SECTION 1. ADMINISTRATIVE INFORMATION

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Project Title:

Community Resilience to Drought Hazard: An analysis of drought exposure, impacts, and adaptation in the south-central United States

Agreement number

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August 12, 2014 – August 11, 2016

Actual total cost of the project

$254,485

SECTION 2. PUBLIC SUMMARY

The threat of droughts and their associated impacts on the landscape and human communities have long been recognized in the United States, especially in high risk areas such as the south-central region. However, little is known on whether existing drought indices can predict the damages and how different human communities respond and adapt to the hazard. This project examines whether existing drought indices can predict the occurrence of drought events and their actual damages, how the adaptive capacity (i.e., resilience) varies across space, and what public outreach and engagement effort would be most effective for mitigation of risk and impacts. The study region includes all 503 counties in Arkansas, Louisiana, New Mexico, Oklahoma, and Texas. Correlation results show that existing drought indices, including the Palmer Drought Severity Index (PDSI) and Palmer Hydrological Drought Index (PHDI), appear to be useful indicators of drought damage. However, as expected, the correlation is confounded by the resiliency of the communities. Resilience assessment reveals distinct spatial variation in the levels of resilience to droughts across the region, with higher-resilience counties located mostly in Oklahoma, western Arkansas, and near large metropolitan areas. A total of 15 socioeconomic variables were found to be statistically associated with the level of resilience. Not surprisingly, these variables suggest that higher resilience is associated with higher socioeconomic condition. Results from the household surveys indicate that perception of drought and adoption of water conservation measures among residents and farmers is far from universal, and therefore, opportunities exist for more rigorous public education and community engagement. This project is among the first to study the linkages between drought indices, community resilience, and residents' adaptive behavior. The findings provide useful baseline information and help in the design of more effective drought management and public engagement efforts.

SECTION 3. PROJECT SUMMARY

Drought is a natural hazard that inflicts costly damage to the environment and human communities. Although ample literature exists on the climatological aspects of drought, little is known on whether existing drought indices can predict the damages and how different human communities respond and adapt to the hazard. This project examines (1) whether existing drought indices can predict the occurrence of drought events and their actual damages; (2) how the adaptive capacity (i.e., resilience) varies across space; and (3) what public outreach and engagement effort would be most effective for mitigation of risk and impacts. The study region includes all 503 counties in Arkansas, Louisiana, New Mexico, Oklahoma, and Texas.

For the first objective, the Palmer Drought Severity Index (PDSI) and Palmer Hydrological Drought Index (PHDI) data, available only at the climate-division level, were downscaled into county-level indices over the 1975-2010 period. The drought damage data, acquired from the Spatial Hazards Events and Losses Database for the United States (SHELDUS™), were tabulated for the same time period. Statistical correlations were conducted between drought indices and drought damages to test whether these indices accurately represent the drought damage in the study region. For the second objective, the Resilience Inference Measurement (RIM) model was utilized to assess the level of resilience for all 503 counties using the exposure, damage, and recovery (population growth) data for 1990-2010. The RIM analysis also extracts key socioeconomic variables from a set of 37 that are statistically associated with the level of resilience. To achieve the third objective, two telephone surveys, one targeted the general population and the other, the agricultural sector, were conducted to identify the factors that influence residents' perception and adaptive behavior.

Correlation results show that the two indices (PDSI and PHDI) appear to be useful indicators of drought damage. However, as expected, the correlation is confounded by the resiliency of the communities. Resilience assessment reveals distinct spatial variation in the levels of resilience to droughts across the region, with higher-resilience counties located mostly in Oklahoma, western Arkansas, and near large metropolitan areas. A total of 15 socioeconomic variables were found to be statistically associated with the level of resilience. Not surprisingly, these variables suggest that higher resilience is associated with higher socioeconomic condition. Results from the household surveys indicate that perception of drought and adoption of water conservation measures among residents and farmers is far from universal, and therefore, opportunities exist for more rigorous public education and community engagement. This project is among the first to study the linkages between drought indices, community resilience, and residents' adaptive behavior. The findings provide useful baseline information and help in the design of more effective drought management and public engagement efforts.

SECTION 4. REPORT BODY

Purpose and Objectives:

The threat of droughts and their associated impacts on the landscape and human communities have long been recognized in the United States, especially in high risk areas such as the south-central region. Although there is abundant literature on the climatological aspects of drought and information on drought monitoring is available, many uncertainties about the drought hazard remain. This project addresses three important, inter-connected issues of drought.

First, unlike many natural hazards (e.g., tornadoes, hurricanes, earthquakes), drought is insidious and difficult to define. Depending on the context, a drought may be defined differently into meteorological, agricultural, hydrological, or socioeconomic drought (NDMC 2013; Wilhite and Glantz 1985). For management purposes, resource planners have found that relying on an operational definition of drought, i.e., some form of index, would be most convenient in helping them decide when to act on a mitigation plan to reduce the damage from droughts. However, existing literature has seldom considered the linkages between drought indices for monitoring and the actual damages to crops and properties. In other words, what indices are most effective in representing the occurrence of drought events and their actual damages? Therefore, the project's first objective was to test the relationships between existing drought indices and drought damage.

