International Journal of Disaster Risk Reduction 96 (2023) 103913

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

# An index of social fabric for assessing community vulnerability to natural hazards: Model development and analysis of uncertainty and sensitivity

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ARTICLE INFO

*Keywords:*
Social fabric index (SoFI)
Flood mitigation
Home buyouts
Quasi Monte-Carlo simulation
Natural hazard mitigation policy
Uncertainty analysis
Global sensitivity analysis

ABSTRACT

Indices of socio-environmental vulnerability, resilience, and sustainability are well-established in assessing, mitigating, and planning for natural hazards in mitigation. Although there are many such indices, we still lack an index to measure connections and cohesion within a community—the social fabric (as we refer to it) that connects its members with each other and with the place. We propose an indicator-based index social fabric index (SoFI) to both measure and map the spatial dimension of the social fabric within and across communities. We investigate approaches to constructing social fabric indices and conduct uncertainty and sensitivity analyses for each stage of constructing the underlying model of the social fabric, which includes indicator transformation, normalization, principal component selection and rotation, and weighting. From this effort, we find that the precision of the index increases with social fabric levels, corresponding to lower social vulnerability. Global sensitivity analysis shows that the coordinate transformation and PCA selection play especially important roles in determining total uncertainty. Furthermore, the preceding step tends to absorb the uncertainty contributions of the following steps through construction interactions. Finally, we consider the importance of the emotional and psychological effects of the social fabric concept and provide suggestions for future work so that we will be able to develop a more transparent, comprehensive, and robust social fabric index model.

## 1. Introduction

Human life and property have a long historical record of being impacted by natural disasters. Over the past century, efforts have been made to mitigate natural disasters. Nonetheless, climate-related disasters have significantly progressed in both frequency and severity [1–5]. For example, flooding is one of the most ubiquitous and costly natural disasters in the U.S., with approximately $17 billion lost annually between 2010 and 2018 [6]. The leading causes of floods are climatic changes, changes in land use such asurban growth and deforestation [7]. Thus, strengthening community resilience and improving natural hazard management strategies are critical to mitigate the negative impacts of natural disasters on society [8].

For years, policies like home buyouts have been applied to mitigate hazardous impacts after floods [9]. Home buyouts provide opportunities for flood-affected homeowners to relocate to places that are unaffected and less at-risk [10]. The purchased properties are

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https://doi.org/10.1016/j.ijdrr.2023.103913
Received 5 January 2023; Received in revised form 8 June 2023; Accepted 30 July 2023
Available online 6 August 2023

often converted to green space, aiming to further enhance the community's future environmental resilience [11]. However, due to limited funds, criteria, and individual connection to the place, this mitigation effort can often lead to a checkerboarding effect in neighborhoods that have experienced flooding where some residents opt into a buyout and others do not, leaving some parcels as greenspace and others with homes. When enough residents leave the community, the social fabric (i.e., a network of interpersonal social connections) can break down, and the tax base for supporting community schools and maintaining public infrastructure can also collapse. In rural communities, the side effect of the loss of community members can be more significant than in urban areas [12]. In general, the adverse impact of the property acquisitions effort is seldom investigated.

Previous studies only evaluated the effects of the home buyouts from an individual or household vulnerability perspective, neglecting the comprehensive post-disaster effects on the broader community after mitigation policies like home buyouts are implemented moving entire households to other places. For instance, after Hurricane Sandy in 2012 [13], gathered information on the home buyout participants' experience with the home acquisition process [11] investigated the economic aspect of home buyouts by using a hypothetic situational analysis for Nashville-Davidson County, Tennessee, in the United States. They concluded that proactive implementation is the best approach toward the value of benefits compared to other hypothetical scenarios [11]. Additionally [14], explored post-implementation impacts on renters of home buyouts and similar managed retreat programs and examined the potential factors that contribute to the cycle of failed relocation efforts for minority renters that are usually ignored. They found that the inequities of socioeconomic status could make minority renters even more vulnerable after a natural disaster [15] conducted a survey of households affected by Hurricane Sandy and participated in home buyouts to measure the change associated with flood hazard risks, and social vulnerability. The survey indicated that most households tend to move to places with even higher social vulnerability and higher risks of exposure to coastal flood hazards. These combined results suggest that how buyout programs reduce flood-affected household social vulnerability remains unknown [15]. More importantly, the [15] study ignored the evaluation of the social fabric aspect of affected communities since the home buyouts accelerated the relocation of vulnerable populations and could cause disruptions of the social connections and cohesion of the original community.

