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Measuring Disaster Resiliency in the Rio Grande Valley

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MEASURING DISASTER RESILIENCY IN THE RIO GRANDE VALLEY

A Thesis

by

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ABSTRACT

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People are now becoming more conscious of the effects of climate change. They are seeking to understand how to manage their resources and prepare for when a disaster strikes. The growing studies of disaster resilience lend that opportunity. In this spatial and temporal study, disaster resilience was measured for each census tract within the four counties of the Rio Grande Valley. Utilizing GIS tools and methods, the study examines resilience patterns between 2010 and 2017.

Results showed that even though various census tracts from each of the four counties increased in resilience from 2010 to 2017, the overall total resilience for each county still decreased throughout the study years. Findings also showed the importance of socio-economic resiliency in the study areas.

DEDICATION

This thesis is dedicated to my father

V.VI.XVIII

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CHAPTER I

INTRODUCTION

Extreme natural events have become increasingly common due to the changing climatic conditions, therefore encouraging individuals to examine how resilient their communities are in the face of disasters. This has been the case for communities in the Rio Grande Valley (RGV), where Presidential Disaster Declarations have been issued due to widespread damage from recent flooding events in 2018 and 2019. In 2014, Susan Cutter measured the inherent resilience of counties around the United States using the BRIC Index and found that counties along the US Mexico border contain the least resilience(Cutter, Ash, & Emrich, 2014, p.71). Residents of the RGV have grown accustomed to saying that the Valley experiences little ‘weather’, compared to some other part of Texas such as Houston (National Weather Service, n.d.). This belief in large part has influenced the way residents, communities, and even government entities have prepared and mitigated for disasters in previous years. Cutter’s results come with no surprise; the mentality around disasters in this area has certainly influenced resilience.

This study internalizes those results and aims to measure inherent disaster resilience for each census tract within the four counties of the Rio Grande Valley. The Rio Grande Valley is made up of four counties: Starr, Hidalgo, Willacy and Cameron. Using the Rio Grande Valley Resilience Index (RGVRI), six resilience capitals are measured in 2010 and 2017. The goal is to determine whether resilience for the Rio Grande Valley has increased or decreased, both spatially and temporally. Although this study does not determine which specific variables within the resilience capitals influence resilience scores, it does give a general idea to which capital is the most resilient and which capital has the weakest resilience. This study hopes to contribute to further resilience research in the Rio Grande Valley as well as begin dialogue for stakeholders to examine all resilience aspects of their communities so that the Valley will be able to adapt, withstand, and recover from future natural hazards.

CHAPTER II

LITERATURE REVIEW

Defining Disaster Resilience

Despite the decades of research on resilience, the term still has various definitions even within the field of disaster studies (Zhou, Wang, Wan, & Jia, 2009, p.22). The term was first coined in 1973 in the realm of ecology, with Holling defining it as "the ability to absorb change and disturbance and still maintain the same relationships that control a system's behavior (Burton, 2014, p.68)." The concept was later defined within the field of natural hazards in 1981 by Timmerman as "the measure of the capacity of a system, or part of a system, to absorb or recover from a damaging event (Burton, 2014, p.68)." Although both definitions read similarly, they were still quite vague.

It wasn't until Hurricane Katrina in 2005 and Hurricane Sandy in 2012 that lawmakers and stakeholders took an interest in defining resilience within their communities. The increasing interest in studying disaster resilience proved effective as many scholars also focused on defining community resilience. Community Disaster Resilience, as defined by Cox, is "the capability of a community to anticipate and reduce risks and vulnerabilities and increase adaptive capacity and the potential for transformative learning in the face of disasters and other major changes (Cox & Hamlen, 2014, p.221)." A similar definition is presented by Susan Cutter, who defines resilience as “the ability of a social system to respond and recover from disasters and includes those inherent conditions that allow the system to absorb impacts and cope with an event, as well as post-event, adaptive processes that facilitate the ability of the social system to re-organize, change, and learn in response to a threat(Cutter et al., 2008, p.599).”

The definitions of resilience have changed and elaborated over time. Earlier definitions were vague and solely focused on the ability of a place to recover from an event or disaster. Later definitions are much more well-rounded, focusing on both the recovery and on the adaptability aspect of resilience (Cox & Hamlen, 2014, p.221). Despite the research and the deeper understanding of resilience within the academic world, there still doesn’t seem to be a consensus for the definition of resilience. This in turn creates confusion when individual communities try to define what disaster resilience looks like within their communities. Without a specific definition, some communities interpret resilience as their immediate reaction to climate change, while others focused resilience efforts on their short and long term goals, such as drainage projects (Torres & Alsharif, 2017, p.406). For simplicity and clarification, this study uses the definition presented by the Federal Emergency Management Agency (FEMA) in its National Preparedness Goal. FEMA defines resilience as the “ability to adapt to changing conditions and withstand and rapidly recover from disruption due to emergencies (Federal Emergency Management Agency, 2015, p.28).”

Measuring Disaster Resilience

Resilience is two-fold, made up of both inherent resilience and adaptive resilience. Inherent resilience defines the pre-existing resilience of a community, whereas adaptive resilience is the way in which individuals or communities are able to learn from and respond to hazard events (Cutter, 2015, p.744). A wide variety of methods for assessing both aspects of resilience exist, ranging from indices, scorecards, and tools. Much like the various resilience definitions, there is no consensus on the correct way to measure resilience because most of the assessments use different methods, such as top-down approaches where they focus on a larger unit of analysis, or vice-versa a bottom-up approach where they start at the smallest unit of analysis (Cutter, 2015, p.745). Recognizing that there are previous models, the Disaster Resilience of Place (DROP) model was the first to specifically measure resilience at a community level. It measures inherent resilience in a quantitative manner using indicators or variables, as well as measuring adaptive resilience in a qualitative manner through feedback and social learning, although this process could take longer to complete (Cutter et al., 2008, p.602). There are multiple approaches and units of analysis that one can use to measure all aspects of disaster resilience, this study focuses solely on measuring inherent resilience, and therefore exploring the Baseline Resilience Index for Communities (BRIC) further.

Baseline Resilience Index for Communities (BRIC)

BRIC takes from the quantitative side of the DROP framework, developed though the idea that “inherent community disaster resilience is a complex process of interactions between various social systems, each with their own form and function, but working in tandem to provide the betterment of the whole community(Cutter et al., 2014, p.66).” It is a place-based metrics approach, aimed to capture all facets of a community that could be integrated toward the goal of enhancing disaster resilience (Cutter, 2014, p.66). BRIC analyses resilience of communities by using Resilience Indicators, the basic system of analysis that measure the inherent resilience at a point in time. Because BRIC was designed to allow for periodic updates, emergency personnel and planners could use this Index to monitor resiliency changes in their communities over time (Cutter & Derakhshan, 2018, p.17).

Susan Cutter's BRIC index is composed of six resilience capitals and 49 resilience indicators. The six resilience capitals are: Social Resilience, Economic Resilience, Community Capital, Institutional Resilience, Housing/Infrastructural Resilience, and Environmental Resilience. Social Resilience is made up of 10 resilience indicators which "capture demographic qualities of a community's population that tend to associate with physical and mental wellness leading to increased comprehension, communication and mobility(Cutter et al., 2014, p.68)." Demographic attributes of social resilience such as the total population of people with a disability or the number of people who speak English as a second language suggests that variables like health and education promote a higher standard of living. This in turn would support a community in having a higher resilience in the face of a disaster (Burton, 2014, p.71). The second capital is Economic Resilience which is composed of 8 indicators. These are "intended to represent community vitality, diversity and equality in compensation, but not represent resilience of individual businesses per se(Cutter et al., 2014, p.68)." Economic resilience indicators such as homeownership and employment status of the whole community will help gauge how the economic profile of a community will aid in their resilience once a disaster takes place. Higher economic stability and resource equity represent a higher economic resilience. Community Capital is the third resilience capital with seven indicators. Community Capital relates to Social Resilience in a way that the characteristics of individuals influence social participation and community cohesion. However, Community Capital measures how the community as a whole responds to emergencies and "represents the level of community engagement and involvement in local organizations and the potential local ties and social networks that can be critical for survival and recovery during disasters (Cutter et al., 2014, p.68).” Indicators that influence this resilience capital include place attachment of a population and the number of civic and religious organizations in a community. Higher levels of participation and activism would lead to a higher community capital and higher resilience even if it is a small rural town.

The fourth resilience capital of BRIC is Housing/Infrastructure with 9 indicators. Resilience indicators “evaluate the community response and recovery capacity” by looking at variables such as the number of emergency management personnel (Burton, 2014, p.71). This capital also looks at the physical capacities within a place to house displaced persons in an event of a disaster and its capacity to provide medical care (Cutter et al., 2014, p.68). Environmental Resilience is the fifth capital originally made up of four resilience indicators. They evaluate the qualities of the environment to “estimate the efficiency with which a community uses natural resources” by looking at variables such as the number of natural wetlands. Environmental Resilience variables also analyze sustainability in the area by looking at developed open space (Burton, 2014, p.74). Lastly, Institutional Resilience is the sixth resilience capital with 10 indicators. This capital is meant to “capture aspects related to programs, policies, and governance of disaster resilience (Cutter et al., 2014, p.70).” Variables in this resilience focus on disaster training programs and population stability in a community. Population stability is an important variable because rapid population change is known to place a strain on local institutions and systems, regardless of an increase or decrease in population.

Analyzing the inherent resilience of a community with a measure such as the BRIC index is useful as it would allow communities to evaluate their resilience levels without any alterations. Temporal trends of inherent resilience are also important because the baseline resilience or a place might increase or decrease over time (Zhou et al., 2009, p.30). By using variables within BRIC, planners and stakeholders could get a sense of what key areas within their communities need to improve to increase their resilience.

CHAPTER III

METHODS

Selection of Study Variables

This study takes inspiration from Susan Cutter's Baseline Resilience Indicators for Communities (BRIC) Index in order to determine and compare the disaster resilience. In this study, a resiliency index was constructed using publicly available data at the census tract level in the four study counties which constitute the Rio Grande Valley.

The original BRIC index examines county-level data and is composed of 49 resilience indicators and 6 different resilience categories: Social, Economic, Community, Institutional, Infrastructural, and Environmental Resilience. Due to the finer scale of this study and the availability of the data, 25 variables make up the 6 resilience categories of the Rio Grande Valley Resilience Index (RGVRI). Social Resilience is composed of 7 variables: Educational Attainment, Pre-retirement Age, Transportation Access, Communication Capacity, English Language Competency, Non-Special Needs, and Health Insurance. Economic Resilience has 5 variables: Homeownership, Employment Rate, Non-dependence on Primary/Tourism sectors, Gender Income Equality, and Federal Employment. Community Resilience was calculated using 3 variables: Place Attachment-Non-Recent Immigrants, Place Attachment-Native Born Residents, and Social Capital-Religious Organizations. Institutional Resilience is composed of 2 variables: Population Stability and Municipal Services. Infrastructural Resilience was calculated using 6 variables: Sturdier House Types, Temporary Housing Availability, Evacuation Routes, Housing Quality, School Restoration Potential, and Internet Access. Lastly, Environmental Resilience was composed of 2 variables, Natural Flood Buffers and Energy Cost.

Most of the variables maintained the original calculations; only 5 variables were modified to better accommodate the census tract level. Social Capital was measured by the total number of religious organizations which are located within a 10-mile buffer area of each census tract, whereas the original variable was measured as the number of religious organizations per 10,000 persons. The 10-mile buffer was determined by the average amount of time it takes a person to travel to the church of their choice, which is roughly 15 minutes. By traveling for 15 minutes at an average speed of 45 miles/hour, a person would travel 10 miles to their church. It is also worth noting that because the census tract level is a smaller study area, it would not be realistic to count the number of religious organizations within that census tract because 1) there might not be any and 2) one metropolitan or rural area might be composed of multiple census tracts, meaning that their resources are split up and they depend on each other which theoretically increases their community resiliency. The same calculation is applied to the Municipal Service variable. Many municipal services are a part of the whole city or county, so they service more than one census tract. The Evacuation Routes variable in this study is described as ‘Major road miles per census tract’, differing from the original BRIC index descriptor: Number of major roads that cross a county boundary per 10,000 persons (Cutter, Ash, & Emrich, 2016, p.1240). In this case, calculating the number of miles within each census tract could prove to be useful because those census tracts without major road miles would negatively impact the resiliency score, allowing for local governments to examine the need within those communities. The

School Restoration Potential was measured to include public schools within a 1-mile buffer from each census tract, instead of counting the number of public schools per 10,000 people like delineated in the original BRIC. The modification to the census tract level is a positive for institutional resilience not just for individual census tracts, but also for the county. During a disaster many schools are used as shelters, and it is imperative that they be a safe and strategic distance away for people to be able to travel there. The fifth variable that was modified was Energy Cost. This variable within Environmental Resilience replaced BRIC's Efficient Energy Use, which calculated the megawatt hours per energy customer. In this study's index, Energy Cost is the annual energy costs based on the area median income. A higher energy cost means a higher amount of spent energy, resulting in a negative impact to resiliency. The list of variables can be seen in Table 1.

