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Temporal and spatial change in disaster resilience in US counties, 2010–2015*

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ABSTRACT
The allure of disaster resilience studies continues to garner interest by policy makers and academics alike. While there are advances in assessing communities' resilience to natural hazards at different scales, monitoring changes in resilience lags behind. This paper updates the 2010 Baseline Resilience Index for Communities (BRIC) using the six different domains of disaster resilience. The purpose is to test for significant spatial and temporal change in county index values by providing a comparative assessment of increased or decreased resilience over a five-year period across the U.S. The significance of monitoring change is to empirically demonstrate the dynamic nature of resilience and the causal mechanisms that lead to increasing or decreasing resilience in places. Such evidence sets the stage for implementing intervention policies or programs designed to enhance disaster resilience. The national distribution of BRIC index values in 2015 is generally similar to the 2010 BRIC distribution, but there are some notable regional differences. For example, there is a decrease in resilience in the South, the Great Lakes states, and the Central U.S., with improved resilience in the west and Pacific Coast states. The individual domains of institutional resilience and community capital, have the highest and lowest level of variation, respectively.

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1. Introduction

Increasing policy and practitioner interest in resilience have facilitated efforts to develop measurement schemes to assess disaster resilience at community to regional scales. Such efforts range from the Rockefeller Foundation's 100 Resilient Cities (Rockefeller Foundation, 2017) to Robert Wood Johnson Foundation's Culture of Health program and its articulation with community resilience principals (Chandra et al., 2011; Plough et al., 2013) to FEMA's community resilience indicators (FEMA, 2016).

The landscape of disaster resilience measurement tools and approaches is quite messy as many researchers have noted (Beccari, 2016; Cutter, 2016a). Some of the approaches are place-specific such as urban (Rockefeller Foundation, 2017; UNISDR, 2017a) or rural areas (Cutter, Ash, & Emrich, 2016), while others take a broader spatial perspective but narrow

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*Data are available on the Hazards & Vulnerability Research Institute (HVRI) website: http://artsandsciences.sc.edu/geog/hvri/hvri-resources.

the measurement to one type of disaster causal agent such as flooding (Szoenyi et al., 2016) or one type of affected environment such as coastal (Sempier, Swann, Emmer, Sempier, & Schneider, 2010) or one specific sector such as critical infrastructure (Petit et al., 2013).

As the number of measurement schemes and tools proliferate, so too has the number of critiques of community resilience measurement (Linkov et al., 2013; Matyas & Pelling, 2015; Ostadtaghizadeh, Ardalan, Paton, Jabbari, & Khankeh, 2015; Sharifi, 2016). At present, the measurement critiques of resilience fall into five thematic areas:

(1) Basic operationalization of the concept with consistent and discrete variables (Sharifi, 2016);
(2) Prediction and validation of outcomes (Linkov et al., 2013)
(3) Scales and units of analysis including the spatial mismatch between local actions, responsibilities, and the processes that shape resilience at regional to global scales (MacKinnon & Derickson, 2013).
(4) Utilization of reductionist approaches to address resilience to what and resilience for whom (Cutter, 2016b; Weichselgartner & Kelman, 2015).
(5) Lack of dynamic approaches to measure changes over time and across space (Cutter, 2016b; Sharifi, 2016).

This paper addresses the last critique of resilience assessments by providing a time series of changes in resilience patterns. Employing a replication of the baseline resilience indicators for communities (BRIC) over two different time periods (2010 and 2015), the dynamic nature of community resilience is illustrated through an examination of spatial and temporal changes in the baseline and the drivers of increasing or decreasing resilience across U.S. counties.

2. Modeling resilience

There are many definitional concerns regarding the term resilience, which are quite variable depending on disciplinary perspective (humanities, social sciences, natural sciences, health sciences, or engineering), methodological approach (qualitative to quantitative), and theoretical orientation (e.g. positivism, realism, pragmatism, post-structuralism) (Alexander, 2013; Weichselgartner & Kelman, 2015). Even when narrowing down the term to focus on community resilience to disasters, it still remains a somewhat amorphous concept, although increasingly there are common elements that define what it means for a community to become resilient (Cutter, 2016a; Patel, Rogers, Amlot, & Rubin, 2017).

For this article, we use the definition put forward in the US National Academies report (USNAS, 2012, p. 1) which defines disaster resilience as 'the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events.' This policy-relevant definition is consistent with the one used by the UNISDR (2017b) as it develops indicators for the implementation of the Sendai Framework:

> "The ability of a system, community, or society exposed to hazards to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management."

2.1. BRIC – The Baseline Resilience Index for Communities

The BRIC measurement follows the theoretical framework of a place-based model for understanding community resilience to natural hazards, called Disaster Resilience of Place (DROP) model (Cutter et al., 2008). DROP conveys the relationship between the inherent resilience (e.g. pre-existing capabilities and assets that allow a community to function during non-crisis time periods) and the adaptive resilience (capacities and flexibility that allow communities to adjust and develop creative solutions to post-event problems) in places (Rose, 2007; Tierney & Bruneau, 2007). Both of these forms of resilience affect the ability of a community to recover from the event. BRIC, however, only measures the inherent resilience (pre-event) within communities. It does not measure the processes or strategies within communities for coping with, undertaking rapid change, or adapting to some adverse event or disturbance in both short and longer term contexts.

BRIC employs a capitals approach to understanding community disaster resilience. A capitals approach suggests that communities are integrated systems, made up of differing and intersecting subsystems (or capitals) – economic, social, natural, and so forth – all of which contribute to its functioning and well-being (USNAS, 2012). While the specific types of capitals may vary depending on the study, there is consistency in the overall types of capitals that influence disaster recovery – natural (environmental), built environment (physical), economic (financial), human, social, political, and cultural (Miles, 2015; NIST, 2016; Ritchie & Gill, 2011). There are six different capitals used as sub-indices in the construction of BRIC and 49 individual variables used to represent the capitals. The variables initially derived from and justified via the extant literature and were then thoroughly tested for their applicability for measuring each of the capitals (Cutter, Ash, & Emrich, 2014, 2016). For example, communities with relatively stable populations are more resilient institutionally, than those that have rapid population shifts which stress provision of government services such as water/sewage, public safety, and building inspections in rapidly growing communities, or significantly reduce such local government services in declining populations. Both situations (rapid growth or decline) stress a community and influence its capacity to respond to and recover from a disaster (Sherrieb, Norris, & Galea, 2010; USNAS, 2012). The variable (population change over previous five-year period) was used to capture such pre-existing conditions. In addition to their known importance in influencing disaster resilience, we used variables found in national databases and open data sources to insure consistency across study units and over time, ease of data collection, and replication. The variables and sub-index structure are as follows (Table 1): social (10 variables), economic (8 variables), community capital (7 variables), institutional (10 variables), housing /infrastructural (9 variables), and environmental (5 variables).

2.2. Data and methods

Data were gathered the same sources as the 2010 construction (Tables 1 and 2) with updates to 2015 or as close to that year as possible from the source data. As was the case for the 2010 BRIC, the primary data source for the 2015 BRIC update was the US Census Bureau's database and American Community Survey five-year estimates from 2010 to 2014. Updated data from American Red Cross and National Flood Insurance

Table 1. Indicator sets and variable descriptions (Cutter et al., 2014).

