



Variability of an adaptive capacity index to construction method and socio-economic context

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Abstract

Vulnerability, resilience, and adaptive capacity are key concepts for understanding the societal preparedness for, and impact of, natural hazards and environmental change. These metrics are often assessed through composite indicators, which are valued for the simplicity of their interpretation and use but are also subject to significant uncertainties associated with the construction process and input data choices. While adaptive capacity is frequently treated as a sub-component in broader vulnerability or resilience assessments, fewer studies focus specifically on adaptive capacity itself or aim to refine its assessment methods. This study addresses these gaps by (1) evaluating how an adaptive capacity composite index is shaped by the index construction process and the context of the sample; and (2) developing a methodology to create an index that synthesizes information from multiple index variants. Using the same methods and spatial scales (U.S. census tracts in the State of Kansas), this research compares the determinants of adaptive capacity across distinct socio-economic contexts—metro, non-metro, and farming counties. The findings confirm that adaptive capacity determinants and index scores vary based on construction method and context, challenging the “one-size-fits-all” approach even within a single state. We propose context-dependent composite indices that can be ensembled, offering a more tailored measure of adaptive capacity for different places that is still relevant to decision-makers operating at higher administrative levels.

Keywords Adaptive capacity · Composite indicators · Composite index validity · Uncertainty · Measurement

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1 Introduction

Climate-related natural hazards such as hurricanes, floods, droughts, extreme temperatures, and precipitation have well-documented negative impacts on human and environmental health, ecosystem productivity, and the economy. In 2023, the United States reported more than \$92 billion in climate-related disaster costs (NOAA 2024), and the global average precipitation is expected to increase by 7% for each degree of climate warming, contributing to greater societal impacts in the future (UCAR 2024). In the coming decades, the anthropogenic activities that lead to greenhouse gas emissions will continue to drive climate change (Houghton et al. 2017; Vincent 2007). However, the impacts of extreme weather events and climatic changes will vary across systems and communities depending upon their existing capacities to deal with and respond to such environmental changes. To better understand current capacities and anticipate future needs, numerous studies have assessed the vulnerability, resilience, and adaptive capacity (AC) of communities, ecosystems, and social-ecological systems, but these assessments are subject to uncertainty (Vincent 2007).

Vulnerability can be understood as the degree to which a system or its parts are likely to be negatively disturbed by a hazard or other type of exposure (Turner et al. 2003), and is multi-dimensional, often dependent upon physical, social, economic and environmental factors (United Nations Office for Disaster Risk Reduction (UNDRR), 2017b). Vulnerability is often conceptualized as being dependent on components of exposure and sensitivity to perturbations, as well as adaptive capacity (Adger 2006; Nelson et al. 2007). Meanwhile *resilience* comes from the Latin word *resilio* which means “to jump back” (Manyena 2006) and can be understood as the amount of change that a system can undergo or absorb without crossing a threshold that would change the function of the system (Berkes 2007; Holling 1973; Nelson et al. 2007). More recent interpretations suggest that resilience is the ability of a system to adapt, transform, recover, and build back better in a timely manner (United Nations Office for Disaster Risk Reduction (UNDRR), 2017a). When applied to communities, resilience includes the ability to cope with stress adding aspects such as learning, social capital, organization, and institutions (Adger 2006; Miller et al. 2010). *Adaptive capacity* can be defined as the latent ability of a system to prepare, adjust, and respond to expected or unexpected disturbances and is frequently seen to be a bridging concept between resilience and vulnerability (Douglass-Gallagher and Stuart 2019; Engle 2011; Smit & Wandel 2006). Adaptive capacity has also been recognized as a decision-making process in which actions taken maintain the capacity to overcome disturbances (Nelson et al. 2007). Others add that adaptive capacity is determined by the resources and processes from which adaptation actions can occur (Adger & Vincent 2005; Nelson 2011). The theoretical attributes of adaptive capacity, also recognized as capitals, are used in models and frameworks (Freduah et al. 2018; Nelson 2011) that aid in its assessment.

In the context of climate change, vulnerability, resilience, and adaptive capacity are frequently assessed using similar approaches including quantitative modeling, participatory research, and composite indices (Adger & Vincent 2005; Marzi et al. 2018; Miller et al. 2010; Spielman et al. 2020). Composite indices are often used and are based on theoretical assumptions about how specific factors influence adaptive capacity (Brooks et al. 2005; Engle 2011; Smit & Wandel 2006). While indicators typically refer to individual variables expected to influence a more complex or immeasurable idea, composite indices summarize complex and multidimensional issues by condensing large sets of indicators

into a single value (Tate 2012). Composite indices related to vulnerability, resilience, and adaptive capacity are used to simplify these complex ideas in a way that aids policymaker and practitioner decision-making (Moreira et al. 2021; Vincent 2007). Some of the widely known examples of composite indicators include the Human Development Index (HDI), the Environmental Performance Index (EPI), and the Gender Inequality Index (GII). One of the most popular indices that has inspired many others in the hazards and vulnerability fields is SoVi, the Social Vulnerability Index (Cutter 2024; Spielman et al. 2020). However, despite their utility, the soundness of using composite indices is contested in the research literature (Rufat et al. 2019; Spielman et al. 2020) in large part because the output scores are highly dependent upon their construction methods and subjective decisions (Moreira et al. 2021; Tate 2012; Urruty et al. 2016; Vincent 2007).

Unfortunately, many vulnerability, resilience, and adaptive capacity assessments using a composite index approach neglect issues of uncertainty and sensitivity (Moreira et al. 2021; Preston et al. 2011). A lack of information about potential variability in index values can undermine the confidence that can be placed in related assessment products and limit their utility. Past studies have investigated the sensitivity of vulnerability and resilience composite indices to differences in data scale (Schmidtlein et al. 2008; Spielman et al. 2020; Vincent 2007), geographic scope (Spielman et al. 2020), and various methodological choices such as indicator variable selection, weighting, and normalization (He et al. 2023; Tate 2013; Wiréhn et al. 2015).

However, adaptive capacity is often conceptualized as one of several sub-components that comprise vulnerability (Gillespie-Marthaler et al. 2019; Kelly and Adger 2000) or resilience (Turner et al. 2003), and therefore few studies specifically evaluate adaptive capacity assessment approaches (Engle 2011). To our knowledge, no previous studies on adaptive capacity composite indices have attempted to quantify how much adaptive capacity indices vary when different methods are used for construction or when they are applied in different contexts, such as those driven by socio-economic factors rather than geography (region). Assessing the variability and uncertainty in AC indices could help decision-makers be more confident in using adaptive capacity assessments by providing insight into the reliability of these indices. These insights can also help guide processes for merging and simplifying variants of AC composite indices, which can increase the relevance and applicability of composite indices for management (Burgass et al. 2017; Cutter et al. 2013).

This study aims (1) to determine the extent to which an adaptive capacity composite index is influenced by index construction method and socio-economic context; and (2) to develop a process that creates a composite index that leverages information from multiple index variants. Hence, this study quantifies the variability of adaptive capacity composite indices in Kansas, U.S., across four computational methods and identifies the key determinants of adaptive capacity in different samples, which we refer to as contexts. In addition, we propose an approach for merging multiple indices into a single simplified index that minimizes the variability across multiple index forms and then quantify the variability in this index across varying sample contexts. This paper moves the adaptive capacity field forward by identifying context-dependencies of adaptive capacity by using the same methods and scale of analysis (U.S census tracts) and comparing the determinants of adaptive capacity in different non-contiguous socio-economic contexts (metro, non-metro, and farming counties).