Second, it is well known in the disaster literature that given the same exposure to a hazard, some communities may suffer less damage and recover faster than others. The question is why the uneven vulnerability and resilience? In other words, what are the social, ecological, and environmental indicators that can be used to characterize and assess the level of resilience of the communities? There is voluminous literature on social-ecological resilience and its related concepts such as hazard risks, vulnerability, adaptation, and sustainability (e.g., Adger 2006; Vogel 2006; Cutter and Finch 2008; Adger and Brown 2010; Turner 2010). However, literature on drought resilience is scanty. Analyzing and assessing how different communities in the region respond to drought and why some communities are more resilient to the drought hazard than others could provide valuable insights into drought management and future adaptation to climate change.

Third, while a broad-scale assessment of drought resilience across a large geographical space is very useful for comparison and monitoring of progress, a survey of residents is needed to help understand adaptive behavior so that effective management strategies can be made.

The specific objectives of this study were to examine whether drought indices are effective in representing the occurrence of drought events and their actual damages, how the adaptive capacity of the communities varies, and what public outreach and engagement efforts would be most effective for mitigation of risk and impacts. The study region included all 503 counties in Arkansas, Louisiana, New Mexico, Oklahoma, and Texas. Three sets of research questions and their corresponding hypotheses were addressed and tested, including:

1. To what extent are drought exposure and damage linked in the south-central United States? ***Hypothesis***: Existing modeled parameters, such as the Palmer Drought Severity Index (PDSI) and Palmer Hydrological Drought Index (PHDI), accurately represent the damage due to droughts in the study region.

2. (a) To what extent are spatial differences apparent in the relationship between drought exposure and associated damage? ***Hypothesis***: Spatial differences exist in the relationship between drought exposure and drought damage among counties in the south-central United States. Counties in the ecotone between humid and arid climatic regimes will have high drought exposure, but may sustain smaller damages, due to greater adoption of mitigation and adaptation strategies by residents and farmers than elsewhere. (b) What socioeconomic indicators can be used to discriminate counties of high resilience from counties of low resilience to droughts? ***Hypothesis***: Counties of higher economic and educational attainment will show higher resilience than counties with lower economic and educational attainment.

3. What are the factors that influence residents' perception of droughts and their adaptive behavior? ***Hypothesis***: Populations with higher socioeconomic status or in counties with high resilience are more amenable to using information about droughts to modify their behavior, because they have been exposed to successful strategies to minimize their vulnerability to a known risk.

We report that all our research objectives have been met. The following sections describe the methods and approaches used and the main results, which are extracted from three publications and unpublished manuscripts (Rohli et al. 2016 for Objective 1; Mihunov et al. 2016 for Objective 2; Reams et al. 2016 for Objective 3).

Organization and Approach:

The project is highly interdisciplinary, which requires expertise in climatology, geography and spatial modeling, and political science. The project involves training of four graduate students. The two LCC collaborators provided input on social and ecological vulnerability and the management priorities at their Landscape Conservation Cooperatives (LCC).

<u>Objective 1</u>:

The research objective was to test if existing drought indices accurately represent the damage due to droughts in the study region. The Palmer Drought Severity Index (PDSI) and Palmer Hydrological Drought Index (PHDI) were used to statistically correlate with the drought damage data acquired from the Spatial Hazards Events and Losses Database for the United States (SHELDUS™). The unit of analysis was at the county level, leading to a total of 503 counties for all five states in the region.

PDSI and PHDI are published weekly and aggregated into a monthly dataset by NOAA, at the climate divisional level. These monthly data were extracted for the 45 climate divisions in the five-state region over the 1975–2010 period, the time corresponding to the rapid population growth over the central part of the study area.

The SHELDUS™ database version 13.1 (Hazards & Vulnerability Research Institute 2014), was used for quantifying drought damage by county. SHELDUS™ data are derived from reports from *Storm Data and Unusual Weather Phenomena* published by National Centers for Environmental Information (NCEI; formerly National Climatic Data Center) and information from the National Geophysical Data Center and the Storm Prediction Center. In SHELDUS™, each drought event causing more than $50,000 in losses (1960–1970), more than $50,000 in losses or any fatalities (1971–1995), and any monetary losses or fatalities (1996–2010) were entered manually into the database. For each drought event, SHELDUS™ records the beginning and ending date, location (county and state), property and crop losses (adjusted to 2011 dollars), injuries, and fatalities in each county. Consultation with NOAA's NCEI confirmed a suspected error for the July 2010 damage in Tensas Parish, Louisiana – the $700 million in damage should have been reported as $700,000 (personal communication, Stuart Hinson, NOAA, 7/17/15); we implemented this change in our data set.

Use of the damage data is not without its cautions. Despite the fact that SHELDUS™ includes damage due to the drought hazard along with that from landslides, winter weather, heat, severe weather, wind, floods, tornadoes, hurricanes, fires, earthquake, volcano, tsunami, and technological and biological hazards, biases exist in the extent of coverage across the different hazard types and across space, due to differences in the extent to which different hazards are monitored and investigated (Gall et al. 2009). Droughts remain notoriously underreported in all databases, including SHELDUS™ (Svoboda et al. 2002; Gall et al. 2009). Gall et al. (2009) caution that a lag of coverage from ~180–600 days is possible in SHELDUS™. Moreover, Mechler and Bouwer (2015) note the importance of vulnerability as a modular of the relationship between the extreme event and/or climatic change and losses, and vulnerability can be difficult to measure. These complications may perhaps explain why little scholarly work to date has assessed economic damage from drought. But yet the high and rapidly escalating losses due to drought call for immediate analysis, even with results that invite caution in interpretation.

