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Emerging disparities in community resilience to drought hazard in south-central United States

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A R T I C L E I N F O

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A B S T R A C T

In search of new insights into the dynamics of hazard resilience, this study assessed the temporal changes of community resilience to the drought hazard in the south-central U.S. The study hypothesized that over time counties with more affluent socioeconomic conditions and more diverse agriculture would improve their resilience while counties with poorer socioeconomic conditions and heavy reliance on agriculture decreased their resilience, thus widening the regional disparities in community resilience to the drought hazard. The study applied the Resilience Inference Measurement (RIM) framework to measure the resilience levels of the 503 counties of Arkansas, Louisiana, New Mexico, Oklahoma, and Texas. Using data of Year 2000, the RIM model selected 10 variables as resilience predictors with a 67.9% classification accuracy and assigned a resilience level to each county. The variables selected in the RIM model are related to the economic performance in the agricultural sector, socioeconomic well-being, and health. The derived discriminant functions from the RIM model were then used to estimate the resilience levels in 2005, 2010, and 2015. Over the 15-year period, 262 counties across the study area improved their resilience, whereas 48 counties, mostly in the Texas High Plains, experienced a decrease in their resilience level. The results support the hypothesis and suggest a widening gap in resilience levels among counties. These results increase our understanding of the complex process underlying communities' response to the drought impacts.

1. Introduction

The risks associated with droughts have long been recognized by farmers, landowners, community managers, nongovernment organizations, and local, state, and federal government agencies [1–3]. A 2011 survey of longtime residents (10, 15, and 19 years) of the U.S. Gulf of Mexico Coast counties (sample size 3856) about their perceptions of changing climate shows that 54% of respondents perceived an increase in the number of droughts over the time of their residence, despite the fact that only 22% of respondents perceived an increased number of hurricanes, 24% perceived an increase in flooding frequencies, and only 22% believed in anthropogenic climate change [4]. The National Oceanic and Atmospheric Administration's (NOAA) National Weather Service (NWS) Storm Events Database contains 50,967 records of drought events in the USA for the period of 1996–2016, which amounts to 2427 events per year, resulting in an average annual cost of $1684 million U.S. dollars (2016 Consumer Price Index CPI-adjusted) [5].

Despite the widespread recognition of the drought threat, with a few exceptions (e.g. Refs. [6,7]), the resilience of human communities to the effects of drought has rarely been studied. Community resilience refers to "the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events" [8,9]. Community resilience is often associated with maintaining functionality after disturbance based on desired performance goals [10]. Such performance goals can include population or economic growth, agricultural productivity, or other measures of community well-being. Furthermore, community resilience is dynamic and varies both spatially and temporally. Understanding the dynamics of resilience is critical to the ultimate goal of improving resilience [11–13]. However, studies on the dynamic changes in resilience levels remain limited. Mihunov et al. [6] assessed the community resilience to drought hazard in the south-central USA at one time point (Year 2000). Building on this previous study, the objective of this research is to assess the temporal changes of community resilience to the drought hazard in the same region at four time points: 2000, 2005,

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2010, and 2015. This study will apply the Resilience Inference Measurement (RIM) model for resilience assessment, and in addition to commonly used socioeconomic variables, variables related to the food-energy-water (FEW) nexus such as agriculture, will be included and tested as potential indicators of resilience.

Specifically, our research questions are: do we see a change in drought resilience in the region over time? Where and why do some counties experience an increase while others suffer a decrease? Do we see a widening gap in resilience levels among counties, i.e., increasing regional disparity in drought resilience, over time? Mihunov et al. [6] confirmed that counties with more affluent socioeconomic conditions generally have higher resilience to drought. This study will test the hypothesis that more affluent counties will continue to improve their resilience, whereas counties with poorer socioeconomic conditions will decrease their resilience over time, leading to a widening gap in resilience levels among counties in the study area. Furthermore, our second hypothesis is that given the potential neighborhood effects, counties near high-resilience counties will increase their resilience, whereas counties neighboring low-resilience counties will decrease their resilience, thus increasing the regional disparity of resilience to drought hazards.

The study area includes 503 counties in Arkansas, Louisiana, New Mexico, Oklahoma, and Texas. This area also coincides with the boundary of U.S. Environmental Protection Agency [14] Region VI. These 503 counties vary in drought threat levels, natural ecoregions, agricultural productivity, urban development, and socioeconomic characteristics. According to Rohli et al. [7]; the counties of the study area experienced on average 139 months of drought during 1975–2010, which amounted to 32.2% of all months of the time period. During that time, drought damage totals amounted to $15.3 billion in 2011 CPI-adjusted US dollars [7]. This damage value mostly consists of crop losses, with property damage being only a small proportion, mainly due to large-scale agricultural production in the region [6,7]. Studying the temporal changes in resilience in this region will provide new insights into the key factors affecting the communities' capacity to absorb stress and recover from damage, not only for this region but also for other regions facing similar drought threats.

2. Background

According to Wilhite et al. [15]; droughts are best defined by their impacts, categorized into four main types – meteorological, agricultural, hydrological, and socioeconomic. The impacts are interconnected and accrue with time (Fig. 1). These operational definitions of drought, introduced by Wilhite and Glantz [16]; provide a straightforward and actionable categorization for both researchers and practitioners. We will follow this categorization in our review of the recent drought research, with an emphasis on studies of socioeconomic drought.

Many studies have been conducted in the field of meteorological drought. Among the most recent ones are historical drought reconstructions using drought indexes, and projections of future drought occurrences based on global climate modeling. For example, Liu et al. [17] reconstructed historical cases of drought and evaluated the risk of future droughts for Blue River Basin, Oklahoma, using Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), and Standardized Runoff Index (SRI). Diffenbaugh et al. [18] found that the strong positive correlation between drought severity and temperature in historical data for California invites concern for future drought based on

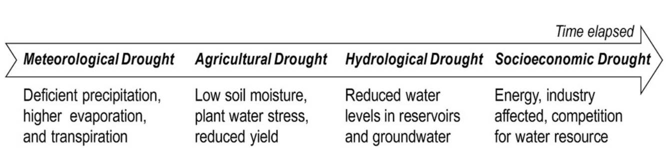

Fig. 1. Operational definitions of drought [15].

GCM projections of precipitation and temperature. Ganguli and Ganguly [19] found that "spatial coverage of extreme meteorological drought in the recent years (post-2010) [in the USA] exceeds that of the iconic droughts of the 1930s (the Dust Bowl era), and the 1950s" and that "drought persistence remains relatively stationary over the last half century."

Several studies conducted in the field of agricultural drought focus on farmers' livelihood resilience, crop modeling, and projected climate change impacts on agriculture. Ranjan [20] created an economic model to study farmers' vulnerability to drought, with results suggesting that more profitable crops are usually water intensive and costly to plant, which leads to trade-offs in choosing crops between accumulating earnings and saving groundwater. Yu et al. [21] used crop modeling to simulate rice, maize, and wheat yields assuming rainfed (no irrigation) and baseline (irrigation demands fully met) scenarios under historical climate conditions (1955–2014) and nine GCMs ensemble projections (2014–2100). They found that future drought induced yield loss under each representative concentration pathway (RCP 2.6, 4.5, 8.5) is higher than that of historical scenario, and is much higher under rainfed than baseline irrigation scenario. Steele et al. [22] conducted a review of possible climate change impacts on local agricultural systems in the southwestern USA and suggested several adaptation strategies for farmers and policymakers.