Studies have also found that managed retreat mitigation strategies like home buyouts could also cause coercion feelings among the flood-affected population, degradation of trust of other people and local government, and loss of attachment to the places they live [10]. For instance Ref. [16], examined the perceptions of local home buyout administrators related to public trust by studying the conditions following Hurricane Matthew's landfall in North Caroline, USA, in 2016. They found that a lack of program clarity, and unclear communications about the program's guidelines across all levels of government deteriorated public trust in local property buyouts. Additionally [17], criticized that managed retreat projects like home buyouts need to incorporate a comprehensive framework of social, political, and environmental implications. Nonetheless, as far as we know, no research has been conducted on evaluating the home buyout program's effects on community social fabric degradation. Therefore, our hypothesis is that large-scale home buyouts can potentially damage the social boundness and connection, and the financial support for public amenities and facilities within a hazards-affected community where the mitigation policy like home buyouts is implemented. This research hypothesis thus promotes one questio: for the current post-disaster mitigation policy evaluation, such as the home buyouts, what are the impacts and how to measure and track the effects on a community's long-term social fabric stability by the implemented mitigation policy, especially after the natural hazards hit?

To better evaluate the post-disaster recovery strategies and policies, such as home buyouts and their potential negative effects on a community's social fabric status, two research gaps still linger: (1) lack of a means to assess a community's social fabric status, which is transferrable and scalable over time and geography (i.e., a social fabric index), (2) lack of a comprehensive assessment framework that can evaluate the validity and the reliability of a community's social fabric index.

Thus, we propose a Social Fabric Index (SoFI) model with publicly available representative indicators that can contribute to the state-of-the-art disaster and social science by addressing the challenge (1) mentioned above. While limitations still exist in this version of SoFI, we believe it could provide useful insights into natural hazard mitigation strategy from community cohesion and social fabric perspective especially combined with uncertainty and global sensitivity analysis.

We organize the paper as follows. An analysis of conceptual literature on community social fabric and cohesion was conducted in the literature review section. Relevant indicators were identified based on social fabric conceptual literature and corresponding data sources. In the meantime, the popular uncertainty and global sensitivity analysis techniques were also reviewed. Davidson County, Nashville, was used as a case study to present the proposed SoFI model. Finally, we summarized the limitations of the SoFI model and its applicability and offered the direction of future research efforts.

## 2. Literature review

### *2.1. General review of community resiliency and vulnerability indices*

Studies have found the usefulness of adopting index models to measure the social status of communities, like social vulnerability and resilience index models. hese index models is to produce a simple index or rank value to represent an area's social status by summarizing a series of theme-related indicators from different dimensions and concepts. Thus, we want to adopt a similar construction framework as the previous social index models to produce a **social fabric** index model for communities that is both transferrable and scalable across spaces and time. Unlike previous social vulnerability and resilience indices, the social fabric index focuses on measuring the social connectedness and cohesion within hazard-affected communities. This can be useful when considering pre- and post-mitigation policy implications for a community. However, it inherits a similar construction framework as the previous index models. Thus, it is essential to connect it with existing social index models as we expand toward consideration of research related to the social fabric concept.