2 Methods

2.1 Study region

Our study focuses on the state of Kansas, which is in the U.S. Great Plains region. Agriculture is a crucial driver and one of the most significant contributors to Kansas' economic output (Kansas Department of Agriculture 2022). However, climate change presents unprecedented challenges for agricultural producers (Douglass-Gallagher and Stuart 2019). Kansas holds the second-highest cropland acreage of principal crops in the United States growing corn, wheat, and grain sorghum, in addition to beef production, and other nonfood crops that are pivotal in Kansas agriculture (Kansas Department of Agriculture 2022). Agriculture is expected to experience particularly severe climate change impacts in the Great Plains region (Douglass-Gallagher and Stuart 2019), and many manifestations of climate change are already evident. The years from 2001 to 2010 were the hottest period in the region's 110-year record, and future projections indicate a further increase in annual average temperatures (Melillo et al. 2014).

This region, including Kansas, is also expected to experience more intense and frequent droughts, longer duration of droughts, and changes in temperature patterns such as more heatwaves, fewer frosts, and reduced cold air outbreaks (Melillo et al. 2014; Ojima 2021). Over each decade from the 1890s to 2015, Kansas has become warmer—primarily driven by increasing minimum daily temperatures, though the wetness and dryness vary across the state given the state's geography and topology (Lin et al. 2017). In the past several decades, there have also been increasing occurrences of extreme high precipitation (Preota et al. 2025). These climate changes are likely to have an overall negative impact on crop yields (Onyekwelu, et al. 2025a; 2025b) and cause disruptions in the global food system (Araya et al. 2017; Obembe et al. 2023).

Additionally, warmer temperatures will lead to increased water consumption by crops (Obembe et al. 2023), further exacerbating the challenges faced by agricultural producers in the region (Melillo et al. 2014). Water withdrawals from the Kansas portion of the High Plains (Ogallala) Aquifer are mainly for corn, wheat, and soybean (Obembe et al. 2023). The aquifer has experienced a significant decline in water levels and Kansas has one of the most substantial decreases in the aquifer's water levels due to water withdrawals exceeding the volume of aquifer annual natural recharge (Butler et al. 2018)—essentially making the aquifer a nonrenewable resource (Sanderson and Hughes 2019). This decline in the aquifer's water levels adversely affects agricultural production in the region and threatens the region's economy (Deines et al. 2020) and the nation's food security (Anandhi and Kannan 2018). As droughts in Kansas become longer and occur with greater frequency, there is a need to adapt across the state, and therefore it is critical to assess adaptive capacity.

In short, climate events may threaten agriculture-based communities' livelihoods, food security, and economic viability, and the ability to adapt and respond to such changes and events may strongly impact their long-term viability and sustainability. Given the dominant role of agriculture in shaping local economies and land use (Harrison 1993; Loizou et al. 2019; Richards 2018) in Kansas, it is important to understand the drivers of adaptive capacity and how they may vary across different types of communities.

2.2 Defining socio-economic contexts

This study aims to expand on the notion that adaptive capacity depends on geographic context by suggesting that context is not necessarily bound within contiguous areas but may be represented by discontinuous places that share the same socio-economic drivers, which are often shaped by environmental factors. Although Kansas is known as an agriculture-dependent state, it has densely populated areas as well as dispersed, low population density areas. Similarly, some areas across the state depend more on agriculture than others. In addition to using all the counties in the state as a sample, this paper uses three additional sample extents composed of county subsets identified as either metro, non-metro, or farming-dependent counties as defined by the USDA County Typology 2015 edition (USDA ERS 2015).

Given the importance of agriculture as a source of livelihoods and economic activity in Kansas, we use the USDA Economic Research Service (ERS) county typology codes, which provide information on county conditions that capture economic base and social characteristics, to identify farming-dependent counties. For a county to be assigned as farming-dependent in the ERS typology codes, it must fall within a predetermined threshold for agricultural economic activity. Specifically, 16% or more of the county average annual employment and at least 25% of county earnings must be derived from farming activities (USDA ERS 2015). Since the general economic structure and demographic composition in rural counties vary significantly from urban counties, we apply the non-metro and metro status classifications from USDA ERS to non-farming dependent counties. The ERS classifies non-metro status as areas outside metropolitan areas with less than 50,000 residents (USDA ERS 2015). Out of the 105 counties in the state, 15 counties are classified as metro (465 census tracts), 44 counties are classified as non-metro (225 census tracts), and 46 counties are classified as farming (80 census tracts), as seen in Fig. 1.

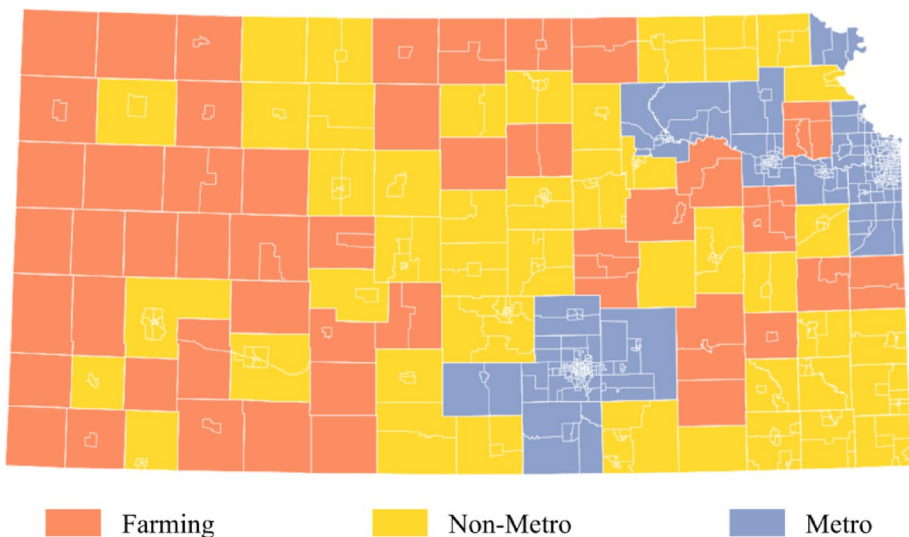


Fig. 1 Context classification for the state of Kansas from the USDA county typology 2015 edition (USDA ERS 2015)

2.3 Composite indices

Siders (2018) notes over a hundred methods for assessing adaptive capacity. However, composite indices are one of the most common approaches used (Vallury et al. 2022; Wiréhn et al. 2015) – and an approach that has seen broad applicability in decision-making (Beccari 2016; Becker et al. 2017). Building an index involves several steps, and decisions are made at each stage of construction, which introduces subjectivity into the modeling process (Tate 2012). The first step is to formulate a conceptual framework and select indicators, then choose a construction approach or structural design, transform or scale variables, assign weights, and finally aggregate the variables (Tate 2012).

Despite not having a single accepted method to assess adaptive capacity that allows comparison across studies, many variables are commonly and consistently used as indicators or proxies of adaptive capacity including access to resources, knowledge, and financial capacity (Mortreux & Barnett 2017). These indicators are related to theoretical attributes that contribute to adaptive capacity which are also recognized as capitals (Freduah et al. 2018; Nelson 2011). The capitals are often used as components of frameworks that represent the adaptive capacity of a system (Freduah et al. 2019). For example, the sustainable livelihoods framework (SLF), which is often used to assess AC, identifies five capitals (human, physical, natural, financial, and social) (Mortreux & Barnett 2017). Based on this five capital framework, Gupta and colleagues (2010) developed the Adaptive Capacity Wheel which showcases five dimensions of adaptive capacity each with a set of criteria. The Adaptive Capacity Wheel can be used to assess and inform social actors about the strengths, weaknesses, potential areas of discussion and reform around institutional systems. On the other hand, Flora's Community Capitals (Flora et al. 2015) highlights seven capitals (natural, cultural, human, social, political, financial, and built) that aid in understanding community interactions and resources that lead to community well-being. Often the capital-based frameworks allow for theoretically guided selection of indicators that align with adaptive capacity (Smit & Wandel 2006).