Technologically advanced modern agriculture in the USA operating under complex supply chains complicates the predictability of drought impacts on the production and marketing process [23]. Risk management tools available to farmers include production, marketing, and future contracts, as well as the Federal Crop Insurance Program (FCIP) and other farm bill programs [24]. To manage the risk of market volatility, a farmer can enter a forward (production and marketing) contract to fix product prices [25,26]. Marketing contract specifies the quantity and quality of the crop to be either delivered at a future date for a fixed price or rated according to a future market price. This way intermediaries would share some price risks with farmers [23]. A futures contract is "a forward contract traded under the bylaws of an organized commodity exchange," with highly standardized methods of trading and delivery terms [27]. These adaptation strategies influence the farmers' resilience and generate economic data suitable for quantitative research.

Hydrological drought has also been examined in the scholarly literature. Although water supply systems are designed to withstand a range of weather-induced impacts, droughts lasting over a year are more straining since they include the period of reservoir/groundwater recharge (i.e., winter), creating chronic stress into the following summer [28]. Typical policy response to hydrological drought involves restricting water use, assisting water transfers, assigning temporary water rights, purchasing water rights or permits to preserve water, and issuing grants and loans to public water-supply systems (Fontaine et al., 2014).

Less scholarly attention has been devoted to socioeconomic drought; research on community resilience and social vulnerability to drought hazard remains limited. Furthermore, the temporal changes in drought resilience have rarely been studied. Murthy et al. [29] developed a composite index for measuring agricultural drought vulnerability by aggregating soil, irrigation, farms, rainfall, precipitation, and remote sensing vegetation data into exposure, sensitivity, and adaptive capacity components of vulnerability. Several studies were devoted to the development, testing, and improvement of Multivariate Standardized Reliability and Resilience Index, which aimed to quantify socioeconomic drought through measuring the ability of hydrological reservoirs to satisfy societal water demand [30–32]. Tortajada et al. [33] analyzed the 2011–2016 California drought impacts on food security and state's adaptations and found that despite the severity of drought, California's food security was unaffected.

There is a need to assess resilience to socioeconomic drought beyond the agricultural sector, such as communities' ability to mitigate damage and experience socioeconomic growth, at various spatial and temporal scales using robust scientific methods. Mihunov et al. [6] assessed the community resilience to drought hazard of all 503 counties of Arkansas, Louisiana, New Mexico, Oklahoma, and Texas at one time point (Year 2000). The study confirmed that higher resilience is associated with higher socioeconomic condition of the counties, with a concentration of high resilience counties found in the ecotone between humid (Eastern Temperate Forests) and arid (Southern Semiarid Highlands or Great Plains) climate regions. This study extends the analysis to examine the temporal changes using a similar methodology but adding the FEW-nexus related variables to better explain the dynamic changes in resilience to socioeconomic drought.

3. Data and methods

3.1. The Resilience Inference Measurement framework

The Resilience Inference Measurement (RIM) framework was applied to conduct the temporal assessment. RIM is a relatively new model for assessment of community resilience that has been applied to measure resilience to coastal hazards in the northern Gulf of Mexico counties [9,12,13], Lower Mississippi River basin [34,35], northeastern USA from Hurricane Sandy [36], and the Caribbean countries [37], earthquakes in China [38], and drought in the south-central USA [6]. A recent study that analyzed 174 refereed journal articles on disaster resilience measurement published from 2005 to 2017 found that the RIM framework is among the few available resilience indices that provide both empirical validation and specific adaptive strategies [10].

In the RIM framework, community resilience is based on the relationships of hazard level, damage, and recovery (Fig. 2). Hazard level is the incidence or intensity of the impact, damage is monetary or human loss resulting from the hazard, and recovery is return of population or economic growth. The relationship between damage and hazard level is defined as vulnerability, whereas the relationship between recovery and damage is considered adaptability. Vulnerability refers to community's susceptibility to higher damages given the same level of hazard as other communities; thus, a community is considered to have low vulnerability when it is subjected to a high hazard level but sustains low damage. Adaptability refers to a community's capacity to recover from damage, thus a community is considered to have high adaptability when it recovers quickly after sustaining high damage. The relationship between adaptability and vulnerability is defined as resilience. The RIM framework considers two dynamic underlying processes of resilience — mitigation and adaptation. These processes are defined as a societal response, i.e. actions taken in the recovery stage to lessen the potential hazard threat (mitigation) or reduce potential damage (adaptation), either of which enhance resilience in the next resilience cycle.

The resilience level of a community (county) is assessed through classifying its pattern of hazard level, damage, and recovery into one of the four categories, and from low to high resilience, they are susceptible, recovering, resistant, and usurper. Given the same level of hazard intensity, susceptible communities are characterized by extensive damage and slow recovery, whereas usurper communities have low damage but high capacity for recovery. Recovering and resistant communities fall in between, with the former generally having average damage and recovery and the latter being resistant to hazard threat and enduring low damage. This four-level classification is borrowed from the ecological literature [39,40] and has been tested extensively in previous studies [9, 34,37,38].

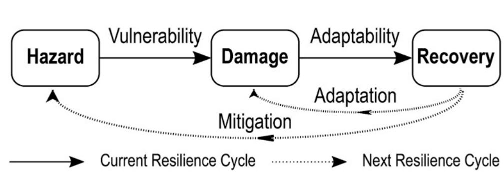

Fig. 2. The resilience inference measurement framework [9].

The RIM framework employs a two-step statistical procedure to estimate the resilience level of a community. The method ensures its empirical validation with real-world hazard threat, damage, and recovery data. First, k-means clustering [41] provides an *a priori* resilience classification based on the three dimensions (hazard, damage, and recovery). The k-means classification assigns each county to one of the four resilience levels: susceptible, recovering, resistant, and usurper (i.e., group 1–4). In the second step, through shrinkage discriminant analysis (SDA) [42], the assigned resilience level is validated using a set of socioeconomic and FEW-nexus variables. The posterior classification, predictions for the consecutive time periods, as well as classification accuracy (agreement between *a priori* and posterior classifications) are then calculated. Fig. 3 is a flowchart showing data inputs, statistical procedures, and output results of the RIM framework for this temporal study.

Application of statistical methods requires us to consider their assumptions. We used the k-means cluster analysis procedure in SPSS Statistics [41]; and this procedure does not require data to be normally distributed. However, it is important to standardize the input variables into a range of 0–1 before the procedure. Discriminant analysis is a statistical inferential technique, which requires the assumptions of normality of the data and equality of variances among groups. However, the technique is quite robust and is considered reliable under minor violations. In this study, visual inspection of the Q-Q plots shows that the data are distributed symmetrically with minor skewness. The Box-M test, which is a test of variance homogeneity, shows an F value of 9.87 and $p < 0.05$; thus, the variances between groups are not equal, likely due to the test's sensitivity to large number of cases and even small departures from homogeneity or normality [41].

