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Prisoners of Scale: Downscaling Community Resilience Measurements for Enhanced Use

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Abstract: As improved data availability and disaster resilience knowledge help progress community resilience quantification schemes, spatial refinements of the associated empirical methods become increasingly crucial. Most existing empirically based indicators in the U.S. use county-level data, while qualitatively based schemes are more locally focused. The process of replicating resilience indices at a sub-county level includes a comprehensive study of existing databases, an evaluation of their conceptual relevance in the framework of resilience capitals, and finally, an analysis of the statistical significance and internal consistency of the developed metrics. Using the U.S. Gulf Coast region as a test case, this paper demonstrates the construction of a census tract-level resilience index based on BRIC (Baseline Resilience Indicators for Communities), called TBRIC. The final TBRIC construct gathers 65 variables into six resilience capitals: social, economic, community, institutional, infrastructural, and environmental. The statistical results of tract- and county-level BRIC comparisons highlight levels of divergence and convergence between the two measurement schemes and find higher reliability for the fine-scale results.

Keywords: resilience indicators; geographical scale; Gulf coast; community resilience

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1. Introduction

The concept of resilience appears in many fields including medicine, ecology, and engineering, and describes conditions of systems and their abilities to bounce back after external stressors or shocks [1]. Social-ecological resilience involves complex, adaptive systems and highlights the capacity to adapt or transform socio-ecological systems to unexpected changes in a manner that benefits human well-being [2]. Resilience in the context of hazards and disasters concentrates on the capacities of places and the people that live there to prepare for, respond to, recover from, and adapt to present and future loss-causing events. The focus on communities' disaster resilience in specific community types such as urban settings (definitions of urban resilience vary by discipline from socio-ecological systems to public health, to engineering; but simply imply the ability of an urban system to withstand shocks) [3–5], rural areas (highlighting the paradoxical nature of rural resilience, unique local cultures, and specific capacities of these communities) [6–8], or urban-rural place comparisons [9] has generated notable research advances. Understanding and measuring resilience is not simple, as the concept is multi-faceted, complex, and contextual [10]. It is also difficult to operationalize and translate resilience indicators into local community actions despite the increasing demand for such tools for utilization in hazards, climate change, and sustainability planning. Even in the application of resilience to the built environment (or socio-technical systems), a gap exists between theory and practice [11,12].

Moreover, there are no consistent or comparative empirically based resilience baselines by which communities can gauge their progress towards improving their resilience.

Overviews of disaster resilience indices highlight the wide range of applications for these empirically derived approaches for assessing community resilience [13–16], where drivers of resilience at the metropolitan, county, or community scales are quantitatively computed by employing secondary data and geospatial analytics [3]. One of the most consistently cited approaches is the Baseline Resilience Indicators for Communities (BRIC) index [17], a U.S. county-level comparative assessment of pre-existing community assets, capabilities, and attributes of resilience to natural hazards. BRIC enables a temporal and spatial assessment of changes in overall county resilience [18] and is now part of FEMA's National Risk Index natural hazards risk planning tool [19]. However, BRIC remains a county-level comparison and does not reflect the variations of resilience at the sub-county scale. In the U.S., geographic areas are organized in a geographic hierarchy, where counties are administrative and political subdivisions of states, and census tracts are statistical subdivisions of a county for which demographic data are collected. Only a finer-scale measurement can reflect variability at the sub-county scale. This limitation of the current BRIC provides the motivation for this paper. Therefore, we raise the question whether a fine-scale measurement scheme is achievable as a tool for communities to gauge inherent resilience variations through time at a local scale, and if so, what it would look like. Our purpose is to (1) assess the fidelity of downscaling CBRIC to the census tract scale (TBRIC), (2) test the relationship between CBRIC and TBRIC, and (3) reconfigure CBRIC by aggregating the new census tract data to county scales to test aggregation bias confronting the scale dependency issue. The BRIC index is re-named CBRIC for county-level BRIC, because in 2020 FEMA launched a pre-disaster mitigation grant program, Building Resilient Infrastructure and Communities (labeled BRIC). At the time the pre-disaster mitigation grant program was established, the BRIC tool (Baseline Resilience Indicators for Communities) was well-established and already incorporated into FEMA's National Risk Index. To avoid further confusion with the use of the acronym BRIC, the resilience index was changed to denote its enumeration unit (CBRIC for county and TBRIC for census tracts).

The processes that drive resilience varies between and among geographic scales, thus findings from one scale might not be applicable at a smaller or larger scale [20]. Downscaling data, which applies the same value to smaller units of an original larger unit, and aggregating data, which summarizes smaller units into a larger one (the scale effect), as well as adapting data from different political and historical boundaries (the zonal effect) results in the Modifiable Areal Unit Problem (MAUP) [21]. Resilience indicators can have implications in decision making by managers and planners that may not be familiar with the MAUP and lead to generalized inferences about an area based on biased results, or the ecological fallacy [22], thus becoming prisoners of scale. To illustrate the variable results the MAUP cautions against, Nelson and Brewer [23] aggregate and disaggregate median household income and cancer diagnosis rates across three scales, showing that less spatially autocorrelated data have a higher chance of showing misleading results at higher aggregations. Additionally, the uncertain geographic context problem (UGCoP) can occur from spatial uncertainty in the actual areas that influence the resilience of communities [24]. Data availability is a large limiting factor in mitigating the MAUP and UGCoP, but sub-county computations are more attainable now due to advancements in our understanding of disaster resilience, data becoming increasingly available, and improving methods.

At present, there have been relatively few efforts to empirically evaluate community resilience at a local scale. For example, Frazier et al. [25] used a set of weighted indicators identified by their focus group to measure a place-specific resilience index for Sarasota County, FL (which also uses BRIC indicators); while Hong et al. [26] analyzed mobility patterns in the context of Hurricane Harvey in Houston, TX, in 2017 as a neighborhood-level measure of resilience. However, these studies are often implemented for a small region or are compiled from datasets that are not publicly available, which complicates the replication of their method for other regions or a larger area. Empirically based resilience studies outside of the U.S. context include Cardoni et al. [27], who employed the PEOPLES analytical framework for a study in Italian regions; Ciccotti et al. [28], where they applied a participatory method to identify community resilience indicators for Brazilian municipalities; and Scherzer et al. [29] and Singh-Peterson et al. [30] who modified the BRIC analytical framework for regions in Norway and Queensland, Australia, respectively.