Resilience concept	Variable description
Social resilience	
Educational attainment equality	Absolute difference between % population over 25 with college education and % population over 25 with less than high school education (Inverted: more equality is more resilient)
Pre-retirement age	% Population below 65 years of age
Transportation Access	% Households with at least one vehicle
Communication capacity	% Households with telephone service available
English language competency	% Population proficient English speakers
Non-special needs	% Population without sensory, physical, or mental disability
Health insurance	% Population under age 65 with health insurance
Mental health support	Psychosocial support facilities per 10,000 persons
Food provisioning capacity	Food security rate
Physician access	Physicians per 10,000 persons
Economic resilience	
Homeownership	% Owner-occupied housing units
Employment rate	% Labor force employed
Race/ethnicity income equality	Gini coefficient (Inverted; more equality is more resilient)
Non-dependence on primary/tourism sectors	% Employees not in farming, fishing, forestry, extractive industry, or tourism
Gender income equality	Absolute difference between male and female median income (Inverted; more equality is more resilient)
Business size	Ratio of large to small businesses
Large retail-regional/national geographic distribution	Large retail stores per 10,000 persons
Federal employment	% Labor force employed by federal government
Community Capital resilience	
Place attachment-not recent immigrants	% Population not foreign-born persons who came to US within previous 5 years
Place attachment-native born residents	% Population born in state of current residence
Political engagement	% Voting age population participating in recent election
Social capital-religious organizations	# affiliated with a religious organization per 10,000 persons
Social capital-civic organizations	# civic organizations per 10,000 persons
Social capital-disaster volunteerism	# Red Cross volunteers per 10,000 persons
Citizen disaster preparedness and response skills	# Red Cross training workshop participants per 10,000 persons
Institutional resilience	
Mitigation spending	Ten year average per capita spending for mitigation projects
Flood insurance coverage	% Housing units covered by National Flood Insurance Program
Performance regimes-state capital	Distance from county seat to state capital (Inverted; closer is more resilient)
Performance regimes-nearest metro area	Distance from county seat to nearest county seat within a Metropolitan Statistical Area (Inverted; closer is more resilient)
Political & jurisdictional fragmentation	# governments and special districts per 10,000 persons (Inverted; less fragmented is more resilient)
Disaster aid experience	# Presidential Disaster Declarations divided by # of loss-causing hazard events for ten year period
Local disaster training	% Population in communities covered by Citizen Corps programs
Population stability	Population change over previous five-year period (Inverted; less change is more resilient)
Nuclear plant accident planning	% Population within 10 miles of nuclear power plant
Crop insurance coverage	Crop insurance policies per square mile
Housing/ Infrastructural resilience	
Sturdier housing types	% housing units not mobile homes
Temporary housing availability	% vacant housing units that are for rent
Medical care capacity	# hospital beds per 10,000 persons
Evacuation routes	Major road egress points per 10,000 persons
Housing stock construction quality	% housing units built prior to 1970 or after 2000
Temporary shelter availability	# hotels/motels per 10,000 persons
School restoration potential	# public schools per 10,000 persons
Industrial re-supply potential	Rail miles per square mile

(*Continued*)

Table 1. Continued.

Resilience concept	Variable description
High speed internet infrastructure	% Population with access to broadband internet service
Environmental resilience	
Local food suppliers	Farms marketing products through Community Supported Agriculture per 10,000 persons
Natural flood buffers	% Land in wetlands
Efficient energy use	Megawatt hours per energy consumer (Inverted; more efficient is more resilient)
Pervious surfaces	Average percent perviousness
Efficient water use	Water Supply Stress Index (Inverted; more efficient is more resilient)

Table 2. Data sources and period of coverage.

Dataset	Data Provider	Time period	
		2015 BRIC	2010 BRIC
United States Federal Government			
USA Counties Database	Census Bureau	2015	2007
Small Area Health Insurance Estimates		2014	2010
County Business Patterns		2014	2009–2010
Tiger/Line		2015	2010
Current Population Estimate		2010, 2015	2005, 2012
American Community Survey 5Year Estimates		2010–2014	2006–2010
Hazard Mitigation Grant Program	Federal Emergency Management Agency	2006–2015	2000–2009
Presidential Disaster Declarations Database		2006–2015	2000–2009
Citizen Corps Councils		2010	2010
National Flood Insurance Program		2015	2010
National Land Cover Dataset	US Geological Survey	2011	2006
National Atlas		2014	2010
Quarterly Census of Employment and Wages	Bureau of Labor Statistics	2015	2010
Census of Agriculture	Department of Agriculture	2012	2007
National Center for Education Statistics (NCES)	Department of Education	2014	2009–2010
Electricity Consumption	Energy Information Administration	2015	2010
Broadband Internet Access	Federal Communications Commission	2016	2010
Water Supply Stress Index	Forest Service	2015	2005
Nuclear Power Plants Database	Nuclear Regulatory Commission	2012	2010
Railroad Network	Oak Ridge National Laboratory	2014	2010
Academic/Non Profit			
Spatial Hazard Events and Losses Database for the US (SHELDUS)	Univ. South Carolina Hazards and Vulnerability Research Institute	2006–2015	2000–2009
Religious Congregations and Membership Study	Association of Religion Data Archives	2010	2010
Farm Subsidies	Environmental Working Group	2014	2010
Map the Meal Gap	Feeding America	2014	2010
2016 Presidential Election	Politico	2016	2012
Volunteers and Preparedness Training	American Red Cross	2016	2013
County Health Rankings and Roadmaps	Robert Wood Johnson Foundation & Univ. Wisconsin	2016	N/A
Million Dollar Database	Dun and Bradstreet	N/A	2010

Program were provided by personal contacts – the same as the previous version. The Hazard Events and Losses Database (SHELDUS) accessed through the Hazards and Vulnerability Research Institute (HVRI) at the University of South Carolina provided estimates of disaster aid experience. The Citizen Corps Councils database is no longer available online, hence the latest available data are from 2010. Overall, there are no major differences in data sources and format between 2010 and 2015 with the exception of the County

Health Ranking and Roadmaps database used in lieu of Dun and Bradstreet's Million Dollar Database (the original source data for the 2010 BRIC formulation).

The 2015 BRIC database includes 3,142 counties including Alaska and Hawaii. These states were not included in 2010 BRIC (which only contained the 3,108 counties in the conterminous U.S. because of limited data availability). Only one county unit (Bedford City, Virginia) appeared in 2010 BRIC but not in the 2015 version as it rejoined Bedford County in 2013.

Given the utilization of national sources, the data update for all counties is consistent in terms of temporal and spatial quality, with the geographic exceptions noted in the previous paragraph. While there was one substitution for a data source between 2010 and 2015, it is the authors opinion that this was minor and did not have any specific implications for the findings given the nature of the overall construction of the index (see below). The variables included in the time-series analysis represent the best and most current data available from national sources.