Table 1. List of Variables

Variables (25)	Variable Description	Source
Social Resilience (7)		
Educational Attainment Equality (Inverted*)	Absolute Difference between % population with college education and % population with less than High School education	American Community Survey 2010 & 2017 5-year estimates
Pre-Retirement Age	% population below 65 years of age	American Community Survey 2010 & 2017 5-year estimates
Transportation Access	% households with at least one vehicle	American Community Survey 2010 & 2017 5-year estimates
Communication Capacity	% households with telephone service available	American Community Survey 2010 & 2017 5-year estimates
English Language Competency	% population proficient English Speakers	American Community Survey 2010 & 2017 5-year estimates
Non-Special Needs	% population without sensory, physical or mental disability	American Community Survey 2010 & 2017 5-year estimates
Health Insurance	% population under age 65 with health insurance	American Community Survey 2010 & 2017 5-year estimates
Economic Resilience (5)		
Homeownership	% Owner-occupied housing units	American Community Survey 2010 & 2017 5-year estimates
Employment Rate	% Labor Force Employed	American Community Survey 2010 & 2017 5-year estimates
Non-Dependence on Primary/Tourism Sectors	% employees not in farming, fishing, forestry, extractive industry or tourism.	American Community Survey 2010 & 2017 5-year estimates
Gender Income Equality (Inverted*)	Negative absolute difference between male and female median income	American Community Survey 2010 & 2017 5-year estimates
Federal Employment	% labor force employed by the federal government	American Community Survey 2010 & 2017 5-year estimates
Community Resilience (3)		
Place Attachment Not Recent Immigrants	% population not foreign-born persons who came to the US within previous 10 years	American Community Survey 2010 & 2017 5-year estimates
Place Attachment Native-Born Residents	% population born in state of current residence	American Community Survey 2010 & 2017 5-year estimates
Social Capital-Religious Organizations**	Religious organizations within 10 miles of census tract	USGS GNIS 2019
Institutional Resilience (2)		
Population Stability (Inverted*)	Population change over previous 5yr period. 2010-2015 and 2013-2017. 5-year periods. Less change means more resilient.	American Community Survey 2010,2013,2015 2017 5-year estimates
Municipal Services**	Number of emergency and law enforcement agencies within a 10-mile buffer from the census tract	USGS GNIS 2019
Infrastructural Resilience (6)		
Sturdier House Types	% housing units not manufactured homes	American Community Survey 2010 & 2017 5-year estimates
Temporary Housing Availability	% vacant units that are for rent	American Community Survey 2010 & 2017 5-year estimates
Evacuation Routes**	Major Road miles per census tract	USGS GNIS 2019
Housing Quality	% housing units built prior to 1970 or after 2000	American Community Survey 2010 & 2017 5-year estimates
School Restoration Potential**	public schools within a 1-mile buffer per census tract	USGS GNIS 2019
Internet Access	% population with access to broadband internet service	American Community Survey 2017 5-year estimates
Environmental Resilience (2)		
Natural Flood Buffers	% land in wetlands	American Community Survey 2010 5-year estimates & USGS GNIS 2019
Energy Cost (Inverted*) **	Annual energy costs based on Area Median Income. A higher cost means a higher amount of spend energy. Negative Impact.	Energy.gov (July 2019)

*Inverted variables show negative impact on resiliency.

**Variables changed and calculated by author to accommodate study area.

Data Collection and Normalization

Datasets used in this study were acquired from the U.S Census Bureau's American Community Survey 5-year estimates for the years 2010 and 2017. Shapefiles and additional datasets were retrieved from USGS GNIS and Energy.gov for 2019, the latest year for which data was available. Although some variables did have to be calculated using data from 2019, the 2-year difference was determined to not significantly impact the comparisons. As mentioned earlier, a total of 25 variables were gathered and calculated for the 6 resilience categories for the four counties, which in total make up 216 census tracts. Starr county is composed of 15 census tracts, Hidalgo county has 112 census tracts, Willacy county has 5 census tracts, and Cameron county is made up of 84 census tracts. Census tract 9800 was omitted for Hidalgo County. Census tracts 9800.01, 9801, and 9900 were omitted for Cameron County, and census tract 9900 was omitted for Willacy County. Census tracts for these counties were not analyzed due to data not being available. The majority of the omitted census tracts are outside the traditional populated areas and are not characterized by any populations. This is the case for coastal census tracts whose boundary constitutes the ocean along South Padre Island. The excluded inland census tract of Hidalgo County could have been omitted because it did not meet the minimum population requirements for the Census Bureau. Starr County did not need to have any census tracts removed.

Once all the raw data was collected for each of the 25 variables, it was normalized using the min-max method.

Normalization = (x-min)/(max-min)

Whereas:

X = the raw value of an individual census tract

Min = the minimum raw value of a variable

Max = the maximum raw value of a variable

The minimum and maximum values of each variable for each census tract within the counties were calculated and normalized using the formula above. The result produced a value between 0 and 1. Normalizing the data is important, as it allows for a clear comparison between all the data sets. Once all the variables were normalized, those that needed to be inverted to show negative impact were calculated by subtracting from 1. The variables from within each resilience category for each census tract of the four counties for both 2010 and 2017 were then summed and divided by the same number of variables to produce the score for each resilience category. For example, all seven normalized variables within the social resilience category were summed and divided by 7, which produced the average social resilience score for that census tract out of 7. The scores for each of the resilience scores were then summed again to produce the overall resiliency score, which was a number out of 25, because there were 25 total variables used in the index. The mean and standard deviation were also calculated for each resilience category in order to visualize the temporal change between 2010 and 2017. Using ArcMap 10.7, maps were created to show which census tracts had High or Low Resilience throughout the 7-year time period.

CHAPTER IV

RESULTS

Analysis

The results of Starr County's Resilience in 2010 and 2017 are shown in Table 2 and Table 3 respectively. From 2010 to 2017, Starr County's resilience largely decreased. The most noticeable decrease was in Institutional resilience. In 2010, the mean Institutional resilience score was 1.165; that decreased in 2017 to a mean of .930. 12 out of 15 census tracts decreased in Institutional resilience- the most likely variable contributor being population stability. Varying populations, regardless of whether they increase or decrease, often happen too quickly for procedures that a community has in place. There may have been too much of a population change between 2010 and 2017, causing resilience to go down. Social, Economic, and Infrastructure Resilience also decreased. Social resilience suffered the less decrease, with only a .01% decrease. Environmental resilience remained constant; one census tract (GEOID 48427950101) did have a slight increase from .434 to .436, but it was not enough to impact the overall resilience score for the category. The only resilience to increased was Community Resilience, jumping from .938 in 2010 to 1.359 in 2017. The variable in that category with the most positive impact could have been the Place attachment of native-born residents. From 2010 to 2017, there might have been an increase in the population born in Texas and decided to remain in Starr county. Although there was an increase in community resilience, the overall Resilience Score for Starr County did decrease in 2017, from a 12.438/25 (50%) to a 12.270/25 (49%). Further analyzing the increase in standard deviation, it appears that there was an even greater disparity in the resilience scores. In fact, while the minimum overall resilience score in 2010 was 9.586, there was an even lower score in 2017 at 8.819. Those minimum scores were from two different census tracts. Although the decrease does not seem as drastic in percentage, losing 1% in resilience should be important, considering resilience is only being scored out of 25 variables.

Table 2. Starr County 2010 Resiliency Scores by Census Tract

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48427950101	5.342	2.057	2.000	1.300	2.219	0.434	13.352
48427950104	4.546	2.591	0.787	1.401	4.285	0.611	14.220
48427950105	3.232	2.231	0.610	0.983	2.193	0.791	10.040
48427950106	2.318	3.271	0.703	1.069	2.574	1.326	11.261
48427950107	3.290	1.996	0.693	0.282	1.903	1.422	9.586
48427950108	5.085	2.992	1.744	1.222	3.121	0.451	14.615
48427950202	4.277	4.329	0.459	1.769	3.116	0.286	14.236
48427950203	3.948	3.135	0.000	0.918	1.973	0.783	10.757
48427950204	3.386	3.090	0.723	1.375	2.410	0.964	11.948
48427950401	4.155	3.277	1.463	0.942	2.330	1.067	13.234
48427950402	3.542	2.676	1.154	1.620	2.802	0.610	12.404
48427950500	3.451	2.708	1.619	0.547	3.738	0.779	12.843
48427950600	3.830	3.189	0.911	0.889	3.790	1.416	14.026
48427950701	2.352	2.722	0.088	1.642	2.186	1.567	10.557
48427950702	3.659	2.780	1.118	1.515	2.710	1.713	13.495
Mean:	3.761	2.870	0.938	1.165	2.757	0.948	12.438
Standard Deviation:	0.824	0.559	0.561	0.403	0.695	0.434	1.598

Table 3. Starr County 2017 Resiliency Scores by Census Tract

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48427950101	4.797	2.882	2.254	0.920	1.456	0.436	12.745
48427950104	6.354	2.784	2.260	1.023	3.324	0.611	16.355
48427950105	4.617	2.092	0.809	0.633	1.934	0.791	10.876
48427950106	3.708	3.211	0.915	0.720	1.921	1.326	11.801
48427950107	4.224	1.438	1.249	0.823	2.824	1.422	11.979
48427950108	4.565	3.447	2.155	0.636	2.680	0.451	13.934
48427950202	3.705	3.340	1.386	1.152	3.338	0.286	13.206
48427950203	2.396	3.249	0.886	0.568	1.436	0.783	9.317
48427950204	2.504	2.541	0.819	0.978	2.786	0.964	10.592
48427950401	3.157	2.498	2.128	1.444	2.848	1.067	13.143
48427950402	3.709	2.945	1.533	0.940	3.140	0.610	12.876
48427950500	3.701	3.090	2.084	0.467	2.844	0.779	12.965
48427950600	3.589	2.500	1.394	0.889	3.595	1.416	13.383
48427950701	1.302	2.288	0.212	1.464	1.986	1.567	8.819
48427950702	2.715	3.085	0.306	1.296	2.945	1.713	12.060
Mean:	3.670	2.759	1.359	0.930	2.604	0.948	12.270
Standard Deviation:	1.162	0.524	0.676	0.297	0.665	0.434	1.810

The results of Hidalgo County's Resilience in 2010 and 2017 are shown in Table 4 and Table 5 respectively. In 2010, Hidalgo County's highest resilience score belonged to Institutional Resilience, with a total score of 1.306 (65.3%), and the lowest resilience score belonged to Environmental Resilience, which had a mean score of .677 (33.85%). In 2017, Social Resilience averaged the highest resilience score with a 4.447 (63.5%), and Environmental Resilience remained constant as the least resilient with a mean score of .652 (32.6%). Environmental resilience actually decreased a small percentage during this time period as well. From 2010 to 2017, Hidalgo County's total resiliency score decreased by 1%, from 12.960 to 12.706. However, the disparity between the scores was higher in 2010. In 2017, the minimum resilience score for an individual census tract was 9.923/25, while in 2010 the minimum resiliency score a census tract received was a 6.285/25. The disparity is indicative that even though at large resiliency dropped by 1%, certain conditions caused a census tract to drastically lose resilience. Environmental and Community Resilience from 2010 to 2017 all decreased by 1%, while Economic Resilience decreased by 3%. Both Social and Infrastructure categories saw a small 1%

increase in their resilience between both years. The resilience category that suffered the most decrease throughout the years was Institutional resilience. In 2010, Hidalgo's institutional resilience score was 1.306 (65%), decreasing to 1.164 (58%) in 2017. Similar to Starr County, the 7% decrease could be the result of the negative effect of population stability. Hidalgo County is home to one of the largest metropolitan areas in the region. From 2010 to 2017, it experienced the most population increase from 774,769 to 839,539. It is possible that in 2010, institutional frameworks were adequate enough for the population of 2010, but as population increased, those frameworks did not get updated and therefore caused institutional resilience, and resilience for the county as a whole to suffer.