2.4 Variable selection and data integration

We used a deductive approach to select adaptive capacity variables guided by the capital frameworks discussed above. We selected and gathered data for thirty-one variables representing human, financial, and biophysical capitals (to see more details and factors, refer to Fig. 2) at the census tract (socioeconomic variables) and county level (agricultural variables). Due to a lack of available data for some capitals, we simplified the capital framework structure by combining social and human capitals under "human capital" and natural and built capitals under "biophysical capital." Cultural and political capitals were not explicitly included due to a lack of direct measures.

In our framework, we consider natural capital to include air, water, soil, vegetation, and weather conditions that influence and may be influenced by human activities. Built capital refers to the infrastructure supporting other forms of capital and community development, including information technologies, chemicals, railroads, and other relevant infrastructure (Crowe 2008; Flora et al. 2015; Freduah et al. 2019). To represent biophysical capital, we used fertilizer expenses, irrigated acres, the proportion of county area cultivated in corn, soy or wheat, and yields for these crops. Human capital consists of each person's assets, includ-

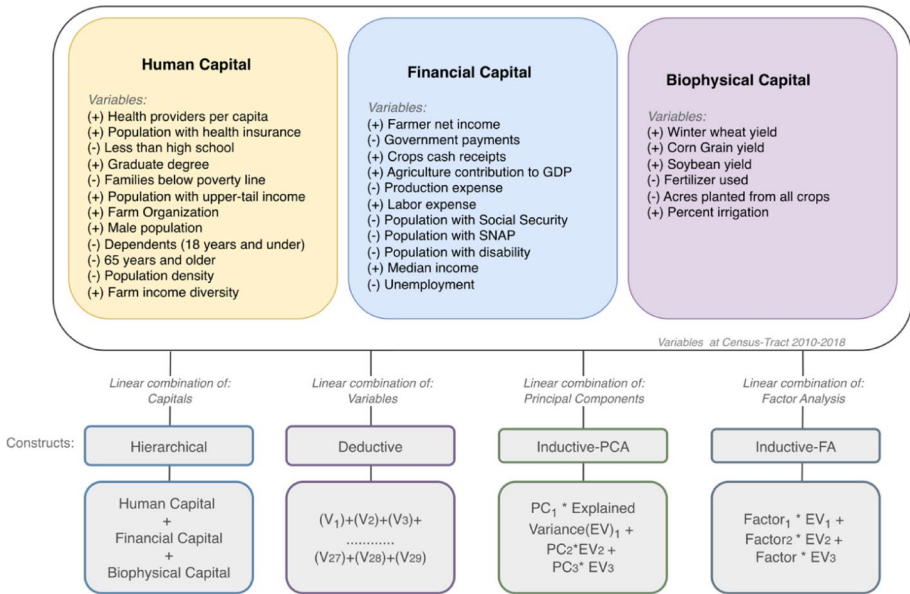


Fig. 2 The framework used for the study showcasing the different variables in each capital, the structural design of the indices, and the inputs into the four-construct methods

ing health, education, knowledge, skills, and their capacity to effectively combine these attributes to maximize returns from various resources (Freduah et al. 2019), for instance, using education, knowledge, and networks to improve productivity or innovation outcomes. In this paper, human capital represents the social structure that influences the community’s health, wealth, education, and demographic makeup. We used population density and the percentage of households under the poverty line, among others, to represent human capital. In comparison, financial capital characterizes the sources and levels of income, expenditures, and labor market. Since we focus on the adaptive capacity of agricultural communities, we particularly emphasize agricultural finances by including variables such as farm net income, government payments, cash crop receipts, and farm labor expenses. (Additional details on the variables selected are provided in the Supporting Materials Table S1).

We collected socioeconomic variables at the census tract level (Census Bureau 2015), county-level gross domestic product and farm economic variables (U.S. Bureau of Economic Analysis, 2023a, 2023b), and agriculture-related variables at the county level (United States – National Agricultural Statistics Service, 2022). Information on all variables was collected for each year from 2010 to 2018. We merged each dataset to a final census tract-annual resolution (for agriculture variables, validation of one to many was necessary). Variables were normalized to represent percentages or proportions, while monetary values were inflation-adjusted. Missing values were linearly interpolated (first forward interpolation followed by backward interpolation) using Python 3.8.8. While we acknowledge that adaptive capacity is dynamic and may change over time, we aimed to develop an index that represents communities’ underlying capacity or character that enables them to respond and prepare for disturbances. To do so, we used a three-year moving average for all variables to smooth the interannual fluctuations that more strongly reflect the impacts of short-term

events while acknowledging that adaptive capacity may change over time and in response to adverse events.

2.5 Assembling adaptive capacity indices

The variability in developing an adaptive capacity index extends beyond the selected indicators and encompasses the construction method, or structural design, employed to aggregate the composite index. Diverse approaches are adopted to derive composite indices, ranging from linear combinations of variables or capitals to statistical methodologies involving dimensionality reduction techniques (Williges et al. 2017). In reviewing others' work, Tate (2012) found three methodologically prominent structural designs for constructing composite indices: deductive, hierarchical, and inductive. Deductive models consist of sets of handpicked variables that are normalized and aggregated into an index. Hierarchical designs combine handpicked variables belonging to the same theoretical dimension (e.g., capitals) to get sub-indices, which are combined into a single index. Finally, inductive approaches use statistical approaches such as factor analysis to reduce dimensionality by identifying a small set of latent variables from a large set of candidate variables. These latent variables are then typically combined into a single index.

Beyond the basic structural design of an index, several construction method decisions (e.g., choice in variable normalization method, indicator weighting, and method of aggregation) can also influence the resulting index. The weighting of variables can occur in one of three ways, consulting experts, equal weighting of variables, and employing statistical methods (Williges et al. 2017). However, in conducting a systematic review of flood vulnerability indices, Moreira et al. (2021) found that the most popular construction method choices included min–max normalization (30.5%), equal weighting (24.2%), and linear aggregation (80%). For this study, we will be using min–max normalization, equal weighting and statistical weighting, and linear aggregation.

We created four adaptive capacity measures by combining standardized variables (z-scores) using different linear combination methods for each census-tract time (Fig. 2). The hierarchical design used a linear combination of unweighted capital sub-indices, while a simple unweighted linear combination of all variables was used to calculate the deductive structural design. For the inductive structural design, we used two statistical approaches, principal component analysis and factor analysis, to reduce the dimensionality of our data. Principal Component Analysis (PCA) is an analytical method that aims to simplify and understand the variance–covariance structure of a set of variables by creating a smaller number of linear combinations (Johnson & Wichern 2007), and factor analysis (FA) aims to describe the covariance relationships among many variables in terms of a few underlying but unobservable random quantities or latent variables called factors by reducing variables grouped by their correlations into a factor (Johnson & Wichern 2007). While largely similar, the techniques can produce different outcomes as PCA is focused on maximizing the variances explained by each component while FA aims to uncover latent or unobserved factors that explain the correlations among the variables. After obtaining components or factors, we used a weighted linear combination of resulting components/factors, as illustrated in Fig. 2. To see the variables' data source and details of processing, units, and capital assignment with justification, refer to Table S1 in the supporting documents.

For each structural design, all variables were scaled (z-scores) before summation, any sub-indices or component scores were min–max normalized, and all final adaptive capacity index (AC) scores were min–max normalized. This approach ensures that all variables and sub-scores have common units and scaling before being combined so that AC scores are comparable across construction design. Variables that prior research suggests are expected to contribute to reduced adaptive capacity were subtracted in linear combinations to reflect their negative impact on overall adaptive capacity. For example, unemployment has been associated with decreasing current adaptive capacity (Wittrock et al. 2011); therefore, we subtracted this variable to represent its adverse effects within the summation process. Less than high school education attainment, percent of families below the poverty line, government payments to farms, amongst others, are some of the other variables that were considered to have a negative influence on adaptive capacity.