The Gulf Coast region extending from South Texas to Florida serves as the testbed for the TBRIC implementation in this study. Given the similarities in hazard experiences in the past two decades with repeated land-falling tropical storms and flooding in both urban and rural locations, significant property and crop losses, and demographic changes, this region has been ground zero for understanding the variability in resilience capacity. The authors also have considerable field experience working in this region [31], understanding resilience-focused longitudinal datasets covering the region [32], and participating in collaborative projects sponsored by the Gulf Research Program of the United States' National Academies of Science, Engineering, and Medicine (NASEM).

2. Materials and Methods

2.1. Index Construction Methodology

The county-level BRIC (CBRIC) is built upon the Disaster Resilience of Place (DROP) model and uses a hierarchical model with 49 quantitative variables selected from open-source government entities and matched to six broad resilience capitals with a system of systems view, including: Social, Economic, Infrastructural, Institutional, Community Capital, and Environmental [17]. Because CBRIC input variables have differing measurement units (percentages, numbers, dollars, rates) their values are transformed using linear min-max scaling (values ranging from 0 (the lowest or least resilient) to 1 (the highest or most resilient) for each variable). The transformed variables are summed for each capital, then averaged to compute a capital score. The six capital scores are then summed to produce an overall BRIC score [17] that theoretically ranges from zero to six. The results are both presented as resilience scores and resilience classes, where classes are defined by scores based on standard deviation from the mean (either in three or five categories). The method is relatively easy to compute making it readily available to the targeted audience: coastal planners and emergency managers.

In this sub-county reproduction labeled as census tract-level BRIC (TBRIC), we maintained the hierarchical model to remain methodologically consistent with CBRIC, and selected census tracts as our enumeration unit. However, the list of variables is altered to adapt to the scale change, both conceptually and statistically. In some instances, there were some changes in the input data in comparison with the county measures, and in some others, there are new and improved proxy variables available at the census tract-level but not county, and vice versa. In every instance, we attempted to use the best available data at the time for the variables at the census tract-level.

The intended set of variables is chosen based on an extensive literature review of representative resilience indicators for TBRIC composed of 72 candidates including those from CBRIC and others, where data have become more available. However, due to limitations in the data's availability, the implementation section and quantification of the indicators consists of 70 variables (a list of variables and quantification details for each are provided in Appendix A). The list of variables is tested for the robustness of the hierarchical methodology of the original BRIC for the census tract scale and further refined using a mixed-method approach including exploratory factor analysis (Principal Component Analysis, PCA), expert judgment (Pedigree analysis), and reliability testing (Cronbach's alpha).

In order to identify the structure of the relationship between the initial set of variables, an exploratory factor analysis using Principal Component Analysis (PCA) is used to test the 70 candidate indicators. Exploratory factor analysis is a variable reduction procedure that assumes a set of latent variables (i.e., factors) can explain the interrelationships among a larger set of variables. The PCA assumes no unique variance (i.e., common variance is equal to total variance explained). The results of PCA are then examined on their conceptual relevance as to whether the multi-dimensional factors represent meaningful resilience capitals. The statistical software SPSS Statistics 28 was used to perform the PCA tests.

The CBRIC methodology employs a hierarchical indexing model that has gone through reliability tests for internal consistency of resilience components, with a similar test performed to gauge the outcomes from census tract measures. The reliability test determines whether the variables were indeed measuring elements of the capital category for which they were initially intended based on the internal consistency results. The Cronbach's alpha (or coefficient alpha) originally developed by Cronbach in 1951 [33], is a widely used measure of internal consistency. The alpha coefficient of reliability ranges from zero to one, where higher values reflect higher co-variances between the variables and most likely assess the same underlying concept (i.e., alpha values of higher than 0.65 are more favorable). Reliability tests were performed for each of the six resilience components and the overall TBRIC score, using the SPSS Statistics 28 software.

To provide a guide for future replications and applications of TBRIC, an expert evaluation of all candidate variables using Pedigree Analysis was performed to qualitatively assess the conceptual basis and empirical contribution of the individual input parameters. All variables are rated in four different categories: applicability and relevance to local scales, statistical contribution and reliability, accessibility of data, and simplicity for replication. Apart from applicability which is a yes/no answer, the other categories have a rating of one to three (e.g., lower number suggesting less access, statistical contribution, and difficulty in replication). Each variable's score is the average of ratings given by evaluators. The range of the rating's epistemic uncertainty is also provided which is measured by the difference between evaluators' ratings divided by the number of evaluators. The coded evaluation form was shared individually with each member, using the Microsoft 365 Excel Spreadsheet Software, along with the rating guide. Once all members finished the rating, the first author summarized the evaluations, and members discussed the differentiation in a meeting to reach an agreement and decide whether variables needed to be discarded or not.

The final TBRIC construct distribution across the study area is tested through spatial statistics of hot spot analysis (i.e., Getis-Ord Gi* statistic) to determine where high/low resilience scores cluster spatially [34], using ArcGIS Pro 2.8 software. Additionally, TBRIC scores are compared with the available county-level BRIC (CBRIC), by aggregating TBRIC scores to parallel with CBRIC, and vice versa (i.e., disaggregating CBRIC to compare with TBRIC), to gauge the impact of scale variations in these measurement schemes, which is done using local spatial autocorrelation tests of Local Moran's I statistic, with a first-order queen contiguity spatial weight matrix and 999 permutations, in GeoDa 1.2 software [35].