Table 4. Hidalgo County 2010 Resiliency Scores by Census Tract

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48215020101	4.562	3.254	1.303	1.183	2.160	0.872	13.335
48215020102	4.680	3.621	0.828	1.081	1.700	0.907	12.817
48215020201	4.410	3.537	0.815	1.156	1.812	0.540	12.269
48215020202	4.414	3.229	0.975	1.242	2.199	0.349	12.408
48215020204	4.900	3.695	0.952	0.987	1.361	0.476	12.371
48215020205	4.029	3.212	1.094	1.366	2.497	0.587	12.786
48215020301	5.082	3.756	1.610	1.461	2.078	0.222	14.210
48215020302	4.980	3.150	1.469	1.412	2.732	0.381	14.124
48215020402	5.070	3.313	1.370	1.189	2.992	0.000	13.934
48215020403	3.668	3.424	1.059	1.670	1.941	0.857	12.619
48215020404	4.406	3.731	0.672	1.525	1.102	0.952	12.388
48215020501	3.363	2.933	1.151	1.543	2.078	0.651	11.718
48215020503	4.614	2.989	1.154	1.276	2.501	0.476	13.010
48215020504	4.187	3.179	1.023	1.346	2.907	0.867	13.509
48215020600	3.072	2.635	1.319	1.722	2.393	0.683	11.824
48215020701	5.239	3.327	1.380	1.388	2.827	0.206	14.368
48215020721	5.040	3.250	1.418	1.593	2.650	0.413	14.365
48215020723	2.812	2.896	1.024	1.502	2.488	0.857	11.579
48215020724	4.849	3.429	1.232	1.448	2.741	0.397	14.096
48215020725	4.864	3.222	2.133	1.607	2.637	0.365	14.828
48215020726	5.084	3.237	1.119	1.523	2.483	0.619	14.065
48215020802	4.442	3.249	1.517	1.313	2.900	0.683	14.103
48215020803	5.336	3.614	1.332	1.551	3.077	0.349	15.259
48215020804	4.233	2.909	1.172	1.526	2.910	0.889	13.639
48215020901	5.627	3.480	1.603	1.583	2.898	0.556	15.748
48215020903	4.596	3.242	1.265	1.441	2.766	0.714	14.024
48215020904	4.445	3.460	1.560	1.673	2.222	0.683	14.042
48215021000	4.157	3.040	1.190	1.770	2.493	0.875	13.524
48215021100	2.316	2.597	1.268	1.570	2.726	0.937	11.414
48215021201	4.689	3.148	1.441	1.653	2.668	0.524	14.122
48215021202	4.464	3.739	1.319	1.323	2.713	0.907	14.465
48215021302	4.848	2.844	1.429	1.224	2.308	0.762	13.414
48215021303	4.271	2.600	1.306	1.431	2.233	0.880	12.722

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48215021304	4.297	3.208	1.069	1.171	2.955	1.273	13.974
48215021305	4.690	3.486	1.013	1.481	2.603	0.964	14.237
48215021401	4.687	3.103	1.541	1.443	2.508	0.952	14.235
48215021403	4.578	3.256	1.702	1.454	1.871	0.746	13.606
48215021404	4.955	2.384	1.374	1.225	1.701	0.893	12.532
48215021500	3.566	3.314	1.316	1.494	2.745	0.635	13.070
48215021600	3.657	2.872	1.625	1.498	2.225	0.794	12.671
48215021701	5.159	3.141	1.269	1.423	2.302	0.873	14.167
48215021702	5.044	3.003	1.598	1.459	1.975	0.698	13.778
48215021803	4.442	3.213	1.581	1.395	2.005	0.603	13.238
48215021804	3.715	2.823	1.737	1.789	2.599	0.603	13.265
48215021805	5.245	3.062	1.439	1.494	1.733	0.746	13.719
48215021806	4.602	3.052	1.449	1.545	1.722	0.635	13.005
48215021901	4.966	3.344	1.224	1.560	1.100	0.868	13.061
48215021903	4.181	2.836	1.421	1.593	1.692	0.730	12.454
48215021904	4.912	3.655	1.378	1.587	1.432	0.762	13.726
48215022001	5.399	3.653	1.748	1.395	2.026	0.683	14.903
48215022003	4.397	3.505	1.381	1.466	1.310	0.889	12.948
48215022004	4.222	2.603	2.273	1.574	1.237	0.587	12.497
48215022103	3.967	3.360	1.401	1.256	2.138	0.841	12.963
48215022104	4.882	3.182	1.480	1.164	1.263	0.756	12.727
48215022105	3.234	2.892	1.111	1.577	1.965	0.896	11.675
48215022106	4.125	3.234	1.371	1.501	1.198	1.422	12.850
48215022201	4.567	3.496	1.281	1.344	1.737	0.556	12.980
48215022203	4.407	3.237	1.447	1.276	2.088	0.746	13.201
48215022204	4.016	3.251	1.160	1.184	1.635	0.444	11.691
48215022300	4.737	3.389	1.228	1.119	2.308	0.508	13.288
48215022401	4.011	3.517	0.909	1.197	2.468	0.571	12.673
48215022402	4.793	3.182	1.196	1.137	2.078	0.365	12.751
48215022501	4.362	2.510	0.875	1.137	1.512	0.651	11.047
48215022502	4.021	2.845	1.099	1.176	2.507	0.780	12.429
48215022600	4.031	3.176	1.160	1.148	2.234	0.508	12.257
48215022701	4.794	3.279	0.747	1.147	1.678	0.857	12.502
48215022702	4.285	3.553	0.766	0.976	0.972	1.023	11.575
48215022800	4.510	3.268	1.431	1.301	1.845	0.706	13.062
48215022900	4.483	3.107	0.847	1.132	1.837	0.996	12.402
48215023000	4.136	3.143	1.316	0.862	2.246	0.540	12.244
48215023102	4.396	3.312	1.165	1.092	2.489	0.370	12.824
48215023103	5.407	2.681	1.147	0.970	2.378	0.508	13.091
48215023104	3.748	2.843	0.972	1.122	2.444	1.177	12.306
48215023503	4.378	3.126	1.041	1.110	1.612	0.741	12.009
48215023504	4.734	2.957	1.460	1.211	2.676	0.762	13.799
48215023507	4.972	3.318	1.428	1.498	1.703	0.619	13.539
48215023509	5.225	4.046	1.487	1.262	2.543	0.175	14.737
48215023510	5.341	4.158	1.269	1.499	2.081	0.206	14.553
48215023511	4.260	3.848	0.864	0.321	1.370	0.508	11.170
48215023512	2.583	1.000	0.942	0.827	0.346	0.587	6.285
48215023513	4.831	2.553	1.148	0.795	1.282	0.556	11.164
48215023514	4.574	3.103	1.481	1.630	1.427	0.780	12.994
48215023515	4.859	3.501	1.475	1.306	1.808	0.524	13.473
48215023600	4.577	3.275	1.579	1.480	2.568	0.730	14.210
48215023700	3.128	2.692	1.509	1.455	2.435	0.778	11.998
48215023801	5.570	3.394	1.623	1.659	2.207	0.556	15.007
48215023802	4.967	4.182	1.509	1.522	2.864	0.635	15.679
48215023902	5.168	3.821	1.528	1.265	3.580	0.519	15.880
48215023903	4.727	2.717	1.434	1.543	2.829	0.794	14.043
48215023904	5.092	3.115	1.575	1.113	3.259	0.952	15.107
48215024000	4.782	2.871	1.407	1.290	3.535	1.000	14.885
48215024105	4.300	3.635	1.115	1.452	1.610	0.693	12.805
48215024106	4.926	3.581	1.618	1.549	2.409	0.222	14.306

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48215024107	3.694	3.378	0.646	1.333	1.496	0.365	10.911
48215024108	3.744	3.451	0.673	1.005	0.974	0.365	10.213
48215024109	4.329	3.365	1.351	1.567	2.325	0.429	13.366
48215024110	4.990	3.060	0.954	1.010	1.781	0.349	12.144
48215024111	4.706	3.221	1.229	1.636	1.575	0.540	12.906
48215024112	4.038	3.118	0.711	0.611	0.824	0.654	9.956
48215024113	3.859	3.564	0.788	1.496	1.210	0.492	11.408
48215024114	3.535	3.638	0.651	0.924	1.184	0.556	10.488
48215024201	3.764	3.285	0.414	0.731	1.626	0.648	10.467
48215024203	4.456	3.634	0.625	0.622	1.055	0.894	11.286
48215024204	3.592	3.488	1.076	1.285	0.896	1.008	11.345
48215024205	3.952	3.659	0.731	1.170	1.953	1.397	12.862
48215024301	5.078	2.994	0.515	0.644	2.522	0.545	12.299
48215024302	4.453	2.635	0.866	1.217	1.762	1.706	12.638
48215024402	4.623	3.376	1.270	0.971	1.521	0.540	12.300
48215024403	3.200	2.363	1.313	0.899	2.148	0.635	10.558
48215024404	5.543	3.772	1.231	1.067	1.379	0.254	13.245
48215024500	4.417	2.712	0.962	0.932	1.827	0.746	11.595
48215024600	4.341	3.230	1.267	1.251	2.357	0.765	13.211
Mean:	4.444	3.212	1.237	1.306	2.085	0.677	12.960
Standard Deviation:	0.630	0.417	0.317	0.272	0.619	0.264	1.375

Table 5. Hidalgo County Resiliency Scores by Census Tract 2017

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48215020101	4.506	2.734	1.092	1.219	1.996	0.814	12.361
48215020102	3.971	3.208	0.711	1.368	1.807	0.798	11.863
48215020201	4.438	2.963	0.588	0.952	1.684	0.540	11.166
48215020202	4.109	2.680	0.785	1.255	2.173	0.349	11.351
48215020204	4.817	2.977	0.878	1.044	1.599	0.476	11.791
48215020205	4.321	2.975	1.001	1.151	2.168	0.587	12.203
48215020301	5.173	3.353	1.178	1.360	2.708	0.222	13.993
48215020302	5.077	2.839	1.734	1.328	2.539	0.381	13.897
48215020402	5.226	2.884	1.683	1.168	3.204	0.000	14.165
48215020403	2.646	2.718	1.304	1.401	2.016	0.857	10.942
48215020404	3.294	3.183	0.672	1.157	1.078	0.952	10.336
48215020501	3.329	2.674	1.870	1.387	1.637	0.651	11.548
48215020503	4.550	2.884	1.190	1.008	3.168	0.476	13.276
48215020504	4.546	2.801	1.110	1.055	2.808	0.679	12.999
48215020600	2.334	2.694	1.160	1.420	2.781	0.683	11.072
48215020701	5.252	3.545	1.177	1.067	2.860	0.206	14.108
48215020721	5.013	3.167	1.272	1.353	3.205	0.413	14.422
48215020723	2.949	2.691	1.281	1.602	2.443	0.857	11.823
48215020724	5.071	3.608	1.087	1.440	2.530	0.397	14.133
48215020725	4.639	3.352	1.229	1.336	2.436	0.365	13.357
48215020726	3.772	3.085	1.208	1.127	2.643	0.619	12.454
48215020802	4.078	2.576	1.355	1.568	2.958	0.683	13.219
48215020803	5.234	3.214	1.435	1.481	2.431	0.349	14.144
48215020804	4.517	2.173	1.302	1.259	2.108	0.889	12.249
48215020901	4.826	3.252	1.349	1.398	2.437	0.556	13.816
48215020903	5.057	2.799	1.276	1.389	2.669	0.714	13.904
48215020904	4.755	2.761	1.230	1.342	2.521	0.683	13.291
48215021000	3.710	2.528	1.319	1.425	2.572	0.859	12.412
48215021100	2.262	2.775	1.029	1.303	2.623	0.937	10.927

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48215021201	3.920	3.046	0.944	1.358	2.503	0.524	12.296
48215021202	4.345	2.353	1.053	1.496	2.775	0.870	12.891
48215021302	3.972	2.808	1.158	1.511	2.277	0.762	12.487
48215021303	4.410	2.912	1.315	1.034	2.329	0.857	12.856
48215021304	3.789	2.883	1.354	1.147	2.666	1.046	12.886
48215021305	4.125	3.476	1.183	0.971	2.834	0.896	13.486
48215021401	4.199	2.669	1.253	1.443	2.445	0.952	12.961
48215021403	4.181	3.028	1.257	1.247	1.815	0.746	12.273
48215021404	4.753	3.036	1.113	1.034	2.377	0.862	13.176
48215021500	2.504	3.135	1.269	1.466	2.050	0.635	11.058
48215021600	4.053	3.082	1.386	1.252	2.871	0.794	13.439
48215021701	5.041	3.347	1.507	1.265	2.042	0.873	14.075
48215021702	4.952	2.782	1.346	1.217	2.577	0.698	13.573
48215021803	4.300	3.328	1.490	1.311	1.586	0.603	12.619
48215021804	4.777	3.377	1.657	1.367	2.392	0.603	14.173
48215021805	4.342	3.094	1.433	1.376	2.640	0.746	13.631
48215021806	4.298	3.123	1.567	1.460	1.996	0.635	13.078
48215021901	4.186	3.357	1.553	1.940	0.950	0.826	12.813
48215021903	3.756	3.263	1.706	1.428	2.147	0.730	13.030
48215021904	5.147	3.570	1.223	1.631	1.591	0.762	13.924
48215022001	4.817	3.659	1.601	0.967	2.262	0.683	13.989
48215022003	4.636	3.231	1.694	1.528	1.158	0.889	13.136
48215022004	4.819	3.070	1.486	1.872	1.172	0.587	13.006
48215022103	4.124	3.230	1.242	1.336	1.841	0.841	12.614
48215022104	4.945	3.195	1.374	1.165	1.064	0.744	12.486
48215022105	4.874	3.283	1.368	1.200	2.086	0.834	13.645
48215022106	4.630	3.302	1.578	1.019	1.326	1.088	12.942
48215022201	5.136	3.383	1.131	1.115	1.962	0.556	13.283
48215022203	4.589	2.894	1.398	0.646	1.795	0.746	12.068
48215022204	4.430	2.921	1.088	1.119	1.781	0.444	11.783
48215022300	4.842	3.193	1.275	0.727	2.671	0.508	13.217
48215022401	4.970	3.385	1.118	0.780	2.056	0.571	12.880
48215022402	4.687	3.437	1.191	0.832	2.557	0.365	13.068
48215022501	4.234	3.585	1.189	0.944	1.618	0.651	12.221
48215022502	4.908	3.176	1.151	1.027	2.897	0.632	13.791
48215022600	2.814	3.487	0.977	1.042	2.445	0.508	11.273
48215022701	3.754	3.261	0.701	0.907	0.978	0.857	10.458
48215022702	4.210	3.006	0.634	0.941	1.171	0.910	10.871
48215022800	4.230	3.162	1.292	1.624	1.855	0.601	12.765
48215022900	3.278	3.203	0.996	1.088	1.792	0.822	11.178
48215023000	5.091	3.457	1.281	0.862	2.659	0.540	13.889
48215023102	4.653	3.473	1.144	0.909	2.056	0.368	12.602
48215023103	5.417	3.108	1.028	0.836	2.302	0.508	13.200
48215023104	3.835	2.859	0.992	0.922	2.270	0.964	11.842
48215023503	5.447	3.496	1.117	0.877	1.567	0.670	13.174
48215023504	5.104	3.030	1.944	1.237	2.559	0.762	14.635
48215023507	4.519	3.551	1.336	1.159	1.744	0.619	12.927
48215023509	5.711	2.918	1.509	0.909	2.757	0.175	13.979
48215023510	5.196	2.611	1.001	1.587	2.297	0.206	12.898
48215023511	4.099	3.115	0.673	0.659	1.204	0.508	10.258
48215023512	5.523	3.535	0.619	0.325	1.391	0.587	11.980
48215023513	4.606	3.115	1.094	0.914	1.442	0.556	11.727
48215023514	4.703	3.198	1.417	1.362	1.592	0.772	13.044
48215023515	5.055	3.589	1.353	0.962	1.864	0.524	13.346
48215023600	5.183	2.992	1.459	1.047	2.449	0.730	13.860
48215023700	4.251	2.904	1.435	1.397	2.558	0.778	13.323
48215023801	5.565	3.406	2.061	0.981	2.777	0.556	15.345
48215023802	5.219	3.622	1.365	1.318	3.380	0.605	15.509
48215023902	4.879	3.424	1.444	1.159	3.845	0.470	15.222
48215023903	4.567	2.623	1.403	1.135	2.695	0.794	13.217