2.3. Data processing

The first step for processing the gathered data is to normalize and convert the raw count variables into percentages, averages, rates, or differences (Cutter et al., 2014). In order to normalize the variables, we use a min–max scaling of 0 to 1 for each indicator. Larger values (closer to 1) represent greater resilience according to the BRIC construction framework, so in some instances indicator values needed to be inverted to reflect this cardinality. The second step is to compute the value for each of the six resilience sub-indices by calculating the mean value in each sub-index. The overall 2015 BRIC score sums the six resilience sub-indices to create the final score. Resilience scores theoretically vary from zero to six indicating lower to higher resilience levels, respectively. Therefore, the final BRIC score provides a relative measure not an absolute measurement of resilience among places.

As was done for 2010 BRIC, we used Cronbach's alpha to test the internal consistency of the 2015 resilience index construction, given the addition of Alaska and Hawaii to the dataset. The alpha value for all the 49 indicators is 0.623, which is a moderate level of interrelatedness and close to the alpha value for 2010 index (0.65) (Cutter et al., 2014). As expected, there is little inter-item correlation among the sub-indices (Table 3) implying general independence from one another. Lastly, there was no significant inter-item covariance between indicators. Social and housing/infrastructural resilience variables are the

Table 3. Cronbach's alpha and inter-item correlation mean for each resilience category's indicators.

Resilience category	Number of indicators	Cronbach's alpha 2015	Inter-item correlation (mean) 2015	Cronbach's alpha 2010 BRIC
Social	10	0.470	0.077***	0.533
Economic	8	0.123	−0.005***	0.242
Community Capital	7	0.344	0.059***	0.317
Institutional	10	−0.117	0.003***	0.074
Housing/ Infrastructural	9	0.428	0.095***	0.411
Environmental	5	−0.126	−0.015***	−0.028
BRIC Total	49	0.623	0.023**	0.650

Based on the ANOVA test: *$p < .05$, **$p < .01$, and ***$p < .001$.

most internally consistent, and the environmental, economic and institutional variables are the least internally consistent, again as was found in the earlier construction of 2010 BRIC.

3. Disaster resilience in 2015

For the entire U.S. including Alaska and Hawaii, 2015 BRIC scores ranged from a minimum of 2.059 to the maximum value is 3.234, with a mean of 2.73 and a standard deviation of 0.147. The spatial distribution of BRIC scores is mapped using standard deviations (Figures 1 and 2). For visualization purposes, maps for Alaska and Hawaii appear separately (Figure 2).

The spatial patterns in 2015 are similar to 2010 BRIC for the continental US. Regionally, higher resilience values extend from the upper Midwest to western Ohio. Southern Louisiana also has very high resilience scores, a seemingly counter-intuitive finding explained below. The lowest resilience scores continue in the West, Southwest, Texas borderlands, and Appalachian counties. Pockets of low resilience also appear in Arkansas, southwestern Florida, eastern Texas, and in eastern Alabama. Alaskan counties have among the lowest resilience scores in the nation.

Resilience scores in each six categories vary statistically and spatially (Figures 2 and 3). Social resilience has a higher average compared to other categories (mean = 0.66), while housing/infrastructural resilience has the lowest average (mean = 0.26) and the most variation in scores (standard deviation of 0.059). The environmental resilience index has the least variation (standard deviation of 0.036).

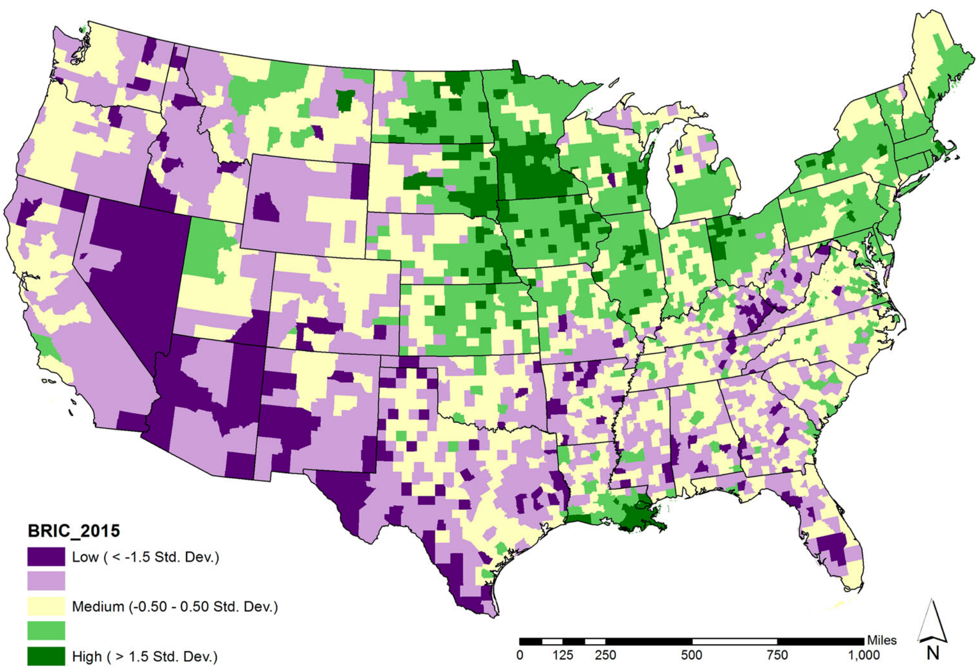

Figure 1. Disaster resilience index for the United States, 2015.