2.2. Gulf Coast Region Implementation

Our study region covers coastal counties from five states: Texas, Louisiana, Mississippi, Alabama, and Florida (Northern Gulf Coast with the inclusion of the Atlantic side of Florida). The 196 counties in this study region, defined by National Oceanic and Atmospheric Administration (NOAA) as coastal counties [36], include 7239 census tracts (census tracts with zero population or housing are removed for data analysis). Identifying compatible and uniform data spanning the five states posed a challenge; therefore, we relied as much as possible on national rather than state-level data at sub-county scales to minimally control for systematic errors in source data including data quality and coverage. Data availability was best at the census tract (or equivalent enumeration unit) level and generally covered timeframes from 2017 to 2021 [37]. In cases where a variable's data did not conform to census tract boundaries (i.e., wetlands, flood risk, etc.), spatial analysis strategies were employed to ensure that the data was represented in the best possible manner. In some cases, a variable's data may have been available at the zip code (ZCTA) level rather than the census tract-level. This limitation was accounted for with a basic geoprocessing of the census tracts within that ZCTA to assign data as correctly as possible.

The time frame goal for variable data was to capture the most recent and most reliable data possible.

3. Index Construction Results

3.1. Exploratory Factor Analysis

The exploratory factor analysis is performed through a PCA analysis for 70 variables from the initial candidate list (Appendix A) since the variables for urban flooding and incorporated areas were not calculated due to a lack of consistent spatial data for the study region. The variance explained by the 70 variables is 66.4% with 16 factors based on eigenvalues greater than 1.0. However, according to the scree plot, the components could be limited to 7~8 factors (where the variance is not changing significantly), and the variance explained would be 52.1% if the number of factors to extract is limited to eight (Table 1).

Table 1. PCA analysis results (with eight components) and identified components for 70 initial variables of TBRIC.

Component	% Variance Explained	Dominant Variables *	Component Loading
1	17.469	Mitigation spending	0.992
		Emergency services (police/fire)	0.984
		Civic involvement	0.979
		Building permits	0.971
		Temporary housing availability	0.938
		Tax-exempt organizations	0.933
		Cultural heritage	0.907
		Local disaster training	0.880
		Art, entertainment, recreation centers	0.637
		Energy burden	−0.664
		Air polluting facilities	−0.965
		Toxic facilities	−0.976
		Water quality risk	−0.987
		FRS sites	−0.989
2	8.488	Educational equity	0.716
		Internet access (speed)	0.819
		Transportation access	0.690
		Internet access (connectivity)	0.614
		Physician access	0.573
		Special needs	0.576
		Health insurance coverage	0.560
3	7.921	Access/evacuation potential	0.756
		Medical access	0.660
		Housing type	0.549
		Housing capital	−0.504
		Natural buffers, wetlands	−0.618
		Pervious surfaces	−0.740
4	5.032	Language competency	0.844
		Place attachment (recent immigrants)	0.837
		Health insurance coverage	0.593
		Energy use	−0.632
5	4.616	Political engagement	0.494
		Air quality (particulate matter)	0.493
		Income to mortgage ratio	−0.661
		Water supply	−0.700
		Place attachment (nativity/tenure)	−0.746
6	3.231	Sheltering needs	0.977
		Multi-purpose retail	0.975
		Social assistance services	0.932
		Art, entertainment, recreation centers	0.756
7	2.567	Military employment	0.521
		Age	0.480
		Mitigation cost share	0.477
		Employment	−0.471
8	2.341	Business size II	0.578
		Business size I	0.562
		Sales rate	0.522

Note: * Only those variables with component loadings of 0.450 or higher are reported here.

The PCA did not result in factors that were conceptually sound and consistent with the contemporary understanding of community resilience and its drivers (Table 1). Whether this is a function of the variables themselves, the inconsistent measurement scale, or their representation in the study region is currently unknown and certainly worthy of further investigation at broader regional and national geographies.

3.2. Reliability Testing for Capitals

The initial reliability testing of the 70 input variables indicates low internal consistency for some of the capitals, particularly for economic and environmental resilience capitals (Table 2). This initial result reveals a need for further experimentation to eliminate or move the variables to other categories, to improve the internal consistency of the measurement of the respective capitals, and readjust the capital assignment in each capital based on the expert judgment results.

Table 2. The reliability test for the initial set of TBRIC components, Gulf Coast Study area.

Resilience Category	Number of Indicators	Initial Cronbach's Alpha TBRIC 2020
Social	10	0.425
Economic	13	−0.285
Community Capital	10	0.246
Institutional	11 *	0.113
Housing/Infrastructural	13	0.310
Environmental	13 **	−0.492

Note: * The initial number of variables for the Institutional capital is 12, but the variable for incorporated areas was not calculated due to a lack of data. ** The initial number of variables for the Environment component is 14, but the variable for Urban/flash flooding was not calculated due to data limitations.

3.3. Expert Judgement

The Pedigree analysis for all 72 considered variables (i.e., 70 measured variables and two variables with data availability constraints) is the result of expert opinion ratings (Appendix B). The judgements, gathered from our team members who were involved in the initial data collection, provided a subjective rating on each variable based on four criteria: applicability for the local scale, statistical contribution to the capital, data accessibility at the local scale, and simplicity for replication (rating guide provided at the bottom of the table).

4. TBRIC Implementation and Analysis

4.1. Final TBRIC Configuration

According to the results from the reliability tests and Pedigree scores, some individual variables were eliminated from further consideration as they did not perform well (e.g., did not meet a statistical threshold for retaining them). Additionally, when the variable could conceptually fit into a different capital, we tested its internal consistency and either retained or eliminated it based on the statistical test of significance. Seven variables were eliminated from further consideration (from the initial 72 variables), while four were assigned to a new capital (Table 3).

Table 3. Variables Eliminated or Reassigned to a Different Capital.

Variable	Decision	Rationale
Incorporated areas	Eliminated	Data limitation/unavailability
Nuclear accident planning	Eliminated	Conceptual inapplicability at local scale and statistical insignificance
Flood risk	Eliminated	Conceptual inapplicability at local scale and statistical insignificance
Urban flooding	Eliminated	Data limitation/unavailability
Air quality-particulate matter	Eliminated	Conceptual inapplicability at local scale and statistical insignificance
FRS sites	Eliminated	Statistical insignificance
Energy use	Eliminated	Statistical insignificance
Internet Access (speed)	Reassigned	Moved from infrastructural capital to social capital, based on concept and reliability test performance. Note, the other variable for internet access (number of actual connections per 1000 households) is kept in infrastructural.
Language competency	Reassigned	Moved from social capital to community capital, based on concept and reliability test performance.
Food access	Reassigned	Moved from social capital to infrastructural capital, based on concept and reliability test performance.
Income to mortgage ratio	Reassigned	Moved from economic capital to community capital, based on concept and reliability test performance.

