories. In the Value field, click on the field which you want to show in the map. Then “add all Values”
4. Click ok and the map will show up
5. Go to layout view, and then click “insert” on the top left and then click “text”. Inside the text box, I typed in the title
6. Similarly to insert legend, click “legend” under insert and chose any style for legend

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