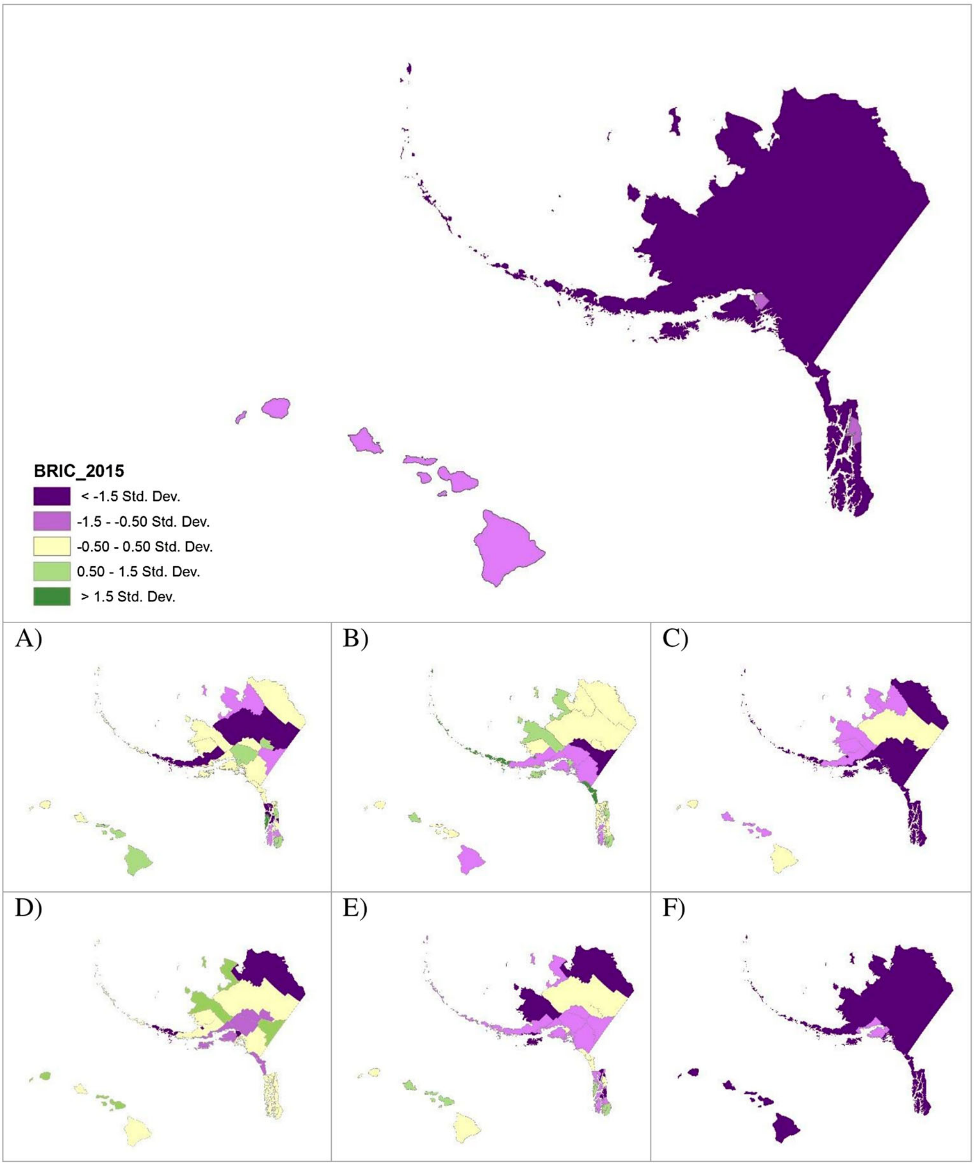

Figure 2. Resilience scores 2015 for Alaska and Hawaii, with scores for six categories: (A) social, (B) economic, (C) community capital, (D) institutional, (E) housing/infrastructural, and (F) environmental.

The spatial distribution of the drivers for the six sub-indexes shows roughly the same pattern as in 2010 (Cutter et al., 2014). For example, the northern counties of U.S. and especially the upper Midwest have more social resilience (Figure 3(A)). Also, the areas of upper Midwest and Northeast have higher economic resilience scores, while the opposite is true in many counties in the intermountain west (Figure 3(B)). The distribution of higher community capital scores (Figure 3(C)) in the South (Louisiana, Mississippi, Alabama) and the upper Midwest (Iowa, Minnesota, Wisconsin) is explained by large percentages of religious adherents as well as low mobility among residents (indicating strong levels of place

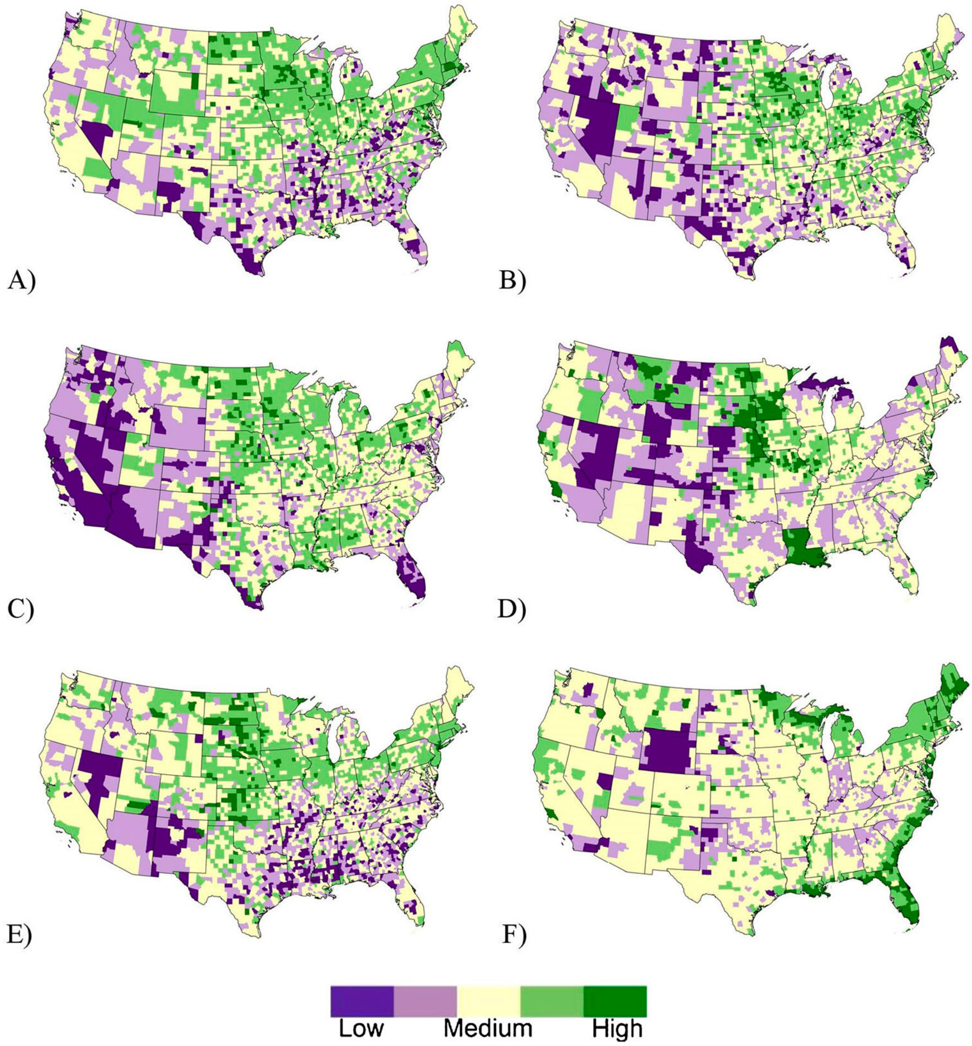

Figure 3. Resilience scores 2015 for the continental U.S. for six categories: (A) social, (B) economic, (C) community capital, (D) institutional, (E) housing/infrastructural, and (F) environmental. Data classified into low, medium, and high using the standard deviation method.

attachment). The western U.S. and Florida have the lowest level of community capital resilience, reflective of less civic engagement, volunteerism, and place attachment. The highest institutional resilience scores (Figure 3(D)) occur in the Midwest and in Louisiana, the latter explained by high mitigation spending as a direct consequence of large and frequent Presidential disaster declarations. In addition to mitigation spending, southern Louisiana also has a large percentage of housing covered by the National Flood Insurance Program (NFIP), another indicator of institutional resilience. The spatial pattern for housing/infrastructural resilience (Figure 3(E)) is similar to social resilience. Lastly, the environmental resilience is higher along the eastern coast and northeast (Figure 3(F)), while Wyoming scores lowest on environmental resilience due to lower levels of efficient energy use. Although the 2015 BRIC shows little spatial variation from the broad regional patterns in the 2010 version, there has been considerable change in individual counties that warrant further discussion.