The final construction of TBRIC utilizes 65 input variables categorized into six distinct resilience capitals. Even though the final construction improves the internal consistency of the resilience categories, only one capital—Social—reaches our goal of Cronbach's alpha = 0.70 (Table 4). Two others show some moderate levels of reliability (community capital and environmental capital), while housing/infrastructural and institutional capitals are weak in their reliability. The economic capital did not perform well.

Table 4. The reliability test for final TBRIC components, Gulf Coast Region (7239 census tracts).

Resilience Category	Number of Indicators	Cronbach's Alpha TBRIC	Inter-item Correlation (Mean)
Social	9	0.699	0.236 ***
Economic	12	−0.103	0.009 ***
Community Capital	12	0.499	0.086 ***
Institutional	10	0.213	0.087 ***
Housing/Infrastructural	13	0.283	0.034 ***
Environmental	9	0.410	0.114 ***
TBRIC Total	65	0.456	0.019 ***

Note: Based on the ANOVA test: *** $p < 0.001$.

The TBRIC scores have an average value of 2.75 across all census tracts in the study region (Figure 1), and score values vary from 2.06 (least resilient) (Tract 37.06 in Miami-Dade County, FL) to 3.205 (most resilient) (Tract 120 in Orleans Parish, LA). The geographical distribution of TBRIC shows considerable variability within and between counties as expected. The areas of higher resilience scores are clustered around Jacksonville, FL, and Baton Rouge, LA, while patterns of lower resilience scores are seen around Miami and Okeechobee in Florida, and in Southern Texas around McAllen (Figure 1). While most census tracts have medium levels of resilience, a significant percentage (7.13%) of the census tracts are in the low resilience category while another 5.59% are in the high resilience category, and there are significant hot spots of higher resilience in Louisiana and northern Florida (Figure 2a).

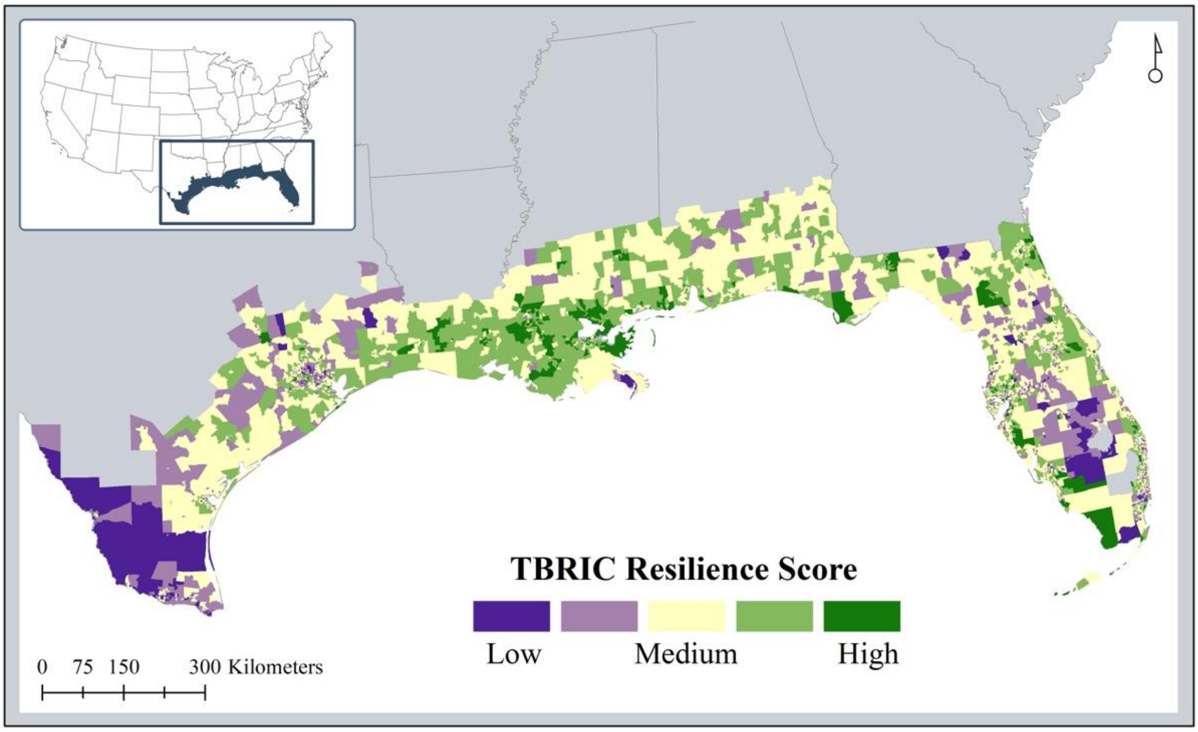

Figure 1. Distribution of TBRIC scores across census tracts in the Gulf Coast region.