3.2. Data collection and analysis steps

As portrayed in Fig. 3, we first collected hazard, damage, and recovery data, which are the input variables for the k-means clustering procedure. The hazard variable is the total number of weeks of severe drought in each of the 503 counties in the 2000–2015 period [43]. The detailed description and justification for the data source can be found in Mihunov et al. [6]. The damage variable is the total amount of insured crop losses (indemnity payments) per capita, which was aggregated by the authors annually by county using the records that are designated as either "drought" or "failure of the water supply for irrigation" [44]. In each year, losses attributed to "all other counties" of the specified state for the specified cause of loss were divided equally among the counties that lacked recorded damage attributed directly to the county. Then, the annual records were summed and divided by population count in 2000. County-level population change rate, tabulated by the authors as the difference in population between 2000 and 2015 divided by the population in 2000, was used as the recovery variable [45,46]. The study then used the county-level hazard, damage, and recovery data to estimate the *a priori* k-means groupings for each of the 503 counties. Table 1 lists the average values of hazard, damage, and recovery variables in each resilience group based on k-means clustering.

In the second step, the output from k-means analysis (*a priori* k-means groupings) was used as a target variable for the correlation-adjusted T (CAT) score variable selection and SDA. A total of 52 indicators related to socioeconomic and FEW characteristics for the year 2000 were used as independent variables in SDA (Table 2). SDA produced posterior groups and a classification accuracy estimate (agreement between prior and posterior groups). Discriminant functions from the SDA were then used to estimate the resilience level of each county at the three consecutive time points using the data at respective time points.

The 52 resilience variables used in the SDA model training were from the year 2000 (preexisting conditions). Table 2 lists the variables, along with their respective abbreviated data sources; the detailed data sources are listed in table's footnotes. These variables are related to

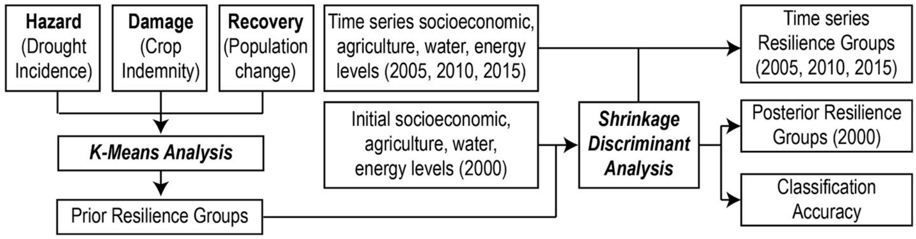

Fig. 3. Flowchart of the procedures used in the Resilience Inference Measurement model.

Table 1
Mean levels of 2000–2015 hazard, damage, and recovery variables in each resilience group derived from k-means analysis.

k-means group	Hazard (Weeks in drought)	Damage (crop indemnities, $ per capita)	Recovery (Population change)
Susceptible (34 counties)	277.18	19,305.67	−0.11
Recovering (205 counties)	110.71	80.75	0.01
Resistant (156 counties)	284.56	1800.73	−0.01
Usurper (108 counties)	251.59	474.42	0.34

socioeconomic, agricultural, water, and energy characteristics of the counties.

The socioeconomic variables were similar to the ones commonly used and repeatedly tested in the resilience and vulnerability literature [50]; see also [6,9,34,35,51–53]. Among them are variables related to economic performance and income (labor force, unemployment, poverty rate, household and per capita income levels, female labor force, agriculture and transportation occupations), housing (renting households, housing in urban areas), education (no high school diploma), household size, population of vulnerable age (over 65 and under 5 years old), as well as community and civic engagement (nativity to home state and election participation), and health (civilians with disabilities).

Including agriculture, energy, and water variables in community resilience assessment is considered innovative. These variables are not common in resilience and vulnerability literature despite being highly relevant to drought resilience and closely related to the FEW nexus. FEW-nexus studies consider the influence of the associations, dependencies, and competition for resources between the water-food, energy-water, water-energy, and energy-food systems [54]. Competition for scarce water resource between all FEW nexus actors during socioeconomic drought makes it most devastating among the four types (Fig. 1; [15]). Variables, such as differences in farmer's resources and farming practices and differences in water and energy consumption, are thus expected to be closely related to socioeconomic drought [54–61].

Table 2
List of 52 variables close to Year 2000 used in the validation of the resilience level.

Variable	Source	Variable	Source
Agriculture		**Socioeconomic**	
% family and individual farm	USDA NASS 1997[c]	% of civilian labor force	BLS-CPS 2000[a]
% farms in federal programs		Unemployment rate	
% farms in fed. conservation, wetlands progr.		% below poverty	Census 2000[a]
% farms paying interest, non-real estate		% born in this state of residence	
% farms paying interest, real estate		% employed in agriculture, forestry	
% farms with animal expenses		% employed in transportation, public utilities	
% farms with chemical expenses		% households renting	
% farms with contract labor		% of female in the labor force	
% farms with feed expense		% over 25 with no high school	
% farms with hired labor		Avg household size	
% farms with rent, cash, land, buildings exp.		Per capita income	
% farms with seeds and plants expense		% over 65 years old	PEP 2000[a]
% tenant farm operations		% under 5 years old	
Agricultural land, buildings - asset value, $/acre		Median household income	SAIPE[a]
Avg expense on taxes, $/farm		% housing in urban areas (popul. > 50,000)	SF1[b]
Avg fuel expense $/farm		% of civilian labor force with disabilities	SF3[b]
Avg operating expense, $/farm		% voted in the election of year	SAGE[a]
Commodity totals - sales, $/farm		**Energy**	
Number of farms per square mile		% housing, bottled, tank, LP gas heating fuel	Census SF1 2000[b]
Water		% housing, electricity as heating fuel	
Industry withdrawals, % ground water	USGS 2000[c]	% housing, no heating fuel	
Industry withdrawals, Mgal/d per 1000 popul.		% housing, oil, keros., coal, coke, other heat.	
Irrigation, % ground water withdrawals		% housing, solar energy heating fuel	
Irrigation, Mgal/d per 1000 irrigated acres		% housing, utility gas heating fuel	
Public supply, % ground water withdrawals		% housing, wood heating fuel	
Public supply, Mgal/d per 1000 population		Annual crude oil withdrawals, bbl per capita	USDA ERS[c]
Average impervious rate	2014[c]	Annual natural gas withdr., 1000 ft[c] per cap.	