Higher scores in the economic and institutional capital along with community capital characterize the most resilient regions. Lower scores on social and community capital appear in less resilient regions, but these differences are not statistically significant between the more resilient and less resilient places. When examining the ten most resilient counties, for example, institutional resilience is the primary driver, with eight counties rating in the 90th percentile on this sub-index (Table 4). The overall top-ranked Louisiana counties rank the highest in institutional resilience and environmental (especially in the percentage of land in wetlands). In addition, six counties of these top counties also appear in the top 90th percentile for community capital and economic capital. In contrast, the primary driver for the least resilient counties is the lack of community capital; all of the counties fall in the lowest 10th percentile on the sub-index. Similarly, eight of the least resilient counties are in the lowest percentile on social resilience. The ten least resilient counties rank in the lowest 10th percentile on at least three of the six sub-indices (Table 4). An interesting aspect of this is the case of Aleutians East, Alaska which is the least resilient county in the nation scoring the lowest in the country on community capital, yet it has the second highest score for economic resilience. This is largely due to higher median household incomes, racial and ethnic income equality, and a diversified economy (e.g. manufacturing including canning and processing of fish and fish products, management/administration, and natural resource extraction). The higher ranking in economic resilience appears as an outlier given the very low placement of the county in the other capitals – notably community and institutional – and is insufficient to improve the overall score given the additive nature of BRIC.

4. The geography of temporal change

The difference between 2010 and 2015 BRIC values range from −0.247 to 0.392 (mean= 0.084, standard deviation = 0.061), with Alaska and Hawaii deleted from the spatial change analysis due to the lack of 2010 BRIC scores. A one-way ANOVA indicates a statistically significant difference between 2010 and 2015 BRIC means ($F = 6.5$, $p < 0.05$). The BRIC scores for each 2010 and 2015 dataset were placed into three classes based on standard deviations from the yearly mean – low (<−0.5 Std. Dev.), medium (−0.5–0.5 Std. Dev.), and high (>0.5 Std. Dev.) and then assigned a numerical value of −1 for low, 0 for medium, and + 1 for high. The difference between values for 2010 and 2015 were calculated (values range from −2 to +2) and then mapped into a five class category based on the resilience change score. The majority of counties (79.2%) had no change in their resilience index score. For those that registered a change in overall score, approximately 11% of counties are more resilient and 9.5% less resilient. The computed changes show a decrease in resilience in the South, in the Great Lakes states, and in the Great Plains states, and improved resilience in the mountain west, Pacific Coast states, and portions of the South (Figure 4).

The Moran's I spatial autocorrelation test for spatial clustering was used to examine the spatial changes in overall resilience. The test showed a significant positive spatial correlation (Moran's $I = 0.22$, $z= 20.64$, $p < 0.05$) with a slight clustering of similar values. Clusters of counties with improved resilience were in the mountain west from Montana in the

Table 4. Counties with highest and lowest resilience scores, with scores and ranks for each category (ranks are in parenthesis).

Rank	County, State	2015 BRIC score	Social	Economic	Housing/Infrastructural	Community Capital	Institutional	Environmental
Most resilient								
1	St. Charles, LA	3.234	0.74 (53)	0.50 (254)	0.27 (1360)	0.41 (423)	0.64 (1)	0.66 (51)
2	St. Bernard, LA	3.150	0.72 (260)	0.46 (1224)	0.30 (646)	0.37 (1267)	0.56 (5)	0.70 (11)
3	St. John the Baptist, LA	3.139	0.68 (1346)	0.48 (597)	0.28 (1097)	0.39 (852)	0.63 (2)	0.66 (48)
4	Brown, MN	3.113	0.73 (95)	0.50 (202)	0.30 (688)	0.47 (19)	0.50 (52)	0.58 (944)
5	Putnam, OH	3.111	0.77 (5)	0.53 (13)	0.27 (1179)	0.48 (11)	0.44 (425)	0.58 (1195)
6	Red Lake, MN	3.097	0.71 (339)	0.52 (50)	0.27 (1263)	0.43 (158)	0.50 (72)	0.64 (102)
7	Nicollet, MN	3.095	0.73 (77)	0.53 (20)	0.27 (1199)	0.41 (370)	0.53 (17)	0.59 (840)
8	Eddy, ND	3.086	0.70 (642)	0.44 (2031)	0.35 (110)	0.55 (2)	0.46 (226)	0.55 (2524)
9	Fillmore, NE	3.084	0.70 (721)	0.47 (754)	0.33 (190)	0.57 (1)	0.43 (647)	0.55 (2749)
10	Waseca, MN	3.084	0.71 (337)	0.51 (116)	0.31 (430)	0.43 (157)	0.52 (25)	0.57 (1454)
Least resilient								
3142	Aleutians East, AK	2.059	0.53 (3121)	0.59 (2)	0.18 (2783)	0.04 (3142)	0.30 (3132)	0.39 (3128)
3141	Kalawao, HI	2.105	0.58 (2977)	0.34 (3113)	0.25 (1828)	0.13 (3140)	0.39 (1749)	0.38 (3131)
3140	North Slope, AK	2.143	0.65 (1874)	0.44 (1948)	0.13 (3070)	0.24 (3080)	0.32 (3107)	0.33 (3142)
3139	Denali, AK	2.145	0.68 (1269)	0.32 (3134)	0.21 (2450)	0.17 (3135)	0.37 (2772)	0.36 (3141)
3138	La Paz, AZ	2.156	0.55 (3079)	0.40 (2817)	0.13 (3076)	0.19 (3130)	0.37 (2775)	0.48 (3097)
3137	Presidio, TX	2.162	0.49 (3137)	0.40 (2792)	0.14 (3063)	0.21 (3119)	0.32 (3108)	0.57 (1564)
3136	Hudspeth, TX	2.193	0.48 (3139)	0.41 (2677)	0.16 (2960)	0.19 (3129)	0.35 (2977)	0.57 (1535)
3135	Esmeralda, NV	2.201	0.57 (3024)	0.30 (3140)	0.24 (2001)	0.20 (3128)	0.31 (3122)	0.56 (2505)
3134	Nye, NV	2.204	0.58 (2942)	0.37 (3047)	0.08 (3138)	0.24 (3077)	0.34 (3058)	0.56 (2376)
3133	Stewart, GA	2.248	0.49 (3138)	0.40 (2891)	0.14 (3037)	0.25 (3065)	0.39 (2034)	0.56 (2238)

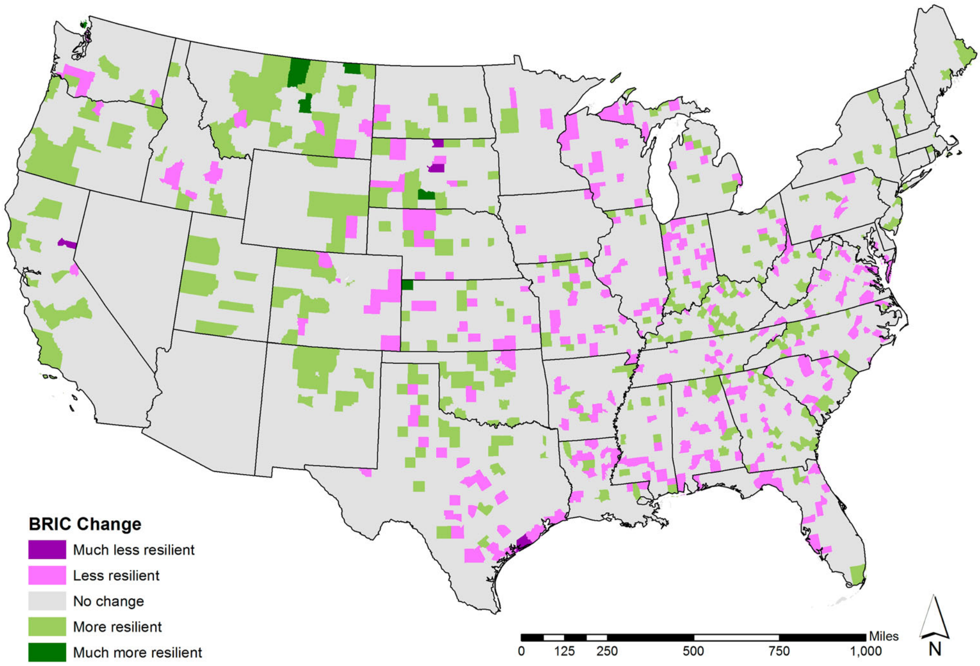

Figure 4. Temporal change in BRIC disaster resilience index for the United States, 2010–2015.