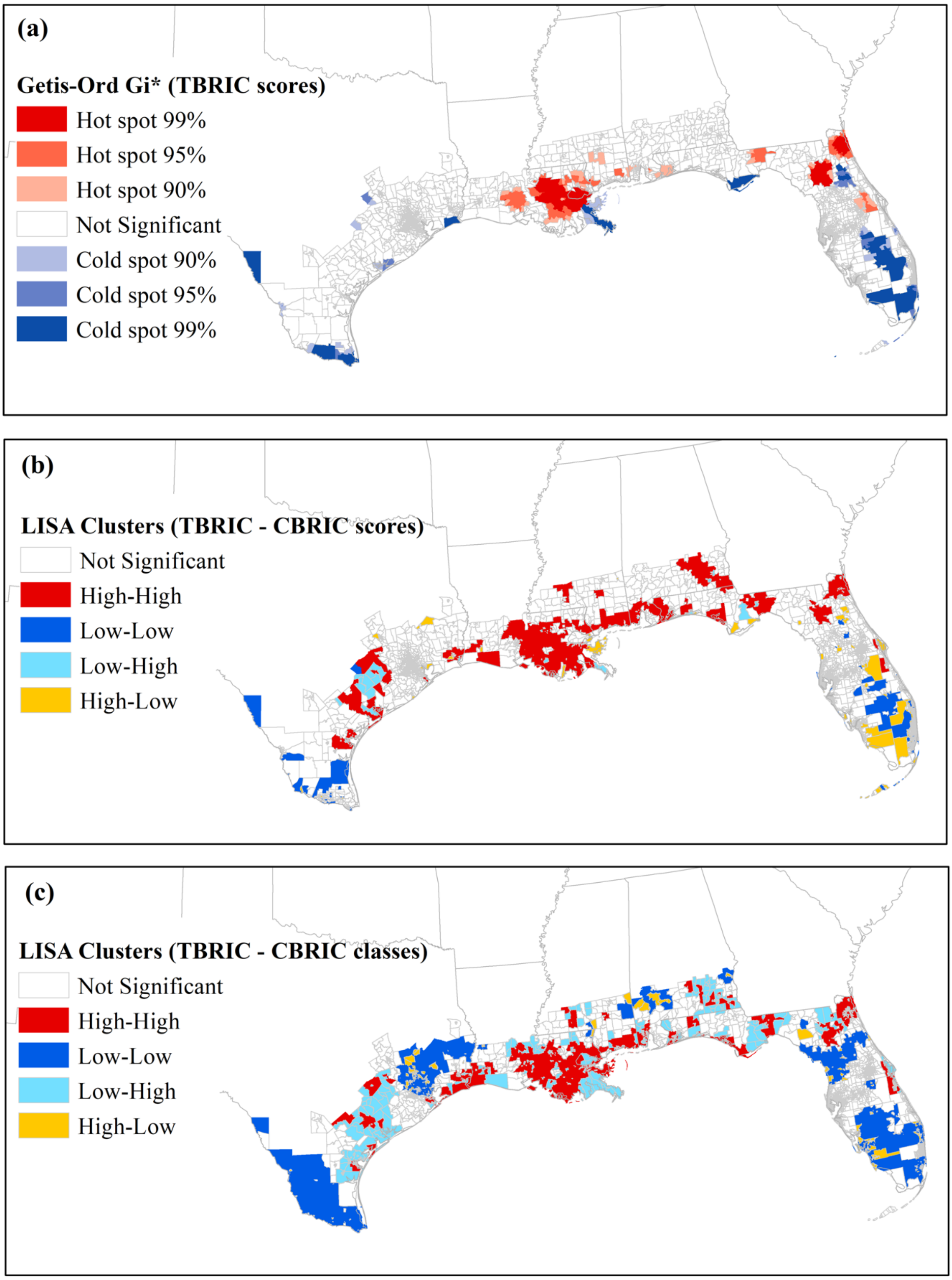

Figure 2. (**a**) Optimized hot spot analysis using the Getis-Ord Gi* Statistics for TBRIC scores; (**b**) Bivariate local Moran's I for TBRIC and CBRIC scores; and (**c**) Bivariate local Moran's I for TBRIC and CBRIC classes.

4.2. Scale Effects: TBRIC vs. CBRIC

Scale effects have significant policy implications, in addition to scientific interest. The measurements of BRIC scores at smaller or larger scales both have applications in comprehensive resilience schemes, mitigation projects, and recovery plans. Apart from the problems of MAUP and UGCoP that can lead to ecological fallacy, failing to select the appropriate scale for quantifying the resilience metrics may hinder the utility of these indicators. Since most of the mitigation and recovery policies are implemented locally, and according to the findings in this study on higher reliability of finer-scale measurements, TBRIC is more appropriate in the sub-national studies that employ BRIC in their analysis.

The economic capital did not perform well at the county scale or census tract scale for this study area, which is a result of negative covariance between equality variables and income/homeownership variables (in this region). The national study area for CBRIC 2015 [18] had greater overall internal consistency (Cronbach's alpha of 0.623) than the Gulf Coast study area with a Cronbach's alpha of 0.550 (Table 5), using the same input variables. The reliability results between resilience categories show consistency in the social, infrastructure, and community capitals between the national and Gulf Coast study region.

Table 5. The reliability test for CBRIC 2015 components, Gulf Coast Region (196 counties).

Resilience Category	Number of Indicators	Cronbach's Alpha CBRIC	Inter-Item Correlation (Mean)
Social	10	0.543	0.103 ***
Economic	8	−0.205	−0.016 ***
Community Capital	7	0.444	0.064 ***
Institutional	10	0.332	0.032 ***
Housing/Infrastructural	9	0.415	0.072 ***
Environmental	5	−0.266	−0.024 ***
CBRIC Total	49	0.550	0.025 ***

Note: Based on the ANOVA test: *** $p < 0.001$.

A test of correlation between TBRIC and CBRIC for the Gulf Coast region shows a moderate but significant association between the two score measures with Pearson's r of 0.483 ($p < 0.01$), and between the resilience score classes with Spearman's rho of 0.389 ($p < 0.01$) (resilience classes are based on standard deviation from the mean). The bivariate Moran's I clusters of TBRIC vs. CBRIC (with Queen Contiguity weights) for both scores (Figure 2b) and the score classes (Figure 2c) indicate that a majority of census tracts do not show a significant association between the two measures. However, in Southern Texas and Central Florida there are few Low-Low clusters (i.e., both indicators measured lower resilience in neighboring tracts), and some High-High clusters are observed in Louisiana, Northeastern Florida, and Southern Mississippi (i.e., both indicators measured higher resilience in neighboring tracts) (Figure 2a). In contrast with these convergent results, there are few sporadic divergent outliers (Figure 2b,c). It appears that both TBRIC and CBRIC identify the extremes of low or high resilience whether looking at the overall scores or the mapped five category classes.