[a] U.S. Census Bureau's Census 2000, Population Estimates Program (PEP) 2000, Small Area Income and Poverty Estimates (SAIPE) 2000, Bureau of Labor Statistics-Current Population Survey (BLS-CPS) 2000, and SAGE Publications 2000 variables were acquired from the U.S. Census Bureau USA Counties Data File Downloads (2014) [45].
[b] Census Summary Files (SF1, SF3) 2000 from the American Fact Finder [46].
[c] Agriculture, energy, and water variables from US Department of Agriculture [47,48] and US Geological Survey [49]; impervious rate (% impervious surface), tabulated by the authors from the U.S. Geological Survey data.
Sources:

Consideration of these variables could make the final prediction model more interpretable and relevant to the stakeholders and policymakers.

The damage variable [44] as well as agricultural variables [47] were adjusted for inflation to 2015 U.S. dollars by the authors using the Federal Reserve Bank of St. Louis Economic Data [62] average annual consumer price (CPI) index for a given year.

3.3. Variable importance ranking and selection

Using the "sda" package (and CAT Score Variable Selection, version 1.3.7 [63], in R [64]), the 52 socioeconomic and agriculture, water, and energy variables (Table 2) were ranked by their importance, and eventually 10 variables were selected based on the "higher criticism" statistic [65–68]. SDA is a form of regularized linear discriminant analysis (LDA) that can be used to select (shrink) the best set of variables for the final model [42]. An advantage of this method is that SDA reduces overfitting by penalizing the complexity of the model. The regularization parameters are estimated using the James–Stein type shrinkage rules for the correlations (the ridge-type estimator), the variances (the shrinkage estimator), and the proportions (the frequency estimator) to minimize the mean squared error. A value of 0 implies no shrinkage and 1 represents complete shrinkage. The optimal shrinkage intensity values can be specified by the analyst, or they can be estimated from the data through minimizing the mean squared error. In this study, the optimal shrinkage intensity was estimated to be fairly low, meaning lower penalization. The final model was optimized using these parameter values: frequencies (0.022), variance vector (0.027), and correlation matrix (0.0417).

The CAT scores method computes the t-scores between the mean of each group and the pooled mean. The method is especially useful for variable selection in the presence of multicollinearity among the independent variables. Another advantage is interpretability; the CAT scores method assigns all variables with an order of importance as well as characterizes their contribution in each group, using the distance of the group centroid from the pooled mean. The number of variables chosen in the model is determined by the Higher-Criticism statistic. In this study, the maximum Higher-Criticism value was found to be at 2.17 when 10 variables were selected. Finally, using the set of 503 cases and 10 variables from Year 2000, the SDA prediction model was developed (i.e., the discriminant functions).

3.4. Time series data collection and resilience score estimation

Data for the 10 resilience variables selected from the SDA model were collected for the three consecutive time points (2005, 2010, 2015), so that their respective resilience levels can be calculated using the discriminant functions derived from the Year 2000 data. Table 3 lists the data along with their respective means, standard deviations, and data sources for all four time points.

In working with disparate data across a relatively large geographical region and at multiple time periods, missing values in certain variables are expected, thus a plausible approach to handling them becomes necessary. We utilized multiple imputations method, a robust alternative to imputations of the mean or listwise deletion, with the help of the "Multivariate Imputation by Chained Equations" (MICE) package (v. 2.46; [70]) in R. The package utilizes predictive mean matching, a general purpose semi-parametric imputation method that will preserve the data distribution such as nonlinear relations [69]. This is done by modeling a distribution for each missing entry and drawing a plausible value from the distribution [70].

In this study, data for the Years 2000, 2010, and 2015 had only up to five out of 503 missing values in several variables, and the default method in MICE was used to impute those values. However, for 2005, five of the 10 variables selected in the final model (% employed in agriculture, % over 65 years old, % civilians with disabilities, median household income, average household size) had 245 missing values (American Community Survey 2007 3-year estimates; [46]). In addition, % civilian labor force had 249 missing values, and agricultural asset value had two missing values. To avoid skipping 2005 and provide temporal assessment of community resilience at even time intervals, the multiple imputations method was used to produce imputations for the seven variables. With the help of the quickpred() function in MICE, 52 variables from Table 1 (Year 2000) were used as additional predictors for the imputations in these six variables, as opposed to the default method in MICE where the only predictor for each variable is the variable itself. This method greatly improves the imputation results.

Table 3
Means, standard deviations, and data sources of the 10 variables at four time points.

	2000		2005		2010		2015	
	mean	*sd*	*mean*	*sd*	*mean*	*sd*	*mean*	*sd*
% employed in agriculture	9.17 *Census 2000*	7.47	9.04 *ACS 2007* 3yr	6.05	9.13 *ACS 2009* 5yr	7.5	10.18 *ACS 2015* 5yr	7.87
% farms in federal programs	0.26 *USDA NASS 1997*	0.25	0.27 *NASS 2002*	0.22	0.3 *NASS 2007*	0.27	0.33 *NASS 2012*	0.27
% over 65 years old	14.88 *Census PEP 2000*	4.1	15.13 *ACS 2007* 3yr	4.04	15.65 *Census 2010*	4.2	16.72 *ACS 2015* 5yr	4.58
% of civilians with disabilities	22.89 *Census SF3 2000*	4.3	16.37 *ACS 2007* 3yr	4.68	15.24 *ACS 2012* 5yr	4.76	17.18 *ACS 2015* 5yr	4.43
Number of farms per sq. mile	0.96 *USDA NASS 1997*	0.73	0.94 *NASS 2002*	0.75	1.01 *NASS 2007*	0.8	0.98 *NASS 2012*	0.82
Agricultural assets, $/acre	1375.17 *USDA NASS 1997*	1419.53	1580.08 *NASS 2002*	2689.24	2076.41 *NASS 2007*	3359.71	2174.95 *NASS 2012*	1502.85
Avg expense on taxes, $/farm	1902.47 *USDA NASS 1997*	1408.41	2226.74 *NASS 2002*	1707.98	2290.63 *NASS 2007*	1638.38	2378.22 *NASS 2012*	1700.42
Median household income	32,072.92 *SAIPE 2000*	7164.89	37,449.12 *ACS 2007* 3yr	9587.85	39,347.21 *SAIPE 2009*	9533.19	43,748.41 *ACS 2015* 5yr	10,615.05
Avg household size	2.6 *Census 2000*	0.21	2.61 *ACS 2007* 3yr	0.26	2.62 *ACS 2010* 5yr	0.25	2.65 *ACS 2015* 5yr	0.27
% civilian labor force	45.53 *BLS-CPS 2000*	5.39	57.5 *ACS 2007* 3yr	6.86	47.04 *ACS 2012* 5yr	6.49	56.19 *ACS 2015* 5yr	7.25

U.S. Census Bureau's Census 2010, Small Area Income and Poverty Estimates (SAIPE) 2009 were from the U.S. Census Bureau USA Counties Data File Downloads (2014) [45].
American Community Survey (ACS) 2007 3-year, 2009, 2010, 2012, 2015 five-year estimates from the American Fact Finder [46].
Agricultural variables from USDA [47].
Sources (for Year 2005, 2010, 2015):

4. Results

4.1. Spatiotemporal variation of hazard and damage

To provide an overview of the spatial-temporal patterns of hazard threat and damage in this region, hotspot maps for the two variables (Fig. 4) were created for the time intervals of 2000–2005, 2005–2010, and 2010–2015, using the 95% confidence level in the “Hot Spot Analysis” tool in ArcGIS Desktop (Version 10.5; [71]).