It was necessary to transform the event-based SHELDUS™ database into monthly county-level economic losses during 1975–2010. Both crop losses and total losses (crop and property) were chosen to represent the damage caused by drought events. Crop losses not only reflect direct responses to hydrological conditions but also contribute to the most of total losses according to historic records. Each event-based crop/total loss was evenly divided into monthly crop/total loss based on the sustaining duration in each month, which was calculated from the beginning and ending date. For example, if a drought event had occurred in Orleans Parish from 27 May 2010 to 15 July 2010 and caused $1,000 in total loss, the duration of this event would have been reported as 5, 30, and 15 days for May, June, and July 2010, respectively, and the total losses from this event would have been 100, 600 and 300 dollars, for May, June, and July 2010, respectively. Finally, the county-level drought index layers and damage layers were connected and output as records of county, year, month, PDSI, PHDI, duration, CPI-adjusted crop damage, and CPI-adjusted total damage. The pre-processing utilized a python script embedded in ArcGIS to handle the 217,296 (503x36x12) records.

The areal interpolation method in the "Geostatistical Analyst" extension in ArcGIS 10.1 (Environmental System Research Institute (ESRI) 2012) was used for statistical downscaling of the climate division-based PDSI and PHDI to the county level for each of the 432 months of analysis. Areal interpolation reaggregates data from one set of polygons (the source polygons) to another (the target polygons) and different approaches can be used to perform this task (Goodchild and Lam 1980; Lam 1983). The ArcGIS extension uses kriging theory to conduct areal interpolation (Oliver and Webster 1990; Krivoruchko et al. 2011; Stein 2012). Downscaling drought indices from climate divisions to counties is a two-step process. In the first step, a smooth prediction surface was created from the attribute data (drought index values) input for each climate division. In the second step this prediction surface of drought indices was re-aggregated to the county level feature class. To create an accurate prediction surface with "Geostatistical Wizard," the covariance curve needs to be fitted. Therefore, lag size value, type parameters (K-Bessel and Stable), and lattice spacing values were selected carefully to fit the model optimally. The mathematical description of the interpolation procedure is described by Krivoruchko et al. (2011). Predictions and standard errors were calculated for all the target polygons. To generate results with at least 90 percent of the empirical covariances falling within the 90% confidence intervals, a covariance model was specified by fitting a proper covariance curve within the kriging framework.

For a given county, drought duration was defined as the number of consecutive months in which the downscaled county-level PDSI (and, in a separate analysis, PHDI) was below –1.0. Then, because of the predominance of months with no drought-related damage reported in SHELDUS™, all months with zero damage were removed from analysis prior to running the correlations. Because of concern about the uncertain and varying lag relationship for reporting drought damage after onset of drought, the county-level damage data were aggregated over a 12-month moving window (including months with no damage) beginning on each month of the time series. This lag was chosen in order to keep one complete growing season within each window to validate comparisons and correlations of intensity/duration to losses, while still taking into account the fact that lags associated with SHELDUS™ could be from 6 to 20 months (Gall et al. 2009). The purpose was to ascertain the extent to which an incipient drought can be used to predict aggregated drought damage over the next twelve months.

Objective 2:

To meet the study objectives and test Hypotheses 2a and 2b, all 503 counties in the study area were assessed using the Resilience Inference Measurement (RIM) model developed previously by Lam et al. (2016). The RIM model overcomes two common problems in community resilience measurement. First, the resilience indices derived in the literature have seldom been validated by real data such as the actual damages resulting from a hazard event. As a result, there is limited confidence on the precision and accuracy with which the derived indices reflect the resilience of a community (Tate 2012). Second, the statistical methods used to develop the indices, such as linear combinations of weighted variables or principal component analysis, are not inferential statistical methods, hence making the generalization of the results to other study areas difficult.

The RIM framework defines community resilience based on the relationship of three elements: exposure, damage, and recovery. Exposure refers to the frequency or magnitude of the hazard, damage is economic loss or human injury or fatality resulting from the hazard, and recovery can be indicated by population return or economic growth following the hazard event. The ratio of damage to exposure is defined as vulnerability, whereas the ratio of recovery to damage is considered adaptability. If a community has high exposure to a hazard but sustains low damage, then the community is considered to have low vulnerability. Similarly, if a community sustains high damage but recovers quickly (e.g., return of population or agricultural productivity), then the community is considered to have high adaptability. Resilience capacity is measured based on the relationship between vulnerability and adaptability. In general, a high adaptability/vulnerability ratio is considered high resilience, while a low adaptability/vulnerability ratio is considered low resilience.