Aggregating the TBRIC scores to the county-level by assigning the average of TBRIC values for their associated county suggests a rather strong significant correlation between the aggregated score and CBRIC 2015 (Spearman's rho = 0.796, $p < 0.01$). The correlation between classified scores (classes by standard deviation) also shows a similar result (Spearman's rho = 0.741, $p < 0.01$). However, if we disaggregate CBRIC to tract-level and normalize by population, the correlation with TBRIC is significant but weak (Spearman's rho = 0.234, $p < 0.01$). Additionally, if we assign the county-level scores directly to the tracts in each county, the relationship with TBRIC is moderate (Spearman's rho = 0.483, $p < 0.01$). Therefore, aggregating values to a larger scale provides a close approximation to the scores calculated at that level, but disaggregating values from the larger scale (proportional to population or not) does not capture the finer-scale values, which has been seen in cases of scale variations in other contexts. For example, Rabby et al. [38] found similar results when comparing the Social Vulnerability Index (SoVI) in the coastal area of Bangladesh. The downscaled SoVI (union to mouza level) had a weak correlation with the mouza level SoVI (Spearman's rho = 0.348, $p < 0.01$) and failed to categorize more than 9% of the highly vulnerable areas. In addition, Paegelow et al. [39] measured the vulnerability to water-related risks (i.e., flooding, and water quality and scarcity issues) in two different scales (regional/smaller and provincial/larger) in the Santiago Metropolitan Region, Chile, and found a significant difference among a quarter of the vulnerability scores, with the higher values in the provincial scale. There have been no tests of the scaling effects of BRIC to date.

5. Discussion and Conclusions

A comparison of reliability results at the census tract-level (TBRIC) and county-level scores (CBRIC) shows stronger internal consistency in the sub-county version for social and environmental components, while it is the opposite for the other components (Tables 4 and 5). However, the overall score shows a slightly lower level of internal consistency at the census tract-level for this study region. This difference could be due to (1) TBRIC input variables being modified and updated for 2020, and (2) CBRIC variables are from the original 2015 BRIC formulation. An updated version of CBRIC in future studies may show a different level of convergence/divergence, and some of the variances could be solely representative of this study region.

Regarding the limitations and constraints in this study, the reconstruction of BRIC methodology for the sub-county level proved to be a tedious and labor-intensive process that could potentially impede the timeliness of replications. Furthermore, data availability and quality were not consistent across the five states in the study region and required advanced geospatial analytical skills to overcome the discrepancies. Therefore, the calculation of a sub-county measure might be challenging for our targeted users (i.e., local planners) depending on their resources. On the bright side, local planners may have access to other refined metrics to substitute certain indicators. Regardless, the availability of BRIC measures at different scales will further help us envision the inter- and intra-county variability and understand the contributing factors to a community's resilience, which is essential in a comprehensive resilience plan.

The community resilience related policies in hazards management are predominantly local, and based on our findings, finer-scale measurements have higher reliability as opposed to downscaling county scores, thus application of TBRIC is encouraged in the sub-national studies that previously employed CBRIC in their analysis. The sub-county measurement of community resilience at the census tract-level for the Gulf Coast (TBRIC) study region is the first reconstruction of BRIC at a finer scale. Despite the arduous process of constructing a finer scale iteration of BRIC, the final index captured the invaluable perspective of sub-county variability and context. While the choice to operationalize either CBRIC or TBRIC would be highly dependent on the intended application and the target audience, the two scales can complement each other and provide two relative tools of resilience metrics. In particular, aggregating TBRIC to compile CBRIC gets you a correlation of 80%, showing a higher utility for local scales. CBRIC computation is easier and faster in comparison with TBRIC but is not reliable for sub-county parallels (correlation of 23% to 48%). There are no previous tests on scaling effects for BRIC but studies on vulnerability index scaling effects have found significant differences between scales, which can directly impact the communities if they are misclassified, and the metrics are used for mitigation policy implementations. Both CBRIC and TBRIC can highlight the resilience variability within a community and the contributing factors to the final resilience level. Replications of the TBRIC method for other regions in our next studies will further investigate the role of geographic scale, applicability, and the patterns of divergence and convergence of TBRIC and CBRIC measurements in other contexts.

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Appendix A

Table A1. Initial set of variables tested for TBRIC.

Variable	Calculation	Changes from Original
Social Resilience		
Educational equity	Percent population with college education or more	Definitional
Age	Percent population between 18 to 65 years old	Definitional
Transportation access	Percent households with at least one vehicle	
Communication capacity	Percent households with telephone service available	
Language competency	Percent population that are proficient English speakers	
Non-special needs	Percent population without a sensory, physical, or mental disability	
Health coverage	Percent of the population (under 65) with health insurance coverage	
Mental health	Psychosocial support facilities per 10 k population	
Food access	Food Insecurity Rate (population at 1 mile for urban areas and 10 miles for rural areas) (Inverted) *	New substitute
Physician access	Number of physicians per 1000 population	
Economic Resilience		
Homeownership	Percent owner-occupied housing units	
Employment	Percent labor force employed	
Income and equality (Race/Ethnicity)	GINI coefficient of income equality (Inverted) *	
Non-dependence on primary and tourism employment	Percent population not employed in farming, fishing, forestry, extractive, and tourism industries	
Income and equality (Gender)	Percent of absolute difference between male median annual earnings and female median annual earnings divided by annual income (Inverted) *	Computation
Business size I	Ratio of number of large (more than 100 employees) to small (less than 10 employees) businesses	
Business size II	Ratio of number of employees to number of establishments	New
Multi-purpose retail	Department stores per 1000 population	
Energy burden	Energy burden as % income (Inverted) *	New
Sales rate	Average sales volume divided by number of businesses	New
Building permits	Average number of building permits per 1000 population (5-year average)	New
Income to mortgage ratio	Median income to loan ratio	New
Military employment	Percent employed Armed Forces	New substitute
Institutional Resilience		
Mitigation spending	Average amount ($) mitigation projects for 10-year period per capita	
Mitigation cost share	Mitigation cost-share percentage (10-year average)	New
Flood insurance coverage	Percent of housing units covered by NFIP policies	
Incorporated areas	Percent incorporated	New
Jurisdictional uniformity	Number of governments & special districts per 10 k persons	
Local disaster training	Number of Citizen Corps programs (local and county) per 1000 people	
Governance connectivity and performance regimes	Proximity to county seat (Travel time from centroid of census tract to county seat; inverted; closer is more resilient) (Inverted) *	New substitute