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48215023904	5.544	2.591	1.815	1.221	2.865	0.952	14.990
48215024000	4.835	2.578	1.380	1.063	3.270	1.000	14.126
48215024105	4.716	3.112	1.288	1.374	2.257	0.674	13.422
48215024106	4.960	2.992	1.288	1.490	2.474	0.222	13.425
48215024107	3.181	3.211	0.540	1.187	1.440	0.365	9.923
48215024108	4.315	3.207	1.223	0.974	1.465	0.365	11.549
48215024109	3.836	2.687	0.914	0.821	2.436	0.429	11.124
48215024110	4.550	2.529	0.995	0.926	2.048	0.349	11.397
48215024111	5.153	3.160	1.596	1.287	1.854	0.510	13.560
48215024112	4.036	2.883	0.702	1.168	1.272	0.697	10.757
48215024113	3.836	3.101	0.847	1.418	1.471	0.492	11.164
48215024114	4.477	2.898	0.768	1.083	1.515	0.556	11.296
48215024201	4.102	3.209	0.517	0.447	1.725	0.606	10.607
48215024203	4.120	3.341	0.410	0.807	1.533	0.760	10.971
48215024204	4.229	2.898	1.339	0.839	1.636	0.921	11.862
48215024205	4.784	3.085	0.721	0.536	2.572	1.117	12.816
48215024301	4.979	2.609	0.868	0.694	2.867	0.546	12.563
48215024302	4.259	1.653	0.914	0.948	1.465	1.761	11.000
48215024402	5.099	3.379	1.319	1.514	1.566	0.540	13.416
48215024403	4.382	2.897	1.312	0.781	2.184	0.635	12.192
48215024404	4.594	3.435	1.134	1.104	1.780	0.254	12.301
48215024500	4.091	3.150	1.168	1.067	2.007	0.746	12.230
48215024600	3.932	3.297	1.060	0.857	2.028	0.632	11.806
Mean:	4.447	3.069	1.210	1.164	2.163	0.652	12.706
Standard Deviation:	0.687	0.334	0.310	0.281	0.585	0.238	1.178

*Census Tract 48215980000 excluded due to insufficient data.

The results of Willacy County's resilience in 2010 and 2017 are shown in Table 6 and Table 7 respectively. From 2010 to 2017, Willacy County's total resilience score decreased by roughly 1%. The mean resiliency score for 2010 was 11.852 or 47.40%, and a score of 11.638 or 46.55% in 2017. Only 2 out of the 6 resiliency categories saw an increase in their overall resilience throughout the years. In 2010 the mean Social resilience score was 3.536 (50.4%), it saw an increase in 2017 resulting in an average social resilience score of 3.879 (55.4%). Similarly, the mean Community resilience score increased from 1.040 (34.6%) in 2010 to 1.077 (35.9%) in 2017. Environmental Resilience saw no change in its overall mean from 2010 to 2017 staying at an average score of .809. In 2010, Infrastructure resilience had an average score of 2.923 (48.7%), Economic resilience averaged 2.538 (50.76%), and Institutional had an average score of 1.006 (50.3%). By 2017 all three resilience variables saw a decrease, resulting in Infrastructure's overall mean score of 2.917 (48.6%), Economic 2.176 (43.5%), and Institutional .778 (39.8%). Willacy County is the only one that has suffered loss of population over the years. In 2010 it held a population of 22,134 and by 2017 that number had gone down to 21,839. This could explain why resilience scores dropped in all census tracts except one from 2010 to 2017. It is possible that population is shifting to the census tract that is home to the largest city, while also moving out of Willacy County altogether.

Table 6. Willacy County Resiliency Scores by Census Tract 2010

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48489950300	3.462	1.604	0.461	0.725	2.746	0.028	9.027
48489950400	2.848	2.012	1.189	0.000	4.311	0.013	10.374
48489950500	3.584	3.563	0.566	1.077	2.921	1.022	12.733
48489950600	3.392	3.813	2.275	2.000	0.600	1.018	13.098
48489950700	4.393	1.699	0.711	1.229	4.036	1.962	14.029
Mean:	3.536	2.538	1.040	1.006	2.923	0.809	11.852
Standard Deviation:	0.497	0.952	0.666	0.653	1.311	0.730	1.857

*Census Tract 48489990000 excluded due to insufficient data.

Table 7. Willacy County Resiliency Scores by Census Tract 2017

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48489950300	5.025	0.402	0.767	0.000	2.857	0.028	9.080
48489950400	1.290	3.225	0.000	1.000	3.811	0.013	9.339
48489950500	4.317	3.026	2.043	0.808	3.088	1.022	14.305
48489950600	4.178	2.955	1.696	1.187	0.557	1.020	11.593
48489950700	4.587	1.273	0.881	0.896	4.274	1.962	13.874
Mean:	3.879	2.176	1.077	0.778	2.917	0.809	11.638
Standard Deviation:	1.327	1.131	0.723	0.409	1.284	0.730	2.188

*Census Tract 48489990000 excluded due to insufficient data.

The results of Cameron County’s Resilience in 2010 and 2017 are shown in Table 8 and Table 9 respectively. In 2010, The total resilience score was 12.785, or 51.14%. The category with the lowest mean resilience was Environmental Resilience with 20.3% and the category with the highest mean resilience was Social resilience with 65.1%. Similarly, in 2017 the same two categories held the lowest and highest positions, with 20.3% and 60.5% being their means, respectively. The temporal shift from 2010 to 2017 resulted in a 1.06 % loss of overall resiliency for Cameron County, as the total score decreased to 12.512, or 50.08%. All resilience categories except for Infrastructure resilience decreased and Environmental, which stayed the same. The category that decreased the most from 2010 to 2017 was social resilience. In 2010, the mean social resilience was 4.560 (65.1%), whereas in 2017, the score decreased 4.6% to 4.238 (60.5%). The category that increased the most in resilience during this time was Infrastructure resilience, going up 7.1% from 2.537 to 2.663. The only category that sustained no significant change was Environmental Resilience.

Table 8. Cameron County Resiliency Scores by Census Tract 2010

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48061010100	5.328	3.347	1.636	0.965	1.800	0.642	13.718
48061010201	5.448	3.349	1.546	1.240	1.943	0.103	13.628
48061010203	5.482	3.058	1.525	1.156	2.646	0.516	14.383
48061010301	5.188	3.297	1.400	1.645	2.569	0.229	14.329
48061010302	5.113	2.977	1.705	1.237	2.409	0.156	13.596
48061010401	5.784	3.943	1.530	1.400	2.246	0.145	15.049
48061010402	5.040	3.923	1.319	1.197	2.134	0.327	13.940
48061010500	3.701	2.770	1.295	1.176	2.953	0.349	12.244
48061010601	5.279	3.242	1.318	0.921	3.442	0.474	14.676
48061010602	5.564	4.422	2.511	1.239	3.874	0.148	17.758
48061010700	5.087	3.259	1.549	1.117	3.527	0.467	15.006
48061010800	5.002	3.110	1.645	1.325	3.631	0.710	15.424
48061010900	4.052	2.497	1.234	1.197	2.966	0.453	12.398
48061011000	4.126	3.192	1.485	1.172	2.702	0.495	13.172
48061011100	4.089	2.994	1.493	1.114	2.897	0.478	13.064
48061011200	4.793	3.100	1.437	1.102	3.282	0.322	14.036
48061011301	4.794	1.883	1.451	1.198	3.721	0.421	13.468
48061011302	5.423	3.640	1.457	0.978	2.916	0.148	14.562
48061011400	5.260	3.768	1.533	0.945	2.640	0.308	14.454
48061011500	4.820	2.798	1.530	1.159	3.271	0.577	14.154
48061011600	3.849	3.286	1.525	1.131	2.549	0.417	12.757
48061011700	4.976	2.478	1.461	1.270	2.579	0.424	13.188
48061011801	5.093	3.036	1.232	1.077	3.561	0.705	14.704
48061011802	4.833	3.545	1.400	1.012	2.746	0.311	13.847
48061011901	4.181	2.816	1.508	1.467	1.911	0.441	12.323
48061011902	4.577	3.104	1.907	1.466	1.445	0.202	12.702
48061011903	3.921	2.210	1.626	1.276	1.505	0.250	10.788
48061012001	5.120	4.140	1.380	1.075	1.905	0.271	13.890
48061012002	5.621	2.913	1.530	1.022	2.070	0.248	13.404
48061012101	4.967	3.806	1.390	1.120	1.727	0.284	13.295
48061012102	4.293	2.384	1.455	0.972	1.508	0.341	10.952
48061012200	4.777	3.099	1.348	0.757	2.120	0.297	12.397
48061012301	5.119	3.222	0.689	0.754	2.736	1.018	13.537
48061012304	4.155	2.930	0.725	0.712	2.141	1.176	11.840
48061012305	3.847	3.173	0.000	0.878	2.061	1.839	11.797
48061012401	5.311	2.876	1.214	0.822	2.039	0.334	12.596
48061012402	5.427	3.100	1.084	0.944	2.746	0.245	13.546
48061012504	5.261	3.155	1.218	0.609	3.047	0.081	13.371
48061012505	4.693	3.366	1.610	1.192	1.756	0.342	12.959
48061012506	4.859	2.981	1.099	1.178	2.381	0.371	12.869
48061012507	4.682	3.280	1.328	1.079	2.343	0.426	13.138
48061012508	5.156	3.603	1.107	0.901	1.297	0.276	12.340
48061012607	4.370	2.054	1.022	0.928	2.398	0.306	11.078
48061012608	5.089	2.861	1.054	0.871	2.142	0.447	12.464
48061012609	3.492	3.657	1.115	0.992	1.846	0.327	11.429
48061012612	5.233	3.615	1.255	1.135	2.451	0.045	13.734
48061012613	5.232	3.371	1.174	1.073	2.602	0.127	13.580
48061012700	5.263	3.164	1.124	1.227	2.550	0.693	14.021
48061012800	4.399	3.242	1.162	0.845	2.960	0.275	12.883
48061012900	4.385	3.220	0.897	0.953	2.604	0.330	12.389
48061013002	4.640	3.215	1.243	1.086	3.184	0.777	14.144
48061013003	4.371	1.875	1.245	1.085	3.470	0.838	12.883
48061013004	4.338	2.992	0.931	0.937	3.372	0.231	12.802
48061013102	5.309	3.230	1.246	0.869	2.638	0.151	13.442
48061013104	4.346	2.753	1.057	1.025	2.263	0.583	12.028
48061013106	4.764	2.788	1.222	0.984	3.215	0.716	13.689
48061013203	3.584	2.394	1.000	1.030	1.440	0.390	9.838