The RIM analysis includes three steps. First, based on the values of exposure, damage, and recovery, the k-means clustering method is applied to classify each county into one of the four possible resilience levels — susceptible, recovering, resistant, or usurper. A susceptible system is considered the least resilient and has a high probability of suffering damage and recovering slowly. A recovering system has average values of exposure, damage, and recovery. Counties assigned as resistant have low damage even though they may have high exposure. Finally, a usurper system has the highest capacity for recovery.

Second, through discriminant analysis, the assigned resilience level is validated using a set of socioeconomic and environmental variables, and the posterior classification as well as classification accuracy (agreement between *a priori* and posterior classifications) is estimated. Discriminant analysis derives the Mahalanobis distance from each case (county) to each of the resilience groups' centroid. The probability of a case belonging to a resilience group is higher if its Mahalanobis distance is shorter. Each case has a probability value for each group and the case is classified to the group that has the highest probability of group membership. These probability values allow for the conversion from the discrete resilience levels to continuous resilience scores using Equation 1 below:

$$I = \sum_{i=1}^{4} i \times P(i) \qquad (1)$$

where *i* is the level of the resilience group (i.e., susceptible is 1 and usurper is 4), and *P(i)* is the posterior probability of a county belonging to a particular resilience group *i*. For example, if a county's probabilities of group membership for groups 1–4 are 0.7, 0.2, 0.05, and 0.05, respectively (the sum of all must be equal to 1.0), then the continuous RIM score will be: $I = 1 \times 0.7 + 2 \times 0.2 + 3 \times 0.05 + 4 \times 0.05 = 1.45$.

In the final step, regression analysis between the continuous RIM score (dependent variable) and the set of socioeconomic and environmental variables extracted from the stepwise discriminant analysis (independent variables) is conducted to determine the variables' significance and contributions (weights) to the resilience score (Cai et al. 2016). This analysis step is designed to simplify, or translate, the results from discriminant analysis and help explain the relationships between the variables and resilience score in a more direct manner, so that the final regression model can be used as a resilience planning tool.

Objective 3:

To find out what factors influence residents' perception of droughts and their adaptive behavior, residents of Texas were surveyed to gauge their opinions on their exposure to drought, how they have been affected by drought, and the actions they are taking to mitigate drought hazards. Two surveys were conducted, one targeting members of the general public of drought-affected counties in Texas and the other targeted the agricultural industry employees in Texas. Both surveys were designed to assess the perceptions of the severity of, and individual preparedness and responsiveness to drought. The surveys were performed by the Louisiana State University Public Policy Research Lab in August and September of 2015. The survey instruments and frequency of responses to each of the questions are documented in the data set – drought adaptation household survey summary.

The general population survey targeted people in counties highly affected by drought, and 42 questions in 5 categories were used to assess their perceptions about the severity of the drought and measure their preparedness and responsiveness. The 18 counties targeted were based on the magnitude of drought and drought-related financial losses among all counties in Texas (Rohli et al. 2016). Residents of these counties were surveyed: Briscoe, Castro, Childress, Cottle, Crosby, Dickens, Floyd, Garza, Hale, Hall, Kent, King, Lubbock, Lynn, Motley, Parmer, Stonewall, and Swisher. Data were collected via telephone interviews conducted from August 15 to August 31 2015. The survey utilized a traditional landline telephone sample (64% of respondents), combined with a sample of cell phone users (36% of the respondents). Random digit dialing in the landline sample ensured representation of both listed and unlisted numbers. The cell phone sample was randomly drawn from known, available phone number banks dedicated to wireless service. The response rates were 13.8% for landline interviews and 4.5% for cell phone interviews, resulting in a total of 481 respondents. These response rates are the percentage of residential households or personal cell phones contacted for which an interview was completed. When analyzed, the total sample was weighted using an iterative procedure that matched race and ethnicity, education, household income, gender, and age to the demographic profile of the combined adult population across the 18 counties. The demographic profile was obtained from data reported in the 2013 Census Bureau's American Community Survey.

Participants for the survey of agricultural industry employees in Texas were found using phone numbers listed on the Texas Market Maker database (https://tx.foodmarketmaker.com/). This database includes a listing of agricultural, seafood and farming companies in Texas. The initial sample from the database included 448 contacts, and attempts were made on 448 phone numbers during September 2015. Of the 448 contacts, 241 were known eligible numbers and 102 (27.8% response rate) resulted in completed interviews. The data were sampled from a population with an unknown demographic profile, thus, the data were not weighted. Also, since the data was a non-probability sample, standard formulas for a margin of error are invalid.

Both surveys were comprised of similar style questions using yes/no, scale, and multiple choice questions. More questions were added to the agricultural survey to address water use in an agricultural work place. Each survey response rate was calculated using the American Association for Public Opinion Research's method for Response Rate 3 as published in their Standard Definitions. For each survey question, frequencies represent weighted percentages of respondents to the question, and percentages may not sum to 100 due to rounding. Regarding the demographics and socioeconomic attributes of the two groups surveyed, agricultural respondents on average were wealthier and nearly twenty years older than the respondents participating in the general population survey. Over ninety-one percent of agricultural respondents were homeowners, while only 57.4% of the general population respondents owned their homes. The gender results were nearly equal, with slightly more males participating in the agricultural survey.