In the first period (2000–2005), hot spots for drought incidence occurred in New Mexico and western Texas, including the southern part of the Texas High Plains and Midland-Odessa area, with the highest-incidence county in Rio Arriba, New Mexico (north of Santa Fe). In the second period (2005–2010), high drought incidence is observed in central and southern Texas, including large metropolitan areas of Houston, Dallas, Austin, and Corpus Christi. The highest incidence in this time period was found in Uvalde County, Texas, west of San Antonio. In the third period (2010–2015), a large part of the study area, including all of New Mexico, all of the Texas High Plains, and western Oklahoma, were affected, reflecting the devastating 2012 drought [72]. The highest incidence in that period occurred in Kendall County, adjacent to metropolitan San Antonio.

The hotspot patterns of damage were similar in the first two five-year periods. In the third five-year period (2010–2015), the damage hotspot had the same “center” but smaller “radius.” The damage hotspot was centered on the agricultural region of the Texas High Plains including Amarillo, Lubbock, Midland-Odessa, Wichita Falls, and Abilene counties. Counties with the highest per capita damage values were Glasscock in Texas in the first two periods and Cimarron (Oklahoma) in the third period (2005–2010). Moreover, the mean values of drought

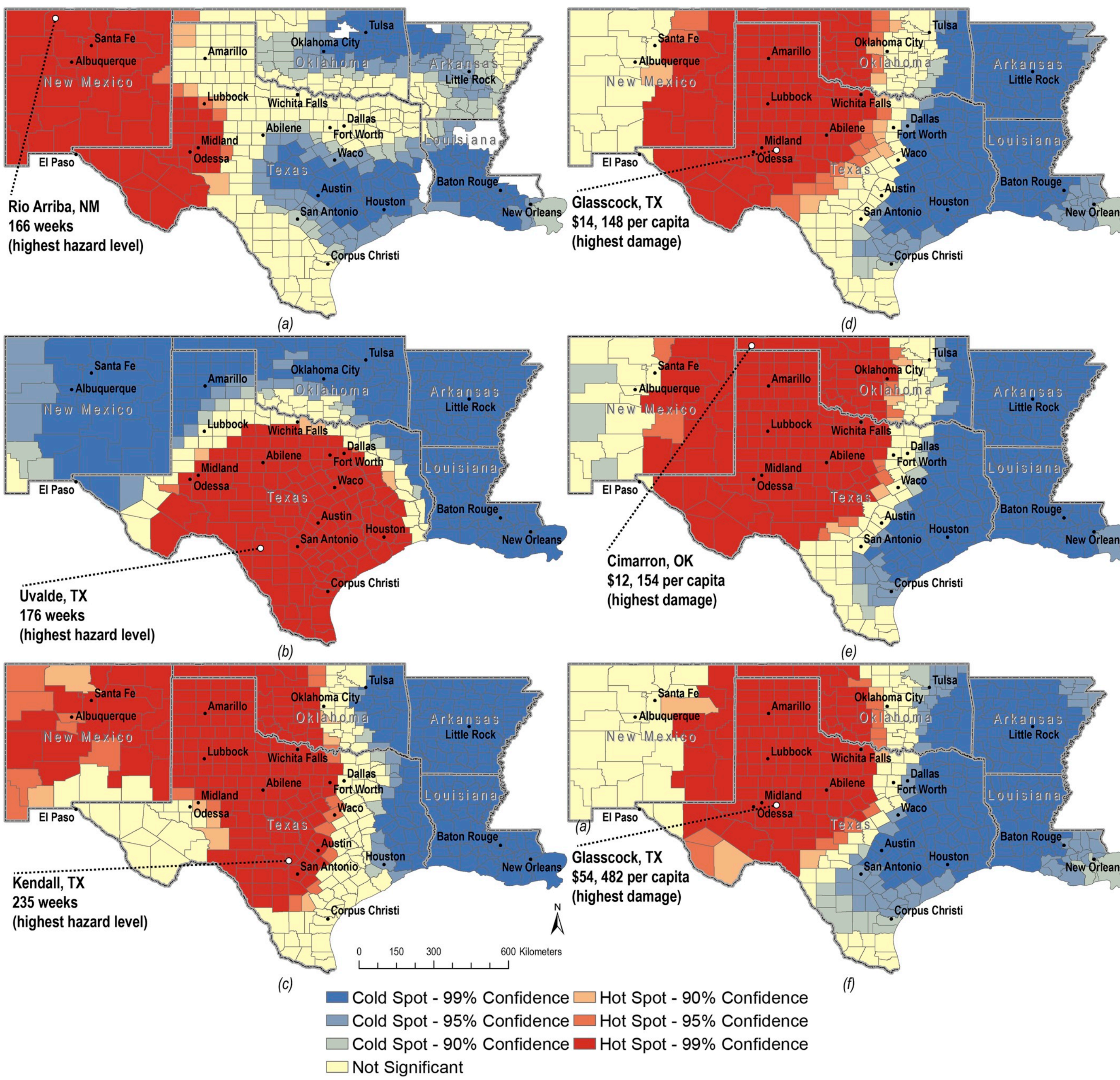

Fig. 4. Hotspot maps of hazard level: (a) 2001–2005 (b) 2006–2010 (c) 2011–2015 and damage (d) 2001–2005 (e) 2006–2010 (f) 2011–2015.

Table 4
Descriptive statistics of exposure and damage variables in 2001–2005, 2006–2010, 2011–2015.

Variable	Year	N	Minimum	Maximum	Mean	Std. Dev
Exposure (weeks in drought)	2000–2005	480	3	166	28.13	32.53
			18 counties in AR, LA, OK, TX	Rio Arriba, NM		
	2005–2010	503	4	176	53.57	36.18
			Marion, Baxter, AR	Uvalde, TX		
	2010–2015	503	18	235	126.55	61.05
			St Helena, LA	Kendall, TX		
Damage (crop indemnity, $ per capita)	2000–2005	474	0.0004	14,147.55	304.23	1102.46
			Bernalillo, NM (Albuquerque)	Glasscock, TX		
	2005–2010	503	0.00004	12,154.47	416.64	1178.22
			Bernalillo, NM	Cimarron, OK		
	2010–2015	503	0.0002	54,481.69	1444.74	4858.93
			Bernalillo, NM	Glasscock, TX		

incidence and damage increased in each five-year period, peaking in the last five-year period, coinciding with the 2012 Texas drought (Table 4; [72]).