GEOID10	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48061013204	4.245	3.233	1.149	0.979	1.222	0.146	10.975
48061013205	4.852	2.652	1.388	0.939	1.371	0.371	11.574
48061013206	5.057	2.544	1.103	1.012	2.063	0.377	12.156
48061013207	4.655	3.140	0.882	1.007	1.463	0.668	11.815
48061013303	5.129	3.208	1.381	0.958	2.641	0.346	13.663
48061013305	4.564	2.878	1.321	1.041	2.523	0.299	12.627
48061013306	4.455	2.508	1.505	1.078	1.696	0.161	11.403
48061013307	2.517	2.763	0.872	0.917	2.205	0.312	9.586
48061013308	4.393	3.233	1.028	1.051	2.443	0.185	12.334
48061013309	4.663	2.556	0.946	0.958	1.558	0.160	10.840
48061013401	3.234	2.330	0.835	1.038	3.219	0.403	11.060
48061013402	3.550	3.220	1.019	0.957	3.063	0.210	12.018
48061013500	4.660	3.491	0.954	1.025	4.433	0.123	14.686
48061013600	3.322	2.747	0.897	0.946	2.907	0.413	11.233
48061013700	3.680	3.245	0.893	0.928	3.106	0.353	12.205
48061013801	2.257	2.140	0.795	1.029	3.186	0.598	10.005
48061013802	2.827	2.154	0.982	0.723	2.705	0.435	9.827
48061013901	3.993	2.999	0.835	0.881	1.801	0.274	10.783
48061013902	4.037	2.622	0.915	1.131	2.631	0.363	11.698
48061013903	4.371	2.277	1.316	0.885	2.790	0.194	11.834
48061014001	1.825	2.367	0.750	0.956	3.052	1.093	10.042
48061014002	3.114	2.582	0.883	0.908	2.689	0.565	10.740
48061014100	4.518	2.981	1.263	0.827	2.164	0.290	12.042
48061014200	4.902	2.997	1.107	1.145	2.502	0.573	13.226
48061014300	4.640	2.746	0.972	0.758	2.320	0.686	12.121
48061014400	5.347	3.561	1.316	0.327	3.170	0.169	13.891
48061014500	5.344	2.970	1.068	0.915	3.288	0.305	13.890
Mean:	4.560	3.020	1.233	1.030	2.537	0.406	12.785
Standard Deviation:	0.776	0.488	0.324	0.191	0.661	0.271	1.439

*Census Tracts 48061980001, 48061980100, and 48061990000 excluded due to insufficient data.

Table 9. Cameron County Resiliency Scores by Census Tract 2017

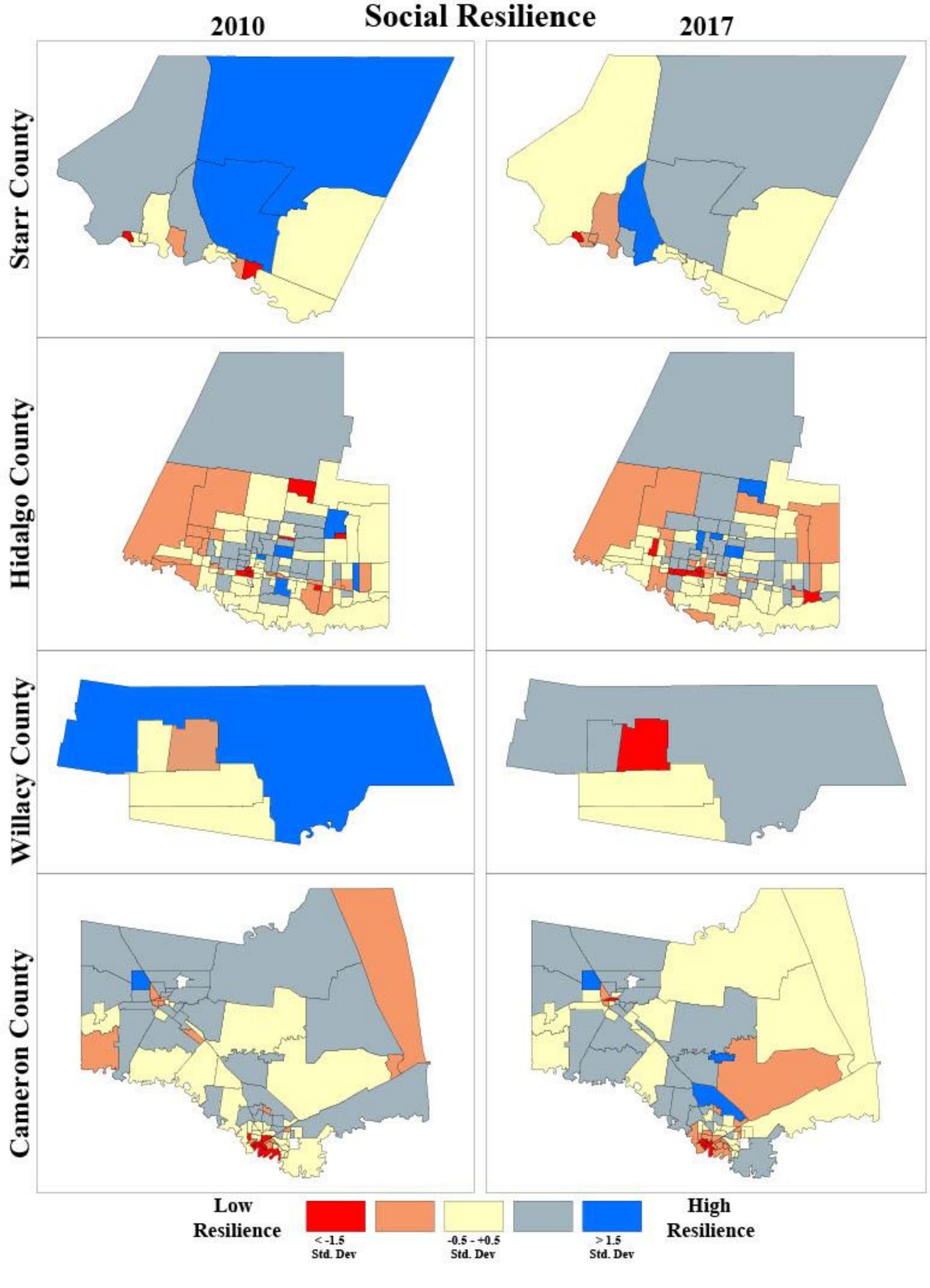
GEOID	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48061010100	4.144	3.007	1.321	0.942	1.642	0.642	11.697
48061010201	5.324	3.682	1.591	1.209	2.138	0.103	14.047
48061010203	4.748	3.344	1.447	1.069	2.501	0.516	13.624
48061010301	4.800	2.764	1.520	1.686	2.538	0.229	13.536
48061010302	5.299	3.504	1.929	1.348	2.776	0.156	15.012
48061010401	5.449	3.129	1.454	0.850	2.367	0.145	13.394
48061010402	4.450	2.913	1.920	0.967	2.090	0.327	12.667
48061010500	3.481	3.039	2.349	1.057	2.690	0.349	12.964
48061010601	5.257	3.304	1.423	1.120	3.599	0.474	15.175
48061010602	4.648	3.057	1.420	1.114	3.707	0.148	14.093
48061010700	4.446	3.158	1.268	1.104	3.303	0.467	13.746
48061010800	4.841	2.630	1.729	0.938	3.538	0.710	14.386
48061010900	3.008	2.371	0.942	1.047	3.169	0.453	10.991
48061011000	3.442	2.707	1.144	1.125	2.649	0.495	11.563
48061011100	4.095	3.217	1.272	1.119	3.218	0.478	13.399
48061011200	4.849	2.317	1.419	1.114	3.231	0.322	13.252
48061011301	5.109	2.281	2.001	1.027	3.338	0.421	14.177
48061011302	4.667	2.853	1.290	0.998	2.503	0.148	12.459
48061011400	4.587	3.231	1.578	1.214	2.533	0.308	13.453
48061011500	4.948	2.838	1.392	0.917	3.013	0.577	13.684
48061011600	3.888	3.503	2.047	1.103	3.527	0.417	14.484
48061011700	4.428	3.031	2.168	1.077	3.207	0.424	14.335
48061011801	5.253	3.254	1.504	0.974	3.427	0.705	15.116
48061011802	4.616	3.269	1.397	1.044	2.593	0.311	13.230
48061011901	4.454	2.693	2.063	1.331	2.006	0.441	12.987
48061011902	4.507	2.936	1.605	1.205	1.453	0.202	11.909
48061011903	4.005	2.198	1.658	1.315	1.367	0.251	10.793
48061012001	4.584	3.005	1.701	0.999	2.449	0.271	13.009
48061012002	5.371	4.098	1.630	1.195	1.982	0.248	14.524
48061012101	4.942	3.497	1.413	1.243	2.002	0.284	13.381
48061012102	5.064	3.261	1.659	1.156	1.822	0.392	13.354
48061012200	5.323	3.492	1.328	1.454	2.256	0.300	14.153
48061012301	4.331	3.257	0.285	0.878	3.165	1.018	12.935
48061012304	4.030	3.795	0.505	0.747	2.047	1.176	12.301
48061012305	4.402	3.726	0.000	0.700	2.175	1.839	12.843
48061012401	5.067	2.833	1.943	1.017	2.046	0.334	13.241
48061012402	5.499	3.479	1.013	0.748	3.208	0.245	14.193
48061012504	5.298	4.152	1.298	0.821	3.166	0.081	14.816
48061012505	4.153	3.456	1.439	1.116	1.749	0.342	12.255
48061012506	4.733	3.288	1.229	1.035	2.602	0.371	13.258
48061012507	4.657	3.467	1.334	0.910	2.970	0.428	13.766
48061012508	4.931	2.735	1.072	0.897	1.413	0.279	11.326
48061012607	3.582	2.678	1.039	0.911	2.201	0.306	10.717
48061012608	4.462	3.065	0.877	0.928	2.136	0.447	11.915
48061012609	3.606	2.377	0.913	1.273	1.904	0.327	10.400
48061012612	4.895	3.618	1.122	0.940	2.412	0.045	13.033
48061012613	3.945	3.097	0.963	0.905	2.567	0.127	11.604
48061012700	4.326	2.545	0.970	1.112	2.994	0.695	12.642
48061012800	3.584	3.233	1.258	0.886	3.042	0.314	12.317
48061012900	4.006	2.634	1.648	0.814	2.840	0.330	12.273
48061013002	4.738	2.638	1.061	0.942	3.552	0.777	13.708
48061013003	4.148	2.479	0.934	0.918	3.173	0.838	12.490
48061013004	3.560	3.044	0.993	0.960	3.539	0.231	12.326
48061013102	4.180	3.050	0.900	0.763	2.634	0.151	11.678
48061013104	3.933	2.891	0.972	0.964	3.349	0.583	12.691
48061013106	4.116	2.870	1.091	0.829	3.379	0.716	13.001
48061013203	3.294	2.496	0.995	0.943	1.691	0.390	9.810

GEOID	Social (7)	Economic (5)	Community (3)	Institutional (2)	Infrastructure (6)	Environmental (2)	Resiliency Score (25)
48061013204	3.534	2.830	1.459	0.781	1.516	0.146	10.266
48061013205	3.895	3.123	0.915	0.852	2.084	0.371	11.240
48061013206	4.095	2.346	1.125	0.824	1.788	0.377	10.555
48061013207	4.155	2.533	1.042	0.827	2.009	0.668	11.234
48061013303	4.963	3.127	0.955	0.950	2.318	0.346	12.659
48061013305	3.871	3.298	1.172	0.720	2.662	0.299	12.022
48061013306	3.782	3.428	0.995	0.895	2.302	0.161	11.563
48061013307	3.724	2.577	0.971	0.795	2.378	0.325	10.770
48061013308	4.218	3.435	1.082	0.736	1.961	0.185	11.617
48061013309	3.870	2.869	0.731	0.888	2.391	0.160	10.908
48061013401	3.262	2.536	1.011	0.838	3.308	0.403	11.359
48061013402	3.634	3.406	0.809	0.821	3.166	0.210	12.046
48061013500	3.761	3.202	0.911	0.982	3.561	0.123	12.540
48061013600	3.446	2.936	0.877	0.969	3.232	0.413	11.872
48061013700	2.802	2.732	0.813	0.823	3.715	0.353	11.238
48061013801	2.706	3.333	0.896	0.931	3.156	0.598	11.620
48061013802	3.242	2.246	0.897	0.910	2.758	0.435	10.489
48061013901	3.678	2.404	0.859	0.925	2.265	0.274	10.405
48061013902	3.846	2.660	0.949	0.794	3.210	0.363	11.822
48061013903	3.207	3.138	1.214	0.957	2.857	0.194	11.566
48061014001	1.109	2.916	0.590	0.830	2.781	1.139	9.364
48061014002	2.422	2.410	0.897	0.887	2.983	0.565	10.164
48061014100	4.990	2.831	1.380	0.509	2.449	0.298	12.457
48061014200	3.526	2.316	0.813	1.055	2.741	0.573	11.023
48061014300	4.316	2.915	0.967	0.896	2.358	0.686	12.137
48061014400	5.600	3.189	1.268	0.327	3.441	0.169	13.994
48061014500	4.913	3.718	0.993	0.994	3.781	0.305	14.705
Mean:	4.238	3.011	1.226	0.973	2.663	0.407	12.521
Standard Deviation:	0.782	0.429	0.410	0.193	0.621	0.271	1.352

*Census Tracts 48061980001, 48061980100, and 48061990000 excluded due to insufficient data.