north to Arizona and New Mexico in the south. Counties with decreasing resilience clustered in the Deep South region stretching from Louisiana to the Florida panhandle. Overall, about 88.9% of counties do not have a significantly higher or lower value compared to their neighboring counties. However, there are 53 outliers (22 change from high–low, 31 change low–high), which represents about 1.7% of all counties. The outliers depicted in Figure 5 indicate counties where their resilience index has changed significantly more than their neighboring counties. Explanations for these changes in resilience appear in the next section.

5. Drivers of spatiotemporal change

To more fully explain the regional outliers and clusters of BRIC values from 2010 to 2015, the variability in each sub-index was calculated and mapped for the continental U.S. only (Figure 6). The greatest variation in the two time periods is seen in institutional resilience (Std. Dev = 0.60), and the least variation is in community capital resilience (Std. Dev = 0.49). The average normalized score for community capital resilience has the greater positive change (more resilient), and institutional resilience has the greater negative change (less resilient). On average, environmental and infrastructural sub-indices are more resilient in 2015 compared to 2010, and social and economic sub-indices are less resilient. Several individual variables influenced the temporal change in sub-indices. For example, the difference in internet access (infrastructural resilience) has the lowest average and greatest variation (Std. Dev= 0.29), reflecting more relative change of internet access among communities. The variation in this variable reflects differences in communities

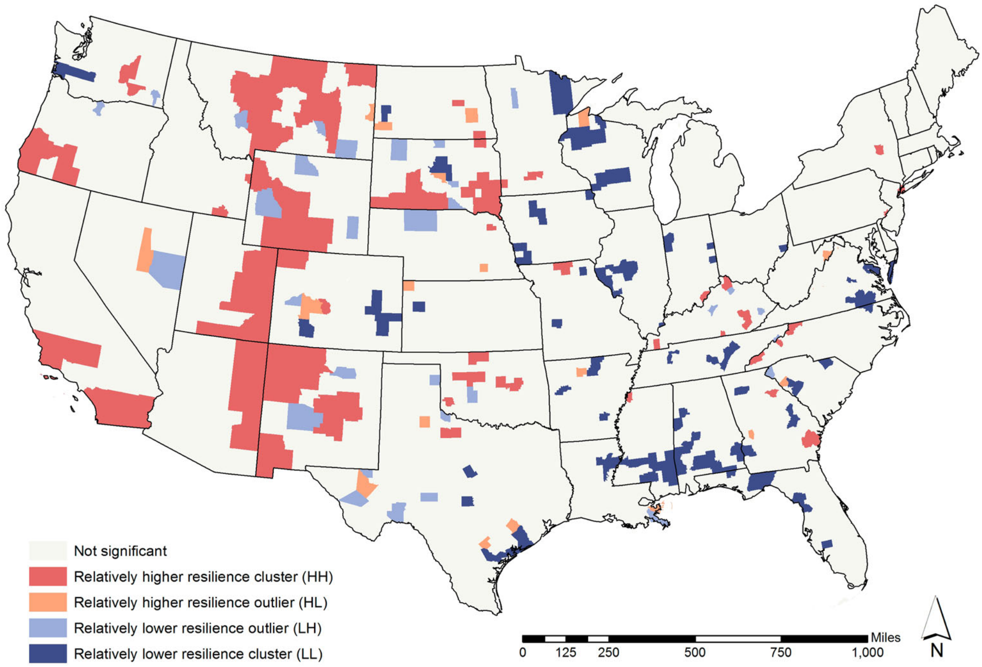

Figure 5. Spatial change in BRIC using spatial clusters and spatial outliers of BRIC from Moran's I, 2010–2015.

that met or failed to meet the advanced threshold for service set by the Federal Communications Commission with an existing speed benchmark is 25 Mbps/3 Mbps for fixed services (it was set at 3 Mbps/768 kbps fixed broadband in 2010) (FCC, 2016).

Another example is disaster aid experience (an input into institutional resilience), showing more Presidential Disaster Declarations per loss-causing events since 2010 in some counties. The average positive change in community capital is due to more political engagement and increases in number of Red Cross volunteers. Improvement in social resilience is partly a function of more people affiliating with religious organizations. Improvements in economic resilience are a function of more race/ethnicity income equality (economic resilience) in selected counties.

In order to compare the spatial distribution of clusters and outliers in each sub-index, the Moran's I spatial autocorrelation test was done for each resilience category (Table 5). The BRIC change data has a statistically significant positive spatial correlation and a

Table 5. Moran's I spatial autocorrelation test for the BRIC change data in each sub-index.

Resilience category	Moran's I	*z*-Score	*p*-Value
Social	0.28	26.20	<.05
Economic	0.07	6.79	<.05
Community Capital	0.17	15.57	<.05
Institutional	0.54	50.22	<.05
Housing/ Infrastructural	0.28	25.92	<.05
Environmental	0.44	41.39	<.05
2015 BRIC	0.22	20.64	<.05