Project Results, Analysis, and Findings:

Objective 1:

Regarding the drought occurrence and persistence, a total of 70,072 (67,974) of the 217,296 county-months (32.2 (31.3) percent) had a PDSI (PHDI) below –1.0. The longest run of consecutive PDSI values below –1.0 was in Jefferson Davis County, Texas (Trans Pecos climate division), for a whopping 70 months – from March 1998 to December 2003. The longest run of a PHDI below –1.0 in its county was for 49 months – from October 2000 to January 2005, in San Juan County, New Mexico (Northwestern Plateau climate division).

Regarding the drought damage, a total of $15.3 billion in 2011-adjusted drought damage occurred across the study area during the 1975–2010 period. The impact was widespread, with damage reported at some point in the period in 249 of the 254 counties in Texas, all 77 counties in Oklahoma, 71 of the 75 counties in Arkansas, all 64 parishes in Louisiana, and 2 of the 33 counties in New Mexico. In all, Texas sustained $9.92 billion in damage over the period, with Oklahoma experiencing $2.03 billion, Louisiana having $1.55 billion, Arkansas experiencing $1.81 billion, and New Mexico sustaining $0.02 billion. The most-damaged county was in Louisiana, with Caddo Parish sustaining $134 million in drought damage, mostly from the exceptional drought of 2010 (which continued beyond the study period into 2011). All other counties on the "top ten" list for drought damage are in Texas, with Childress County, in the rural southeastern Texas panhandle, sustaining almost $118 million, followed by Briscoe and Hall ($115 million each), Swisher ($114 million), Castro and Palmer ($112 million each), Kent and Stonewall ($110 million each), and King ($108 million) rounding out the list. These results generally suggest that crop damage occupies the vast majority of drought damage. Moreover, drought damage is episodic in each state, not surprisingly with far more damage in Texas than any other state. Drought damage is reported throughout the year in Texas, but more damage tends to be reported in summer months than in other months in all states, with a spurious spike in reporting in Texas in December.

The correlation analysis between drought damage and drought indices indicates the existence of relatively strong negative correlations between monthly drought index (for both the PDSI and PHDI) and non-lagged monthly drought damage, when analyzed across all 503 counties in the study area. Statistically significant negative correlations occur in all seasons except autumn for both the PDSI and PHDI analysis. All months from January through April and June through July also showed statistically significant negative correlations to damage for both indices, with May and September displaying significantly negative correlations for the PDSI only. The correlations were comparable for both the PDSI and PHDI at the monthly scale of analysis. However, the presence of small frequencies of months with drought damage in general seems to support the notion that drought damage is likely to be under-reported and invites caution in the interpretation of results.

New Mexico had only 3 county-months of drought damage and therefore no further conclusions are drawn for that state. Significantly negative correlations between drought indices and damage were observed for Arkansas and Texas counties, slightly weaker but still significantly negative correlations were found for Louisiana parishes, and Oklahoma counties actually displayed signs of a spurious positive association between drought indices and drought damage, especially for the PHDI. The positive correlation in Oklahoma could reflect a dependence on irrigation for averting losses in hydrologic drought conditions. In Oklahoma, Texas, and Louisiana, the PHDI offered stronger year-round correlations than the PDSI.

Regarding the relationship between drought duration and drought damage, the results suggest that drought duration, defined as the number of consecutive months in which the drought index (PDSI and PHDI, respectively) falls below –1.0 for that county-month, is also linked (positively) to monthly drought damage.

In recognition of the notion that drought damage may only be reported months after its occurrence, 12-month aggregated damage beginning on the month associated with a given drought index were computed and correlated with drought indices, again by county-month. In general, these correlations were strong, but not quite as strongly negative as those for real-time monthly reported damage. Interestingly, at the state level for all states except Texas, many of the correlations become positive when damage is accumulated over the 12-month window. Perhaps losses can be mitigated over longer periods, as once the damage is done, there is little else to damage, even if the drought indices remain low for the duration of the 12-month period.

<u>Objective 2</u>:

Visual analysis of the exposure, damage, and recovery data for 1990-2010 using the hotspot maps shows distinct spatial variation of the three key resilience elements across the study area. Levels of exposure and damage did not coincide spatially. Significantly high exposure levels covered larger areas of Oklahoma, as well as the metropolitan area of Dallas, Texas. By contrast, only two distinct hotspot clusters of damage were found – both in the Texas High Plains, concentrated in the Lubbock and Midland-Odessa region. This region has heavy reliance on agricultural activities and is highly dependent on irrigation. Its irrigation water use accounts for around 89% of the total freshwater consumption, as compared with around 60% in the state of Texas (Venkataraman et al. 2016). These maps indicate the general areas of low resilience (high damage and low recovery) such as in western Texas, but the magnitude of the resilience by county will need to be quantified by the RIM model, as discussed below.

The k-means algorithm in SPSS was used to cluster the 364 counties with drought incidence recorded in SHELDUS into four resilience levels – "susceptible," "recovering," "resistant," and "usurper". Then stepwise discriminant analysis was used to validate the classification and extract key socioeconomic and environmental variables from a set of 37 variables. This analysis resulted in a classification accuracy of 73.9% and 18 variables selected. The resilience level of the 139 remaining counties were predicted based on the discriminant functions derived from the counties having drought events with damage. Results show that higher-resilience counties are concentrated in Oklahoma and northwestern Arkansas, while low-resilience counties are located along the Gulf of Mexico, western Texas, the majority of Louisiana, and eastern Arkansas. Nine counties were classified into the highest-resilience category; these are located near large metropolitan areas including Albuquerque, Austin, Dallas, Houston, and San Antonio.