These hotspot maps show clearly that while the level of drought hazard changed spatially in each period, counties that endured high damage remained similar. Glasscock, Borden, and Lynn counties in Texas, as well as Cimarron County in Oklahoma, endured the top-10 highest damage in all three five-year periods (not listed in the tables). Martin, Hall, Foard, and King (Texas) were the counties that endured top-10 highest damage twice. Val Verde, Real, Kerr, Edwards, and Maverick (Texas) were subjected to top-10 highest drought incidence twice – in 2005–2010 and 2010–2015. All top-10 highest drought incidence counties of 2000–2005 were in New Mexico, and no county was subjected to the top-10 highest incidence three times.

4.2. Ranking and contribution of the indicators of community resilience

SDA resulted in a 10-variable solution with a classification accuracy of 67.9% (65.8% with cross validation). Fig. 5 shows the CAT for each variable selected in the final model in order of importance. The CAT scores estimate an individual variable's contribution in discriminating the groups, after removing all other variables' effects. In Fig. 5, CAT scores are portrayed as distance between a group centroid and a pooled mean in either the positive or negative direction, to represent the contribution of the variable in each group.

The CAT scores are revealing; they show that counties with the lowest resilience (i.e., in the susceptible category) had high percentages of people employed in agriculture and people over 65 years old, more farm recipients of federal programs, lower value of agricultural assets, lower numbers of farms per square mile, and higher tax expenses per

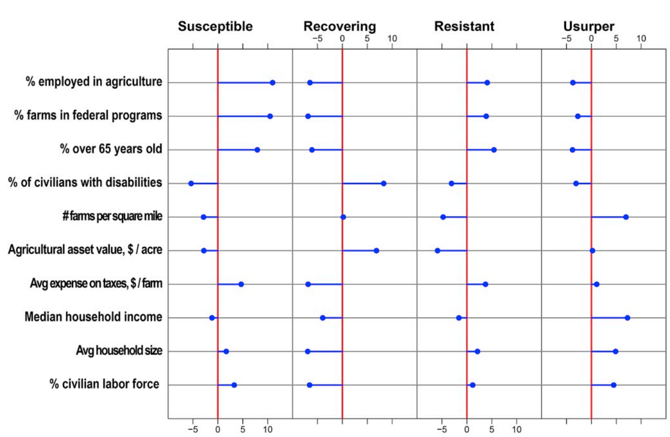

Fig. 5. Top-10 variables selected in the model in the order of importance. Horizontal lines represent distance of Centroid from Pooled Means or CAT scores (decorrelated t-statistic).

farm operation. Counties assigned as "recovering" had relatively high values of agricultural assets and higher percentages of adults with disabilities, but relatively low levels of the other variables. Resistant counties had relatively low values of agricultural assets and high percentages of population over 65, and notably few farms per square mile.

The most resilient (i.e., "usurper") counties had relatively high numbers of farms per square mile, but low percentages of the population employed in agriculture. In addition, socioeconomic affluence is relatively high in these counties, with high median household income, young populations, and smaller disabled populations in the civilian labor force. This suggests that even though counties of highest resilience have higher density of farms, agriculture may not be a primary source of economic productivity in these counties.

In addition, the descriptive statistics for the 10 variables (shown in Table 3) indicate that a growth of agricultural land and buildings asset value is evident at each five-year period, but with only a slight increase in percentage of agricultural employment in 2015 and a slight increase in percentage of older population. Median household income grew as well. There was a slight increase in percentage of farms receiving of federal government aid, as well as a gradual growth of farms' expense on taxes from 2000 to 2015. At each time point the number of farms per square mile remained near 1.0.

4.3. Spatial and temporal variation in community resilience

Fig. 6 shows the final (posterior) resilience levels at each time point and their temporal changes. At the starting point (Year 2000; Fig. 6a), usurper counties were found mostly in or around metropolitan areas while susceptible counties were located in the Texas High Plains. Recovering counties was the largest group and were concentrated in Arkansas, Louisiana, eastern Oklahoma, and Texas. Resistant counties made up the rest of the study area. These posterior resilience levels are largely consistent with the results from Mihunov et al. [6].

In the first five-year period (2000–2005), many recovering counties in the eastern part of the study area improved their resilience level by one or two categories, with more counties classified at resistant and usurper levels (Fig. 6e). Furthermore, improved resilience was found to be mostly in counties adjacent to those with high baseline resilience. Notably, New Mexico was a hot spot of high drought incidence in 2000–2005, but many counties in that state showed an improvement in their resilience levels. On the contrary, many counties in the Texas High Plains suffered a decrease in their resilience levels, leading to more susceptible counties than in the baseline year. The 2005 results should be interpreted with caution because of the many imputed data points used in that year.

In the second period (2005–2010, Fig. 6f), resilience in many counties of Arkansas, Louisiana, eastern Oklahoma, and New Mexico declined by one or two levels, whereas six counties in the Texas High Plains (King, Kent, Borden, Glasscock, Gaines, and Yoakum) decreased in resilience by three levels (from usurper to susceptible).