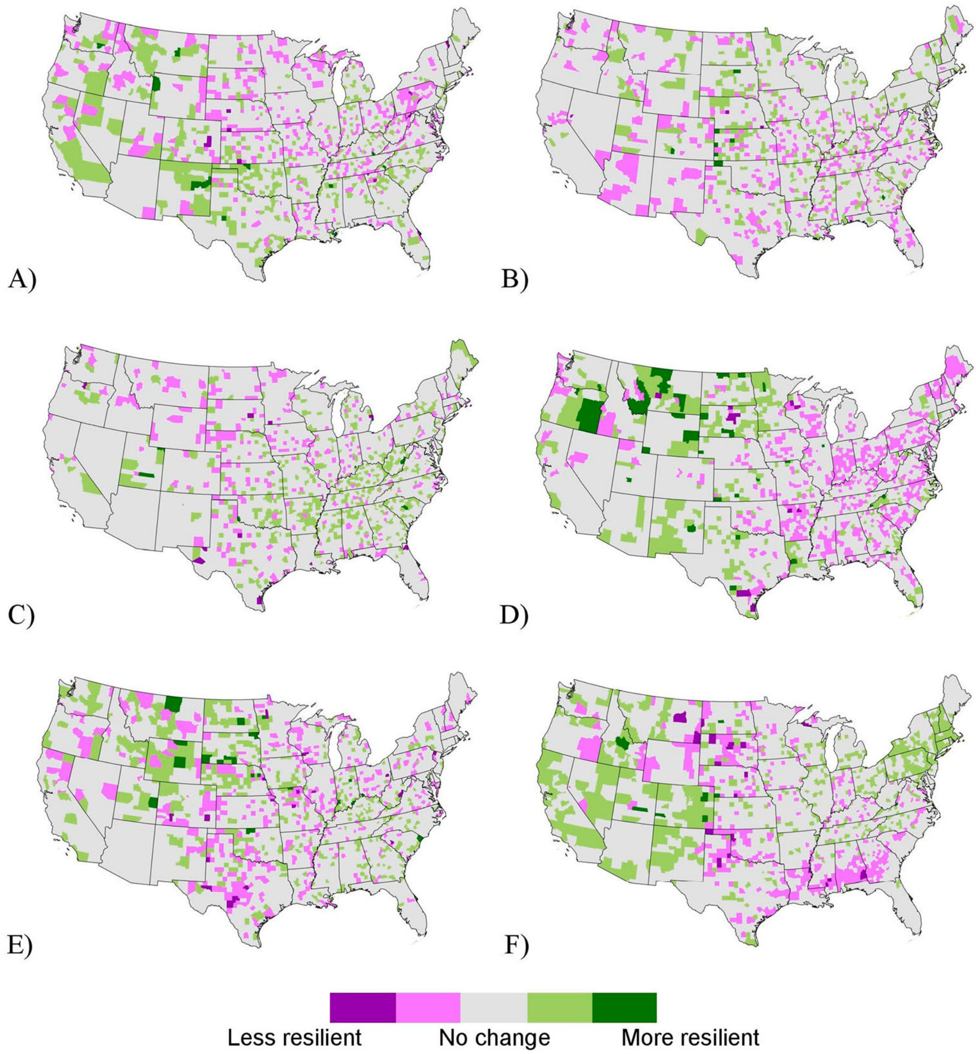

Figure 6. BRIC change 2010–2015 for six categories: (A) social, (B) economic, (C) community capital, (D) institutional, (E) housing/infrastructural, and (F) environmental. Data classified into low, medium, and high using the standard deviation method.

clustering of similar values in all sub-indices. However, the institutional resilience change (Moran's I = 0.54) is more spatially clustered than other sub-indices. On the other hand, the economic resilience change has the lowest level of spatially clustered values among sub-indices (Moran's I = 0.07) and there are no distinct patterns of clusters or outliers in this category. However, the number of outliers (high–low and low–high) in the economic resilience change includes 74 counties (2.4% of all counties), which is more than other categories and illustrates communities with drastic change from 2010 to 2015 in their economic resilience.

The counties exhibiting the most change in their BRIC scores (change values of −2 much less resilient; +2 much more resilient) are shown in Table 6 (and Figure 4). Counties that

Table 6. Counties with highest variation, with differences between 2010 and 2015 scores in each category and their five level class in parenthesis (−2 to +2).

County, state	BRIC difference	Social	Economic	Housing/ infrastructural	Community capital	Institutional	Environmental
Much less resilient (Score class −2)							
Sully County, SD	−0.192	0.022 (0)	0.042 (0)	0.017 (1)	0.011 (0)	−0.10 (−2)	−0.18 (−2)
Campbell County, SD	−0.169	−0.02 (−1)	−0.02 (0)	0.023 (0)	0.005 (0)	−0.09 (−2)	−0.05 (−1)
Richmond County, VA	−0.164	−0.10 (−2)	0.035 (0)	−0.06 (0)	0.001 (0)	−0.006 (−1)	−0.02 (−1)
Matagorda County, TX	−0.131	0.018 (0)	0.071 (0)	−0.05 (−1)	−0.14 (−1)	0.027 (0)	−0.04 (−1)
Sierra County, CA	−0.080	−0.02 (−1)	0.025 (−1)	−0.10 (−1)	−0.01 (0)	0.016 (0)	0.019 (1)
Much more resilient (Score class + 2)							
Mellette County, SD	0.357	−0.01 (0)	0.086 (1)	0.120 (2)	0.017 (0)	0.082 (2)	0.064 (1)
Petroleum County, MT	0.353	0.107 (2)	0.098 (0)	0.072 (1)	−0.01 (−1)	0.102 (1)	−0.01 (0)
Daniels County, MT	0.346	0.057 (0)	0.077 (1)	0.111 (0)	−0.003 (0)	0.147 (0)	−0.04 (−1)
Lexington city, VA	0.308	0.134 (2)	0.068 (0)	0.010 (0)	0.050 (1)	0.017 (0)	0.026 (0)
Blaine County, MT	0.286	0.015 (0)	0.069 (1)	0.090 (2)	−0.01 (0)	0.105 (2)	0.019 (1)
San Juan County, WA	0.273	0.016 (0)	0.045 (0)	0.020 (0)	0.130 (1)	0.041 (0)	0.018 (0)
Cheyenne County, KS	0.265	0.013 (0)	0.125 (2)	−0.02 (−1)	−0.01 (−1)	0.048 (0)	0.117 (1)
Winchester city, VA	0.248	0.057 (1)	0.069 (1)	−0.01 (0)	0.082 (1)	0.017 (0)	0.033 (0)

became less resilient over the five-year period did so because of lower environmental, social and institutional scores. On the other hand, those counties that became more resilient improved in their economic, social, and institutional resilience compared to other counties. The 2015 resilience score for Sully County (2015 population 1,426) and Campbell County (2015 population 1,397) in South Dakota, for example, is lower than their score in 2010 due to reductions in the environmental and institutional resilience sub-indexes. Specifically, the loss of resilience is a reflection of less efficient energy use, fewer local food suppliers, less mitigation spending, and less crop insurance coverage in these two counties. Richmond County, Virginia (population 8,774) also became less resilient due to a reduction in its social and environmental resilience, specifically less equality in educational attainment and less efficient energy use. The reduction in resilience in Sierra County, California (population 2,947), on the other hand, was driven by less health insurance coverage and access to physicians, as well as decreased employment and homeownership rates.

The resilience score of Mellette County in South Dakota has the greatest positive change in all counties since 2010, based on changes in institutional and infrastructural resilience – a function of more internet access, disaster aid experience, and population stability (population 2,102). The improved score of Petroleum County (population 489) in Montana is reflective of greater social, infrastructural and institutional resilience in the five-year period. The county improved its disaster resilience due to improved health insurance coverage, more mental health support facilities, more disaster aid experience, and sturdier housing types. Greater economic resilience is the main factor for the improved score in Daniels County, Montana (population 1,755), primarily due to higher employment rates and more income equality since 2010.

Overall, the significant improvement in resilience among those counties with the greatest change results from increases in economic resilience and institutional resilience from 2010–2015. However, when examined individually as mentioned above, the capitals driving the change are quite variable for individual places as expected. The same is true for those counties experiencing the greatest decline in resilience.