Changes in Social Resilience can be analyzed in Figure 1. Social Resilience scores are calculated out of a total of 7 variables. In Starr County, mean social resilience scores are higher for 2010 than in 2017, with scores of 3.761 and 3.670 respectively. 9 out of the 15 census tracts in Starr county saw a decrease in their individual average resilience scores. For Hidalgo County, resilience remained almost constant throughout the years, with a score 0.1% higher in 2017. In 2010, social resilience scores averaged 4.444, and this increased to 4.447 in 2017. 59 out of the 112 census tracts in the county saw a decrease in their individual scores. Many of these census tracts were concentrated in the center of the county. In Willacy County, social resilience was higher in 2017 with an average score of 3.879, while in 2010 the average score was 3.536. 4 out of the 5 census tracts experienced a positive increase in resilience. The outlier in this county that reduced its social resilience is obvious in Figure 1. Lastly, Social resilience for Cameron County was higher in 2010 than in 2017, with scores of 4.560 in 2010 and 4.238 in 2017. 60 out of the 84 census tracts in the county saw a decrease in their individual resiliencies. In 2010, the county with the highest social resilience score was Cameron County. In 2017, Hidalgo County surpassed Cameron as the county with the highest social resilience.

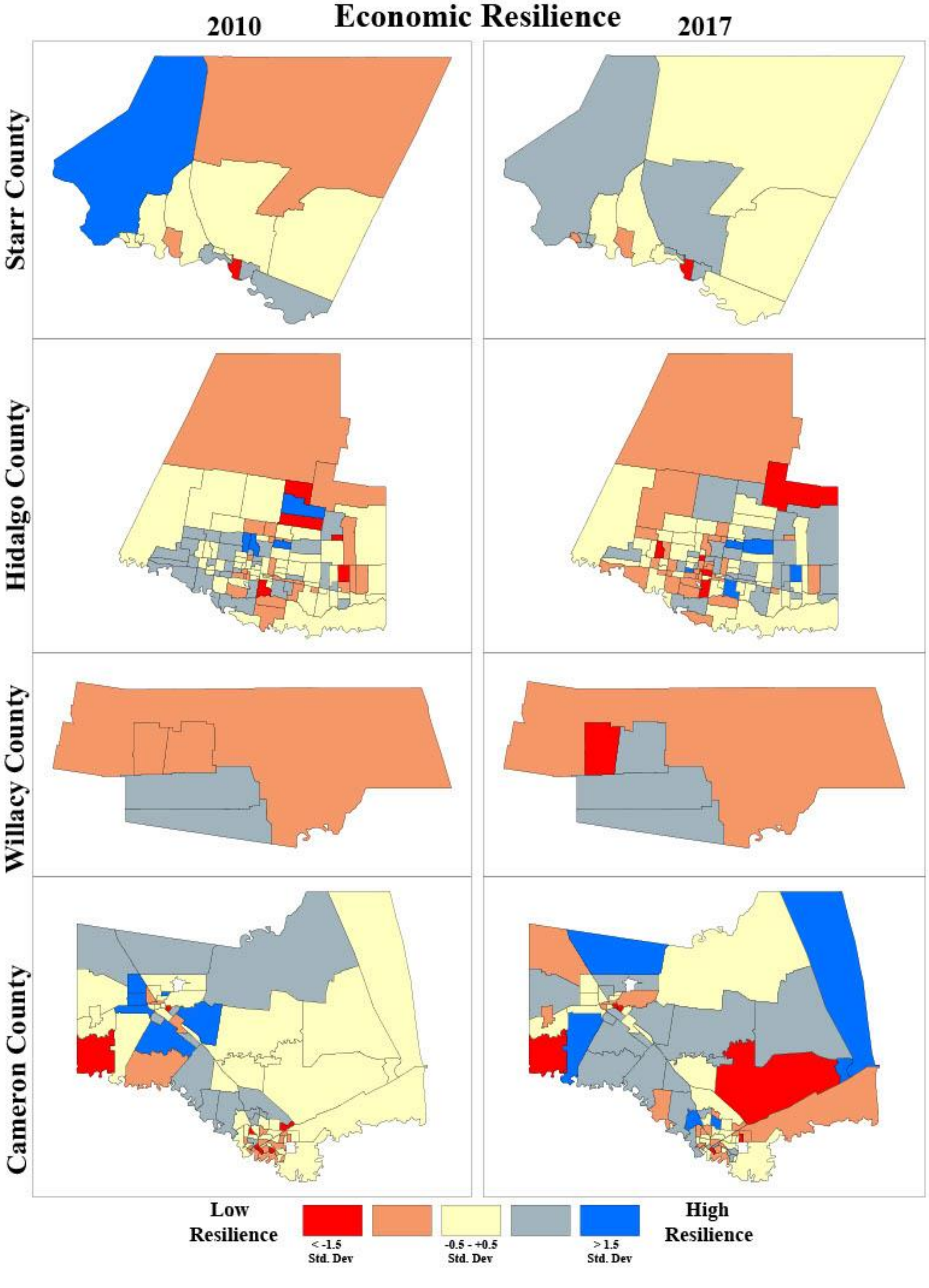
FIGURE 1. SOCIAL RESILIENCE IN THE RIO GRANDE VALLEY



Changes in Economic Resilience can be analyzed in Figure 2. Economic Resilience scores are calculated out of a total of 5 variables. Starr County's mean economic resilience decreased from 2010 with a score of 2.870 to 2017 with a score of 2.759. 8 out of the 15 census tracts saw a decrease in their individual resilience. Hidalgo County's resilience also decreased during this time period, going from a 3.212 in 2010 to 3.069 in 2017. 70 out of the 112 census tracts experienced a decrease in their individual resilience scores.

Willacy County saw the most dramatic decline in their economic resilience with an average score of 2.538 in 2010 to a 2.176 in 2017. 4 out of the 5 census tracts in this county also had low resilience scores. Cameron County's economic resilience declined slightly, and although Figure 2 depicts various changes in the census tracts, the overall score was not statistically significant. In 2010, this county's economic resilience score was at a 3.020, dropping slightly to 3.011 by 2017. Only 38 out of the 84 census tracts saw a slight decrease in their individual scores, and there was less disparity between the scores in 2017 compared to 2010. Although all counties suffered a decrease in economic resilience over time, Hidalgo county had the highest economic resilience score for both 2010 and 2017.

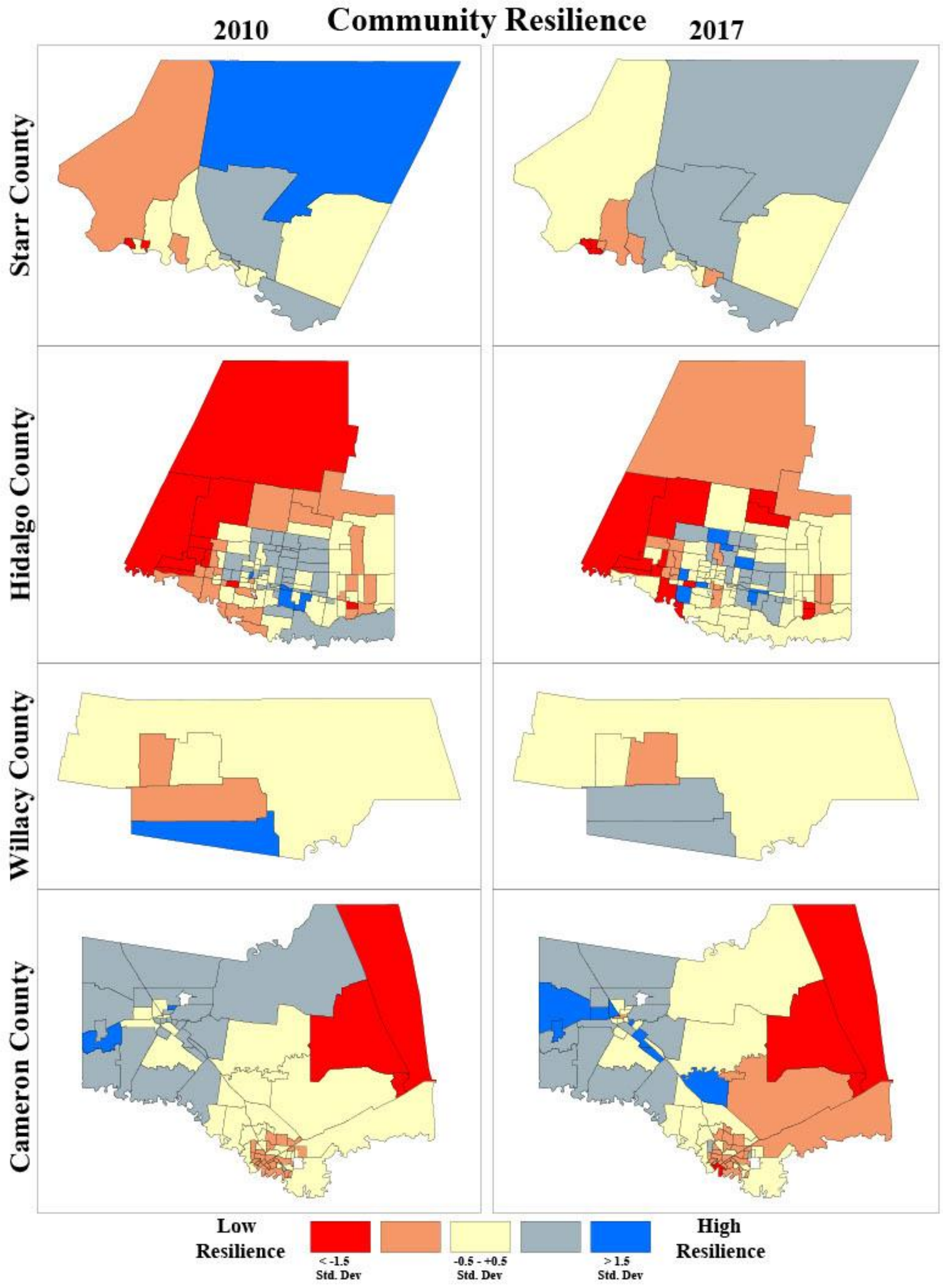
FIGURE 2. ECONOMIC RESILIENCE IN THE RIO GRANDE VALLEY



Changes in Community Resilience can be analyzed in Figure 3. Community Resilience scores are calculated out of a total of 3 variables. Community Resilience scores for Starr County significantly increased from 0.938 in 2010 to 1.359 in 2017. Only one census tract saw a decrease in its mean resiliency score. In Hidalgo County, 2010 saw mean resiliency scores of 1.237, which declined to 1.210 in 2017. 66 out of the 112 census tracts also decreased in their individual community resilience scores. The mean Community resiliency score for Willacy County also increased slightly during this time period. In 2010, the mean score was 1.040 and that increased to 1.077 in 2017. Only 2 out of the 5 census tracts saw a significant decrease in their individual mean scores. Lastly, Cameron County decreased in community resilience from 2010 to 2017. The score for 2010 was 1.233 whereas in 2017 it dropped to 1.226. 44 out of the 84 census tracts saw a decline in their individual resilience scores throughout time.