For the hierarchical structural design, normalized and scaled variables were first summed within capital groups to create capital sub-scores which were min–max normalized prior to summing the capital sub-scores to create an AC score, which was also min–max normalized. For the deductive structural design, the 29 normalized and scaled variables were summed, and the score was min–max normalized. For the two inductive structural designs, component scores were min–max normalized and weighted by the value of the explained variance of that component/factor; then, a linear combination of components/factors was added to create an AC score, which was also min–max normalized.

For the inductive structural designs the directionality of the components summed to create the final AC score was determined by considering the loadings of the variables on each principal component or factor. If the variables that loaded highest on a component /factor contributed to increased adaptive capacity (for example, higher farmer net income, higher median income, and higher percent population with graduate degrees), then the component would be assigned a (+) and would be added to the linear combination of components. On the other hand, if the highest loadings on a component/factor were associated with reduced adaptive capacity (for example, higher unemployment, the population on food assistance programs, or low education), then the component would be assigned a (-) and would be subtracted in the linear combinations of weighted components. The final AC scores had values between zero and one, where one indicates high relative adaptive capacity and zero indicates low relative adaptive capacity.

The Scikit-learn decomposition package for Python (Pedregosa et al. 2011) was used to conduct the principal component analysis on all 29 variables, while Python's factor_analyzer package (Biggs and Madhani 2022) was used to transform the 29 variables into factors using factor analysis. The conceptual aspects that constitute adaptive capacity imply interdependence across variables. Therefore, the loading matrix for the factor analysis used an oblique rotation, allowing for correlated factors. In addition, the pathviewr package was used in R Version 2023.12.1 (Baliga 2023) to identify the recommended number of components using eigenvalues, the cumulative explained variance, and skree plots. These assessment methods indicate that between two to four components were optimal for each PCA and FA. To maintain a streamlined analysis, three components were used for all samples and both inductive structural designs. Scree plots (Fig. 8) and loading matrices (Table S2) are available in the supplemental materials. Structural designs will be referred to as “constructs” for the remainder of the paper.

2.6 Structural design models variations—uncertainty evaluation

To assess AC variability across construction methods for each census tract time, we computed the standard deviation and relative standard deviation (RSD). RSD is calculated by multiplying the standard deviation by 100 and dividing the product by the mean. The RSD is expressed as a percentage and was processed for all contexts (State, Metro, Non-metro, Farming).

2.7 Key determinants of adaptive capacity in different contexts

Across different contexts, we aimed to identify the driving variables that explain most of the variability in the produced AC measures. We conducted regression analyses for each context, utilizing a stepwise Ordinary Least Squares (OLS) approach to achieve this. For each context, each construct's AC index score was used as a dependent variable in a stepwise OLS analysis. The 29 original variables used to create the index were used as independent variables. Scikit-learn (Pedregosa et al. 2011) was used to conduct the OLS, and the mlxtend Sequential Forward Selection python package (Raschka 2018) was used to select the top five variables, scored by negative mean squared error for each construct and context. These top five variables represent the variables that have the most influence on the index scores of each construct and context.

We then combined the five candidate variables from the four constructs into a linear combination. A variable was used in the linear combination only once, even if the variable was selected in each of the four constructs. In the linear combination, we followed the (+) or (-) shown in Fig. 2 to ensure consistency in the theoretical orientation of the variables with respect to adaptive capacity. The resulting index was regressed against the original 29 variables used to create the index minus those used to create the linear combination. We iteratively added or removed candidate variables from the linear combination, regressing the new linear combination against the full set of original variables minus those used to create the index. Variables that lowered the adjusted r-squared were removed from the linear combination. We iterated this process until the least number of variables in the linear combination explained at least 88% of the variance in the original set of 29 variables. We labeled this final linear combination “reduced AC score.” This process is illustrated in Fig. 3 and is repeated for each context.

2.8 Assess AC variability across context selection

We assessed AC variability distribution across contexts by comparing the quantile positions of counties in farming, metropolitan, and non-metropolitan areas to those of the entire state context. To do this, we employed the reduced AC scores described above. Quantile values were reclassified to ‘Low’ (0-25th percentile), ‘Medium Low’ (26-50th percentile), ‘Medium High’ (51-75th percentile), and ‘High’ categories (76-100th percentile). Counts of category switching across the entire state context and context-specific metrics were obtained. We further evaluate the percentage of cases in which a census tract had the same quartile classification at a particular time when comparing the reduced AC for the entire State to the Metro, Non-Metro, and Farming contexts. When both the scores compared were in the same quartile classification (e.g., “Low” & “Low”), we classified it as “Same.” If the

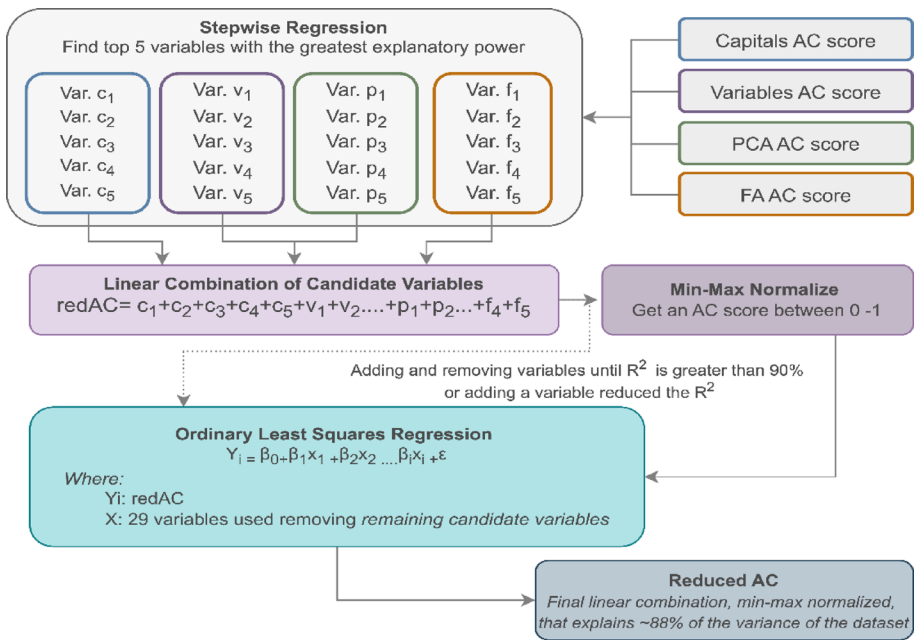


Fig. 3 Methods followed to address objective 2. For the final score of each construct, we conducted a stepwise regression that selected five variables. We iteratively added and removed candidate variables until the calculated score explained ~88% of the variation in the dataset

classifications were different but adjacent, such as “Low” & “Medium Low,” we labeled it as “Similar”. Finally, a classification was labeled as “Different” if the quartiles were not adjacent (e.g., “Low” & “Medium High” or “High” & “Low”).