Higher resilience to drought in Oklahoma may be due to a long legacy of drought occurrence (such as severe droughts of the 1910s, 1930s, 1950s, 1970s, and 1980s) and subsequent lessons of adaptation (McLeman et al. 2008). Quite unexpectedly, Louisiana was identified to have low resilience to drought. Errors introduced by the impact of coastal hazards (instead of drought events) on low population growth would not be likely to have a severe impact on the results here because the socioeconomic conditions of most parishes (counties) in Louisiana would predict a low resilience regardless of the cause for low population growth. In other words, the resilience scores have been validated by the socioeconomic and environmental variables that represent the community's adaptive capacity. Moreover, in the first decade of 1991–2010, Louisiana did face drought exposure and damage levels comparable to the rest of the study region, in addition to the coastal hazards. However, in order to eliminate this uncertainty in future studies, it is possible to use another recovery indicator, such as agricultural productivity, so that the results between different recovery performance goals can be compared.

To address the research question regarding the spatial variation of resilience levels, the 72 ecotone counties that are transitional between Eastern Temperate Forests and Great Plains were compared with the 431 non-ecotone counties using the means of resilience score, exposure, damage, and recovery variables. The t-test reveals no significant difference between the two groups in the final resilience score, but significant differences exist in all three resilient variables (p < 0.05). This result does not support the first hypothesis that ecotone counties have higher resilience than non-ecotone counties.

To address the research question regarding factors affecting resilience and test the second hypothesis that counties with higher socioeconomic conditions have higher resilience, stepwise regression analysis between the continuous RIM scores and the 18 socioeconomic variables selected by the stepwise discriminant analysis was conducted. This analysis step further removed three variables that were not significant, resulting in 15 explanatory variables with an adjusted R^2 of 0.834. Of the 15 variables, five correlate positively to the RIM score, including "% civilian labor force," "median household income," "median value of owner occupied housing", "local government finance, expenditure for education", and "average impervious rate". The 10 variables which correlate negatively with resilience are "average number of people per household," "% under 5 years old," "% female-headed households," "unemployment rate," "% people living below poverty", "% of housing units with no telephone service", "mobile home per square mile", "percent of population born in this state", and "average water rate". These results affirm the second hypothesis that counties with higher socioeconomic conditions have higher resilience.

An important observation of the regression results is that the explanatory variables extracted from this study are consistent with the set of variables extracted from previous studies that applied the RIM model to other types of (coastal) hazards (Cai et al. 2016). This suggests that adaptation activities and policies for one natural hazard could also have a positive effect on the resilience to other hazards. This finding offers encouragement to communities investing in practices that promote resilience, as investments may address multiple hazards simultaneously.

<u>Objective 3</u>:

Results from the two surveys (general population: 481; agriculture: 102) are numerous. Here we highlight the major results pertaining to the three elements of resilience: exposure, vulnerability, and adaptability. We also report on the results related to the household water conservation strategies.

First, regarding the relationship between exposure to environmental hazards and adaptive behavior, the survey results show that exposure to more drought days between 2000 and 2010 within respondents' counties of resident was significantly correlated with the number of water conservation actions taken within the household. This result lends support to the resilience theoretical framework that considers exposure to hazards as an important component in understanding or anticipating the adaptations communities may make to become more resilient to future disturbances. Also, the reported direct experience with negative effects of recent drought conditions was found to be significantly associated with more conservation actions being implemented. This indicates that respondents who have experienced drought related impacts in recent years may be more likely to have adopted water conservation measures, practices that may become routine and will help them prepare and cope more effectively with future drought events.

Second, regarding the social vulnerability to hazards, the resilience framework considers the vulnerability of residents as a factor in understanding or predicting the overall resilience of communities to adapt to changing risks. The presence of more socioeconomically vulnerable residents is presumed to make it harder for individuals and communities to bounce back or cope with slow-moving disturbances such as drought. The variables used to indicate socioeconomic or demographic vulnerability were age, income, education, and Hispanic ethnicity. Significant positive correlations were found between educational attainment and household water conservation efforts. Higher educational attainment was associated with the adoption of more water conservation measures taken outside the home (Pearson $R=.102$; $p <.025$). Hispanic ethnicity was found to be significantly associated with fewer water conservation measures being adopted and implemented both outside the home and in total (Difference of Means T Test = 3.72; $p<.05$). It is noteworthy that the Hispanic respondents in the general population survey reported having more difficulty than the rest of the respondents in obtaining information about drought conditions and water conservation actions. A possible explanation could be the presence of language barriers, creating obstacles to sharing information about water conservation best practices for residents. Other indicators of social or economic vulnerability, including age and income of the respondents, were not found to be associated with adoption of water conservation measures at the household level.