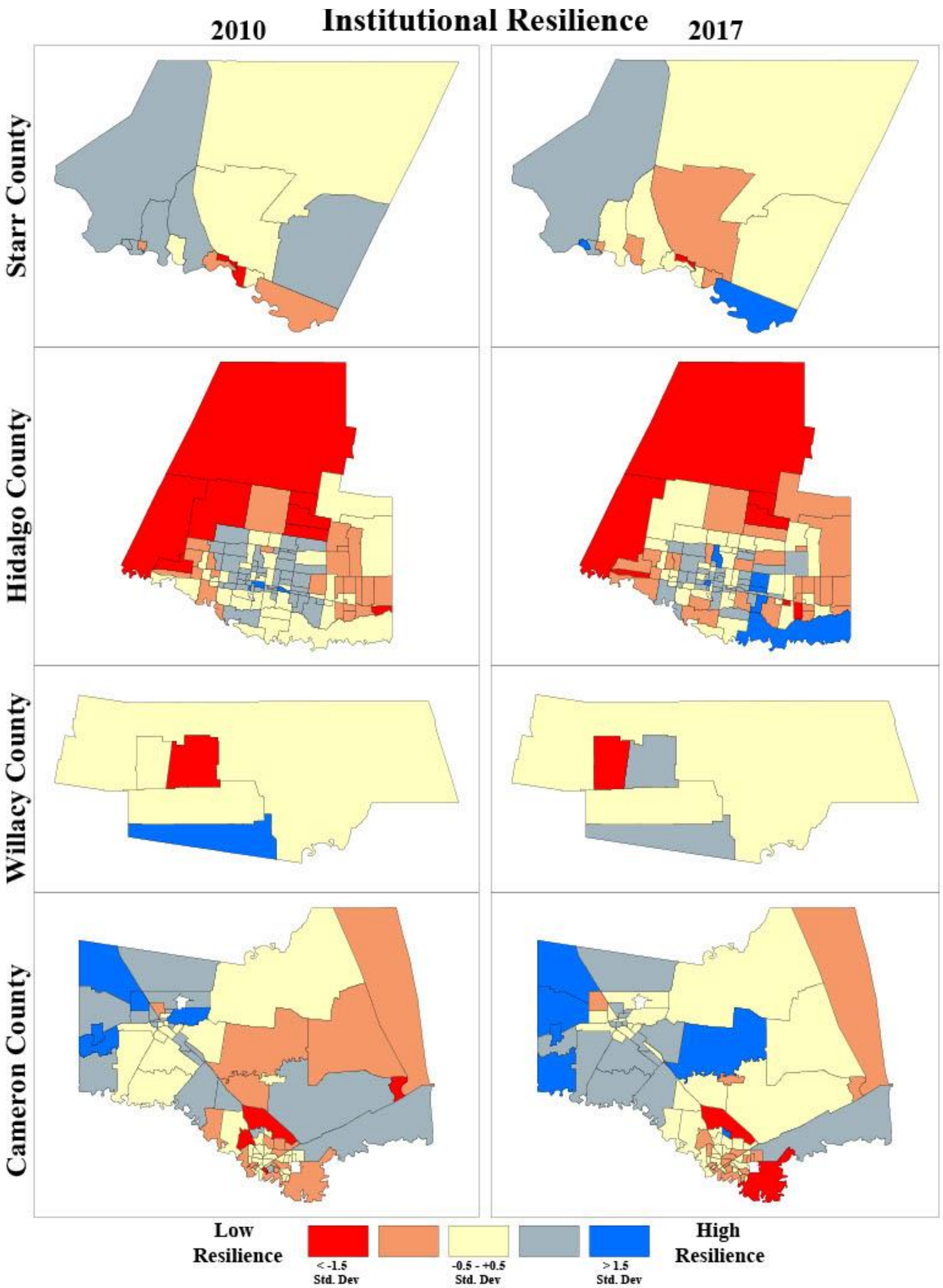
Hidalgo county had the highest mean community resilience for 2010, and Starr county had the highest community resilience score for 2017.Starr county was also the only county that increased their Community Resilience over time.

FIGURE 3. COMMUNITY RESILIENCE IN THE RIO GRANDE VALLEY



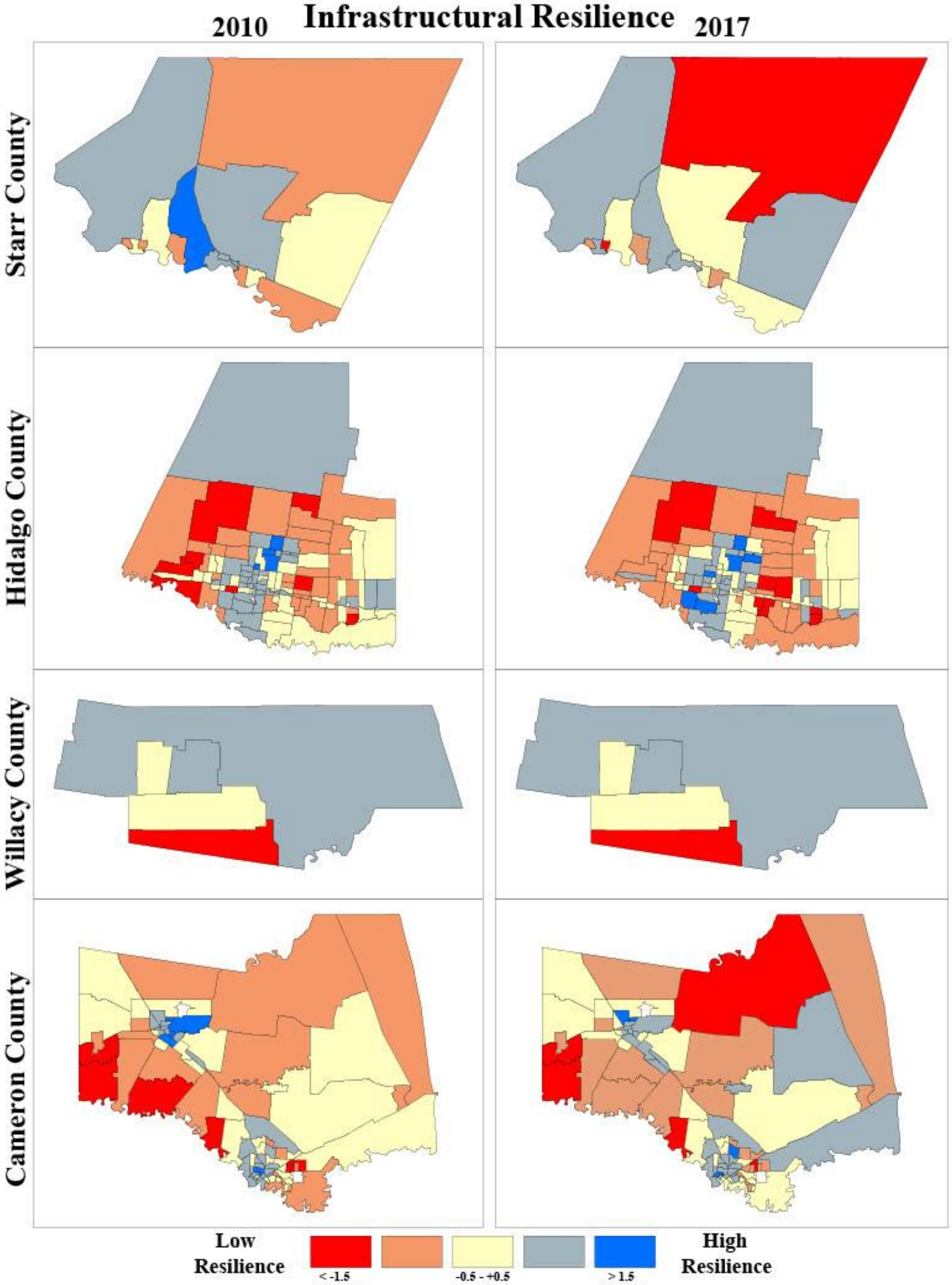
Changes in Institutional Resilience can be analyzed in Figure 4. Institutional Resilience scores are calculated out of a total of 2 variables. Institutional Resilience for Starr County decreased from 2010 to 2017 with average scores of 1.165 and .930 respectively. 12 out of the 15 census tracts saw a decrease in their individual institutional resiliency scores. Hidalgo County's resilience also decreased, having an average score of 1.306 in 2010 and decreasing to a 1.164 in 2017. 83 out of the 112 census tracts also had a decrease in their resiliency scores. In 2010, Willacy County averaged a score of 1.006, which dramatically decreased to .778 by 2017. Almost all of the census tracts, 4 out of the 5, also suffered a decrease. The Institutional Resilience for Cameron County in 2010 was 1.030, which later decreased to .973 in 2017. 56 out of the 84 census tracts also saw their scores reduced. Overall, Institutional Resilience decreased from 2010 to 2017. In 2010, the county with the highest institutional resilience was Hidalgo County, and it was no different for 2017.

FIGURE 4. INSTITUTIONAL RESILIENCE IN THE RIO GRANDE VALLEY



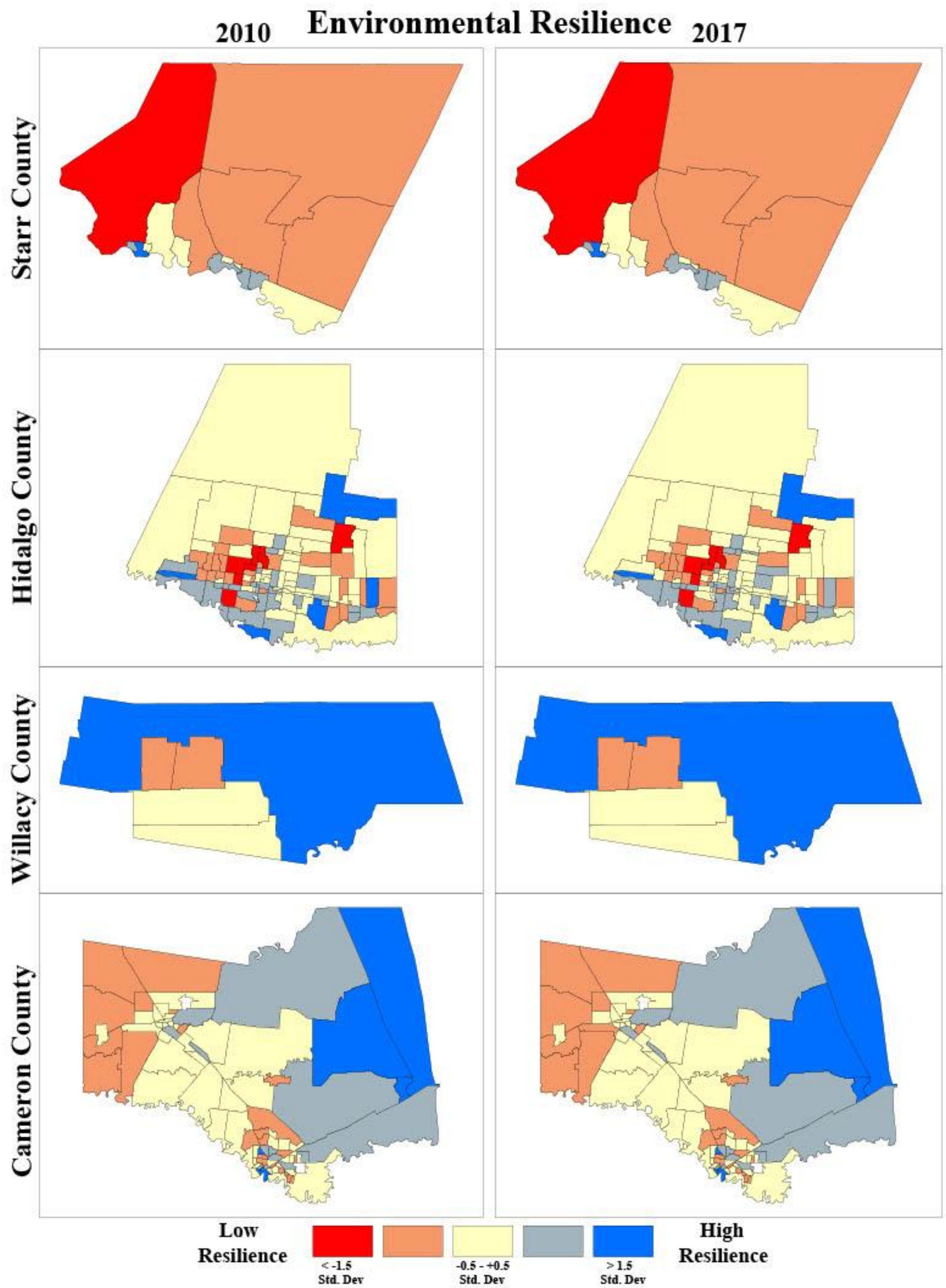
Changes in Infrastructural Resilience can be analyzed in Figure 5. Infrastructure Resilience scores are calculated out of a total of 6 variables. In Starr County, the mean Infrastructure resilience score was higher for 2010 than 2017. The score for 2010 was 2.757 and it decreased to 2.604 in 2017. 9 out of the 15 census tracts in Starr county saw a decrease in their individual average Infrastructural resilience scores. For Hidalgo County, resilience was a little higher in 2017. The average score in 2010 was 2.085, which increased to 2.163 in 2017. However, 45 out of the 112 census tracts in the county saw a decrease in their individual infrastructure resiliency scores. In Willacy County, infrastructure resilience was higher in 2010 with an average score of 2.923 resilience, while in 2017 the average resilience score was 2.917. 2 out of the 5 census tracts experienced a decrease in resilience. Lastly in Cameron County, resilience was higher in 2017 than in 2010. The average score in 2010 was 2.537 and that increased to 2.663. 30 out of the 84 census tracts in the county saw a decrease in their individual infrastructural resiliency scores throughout this time period. For 2010, the county that showed the most infrastructural resilience was Willacy County, as well as for 2017.

FIGURE 5. INFRASTRUCTURAL RESILIENCE IN THE RIO GRANDE VALLEY



Changes in Environmental Resilience can be analyzed in Figure 6. Environmental Resilience scores are calculated out of a total of 2 variables. The mean environmental resilience scores for Starr County remained the same for both 2010 and 2017 at a mean score of .948. There was one individual census tract that did increase in resilience during this time period. In Hidalgo County, the mean environmental resilience decreased slightly from 2010 to 2017. In 2010, the mean resilience score was .677, whereas in 2017 it was .652. 23 out of the 112 census tracts in the county saw a decrease in their individual environmental resiliency scores. For Willacy County, environmental resilience scores remained the same for both 2010 and 2017 at a mean score of .809. Only one census tract increased in individual resilience since 2010. In Cameron County, resilience was slightly higher in 2017 than in 2010. In 2010 the score was 0.406, and 0.407 in 2017. 7 out of the 84 census tracts in the county saw an increase in their individual environmental resilience. For both 2010 and 2017, the county that showed the most environmental resilience was Starr County.