3 Results

3.1 Adaptive capacity index distributions

Comparison of AC scores developed using different construction methods and sample contexts indicates that the distribution of scores can vary significantly (Fig. 4). Across the contexts, the deductive and hierarchical constructs tend to have similar mean and distribution patterns. However, the two inductive constructs have distinct distributions across contexts. For the entire State (and across all times), the hierarchical construct has a mean of 0.52 (± 0.08), the deductive construct has an average of 0.49 (± 0.14), and the PCA construct has a mean of 0.44 (± 0.14). The ‘State’ is the only context in which the median AC score for the inductive-FA construct is higher than the other constructs, with a mean score of 0.62 (± 0.13). The Metro, Non-Metro, and Farming contexts all display different patterns. For instance, in the Metro context, the hierarchical construct has the highest mean (0.55 \pm 0.1), followed by the deductive construct (0.49 \pm 0.16), the PCA construct (0.44 \pm 0.17), and finally the FA construct (0.35 \pm 0.18). In the non-metro context, the hierarchical (0.47 \pm 0.9) and deductive (0.48 \pm 0.15) had the highest average scores, while both of the inductive

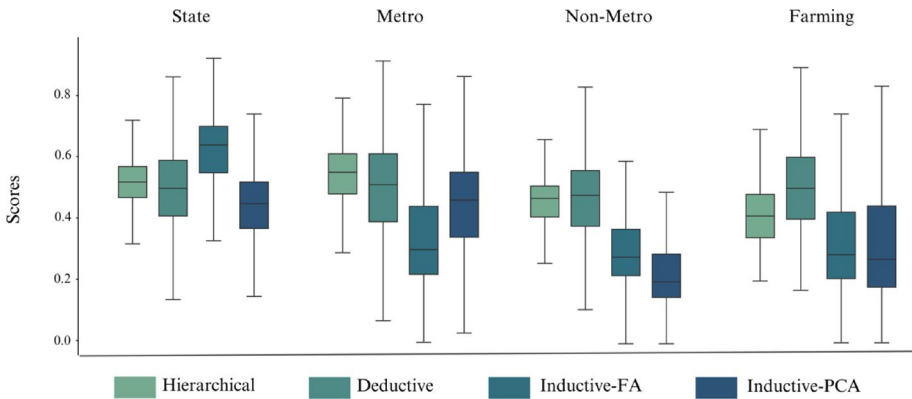


Fig. 4 Distribution of the county average index score across time for each context and construct. Outliers not represented

models had lower overall scores. For instance, the inductive-FA construct had a mean of $0.32 (\pm 0.14)$, and the inductive-PCA scores were even lower (0.26 ± 0.17). More variability across the hierarchical and deductive constructs is seen in the Farming context, where the deductive construct (0.51 ± 0.16) has the highest distribution, followed by the hierarchical construct (0.41 ± 0.10), while both the inductive-FA (0.34 ± 0.18), and inductive-PCA construct (0.33 ± 0.21) tend to have noticeably lower scores.

The deductive and hierarchical construction methods appear to be more stable, as their distributions remain quite similar across contexts, although there are some changes in ranges and variance. A Spearman correlation analysis (Table S3) suggests that for every context, the hierarchical and deductive constructs have a strong positive correlation ranging from 0.84 in the metro context, to upper 0.90's in the other contexts. On the other hand, inductive constructs seem to show greater variability in distributions and lower correlation with the other constructs. For example, the FA construct for the non-Metro context has a correlation of -0.05 with the deductive construct, while for the Farming context, the correlation between FA and deductive is 0.75. Similarly, the PCA construct has a moderate (0.35) positive correlation with the FA construct in the State context and a high positive correlation (0.89) with the deductive construct in the Farming context. (Table S3). Meanwhile, across contexts, constructs have a weak correlation, near 0 in all instances (Table S4). Finally, the AC index distributions remain relatively stable across time for each sample and construct (Figure S10 and Table S5 in the supplemental materials).

Not only is the range and distribution of scores similar for the hierarchical, deductive, and PCA constructs in the State and Metro contexts (Fig. 4), the spatial distribution of these three constructs seems to follow similar spatial pattern (Fig. 5). For the State, consistently across constructs, the metro core areas (clustered small census tracts) seem to have relatively lower AC than their surrounding suburban counterparts. In addition, the southwest part of the state and some counties in the northeast seem to have relatively higher AC, while the southeast and north central areas of the state tend to have lower AC scores. These broad trends are generally consistent across contexts and constructs (Figure S11 in supplemental materials). Temporally, there are no clear patterns of change, but some counties have sporadic temporal changes (Figure S12 in supplemental materials).

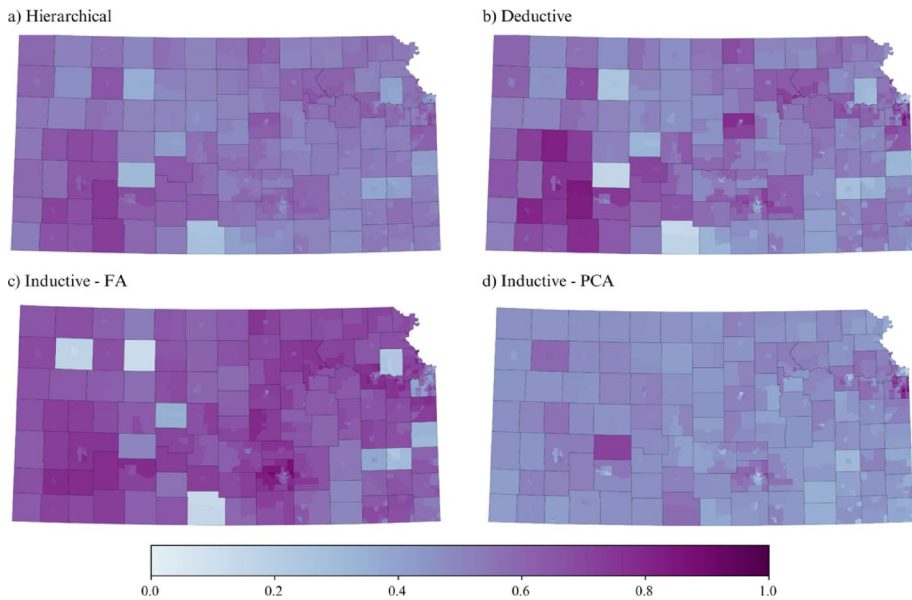


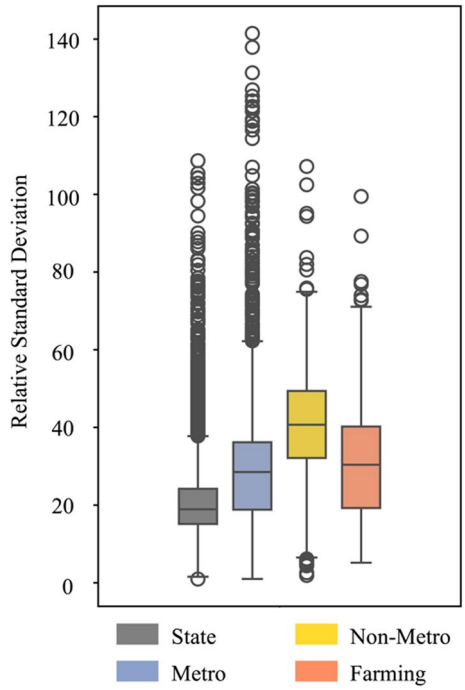
Fig. 5 AC index scores across construct methods for the State context. Values presented are the average over time for each census tract

3.2 Variability across constructs

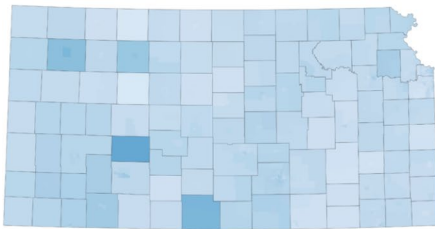
The census tract-level relative standard deviation (RSD) across AC constructs suggests considerable variability in AC scores regardless of the context. In general, greater variation is observed in the non-metro context with a median RSD of 40, followed by the farming context (30), metro context (29), and the state context (19) (Fig. 6). This indicates that, for example, we can expect the AC score for an average county in the farming context to vary by ~30% based on the construction approach used. Although the state has the lowest median RSD and smallest interquartile range compared to the farming and non-metro contexts, it has numerous outliers – as does the Metro context. While in some instances, county AC scores in the state context can vary by as little as ~0.98%, in others they may vary by as much as ~108% depending on the construction method.