Table A1. *Cont.*

Variable	Calculation	Changes from Original
Population Stability	Absolute value of population change base year/current year	
Nuclear accident planning	Census tracts within 10 miles of nuclear power plant (Binary 0/1)	
Social assistance services	Number of social assistance services per 1000 population	New
Community housing and emergency and relief services	Number of community housing and emergency and relief services per 1000 population	New
Emergency services	Number of emergency services per 1000 population	New
Housing/Infrastructural Resilience		
Housing type	Percent housing units that are not mobile homes	
Temporary housing availability	Vacant rental units per 1000 population	
Medical care capacity	Hospital beds per 1000 population; Buffer 10 mile for hospitals (to match food access buffer), measured by population of tracts within the buffer then assigned to the tracts, for buffers more than 1, the average is assigned to the underlying tract	Computation
Medical care access	Average travel time to hospitals from tract centroid	New
Access/Evacuation potential	Intersection density (n_real nodes/tract_area_sq miles)	New substitute
Housing age	Percent housing units built before 1970 or after 2000	New substitute
Sheltering needs	Number of hotels/motels per 1000 population	
School restoration potential	Number of public schools per 1000 population	
Bridge rating	Average sufficiency rating of all bridges within tract	New
Dam age	Average age of dams within tract (Inverted) *	New
Tax-exempt organizations	Tax-exempt organizations per 1000 population	New
Internet Access–connectivity	Number of actual connections per 1000 households	New
Internet Access–speed	Percent population with broadband internet subscription	New substitute
Community Capital		
Place attachment (not recent immigrants)	Population who are foreign-born and moved to US in previous 5 years per 1000 population	
Place attachment (nativity/tenure)	Percent population born in a state that still resides in that state	
Political engagement	Percent voter participation in a Presidential election (Precinct level data)	
Social capital—religion	Number of religious organizations per 1000 population	
Social capital—civic involvement	Number of civic organizations per 1000 population	
Social capital—volunteerism	AmeriCorps volunteers per 1000 population	New substitute
Community engagement	Number of art, entertainment, and recreation establishments per 1000 population	New
Place security/Evictions	Evictions per 1000 population (Inverted) *	New
Sense of security	Crime rate (property and violent crime), 5-year average, per 1000 population (Inverted) *	New
Cultural heritage	Museums, historical sites, and similar institutions per 1000 population	New
Environmental Resilience		
Natural buffers	Percent Land in wetlands	
Energy use	Energy Use (megawatt hours) per Energy Consumer	
Pervious surfaces	Average Percent Perviousness	
Water supply stress	Domestic per capita use self-supply (in gallons/person/day)	New substitute
Flood risk	Percent land in flood plain	New
Urban flooding	Average Flash Flood Potential Index (FFPI) value (Inverted) *	New
Air quality-particulate matter	Average PM value of particulates less than 2.5 (PM2.5) by census tract from 1998 to 2016 (Inverted) *	New
Toxic facilities	Number of Superfund or LQG hazardous waste facilities in census tract per 1000 population (Inverted) *	New
Federal Registry Service sites	All FRS sites in census tract per 1000 population (Inverted) *	New
Water quality risk	NPDES point source pollution facilities in census tract per 1000 population (Inverted) *	New
Air polluting facilities	Number of critical/hazardous air polluting facilities in census tract per 1000 population (Inverted) *	New
Change in pervious surfaces	Average Percent Perviousness change 2006–2016	New
Open space	Percent land in parks	New
Local food environment	Farmers' markets per 1000 population (2018)	New

Note:* Higher values indicate greater resilience (1 = high, 0 = low). Values were inverted ($1 - x$) when smaller values indicated greater resilience.

Appendix B

Table A2. Pedigree results by variable (72 initial variables).

Pedigree Results by Variable Including Average Rate and Range of Rating's Epistemic Uncertainty *				
Variable name	Applicability for local scale (1–2)	Statistical contribution (1–3)	Accessibility (1–3)	Simplicity for replication (1–3)
Educational equity	2 (±0)	3 (±0)	3 (±0)	3 (±0)
Age	2 (±0)	3 (±0)	3 (±0)	3 (±0)
Transportation access	2 (±0)	3 (±0)	3 (±0)	3 (±0)
Communication capacity	2 (±0)	3 (±0)	3 (±0)	3 (±0)
Language competency	2 (±0)	3 (±0)	3 (±0)	2.5 (±0.5)
Special needs	2 (±0)	3 (±0)	3 (±0)	3 (±0)
Health coverage	2 (±0)	3 (±0)	3 (±0)	3 (±0)
Mental health	2 (±0)	2.5 (±0.5)	3 (±0)	2.5 (±0.5)
Food access	2 (±0)	1.5 (±0.5)	3 (±0)	2.5 (±0.5)