6. Discussion

In this study of 2015 BRIC, the regional concentration of highest and lowest resilience index values is similar to the 2010 BRIC distribution for the continental US. While, the distribution of changes in the BRIC index from 2010 to 2015 indicates a decrease in resilience in the South, in the Great Lakes states, and in the Central US states, improved resilience occurred in the mountain west and Pacific Coast states. The drivers of change in improving resilience were institutional variables, particularly more political engagement as measured by the percentage of the voting age population participating in the 2016 election. Improvements in internet access also account for greater resilience among counties. Among the six sub-indexes, the most stable element in resilience change is community capital which shows minimal variability over the 5-year time period. On the other hand, institutional resilience appears to be the most volatile with the highest variability among all the sub-indexes. Specifically, differences in the five-year average of mitigation spending, flood and crop insurance coverage, population stability, and disaster-aid experience offer concrete explanations as to why some counties increase or decrease in their resilience. Clearly, we need more detailed analyses at the local scale to completely understand the landscape of resilience for local places.

The temporal analysis suggests a measurable improvement in overall in BRIC scores during the five-years. The community capital and housing/infrastructure capital remain static during the time-frame, while environmental resilience has declined slightly. The policy implications of this finding are insightful. For example, the community capital appears to be an ascribed characteristic of communities that is not easily changed because it relates to the basic core culture, essence, and ethos of communities. If this capital is not present within a community, there is little that national or state-level policies can do to improve this. Another capital that remains somewhat constant is housing/infrastructure resilience, although it was slightly lower in 2015 than in 2010. Interestingly, the housing and infrastructure in many communities is built out, that is, there is little opportunity to change many of the variables within the sub-index such as rail miles per square mile, or the per capita number of schools, medical care facilities, or hotels/motels in such a short time frame (5 years). The one variable that did change within the sub-index was access to broadband internet as noted previously.

More opportunities for change appear in the social, economic, and institutional capital. Often predicated on external (national) policies implemented at state levels, improvements in educational equality (compulsory education), provision of affordable health insurance, disaster insurance coverage (crop and flood), and mitigation spending are all dependent on federal resources sent to states and counties. The receipt of federal disaster assistance (post-event response and longer term recovery) improves institutional resilience as seen by the relatively high overall resilience in scores like southern Louisiana. Such financial disaster assistance also may help stimulate local economies post-event that are otherwise ailing by improving employment rates, incomes, and changes in employment sectors. There is considerable speculation in the literature on the role of disasters (and the resources that flow from Presidential Disaster Declarations) as economic engines, although this is has not been systematically addressed (Strobl, 2011; Xiao, 2011).

Environmental resilience shows a decline nationally based on the last five years, but has both regional and local significance because of local land use and development regulations. The decrease in pervious surfaces is often due to development pressures and local decision-making about growth and prosperity. Locally-driven policies to restrict development especially in sensitive environments may be the most efficient way to improve environmental resilience, but such policies are controlled by municipal and/or unincorporated county jurisdictions, who may be averse to such restrictions, because of other priorities.

The field of disaster resilience measurement, especially in the US is still in the development stage with very few empirically-based studies at the national scale. This partially explains the descriptive nature of this paper in examining temporal and spatial changes in county-level disaster resilience. The lack of validation is an ongoing issue of concern, not only for this research but also for the disaster resilience field in general. For example, there are few studies that attempt validation of resilience metrics (Burton, 2015; Sherrieb et al., 2010) using external measures. Using Mississippi counties, Sherrieb et al. validated their capital measures – economic development, social – using survey data on collective efficacy (as a measure of capacities) and the Social Vulnerability Index (SoVI) in an effort to examine the county's ability to bounce back and reduce the physical and mental health problems after disasters. The other study, also focused on Mississippi examined the role of community resilience in predicting disparities in the temporal and spatial patterning of disaster recovery, finding that social and economic resilience were the primary drivers of recovery, five-years after Hurricane Katrina destroyed much of the Gulf Coast (Burton, 2015). Lastly, there have been no formal studies examining the validity of inherent resilience in moderating the impact of and recovery from disasters, although both the Sherrieb et al. (2010) and Burton (2015) studies suggest that the pre-existing resilience within communities does partially influence post-disaster outcomes in terms of recovery trajectories as well as reductions in health outcomes.

7. Conclusion

We cannot manage what we do not measure and this statement belies the policy relevance of resilience measurement. Yet, there is the fundamental issue of perspective – should we measure **what is** in order to establish some starting point by which to assess how various policies or interventions work to improve disaster resilience? Or should we measure **what should be** in order to predict a desired outcome (e.g. less deaths, fewer economic losses, faster recovery)? The latter brings up a number of ongoing and interesting issues starting with the very nature of the outcome – Resilience for whom? Resilience to what? These questions posit a differential in the assessment of the outcome that could have dramatically dissimilar results depending on for whom and to what. Such questions may or may not be amenable to statistical prediction. Moreover, focusing on predicted quantitative outcomes ignores the process role of resilience as a capacity building endeavor, its articulation best captured by qualitative methods.

The Baseline Resilience Index for Communities (BRIC) is a first approximation for measuring **what is** – documenting a baseline for estimating and comparing the communities' resilience to natural hazards, spatially and temporally. Community leaders and policy makers can monitor progress over time for each county, assess how a county compares to neighboring counties, identify the capitals contributing to higher or lower levels of resilience, and *de facto* show where improvements are possible. Such information provides a basis for longer term spatial (or development planning) in addition to emergency preparedness. BRIC provides a suitable descriptive and dynamic monitoring tool to identify larger-scale patterns and drivers of changes in disaster resilience. Whether at the individual county level or a larger regional scale, BRIC captures and describes the pre-existing inherent resilience within places. At a broad policy level BRIC is currently in use as part of the US Federal Emergency Management Agency's National Risk Index (USFEMA, 2017), an interactive tool designed for state and local officials to provide a more holistic picture of 'at risk communities.' The National Risk Index combines hazard likelihood, social vulnerability, built environment exposure, and community resilience into a baseline multi-hazard product at both the county and census-tract levels. The purpose is to provide the risk-based knowledge for inclusion in local, state, and federal mitigation plans. BRIC is the community resilience component in the index.

But at this juncture, the BRIC measurement does not address the discrepancies between local actions, roles and responsibilities of key stakeholders, and governance structures and capacities which influence the underlying processes of enhancing resilience that ultimately produce differential resilience patterns on the landscape that are evident today. More detailed and contextually specific analyses of local places are needed to address this concern and possible policy remedies for improvement. The findings presented here demonstrate the variability in disaster resilience patterns and that they do change over relatively small time periods. Many of the counties with the greatest change in scores – improving resilience or declining resilience – are sparsely populated with low densities. This could account for higher percentages of change given the low numbers. This aspect of the empirical measurement of change certainly warrants further attention.

The truism, all disasters are local implies that differences in exposure and vulnerability within a community means that the impacts are also variant within the affected region. It makes sense that disaster resilience is also locally variable and while national policies may set the stage or context for improvement, ultimately it is left to the community to articulate and implement resilience goals and ways to measure its progress in achieving them. The variations in and drivers of disaster resilience aptly illustrates that one size fits all, top-down (national to local) policy interventions to improve resilience become problematic at best, and ineffective at worst as it ignores the uniqueness of places and the willingness of communities to enhance their resilience to the next disaster coming their way.

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