In 2010–2015, resilience in 121 counties across the study area

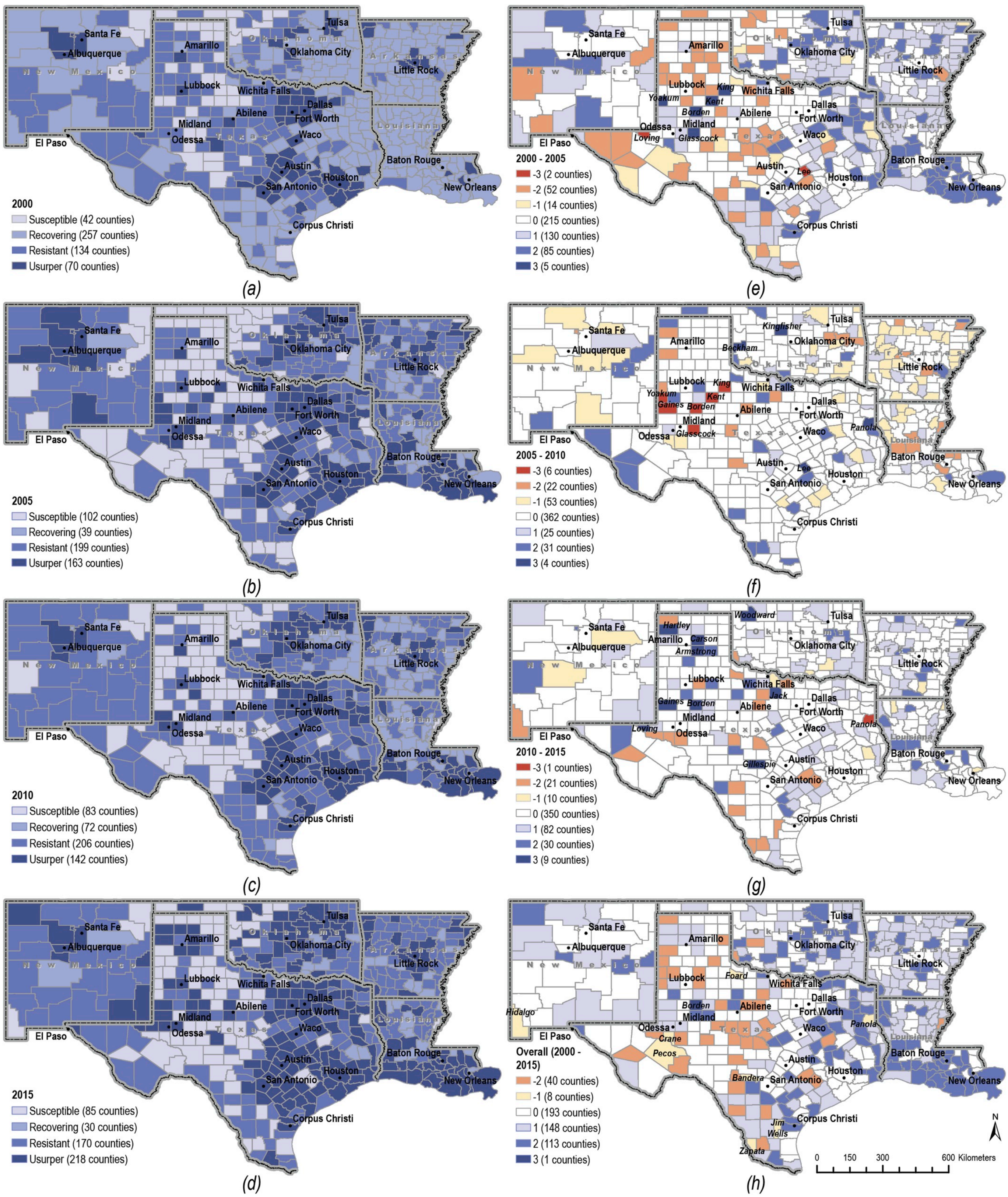

Fig. 6. Resilience levels for (a) 2000, (b) 2005, (c) 2010, (d) 2015, change in resilience levels for (e) 2000–2005, (f) 2005–2010, (g) 2010–2015, (h) 2000–2015.

improved. Despite the intensity of drought and damages inflicted, many counties in the Texas High Plains improved in resilience, as well as some counties of Arkansas, Louisiana, eastern Oklahoma, and southern Texas (Fig. 6g). Urban counties of Texas High Plains and across the study area were generally able to maintain their high level of resilience, whereas many rural counties in the Texas High Plains remained susceptible. A total of 32 counties scattered across the study area experienced a decline in resilience level.

Overall, throughout 2000–2015, resilience improved by one level in 148 (29.4%) counties and by two levels in 113 (22.5%), with the latter

Table 5
Resilience levels in 2000 (row) by resilience level change for the entire study period (2000–2015) (column).

	−3	−2	−1	0	+1	+2	+3
1 – Susceptible (42)	N/A	N/A	N/A	38 (90.5%)	0	3 (7.1%)	1 (2.4%)
2 – Recovering (257)	N/A	N/A	7 (2.7%)	30 (11.7%)	110 (42.8%)	110 (42.8%)	N/A
3 – Resistant (134)	N/A	40 (29.9%)	0	56 (41.8%)	38 (28.4%)	N/A	N/A
4 – Usurper (70)	0	0	1 (1.4%)	69 (98.6%)	N/A	N/A	N/A
All counties (503)	0	40 (8%)	8 (1.6%)	193 (38.4%)	148 (29.4%)	113 (22.5%)	1 (0.2%)

counties concentrated in the eastern part of the study area (Fig. 6h). A total of eight counties (1.6%) decreased their resilience by one level, and 40 (8%) by two levels; these were mostly in the Texas High Plains area. A total of 193 counties, or 38.4% of all counties in the study area, maintained the same resilience level.

This is an optimistic result, since the majority (52.1%) of the counties improved their resilience level, and only a small percentage (9.6%) decreased their resilience level. Some counties that endured high damage – Glasscock, Martin, and King in Texas, and Cimarron County, Oklahoma, were classified as susceptible in 2000 and remained susceptible in 2015. Foard and Hall counties in Texas decreased their resilience level by one and two levels, respectively, and became susceptible in 2015. Lynn County, Texas, a part of Lubbock Metropolitan Statistical Area, endured the third-highest damage overall in 2000–2015, but improved resilience by two levels and became resistant in 2015.

4.4. Evaluation of hypotheses

To further understand the dynamics behind these changes, the two original hypotheses were evaluated: (1) more affluent counties will continue to improve their resilience, whereas counties with poorer socioeconomic conditions will decrease their resilience, leading to a widening gap in resilience levels among counties over time; (2) given the potential neighborhood effects, counties with high-resilience neighbors are likely to have high resilience, whereas counties near low-resilience neighbors are likely to have low resilience, and this effect will likely strengthen over time, thus increasing the regional disparity of resilience to drought.

For Hypothesis 1, the resilience levels in 2000 (1 – susceptible, 2 – recovering, 3 – resistant, 4 – usurper) were cross-tabulated with the difference in resilience level between 2015 and 2000 (−2, −1, 0, +1, +2, +3; Table 5). The results show that resilience did not improve in the vast majority (90.5%) of the susceptible counties. Counties with the recovering rating showed the most improvement, with 85.6% of them improving their resilience level by one or two levels. Only 11.7% of the counties in this category maintained the same resilience level in 2015, and only 2.7% of the counties in this category showed a decrease in their resilience by one level. Counties in the third (resistant) category also showed improvement, but the pattern is not straightforward. A total of 41.8% of the counties remained resistant and 28.4% improved by one level (from resistant to usurper). However, about 29.9% of them decreased by two levels into susceptible, and no counties decreased by one level. Finally, 98.6% of the counties in the highest resilience group (usurper) did not decrease their resilience level.

These results largely support the first hypothesis but with some modification. A majority of the counties with the lowest resilience did not improve and a majority of the counties with the highest resilience did not decrease their resilience level. However, a majority of counties in the second-lowest resilience group (recovering) showed improvement, whereas about the same percentage of counties (about 30%) in the second-highest resilience group (resistant) moved into either the lowest or highest resilience category in the next resilience cycle.

To further analyze how the initial levels of the resilience predictors in 2000 contributed to consecutive resilience change from 2000 to 2015, we conducted an ANOVA test between the groups of counties that increased, decreased, and maintained their resilience level (Table 6). The test reveals that all variables except average household size had a significant difference in means between the three groups. Counties that improved in resilience had lower initial level of agricultural employment, lower farmers' average tax expenses, and higher agricultural asset price. In contrast, counties that decreased in resilience started with the highest % agricultural employment, lowest agricultural assets, and highest farmers' tax expenses among the three groups.

Table 6
Mean values of resilience variables in 2000 in counties that increased, decreased, or did not change their resilience level from 2000 to 2015.