Table A2. *Cont.*

Pedigree Results by Variable Including Average Rate and Range of Rating's Epistemic Uncertainty *				
Health access	2 (±0)	3 (±0)	3 (±0)	2.5 (±0.5)
Housing capital	2 (±0)	2.5 (±0.5)	3 (±0)	3 (±0)
Employment	2 (±0)	3 (±0)	3 (±0)	2.5 (±0.5)
Income and equality (Race/Ethnicity)	2 (±0)	1.5 (±0.5)	3 (±0)	3 (±0)
Non-dependence on primary/tourism employment	1.5 (±0.5)	2 (±0)	3 (±0)	2.5 (±0.5)
Income and equality (Gender)	2 (±0)	3 (±0)	3 (±0)	3 (±0)
Business size I	1.5 (±0.5)	3 (±0)	2.5 (±0.5)	2.5 (±0.5)
Business size II	1.5 (±0.5)	3 (±0)	2.5 (±0.5)	2.5 (±0.5)
Multi-purpose retail	1.5 (±0.5)	2 (±0)	2.5 (±0.5)	2.5 (±0.5)
Energy burden	2 (±0)	2.5 (±0.5)	3 (±0)	3 (±0)
Building permit	2 (±0)	2 (±0)	3 (±0)	2.5 (±0.5)
Sales rate	2 (±0)	3 (±0)	2.5 (±0.5)	2.5 (±0.5)
Income to mortgage ratio	2 (±0)	2 (±1)	3 (±0)	3 (±0)
Military employment	2 (±0)	2 (±0)	3 (±0)	3 (±0)
Mitigation spending	1.5 (±0.5)	3 (±0)	3 (±0)	2.5 (±0.5)
Mitigation cost share	1.5 (±0.5)	3 (±0)	3 (±0)	2.5 (±0.5)
Flood insurance coverage	1.5 (±0.5)	2 (±0)	3 (±0)	2.5 (±0.5)
Incorporated areas	1 (±0.5)	1 (±0.5)	1 (±0.5)	1 (±0.5)
Jurisdictional uniformity	1.5 (±0.5)	3 (±0)	2 (±0)	3 (±0)
Local disaster training	2 (±0)	3 (±0)	3 (±0)	2 (±0)
Performance regimes—Distance to county seat	2 (±0)	2 (±0)	1.5 (±0.5)	1 (±0)
Social assistance services	2 (±0)	3 (±0)	2 (±0)	2 (±0)
Community housing and emergency services	2 (±0)	3 (±0)	2 (±0)	2 (±0)
Population Stability	2 (±0)	3 (±0)	3 (±0)	3 (±0)
Nuclear Accident Planning	1 (±0)	1 (±0)	3 (±0)	2 (±0)
Emergency Services (Police/Fire)	2 (±0)	3 (±0)	3 (±0)	2 (±0)
Housing type	2 (±0)	3 (±0)	3 (±0)	3 (±0)
Temporary Housing Availability	2 (±0)	2.5 (±0.5)	3 (±0)	3 (±0)
Medical capacity	2 (±0)	2.5 (±0.5)	3 (±0)	1.5 (±0.5)
Medical access	2 (±0)	3 (±0)	2.5 (±0.5)	1 (±0)
Access/Evacuation potential	2 (±0)	3 (±0)	1 (±0)	1.5 (±0.5)
Housing age	2 (±0)	3 (±0)	3 (±0)	3 (±0)
Sheltering needs	2 (±0)	2.5 (±0.5)	2 (±0)	3 (±0)
Recovery potential	2 (±0)	2.5 (±0.5)	3 (±0)	2.5 (±0.5)
Bridge Rating	2 (±0)	2.5 (±0.5)	3 (±0)	2 (±0)
Dam Age	1.5 (±0.5)	2.5 (±0.5)	3 (±0)	2 (±0)
Tax-exempt organizations	2 (±0)	2.5 (±0.5)	2.5 (±0.5)	2.5 (±0.5)
Internet access (2 variables)	2 (±0)	2.5 (±0.5)	2 (±0)	2.5 (±0.5)
Place attachment (recent immigrants)	2 (±0)	2 (±1)	3 (±0)	3 (±0)
Place attachment (nativity/tenure)	1.5 (±0.5)	3 (±0)	3 (±0)	3 (±0)
Political engagement	1.5 (±0.5)	3 (±0)	3 (±0)	3 (±0)
Social capital—religion	1.5 (±0.5)	2.5 (±0.5)	1.5 (±0.5)	2.5 (±0.5)
Social capital—civic involvement	2 (±0)	3 (±0)	2 (±0)	3 (±0)
Social Capital—volunteerism	2 (±0)	2 (±0)	2 (±0)	3 (±0)
Art, entertainment, and recreation centers	2 (±0)	2.5 (±0.5)	2 (±0)	2.5 (±0.5)
Evictions	2 (±0)	2 (±0)	2 (±0)	3 (±0)
Sense of security	1.5 (±0.5)	3 (±0)	2.5 (±0.5)	2.5 (±0.5)
Cultural heritage	2 (±0)	2 (±0)	2 (±0)	3 (±0)
Natural buffers	1.5 (±0.5)	3 (±0)	2 (±1)	2 (±1)
Energy use	1.5 (±0.5)	1 (±0)	3 (±0)	3 (±0)
Pervious surfaces	2 (±0)	2 (±1)	2 (±0)	2 (±0)
Water supply stress	1.5 (±0.5)	2 (±0)	2.5 (±0.5)	2.5 (±0.5)
Flood risk	1.5 (±0.5)	1 (±0)	2 (±1)	2 (±1)
Urban flooding	1.5 (±0.5)	1 (±0)	1 (±0)	1 (±0)
Air quality-particulate matter	2 (±0)	1.5 (±0.5)	2.5 (±0.5)	2 (±1)
Toxic facilities	2 (±0)	2 (±0)	3 (±0)	2.5 (±0.5)
FRS sites	2 (±0)	2 (±1)	3 (±0)	2.5 (±0.5)
Water quality risk	2 (±0)	2.5 (±0.5)	3 (±0)	2.5 (±0.5)
Air polluting facilities	2 (±0)	2.5 (±0.5)	3 (±0)	2.5 (±0.5)
Change in pervious surfaces 2006–2016	2 (±0)	2.5 (±0.5)	2.5 (±0.5)	2.5 (±0.5)
Open space	2 (±0)	3 (±0)	2.5 (±0.5)	2.5 (±0.5)
Local food environment	2 (±0)	2.5 (±0.5)	3 (±0)	3 (±0)
* Rating guide	Applicability for local scale	Statistical contribution	Accessibility	Simplicity for replication
	1 (Not applicable) 2 (Applicable)	1 (No contribution) 2 (Low significance) 3 (Significant)	1 (Difficult to find/clean data) 2 (Time-consuming but available) 3 (Easily accessible)	1 (High computational skill required) 2 (Medium computational skill required) 3 (Easily computable)

The "*" refers to the rating guide (also marked with "*") at the bottom of the table.

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