FIGURE 6. ENVIRONMENTAL RESILIENCE IN THE RIO GRANDE VALLEY



Changes in Total Resilience can be analyzed in Figure 7 and 8. Total Resilience scores are calculated out of a total of 25 variables, which is the sum of all of the previous resilience capitals. Total Resilience for Starr County decreased from 12.438 in 2010 to 12.270 in 2017. 9 out of 15 census tracts also saw a decrease in their total resiliency scores. In Hidalgo County, the mean total resiliency score for 2010 was 12.960. This decreased to 12.706 in 2017. Along with this decrease, 70 out of the 112 census tracts decreased in their individual scores. Willacy County's mean total resilience decreased slightly during this time period. In 2010, the mean score was 11.858 and that decreased to 11.638 in 2017. 3 out of the 5 census tracts saw a significant decrease in their individual mean scores. Lastly, Cameron County's Total resilience also decreased from 2010 to 2017. The score for 2010 was 12.785 whereas in 2017 it dropped to 12.521. 48 out of the 84 census tracts saw a decline in their individual resilience scores. In both 2010 and 2017, Hidalgo county had the highest mean total resilience score.

FIGURE 7. TOTAL RESILIENCE IN THE RIO GRANDE VALLEY

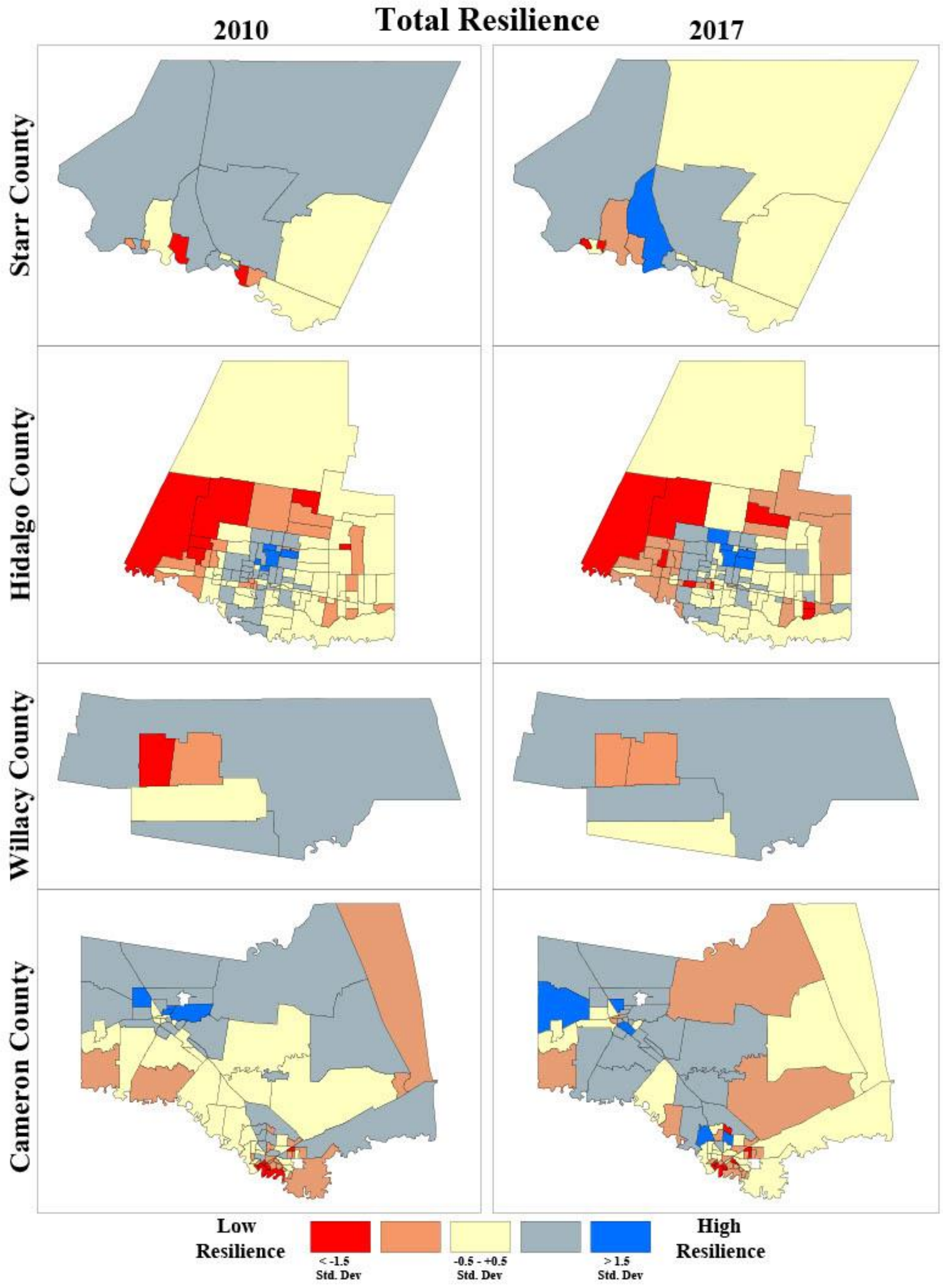
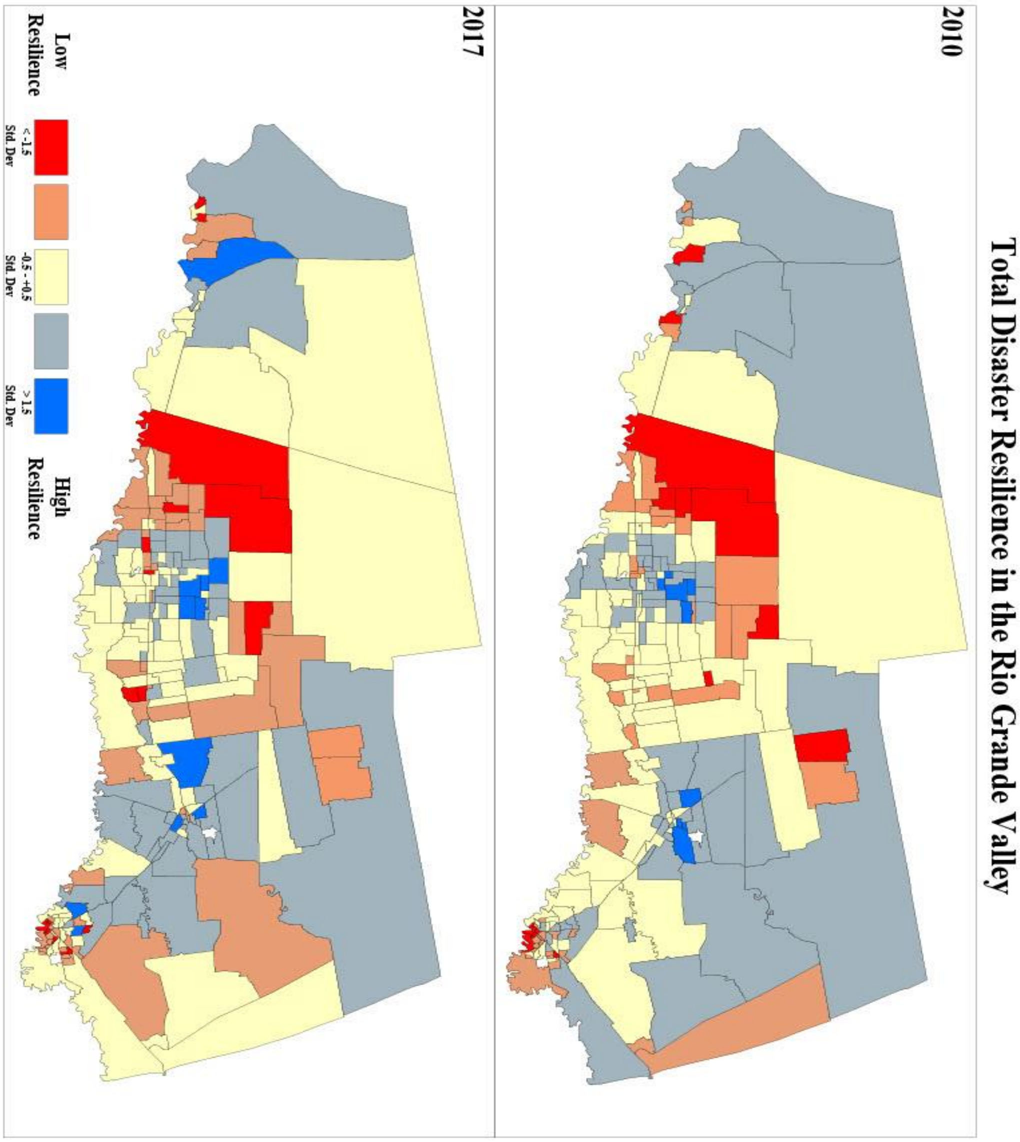


FIGURE 8. TOTAL DISASTER RESILIENCE IN THE RIO GRANDE VALLEY



Discussion

Our results showed that all of the counties decreased in Total Resilience from 2010 to 2017. Hidalgo County's mean total resilience score was the highest for both 2010 and 2017. Although this is the highest resilience score for the Rio Grande Valley according to our index, it still shows that resilience in the Rio Grande Valley is only at about 50%. Scores in each of the resilience capitals, regardless of whether they have increased or decreased, have not ever met their maximum score. Looking at the RGV as a whole in Figure 8, resilience scores sit in the middle of the spectrum, with only a few census tracts having extremely low resilience and others extremely high resilience. Although seven years might not seem like a long time, it is more alarming that only one out of the four counties slightly increased their total resilience. More attention needs to be paid to the inherent resilience factors in the Rio Grande Valley; this can be done by raising awareness of the importance of resilience variables and how they impact the community. This awareness will in turn spark the adaptive capacity that will increase inherent resilience in the long run. Additionally, counties and communities must recognize the importance of census tract data and their value towards their community development. Census tract data is gathered not just for enumeration, but also to provide communities with the resources and the funding that they need, such as infrastructure grants. The results of this study might persuade key stakeholders that it is important to invest in programs that might seem trivial now, such as encouraging residents to participate in the upcoming Census or CERT trainings.

CHAPTER V

CONCLUSION

Conclusion and Limitations

The purpose of this study is to measure resiliency and to track changes in resilience in the Rio Grande Valley from 2010 to 2017. By focusing on the census tract level, findings show resiliency and its changes in each county. The construction and implantation of the Rio Grande Valley Resiliency Index support the results obtained by Susan Cutter's original study: the counties along the U.S-Mexico border are among the least resilient in the United States. This study has some positive impacts on policy. By examining the inherent resilience findings, stakeholders and decision-makers could evaluate their own communities and implement policies to increase resilience for their constituents. This would require not just an input from the local government, but from other key stakeholders such as local school, churches, emergency management offices and local businesses. Working together as a whole community will ensure that all areas of resilience are considered, therefore building more resilient communities for the next 10 years.

With any study there are limitation, there first of which due to only using publicly available data. Most of the data used was current up to 2017, but it would have been beneficial to have data from 2018 or 2019. Many of the variables that were absent from this study were due to data not being accessible. There were several census tracts from Hidalgo, Willacy and

Cameron that did not have data sets collected by the Census Bureau, so those had to be omitted. Time and monetary resources will always be a limitation. With enough time and resources, the Rio Grande Valley Resilience Index would potentially have been more complete and well rounded. There are many ways to measure disaster resilience and this study focused on the inherent quantitative aspect, but as we know, quantitative data does not give personal accounts to what could be impacting each census tract. For further research, it would be important to combine both qualitative and quantitative data to have a more well-rounded approach to disaster resilience in the Rio Grande Valley.

Another potential limitation is in the way the Rio Grande Valley was analyzed. In this study, census tracts were the units of analysis. In hindsight, it is unfair to compare census tracts in rural areas to those in metropolitan areas. Although some variables in the RGVRI were adjusted to account for this fact, it would be beneficial for future research to study resilience within metropolitan areas in the Rio Grande Valley. Metropolitan areas are where most decision-making takes place and where most changes are implemented; it would be interesting to see if the resilience of place is different. Future research should also look into analyzing more variables for census tracts. Census tracts are what the census uses to determine what areas get more financial support for the following 10 years. It would be important for jurisdictions to focus in compiling census tract data, so that they can at least use it for their own benefit internally and start making positive changes within their own communities.

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BIOGRAPHICAL SKETCH

Alma R. Provencio, who is a first-generation college graduate, received a B.A in Geography in 2015 from Villanova University. In December 2019, she obtained an M.A in Disaster Studies from the University of Texas -Rio Grande Valley. Ms. Provencio is currently working as the GIS Manager, Engineering Department for the City of Pharr.

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