To geographically visualize the variation across constructs for each context, we mapped the standard deviation across constructs. The State context has the highest variability in the western part of the state, mainly in counties with more sparse populations, like the non-metro and farming areas. On the other hand, the metro context has the highest variability in the northeast corner (Fig. 7b). Variability in the Non-Metro and Farming contexts has no clear spatial pattern. These results suggest that AC scores vary widely depending on the methods used to assess AC. In some places, we can be more confident in AC scores because they have less variability across the constructs.

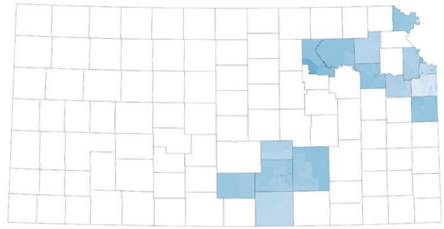
Fig. 6 Relative standard deviation in AC scores across constructs for the four contexts



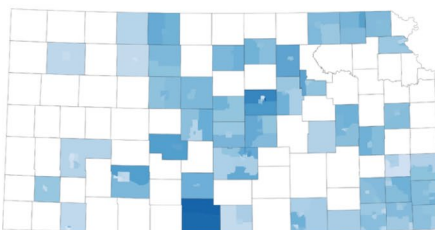
a) State Context



b) Metro Context



c) Non-Metro Context



d) Farming Context

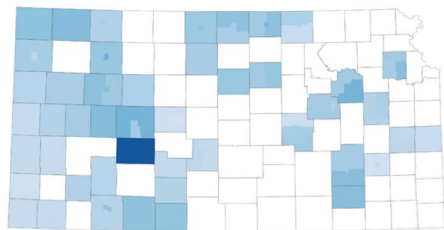


Fig. 7 Standard deviation across construction methods at the census tract level. Values displayed represent the average of the cross-construct standard deviation over time in each census tract

3.3 Context specificity

The candidate variables (Table S6) selected by the stepwise regression for each context and construct method illustrate how different construction processes can produce indices that emphasize different characteristics of AC even when starting with the same variables and context. Interestingly agricultural variables are included as candidate variables in most constructs and contexts, including the Metro context. We note that even if a county is assigned as ‘Metro’ and not farming-dependent in the USDA ERS County typology, the county can still have agricultural activities, though they do not meet the threshold to be labeled ‘farming’. While there is overlap in the variables with the greatest explanatory power across constructs, no two sets of highly explanatory variables are identical in any context.

Across all contexts, the candidate variables reveal consistent themes linking education, poverty, and agricultural productivity as key determinants of AC. In the State context, higher education and poverty levels are the most influential variables, with agricultural yields and disability rates further shaping socioeconomic outcomes. Within the Metro context, educational attainment and income are important, complemented by agricultural productivity indicators which could signal urban–rural interconnections. The non-metro context emphasizes farm organization and farm income diversity, poverty and aging population, pointing to the structural and livelihood dimensions of rural economies. In the farming context poverty, agricultural GDP contribution, and government payments emerge as central, underscoring the economic and policy factors influencing agricultural systems. Overall, hierarchical and deductive constructs prioritize socioeconomic structure, while inductive methods (FA, PCA) uncover broader, latent linkages between demographic, economic, and agricultural systems. In other words, inductive constructs reveal a complex interplay of human capital, economic stability, and production capacity across contexts. These candidate variables with the greatest explanatory power (Table S6) were used to identify the final linear combination of variables that explain the most variance while using the least number of variables (reduced AC score). The principal variables in the final linear combination across each context (Table 1) further illustrate that the key determinants of AC vary across each context. The reduced models show strong explanatory power across all contexts (Adj.

Table 1 Linear combination of variables for each sample

	Reduced AC Final linear combination			
	state context	Metro context	Non-metro context	Farming context
	(+) Graduate Degree	(+) Graduate degree	(-) Pop. 65 years & older	(-) Pop. 65 years and older
	(+) Crop Cash Receipts	(-) Families below poverty line	(+) Farm income diversity	(+) Farm income diversity
	(+) Median income	(+) Median income	(-) Pop. with disability	(-) Pop. with SNAP
The ordinary least squares (OLS) results show the r-squared values when regressing the reduced AC scores against all variables from Fig. 2 minus the ones used for the reduced AC	(+) Ag. labor expenses	(-) Less than high school (-) Unemployment	(+) Soybean yield	(+) Soybean yield (+) % Land irrigated
	OLS Adj. R-squared:	Reduced AC as the dependent Variable		
	0.95	0.92	0.897	0.887

$R^2=0.88-0.95$), indicating that a small, well-balanced set of socioeconomic and agricultural variables effectively explains variations across each context. While the final sets of context-specific determinants are not entirely mutually exclusive, at most, we find an overlap of one variable in an adjacent (e.g., Non-Metro – Farming, or State – Metro) context. The Metro context shares no final variables with the Non-Metro nor Farming context, but it shares two final variables with the State context (Graduate Degree and Median Income).

The State context is jointly driven by a combination of education attainment, income, and agricultural investment (labor expenses and crops cash receipts), underscoring the synergy between socioeconomic development and agricultural systems across Kansas. When these four variables are combined into a linear combination (Reduced AC score) and used as the dependent variable in an OLS regression (with the 27 other variables as regressors), they collectively explain approximately 95% of the variance. Like the state context, 92% of the variance in the metro context is explained by education attainment, income, and economic vulnerability (poverty and unemployment). Despite being included in the set of candidate variables, ultimately, we find that agricultural variables do not strongly or consistently influence the AC scores for the Metro context. In the Farming and Non-Metro context, a combination of agriculture-specific and vulnerable population (older adults, and population in government assistance programs like disability or Supplemental Nutrition Assistance Program) drive AC scores. Farm income diversity, crop yield, aging population, and disability, explain around 89% of the variance in the non-metro context. Similarly, the farming context is driven by farm income diversity, irrigation, crop productivity, as well as vulnerable population. Overall, these models suggest that regions combining education, income growth, and diversified agricultural systems will demonstrate the greatest adaptive capacity across spatial contexts.

Spatially, the reduced AC score for the State context (Fig. 8a) closely mirrors the pattern observed in for the original constructs (Fig. 5), though with minor variations. With the reduced AC the metropolitan core continues to exhibit lower adaptive capacity compared to its surrounding areas, while the northeastern corner shows relatively higher AC. A few counties in western Kansas also display elevated capacity. Because the Metro, Non-Metro, and Farming contexts are mutually exclusive, their reduced AC scores can be combined to represent the entire state (Fig. 8b). The ensembled reduced AC maintains the overall pattern of lower adaptive capacity within core metro areas and higher capacity in the surrounding regions. However, the pattern of higher AC in surrounding core metro areas is more prominent in the reduced AC ensemble (Fig. 8b) than in the State context reduced AC (Fig. 8a). Notably, in the southwestern corner, clusters of farming and non-metro counties stand out with particularly high AC, suggesting localized strengths in agricultural and rural adaptability that may be associated with irrigation that is common in this region over the High Plains Aquifer.