Third, regarding the adaptive capacity of residents, the survey results support the importance of this dimension of resilience. Three indicators of the capacity, or ability of residents to take steps to reduce exposure risks, were found to be associated with adoption of water-conservation practices. (i) Respondents who were familiar with and knowledgeable about drought conditions were found to have implemented more water conservation measures. (ii) Respondents who expressed higher levels of concern about drought were found to have adopted more water conservation measures inside and outside the home. (iii) Respondents who own their homes reported significantly greater adoption of water conservation measures outside the home, as well as in total, when compared to respondents who are renters. Educating renters concerning the value of water conservation may be challenging if their water bill is included for example in their monthly rent. Also, renters may have less control or even access to outside water conservation measures such as watering the lawn earlier in the day, planting drought-resistant shrubs, or installing water catchment systems. By contrast, homeowners typically have more control over their water use and may thus seek to be more informed on monitoring their use.

Finally, regarding the household-level water conservation strategies, on the inside of the home, the most-often adopted measures for water conservation by both types of respondents involved checking for leaks from faucets, showerheads, and toilets inside the home. For the general public, the less-adopted measures reported were installation of new, more efficient shower heads, with only 50.3% respondents having done so, and insulating water pipes, an activity conducted by only 48.3%. By contrast, almost 72% of the agriculture sector respondents reported that they have insulated pipes to stop water being lost through leaks or breaks.

Outside the home, some differences between the general population and agriculture sector respondents are apparent also. The agriculture group reported activities involving planting and maintenance of lawns and shrubs as the most often-adopted water conservation actions, with over 80% planting drought-resistant grass and bushes, and almost 60% placing mulch around plantings to hold water. By contrast, members of the general public relied more on watering strategies such as placing lawn sprinklers carefully to avoid watering sidewalks and driveways, and watering earlier in the day. Roughly 38% of this group reported planting drought-resistant grass and shrubs, and fewer than 46% reported placing mulch around plantings. This difference in strategies adopted outside the home may reflect greater ease and experience working outside conducting plantings and related activities by those employed in agricultural endeavors. While the agriculture sector respondents reported greater use of water-catchment systems like rain barrels compared to the general public, utilization of these items remained low. Less than 15% of general public respondents and roughly 30% of agriculture respondents reported use of these items designed to hold rain water.

Overall, these results suggest several opportunities for public agencies, non-governmental organizations, schools, and other groups to educate, engage, and encourage the public to conserve water during times of drought. First, the general public may benefit from guidance about how to implement some water conservation actions that may not be self-evident or may require some skill or materials, such as insulating pipes. Also, the public could be encouraged to purchase and install more efficient showerheads through how-to guides and demonstrations of showerhead replacement at stores and public gatherings. Similarly, the low rate of use of rain barrels by respondents from both groups suggests an opportunity for outreach and education, similar to efforts designed to encourage household recycling efforts. Rain barrels could be demonstrated and sold to the public at environmental fairs, malls, and hardware stores throughout drought affected communities.

Conclusions and Recommendations:

Based on our analysis, we can conclude the following. First of all, on the whole, drought indices, including PDSI and PHDI, appear to be useful indicators of drought damage, at least at the monthly temporal scale and/or county-wide spatial scale. This is an important finding, as long-lead climate outlooks continue to provide rapid improvement in our ability to anticipate, plan for, and mitigate the effects of incipient drought. Nevertheless, caution must be exercised in the extent to which drought index is used as a predictor of drought damage. Undoubtedly, the human factor also confounds the correlations. For example, irrigation practices differ spatially and temporally, thereby weakening the relationship, whether lagged or not.

Secondly, there is distinct spatial variation among the 503 counties in their levels of resilience to drought. Higher-resilience counties are located mostly in Oklahoma and western Arkansas, with the highest few counties located near large metropolitan areas such as Albuquerque, Austin, Dallas, Houston, and San Antonio. Less-resilient counties are concentrated in western and central Texas, along the Gulf Coast, and most of Louisiana. The RIM analysis extracted 15 socioeconomic and environmental variables that are correlated with the level of resilience. Not surprisingly, these variables suggest that higher resilience is associated with higher socioeconomic conditions of the counties. But more importantly, these 15 variables and the regression equation were objectively derived; they can be used as a resilience planning tool to assess how changes in a variable would affect the final resilience score. Furthermore, since the 15 explanatory variables extracted from this study is very similar to those extracted from previous studies that applied the RIM model to other types of hazard in other study areas, it implies that strategies used to promote resilience to the drought hazard may also help improve resilience to other hazards.

Third, the survey results suggest that adoption of water conservation behaviors among the residents in Texas is far from universal, and therefore, opportunities exist for more vigorous public education and community engagement. The study yielded evidence that "adaptive capacity" is particularly relevant to understanding and encouraging exposure-reducing behaviors. Residents who are better educated, non-Hispanic, and homeowners tend to adopt more water conservation measures. Furthermore, residents who believe that they are well-informed about drought and water-conservation strategies, and expressed higher levels of concern, were found to be more likely to have adopted water conservation measures. This finding of knowledge and confidence levels among residents may be linked to adaptive behaviors is good news for those working in public education and community outreach programs, as these are attitudes and skills that can be nurtured and probably improved. While factors associated with "exposure" and "vulnerability" to hazards such as drought are difficult to change in communities like those in Texas, knowledge of water-conservation strategies and confidence in one's abilities to implement them could be improved through well-designed public education efforts. Educational outreach programs that deliver information about drought conditions within the community, including changing threat levels and the specific strategies and mitigation tools for reducing the negative impact, should raise knowledge and confidence, and thus enhance the adaptive abilities of residents living with acute and/or chronic exposure to drought.