Resilience variables in 2000 (preexisting conditions)	Resilience decrease	No change in resilience	Resilience increase	ANOVA F-value
% employed in agriculture	15.20	10.13	7.36	27.57[a]
% farms in federal programs	0.37	0.28	0.23	7.94[a]
% over 65 years old	17.31	14.99	14.36	11.03[a]
% of civilians with disabilities	24.14	21.22	23.90	26.24[a]
Number of farms per sq. mile	0.65	0.99	0.99	4.75[a]
Agricultural assets, $/acre	725.66	1497.45	1404.09	5.91[a]
Avg expense on taxes, $/farm	2540.51	2136.79	1612.96	13.80[a]
Median household income	29,547.98	34,650.83	30,636.52	22.52[a]
Avg household size	2.60	2.57	2.62	2.47
% civilian labor force	45.53	47.77	43.87	32.78[a]

[a] Asterisk are p-values < 0.05 showing significant difference of means between groups.

To test the second hypothesis – that the resilience of the counties will become more spatially clustered, leading to further regional disparities – the spatial autocorrelation of the counties' resilience scores in Years 2000 and 2015 were evaluated and compared using the Spatial Autocorrelation (Global Moran's I) tool in ArcGIS Desktop [73]. The method's spatial relationship was specified as inverse distance and the distance threshold was computed and applied automatically at 116.73 km. The Global Moran's I measures spatial autocorrelation of the features' values based on their locations and tests whether their spatial pattern is clustered, dispersed, or random [73,74]. Significant p-value in the Moran's I detects non-random patterns, with positive z-score suggesting that the values are clustered and negative z-score indicating spatial dispersion. In the Year 2000, the resilience of the counties was found to be clustered at 1% significance level with z-score of 15.22. In the Year 2015, the resilience scores in the study area were also clustered significantly at 1% confidence level but with a higher z-score of 16.12. The increase in Moran's I z-score shows an increase in spatial divide (clustered pattern) in counties' resilience, and thus confirms the second hypothesis.

5. Discussion

Like most large-scale studies with multiple time points, this study has faced a number of issues. First, data availability, quality, and intercomparability at each time point posts a serious challenge in conducting a temporal study. Median rent is the variable that was selected as significant in Mihunov et al. [6]; but it was removed in this study to comply with the U.S. Census Bureau guidelines for suitability of the Census 2000 and ACS data for temporal comparison [75].

Second, the many missing values in 2005 post another challenge for estimating resilience levels for that year. The multiple-imputations method was used to impute missing values. Authors of the MICE package suggested that the multiple imputations framework is suitable for statistical inference, because it does not disturb the data distribution as in the simple mean imputation, does not artificially increase correlations like regression imputations, and is not subjected to biases of listwise deletion. The method creates several (five by default in MICE) iterations of the imputed data by replacing the missing values with plausible values. The method allows analyses to be performed, such as building a linear regression model with each of the multiple imputed datasets and then combining separate estimates of standard error for each analysis into an overall estimate of standard error, confidence intervals, and p-values. This allows estimation of uncertainties and sensitivity analysis when building a model with imputed data [70]. In this study, the diagnostic plot from the imputation process shows that the imputed values follow the original data closely; hence, the missing values and the subsequent estimated resilience levels in 2005 should be plausible.

Nevertheless, the significance of this study is two-fold. First, from a theoretical point of view, the study offers new insights into the patterns and processes of community resilience to the drought hazard in this region. The hotspot maps, the 10 variables selected, and the computed RIM scores provide baseline information on how and why resilience in these counties have changed. In addition to the statistically derived results and hypothesis testing, the study provides useful descriptive information from multiple real-world data variables to support the validity of the model results and conclusions.

Second, the study provides a practical decision-making tool that is based on quantitative assessment and validation using empirical data (hazard, damage, and recovery). The RIM model presented in this study captures a community's ability to withstand drought impacts, its susceptibility to monetary damage, and its capacity for population growth under the drought stress. The ten resilience predictors are actionable and quantifiable features of the communities that discriminate them into the four resilience groups, each one of which is characterized by a distinct pattern of absorbed drought incidence (hazard intensity), endured damage, and population change (recovery). The resilience predictors identified and their quantitative contributions to the final community resilience level derived from this study should help inform policymakers in devising their local and regional adaptation strategies, such as identifying which variables should be promoted. For example, stakeholders might interpret lower agricultural employment and higher number of farms per square mile in counties would increase resilience, hence promoting diversity in agriculture and growth of non-agricultural economic activities might be beneficial to their communities as a long-term adaptive strategy.

Moreover, the inferential ability of the RIM model is particularly useful, since the discriminant functions derived in the RIM model can be applied to a different study area or time period provided that the statistical assumptions are met. The same model can be applied to simulated data under hypothetical scenarios.

6. Conclusion

This study assessed the temporal dynamics of community resilience to drought hazards in the south-central U.S. from 2000 to 2015 using the Resilience Inference Measurement (RIM) model. The research aimed to answer three questions: (i) is a change in drought resilience in the region evident over time? (ii) where and why did some counties experience an increase while others suffered a decrease in resilience? (iii) is there a widening gap in disparity in drought resilience over time? For this question, two related hypotheses were tested: (1) more affluent counties will continue to improve their resilience, whereas counties with poorer socioeconomic conditions will decrease their resilience, leading to a widening gap in resilience levels among counties over time; (2) counties near high-resilience neighbors will likely increase their resilience, whereas counties near low-resilience neighbors will likely decrease their resilience, thus increasing the regional disparity of resilience to drought hazards. The study used shrinkage discriminant analysis and a total of 52 socioeconomic, agriculture, energy, and water-related variables for the RIM analysis, which led to ten variables selected, with a classification accuracy of 67.9%. The ten variables selected in the final model are related to the economic performance in the agricultural sector, socioeconomic well-being, and human health.

In addressing the three research questions, the study results show that (i) there are spatial-temporal changes in community resilience among the 503 counties in the region. (ii) Overall, throughout 2000–2015, 29.4% (148) counties improved their resilience by one level, and 22.5% (113 counties) improved by two levels. Counties that improved their resilience had lower initial level of agricultural employment, lower farmers' average tax expenses, and higher agricultural asset price. In contrast, counties that decreased resilience started with the highest % agricultural employment, lowest agricultural assets, and highest farmers' tax expenses among the three groups (resilience decrease, no change, resilience increase). (iii) Finally, through testing and confirming the two hypotheses, the study reveals increasing regional disparity in community resilience to drought hazards in the region.

Drought impacts on society are complex, multifaceted, and difficult to quantify. Building on the previous study by Mihunov et al. [6]; this research is among the first to assess and analyze communities' performance under pressures of drought impacts at an extensive spatial and temporal scale. Findings from this study provide several baseline suggestions on how and why communities perform differently under drought conditions. For instance, the make-up of the agricultural and socioeconomic variables in the usurper group found in this study suggests that sustainable farming is key to drought resilience in agricultural communities. Moreover, diversification of economy beyond farming is beneficial for counties strongly relying on agriculture. These efforts will not only influence a community itself but also its neighbors, based on the confirmed second hypothesis. These findings can be further refined in future studies to simulate community resilience projections using scenarios generated from the Global Circulation Models (GCMs). The findings provide insights into future survey-based research and detailed case studies on drought resilience.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2019.101302.

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