Finally, a comparison between the reduced scores of the State context and the ensemble of contexts reveals differences in reduced AC across contexts. The Metro context shows the strongest alignment with the State context, with AC quartile classifications matching 64% of the time, being similar in 29%, and differing only in 7%. In contrast, the Non-Metro context displays the greatest divergence from the State scores, with 32% of tracts classified in the same quartile, 42% classified similarly, and 26% differing. The Farming context demonstrates a moderate level of consistency, sharing the same quartile with the State scores 32% of the time, showing 45% similarity, and differing in 23% of cases. These comparisons

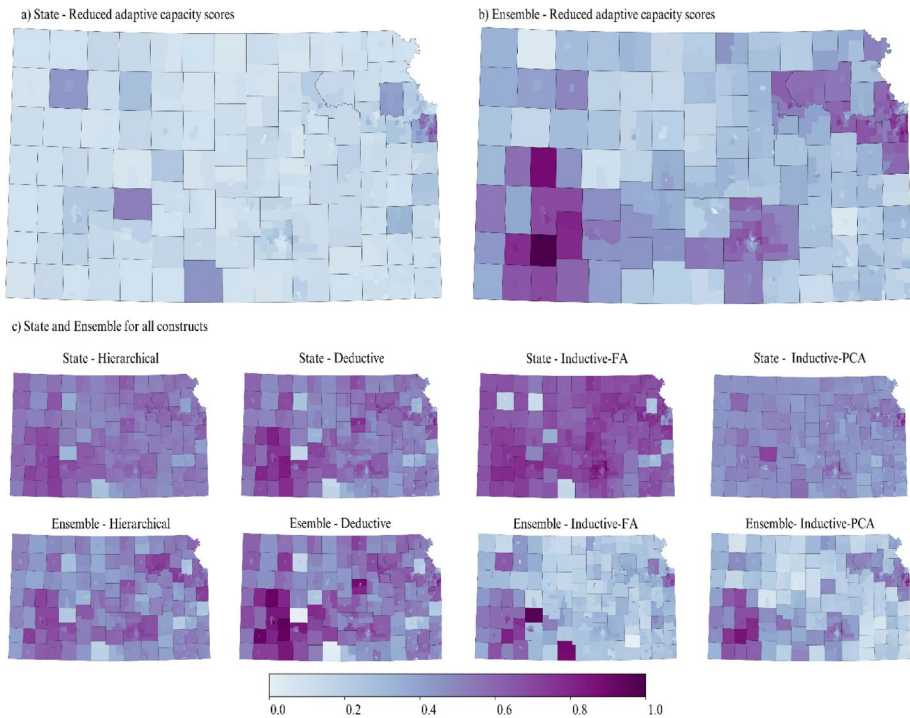


Fig. 8 Reduced adaptive capacity scores for the State context (panel a) and context ensemble (panel b). The first row in Panel C shows the adaptive capacity scores for the state context across each construct method, while the bottom row presents the scores for each construct, assembled from the different contexts

Table 2 Count of census tracts and percent of all census tracts in which the reduced form adaptive capacity score for a specific context varied from the adaptive capacity score of the state context in quantiles

	Metro (n=3255)	Non-metro (n=1575)	Farming (n=560)
Different	222 (7%)	408 (26%)	129 (23%)
Similar	951 (29%)	660 (42%)	252 (45%)
Same	2082 (64%)	507 (32%)	179 (32%)

‘Different’ signifies a shift across at least two quantiles representing low to high AC or vice versa. ‘Similar’ represents a shift of one quantile, and ‘Same’ represents a score falling within the same quartile

(Table 2) indicate that while metro areas generally align with the overall state-level patterns, rural and farming contexts exhibit greater need for contextualization in assessments.

4 Discussion

The assessment of vulnerability, resilience, and adaptive capacity composite index score variability has been studied across scales, contexts, indicator selections, and index structural design (He et al. 2023; Schmidlein et al. 2008; Spielman et al. 2020; Tate 2013; Vincent 2007; Wiréhn et al. 2015), though most literature examining the sensitivity of composite

indices has focused on vulnerability (specifically social vulnerability). In a study examining the sensitivity of the Social Vulnerability Index (SoVI) to the construction methods, scale, set of variables used, and geographic context, Schemidtlein and colleagues (2008) found strong similarities between the two indices they created (one using 33 variables and the other one using 26 variables), but found that the level of data aggregation increases the correlation between variables. Going further, Tate (2012) assessed which social vulnerability index construction decisions have the greatest influence on the stability of output rankings for Norfolk, VA, Sarasota County, FL, and Nueces County, Texas, using a global sensitivity analysis. Tate (2012) further suggests that descriptive statistics such as variance, confidence limits, median, and coefficient of variation can be evaluated as measures of index uncertainty. Hence, in this study we use such measures to characterize score variability. More recently, assessing SoVI, Spielman and colleagues (2020) evaluated the variability of the vulnerability of the same places, using the same county-level data and methods, but varying the geographic extent of data that was used to construct the index (e.g., all counties in a state, all counties in the state's FEMA region) and found significant shifts in index scores depending on sample geographic extent used. The present study extends this approach by applying non-contiguous sample contexts and focusing on using the same variables but varying the indicator construction process.

4.1 Sensitivity to construct and context

The comparison of AC scores developed using different construction methods and sample contexts reveals significant variability in score distributions, which highlight the strong spatial and contextual dependency of AC across Kansas. Even when using the same data and context, the choice of construction methods can lead to substantial differences in adaptive capacity scores. While some census tracts showed minimal variability, others exhibited wide discrepancies based on only differences in the construction approach. This result supports prior research noting the critical importance of carefully selecting construction methods for indices (Schmidtlein et al. 2008; Spielman et al. 2020; Tate 2013). Going further, our findings suggest that even within a single state calculated AC indices yield different results when considering the entire area vs focusing the sample to counties with similar socio-economic drivers. These findings further echo those of Spielman and colleagues (2020) who found that the geographic extent of the sample used for data construction had a strong impact on the resulting composite social vulnerability index. Thus, we confirm that the indices are sensitive to both construction methods and contextual factors.

While prior work has focused on contiguous geographic regions as context, we found that index scores and the determinants of adaptive capacity also vary by socio-economic drivers of a county, or as referred to in this paper, socio-economic contexts. Past work has found that different places or contexts are driven by different variables or forces, alluding to context-specificity (Binder et al. 2013; Harrington 2016). For example, a study conducted to assess the social adaptive capacity of local communities in 29 small-scale fisher communities in Madagascar and Kenya (D'agata et al. 2020) found that higher education had a positive relationship with adaptive capacity while isolation from a market and climate disturbances had a negative association with adaptive capacity. On the other hand, Chepng'etich and colleagues (2024) found that risk-taking and proactiveness, age, gender, education level, income diversity, and access to credit strongly influence higher adaptive

capacity in Kenyan livestock-producing households. While both studies had an overlapping study area, Kenya, their findings for AC determinants depended on the economic driver or system studied, fisheries versus livestock. Some variables are relatively consistent across studies, but in many cases, the findings are unique to their context or foci. We found that while there are similarities in the themes across contexts (education attainment, vulnerable population, economic well-being), the drivers or selected variables were different. For instance, in the State and Metro context, median income was selected as an economic driver, but in the non-metro and farming context, farm income diversity was selected. This suggests adaptive capacity assessments must be tailored to specific contexts, using appropriate key variables—addressed by our proposed methodological process.

Nonetheless, a composite indicator is successful when it demonstrates both internal and external validity, meaning that it measures what it intends to assess and performs consistently within and beyond its development context (Jacob et al. 2022; Messick 1995). Internal validity ensures theoretical and methodological soundness through uncertainty and sensitivity analyses (Aroca-Jiménez et al. 2020; Birkmann et al. 2022; Fekete 2009; Spielman et al. 2020), which has been the main focus of this study. Nonetheless, incorporating qualitative approaches and local expert insights could further strengthen local contextual conclusions (Schmidtlein et al. 2008; Spielman et al. 2020). While external validation remains challenging for latent constructs such as adaptive capacity (Aroca-Jiménez et al. 2020; Fekete 2009), indirect evidence of contextual validity is observed through spatial consistency and interpretability. For instance, the reduced AC ensemble (Fig. 8b) reveals a cluster of high adaptive capacity in southwest Kansas, corresponding to the region's groundwater-based irrigation practices that buffer drought impacts in farming counties. However, long-term aquifer depletion may ultimately reduce this capacity. These results suggest that the index captures meaningful spatial variation reflective of local realities, underscoring the need for future work to integrate local validation to ensure that adaptive capacity assessments are both robust and contextually grounded. A future study direction is to externally validate the composite indicator using an independent data set on real observable outcomes (e.g. drought impact) to assess if the indicator is measuring what it was intended to characterize.