Drought is a climatological hazard of a continuous nature. It has profound impacts on the social, economic, and infrastructure sectors of the communities. This project is among the first to quantify the linkages from drought indices, drought damage, to drought resilience across the 503 counties in south-central United States. The project generates analytical tools for drought index analysis, community resilience assessment, and original household survey data on attitudes and adoption of water conservation measures, all of which are relevant for policy makers. Results from this project offer foundational knowledge and useful baseline information of drought, which can be refined in future studies to monitor the temporal changes of community resilience or community resilience based on a specific sector such as agriculture.

In addition to the scientific contributions discussed above, the project has produced a number of tools and deliverables: (1) a number of data sets for the study region including county-level historical data on drought indices, drought incidents, drought damages, and socioeconomic-environmental variables, and household telephone survey data; (2) a refined model to measure the resilience levels of communities to droughts or other hazards; (3) identification of key indicators of resilience; (4) a summary of drought mitigation plans; (5) identification of the factors that influence residents to adopt adaptive measures, and (6) a project website that contains the project information. .

Recommendations for future studies include: (1) A comprehensive analysis of the utility of SHELDUS™ for assessing drought damage should be undertaken. This project calls for a better method to record the damage data by different agencies, especially by improving the locational information of the damage data. More accurate damage data are needed to improve the accuracy of our analysis and will contribute substantially to hazards and resilience research. (2) Research is needed to determine the most appropriate indicator of recovery; instead of using population growth as a cumulative and broad-based indicator, recovery, including for example using agricultural production or productivity as recovery indicators. (3) One weakness of the survey is that the vast majority of the general survey respondents came from the same county. This occurred because Lubbock County has the highest population among the surveyed counties, so residents of Lubbock were more likely to be called to participate. A greater number of counties should be targeted in future surveys to gain data from a more diverse set of respondents.

Outreach and Products:

<u>Publications</u>:

Rohli RV, Bushra N, Lam NSN, Zou L, Mihunov V, Reams MA, Argote JE. 2016. Drought indices as drought predictors in the south-central USA. *Natural Hazards*. DOI 10.1007/s11069-016-2376-z.

Mihunov VV, Lam NSN, Zou L, Rohli RV, Bushra N, Reams MA, Argote JE. 2016. Community resilience to drought hazard in south-central United States. (under review)

<u>Manuscripts in Preparation</u>:

Bushra N, Rohli RV, Lam NSN, Zou L, Mihunov V, Reams MA, Argote JE, 2017. Assessing the validity of drought indices in the South-Central United States. To be submitted to *Natural Hazards*.

Mihunov VV, Lam NSN, Zou, Rohli RV, Reams MA, et al. Changes in drought resilience in south-central USA between 1990-2010.

Reams MA, Argote J, Lam NSN, Rohli R, et al. An examination of policy approaches and tools for drought mitigation planning.

Reams MA, Argote J, Lam NSM, Rohli R, et al. Influences on household-level water conservation efforts among residents of droughts-affected counties in Texas.

<u>Presentations</u>:

Bushra N, Rohli RV, et al. 2016. GIS for statistical downscaling of drought indices to assess drought severity and damage in the south-central United States. Paper presented at the Louisiana Remote Sensing and Geographic Information Systems Workshop, Lafayette, Louisiana, April 27, 2016.

Bushra delivered a paper presentation entitled, “Statistically downscaled Palmer Drought Severity Index and Palmer Hydrologic Drought Index for drought severity and damage assessment” at 2016 Annual Meeting of the American Association of Geographers, San Francisco, California, March 29

Lam NSN, Qiang Y, Li K, Cai H, Zou L, Mihunov V. 2016. From resilience assessment to dynamic system modeling: some perspectives on human dynamics and climate change research. *Abstracts, the 2016 Annual Meeting of the American Association of Geographer*s, San Francisco. March 29, 2016.

Mihunov V, Zou L, Lam NSN. 2016. Community resilience to drought hazard in South-Central U.S. *Abstracts, the 2016 Annual Meeting of the American Association of Geographer*s, San Francisco. March 29, 2016.

Rohli RV, Bushra N, et al. 2015. Validity of drought indices as drought predictors in the south-central United States. Poster presentation at the AGU fall meeting in San Francisco, December 14, 2015.

Lam NSN. 2015. Community resilience to drought hazard: An analysis of drought exposure, impacts, and adaptation in the south-central USA. Web presentation to the South-Central Climate Science Center Partners. Aug 19, 2015.

Workshop Participation:

Mihunov was selected to participate in the South Central CSC Early Career Professional Development Training Workshop, which was held in June 2016 in Lubbock, TX.

Website Created for the Project:

www.rsgis.envs.lsu.edu/drought

Data Sets Created:

1. County-level drought indices, 1975-2010
2. Combined county-level drought incidence, damage, and census data, 1990-2010
3. Drought adaptation household survey summary

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