4.2 Policy implications

Both the methodological approach of index construction and the choice of context selection carry significant policy implications. For example, using the State–Inductive FA model would make it difficult to prioritize specific areas for intervention, as the resulting AC scores appear relatively homogeneous. Even so, one might allocate resources to the two non-metro counties in the northwest, the farming counties in the east, and select metro areas that display comparatively lower capacity. In contrast, the Ensemble–Inductive FA model directs attention toward the north-central and southeastern parts of the state, where lower AC is more clearly delineated. A similar pattern emerges when comparing the reduced AC scores from the state and ensemble constructs; however, the ensemble approach enables decision-makers to more precisely identify areas requiring assistance, while the underlying variables help anticipate how to help (e.g., providing healthcare access to aging populations). Misinterpreting or generalizing AC measures without accounting for contextual variation risks reinforcing inequities by diverting support away from the most vulnerable regions. Thus,

while the state model offers an accessible overview, the ensemble framework provides a more targeted foundation for place-based planning.

4.3 Uncertainties and methodological limitations

Given the uncertainties that composite index construction methods pose, approaches to leveraging information from multiple index variants should be developed and utilized (Tate 2013). This study establishes a process that addresses this need. Our proposed methodology combines information from multiple index constructs and reduces the number of variables used to calculate adaptive capacity for each sample or socio-economic context, emphasizing key variables over components, though variables used may differ across studies. For example, both Williges et al. (2017) and Sheng et al. (2018) used Ellis's Sustainability Livelihood Approach, but Williges et al. (2017) measured financial capacity in terms of insurance penetration, farm solvency, and total farm cash flow while Sheng et al. (2018) used average gross income, expenditure proxy, and diversity of commodities produced per farm. Nevertheless, in a variable-wise index (when variables are used instead of components) the face value of a metric is less obscured. Component-wise indices, such as those frequently used in assessing vulnerability, resilience, or adaptive capacity can obscure the contribution of input variables, making it difficult to understand their specific influence, whereas a variable-wise index enhances the theoretical consistency of indices (Spielman et al. 2020) and allows for easier interpretation.

Our proposed methodology filters context dependent variables for each construction method or construct. After creating the AC scores using each construct method, we propose using stepwise regression analysis to obtain candidate variables for each construct and context, as shown in Table S6. Although some variables are similar, each construct pulls a distinct set of variables for each context. Finally, the linear combination of candidate variables hones down the context specificity and settles on the most parsimonious model.

While our proposed methodology demonstrates the potential to generate simplified, variable-wise, context-specific adaptive capacity (AC) indices, several methodological limitations and biases warrant exploration. First, decisions related to variable selection and assumed directionality were necessarily subjective. Although these were guided by established literature, the relationships among variables and adaptive capacity may vary across geographies and socioeconomic contexts and may not always follow linear trends. Moreover, the process of filtering context-dependent variables and constructing indices is computationally intensive and may limit operationalization beyond a research setting.

Going forward, a key limitation stems from our reliance on the U.S. Department of Agriculture's Economic Research Service (ERS) County Typology to define "metro," "non-metro," and "farming-dependent" contexts. This typology extends beyond a simple rural-urban dichotomy by incorporating dominant industry sector income and employment characteristics; however, applying these classifications at the county level can still obscure important intra-county variation, as metro and non-metro counties may include agricultural areas, and non-metro or farming-dependent counties may contain small urban centers. Future work could explore alternative or more nuanced classifications that go beyond the rural-urban dichotomy, in order to better capture heterogeneity in county-level economic structures.

In addition, while our analysis did not directly include indicators of political capital or environmental policy engagement, we recognize that governance structures play an important role in shaping adaptive capacity. Future work could explore how variations across nested governance levels (e.g., county, municipal, groundwater management districts, and watershed authorities) influence local preparedness and resource allocation. This may include developing or integrating proxy indicators such as environmental protection expenditures or investment in environmental goods and services (Sibilia et al. 2024). However, consistent spatial and temporal data for these measures are currently limited for our study area, constraining their inclusion in the present analysis.

Finally, our study was also based on census tract and county-level data from the American Community Survey. This aggregated data presents issues inherent to the modifiable areal unit problem (Openshaw 1984). The present study does not validate the output of the reduced AC models using an independent and external dataset and, therefore, cannot provide any guarantees on the ability of the indices to reflect the true adaptive capacity of the study area. Such validation efforts remain a high priority for future research on adaptive capacity. Lastly, while we propose a generalizable approach for developing variable-wise indices that leverage multiple construction approaches, our findings are based on a limited case study and may not be generalizable outside of the boundaries of our study area.

5 Conclusion

As Preston and colleagues (2011) mention, there is an absence of clear guidance on the approaches to assess adaptive capacity, including methods and tools used in specific contexts, leading to the employment of arbitrary processes. Composite indices are a popular assessment approach that has been used at local, state, and federal levels (Tate 2012) to aid decision-making but are subject to uncertainties and tend to offer a one-size-fits-all result. While uncertainty assessments or analysis of score variability allows us to improve the transparency and credibility of indices (Singh et al. 2012) the implications of the uncertainties in these indices, academically or practically, have not been extensively studied. In this paper, we proposed a process for arriving at the key determinants of AC in differing socio-economic contexts that offers a streamlined framework for practical applications, balancing simplicity with predictive accuracy. We also echo Tate's (2013) call for pausing the application of index scores uniformly and conclude, like Vincent (2007), that there is no 'one size fits all model' – indicators should properly capture specific contexts.

Overall, this work adds to understanding of the context specificity of adaptive capacity by highlighting the strong divergence in key determinants of an AC index across non-contiguous socio-economic contexts within the same state. This divergence suggests that the context-specificity of composite indices for concepts such as adaptive capacity and vulnerability should extend beyond geographic regional differences and account for differing socio-economic or social-ecological characteristics. In other words, the determinants of adaptive capacity are specific to the system and its unique characteristics (Adger and Vincent 2005). We suggest that context-dependent composite indices can be constructed and ensembled rather than using a one-size-fits-all approach for composite indices so that each place has a context-appropriate score. In applying such an approach, we found that the one-size-fits-all (State context) AC index varied significantly from context-specific AC indices, particularly

for the non-metro context, as the state context index would result in an erroneous conclusion regarding the state of adaptive capacity in these communities in at least 26% of cases. Such misrepresentations of the state of adaptive capacity could lead to inefficient or ineffective use and distribution of resources.

The inconsistency we find in AC scores across different construction methods and contexts underscores the challenges practitioners and policymakers face in selecting an approach for developing a composite index. Selecting an approach introduces empirical uncertainties that lead to output variability, hence reducing the certainty of scores. Our study quantified the variability in AC scores resulting from different methods and contexts, revealing the extent of confidence practitioners can have when relying solely on quantitative methods for decision-making. The conclusion is clear: quantitative methods alone do not provide sufficient confidence. Before using these indices for policy-making or other risk-reduction efforts, composite indices must undergo rigorous evaluation and demonstrate their utility before being applied. If quantitative methods are employed, we recommend adhering to Spielman et al. (2020) seven-point criteria for evaluating composite indicators. We emphasize the importance of integrating qualitative methods and local experts' opinions (Schmidtlein et al. 2008; Spielman et al. 2020), as these insights can provide robust support that complements quantitative measures.

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Declarations

Conflict of interests Authors report no competing interests.

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