Existing resilience and vulnerability indices models can be ambiguous and of contested concepts [18–20]. Both concepts often hold a community's pre-disaster condition as the reference point for evaluating the impacts of disaster and the mitigation policy for recovery. Thus, composite index models are useful for assessing community vulnerability and resilience. For instance, resilience is a socio-environmental system's ability to adapt to external social, political, and environmental disruptions [21]. Concerns over growing exposure to natural hazards and lack of community preparedness have stimulated interest in quantitative measurements of resilience [22]. Composite index models have been verified as useful to evaluate resilience and vulnerability because they combine many dimensions of vulnerability or resilience into a single metric, which allows easy assessments of differences across different communities, and of changes over time [22]. This also motivates the adoption of a similar composite index model to evaluate social fabric structure for communities across spaces and time.

Numerous indices of community resilience have been proposed to assess communities and aid in planning [23–26]; Plyer, 2013; [27]. For example, the Community and Regional Resilience Institute (CARRI) quantifies the community's functional capacity to adapt to environmental disruptions [23]. The Coastal Resilience Index applies a self-assessment strategy for evaluating historical records and generated resilience indices for each considered sector [25]. The New Orleans Index uses economic growth, inclusion, quality of life, and sustainability indicators to track the recovery of New Orleans neighborhoods since Hurricane Katrina in 2007 [28]. While these resilience measurement approaches provide valuable insights for assessments and planning, many are limited by specificity to geographic areas or types of hazards and lack of explicit quantitative outcomes, which can prevent their generalized application [22].

Similar to resilience, community vulnerability is an ambiguous and contested concept. Here, we define vulnerability as a community's susceptibility to the disruptions of natural disasters [29]. Examples of factors that might affect a community's social vulnerability include socioeconomic condition, gender composition, race and ethnicity, family structure, education, and medical services [30]. Many social vulnerability indices have been created, including the Social Vulnerability Index (SoVI) to natural hazards [30]; the Social Vulnerability Index (SVI) for disaster management [31]; the Environmental Vulnerability Index (EVI) [32]; the Coastal City Flood Vulnerability Index (CCFVI) [33]; and the Human Development Index (HDI) [34]. SoVI is constructed using county-level socioeconomic and demographic data for the U.S. based on 1990 data [30]. Using Principal Components Analysis (PCA), an initial set of 42 variables was reduced to 11 independent components, which account for 76% of the variance. These components were combined to calculate a summary score for each county-the SoVI Social Vulnerability Index. The EVI was constructed using a theoretical framework that identified three aspects of environmental vulnerability: threats to the environment, the innate ability of the environment to cope with the dangers and ecosystem integrity, with the index representing a weighted sum of separate indices of these three aspects of vulnerability [32]. The CCFVI assesses vulnerability to coastal flooding, based on exposure, susceptibility, and resilience scores. The final index represents a weighted sum of hydrological, socioeconomic, and political-administrative sub-indices [33,35].

### *2.2. Social fabric research*

The social fabric concept has a long record of being investigated in the community development and sociology area. The social fabric is defined as the interaction and connections between population who resides in one community. Research has stressed the importance of the social fabric for community populations to feel mentally fulfilled and satisfied. For instance Ref. [36], pointed out that the experience of perceived social isolation has significant negative consequences related to human psychological well-being during the pandemic. Besides, social connection and feelings of belonging were found to be related to life satisfaction in older adults [37]. Moreover, the study also found that social connectedness has been identified as an important aspect of human physical well-being and has been shown to be essential in predicting individual health outcomes [38]. Thus, it is essential to evaluate social fabric's role to contribute to the post-hazards' recovery process.

For social fabric research in the post-disaster recovery context, some studies found that although the long-term recovery process is substantially complicated and that not all forms of social capital development can be beneficial to its overarching goal, building social cohesion is a key to a sustainable recovery in a dynamic changing society [39]. Also, in disaster resilience and vulnerability research, social networks are essential for increasing resilience and reducing disaster vulnerability in preparing for and responding to a natural hazard [30]. Thus, social connections and networks are critical to reduce social vulnerability for environmental hazards [30]. Nonetheless, few previous studies have developed a numerical model to practically measure the concept of community social fabric and cohesion using an index model approach. Thus, a gap exists where social fabric research needs an index model to measure and track the change of social fabric and cohesion status for hazard-affected communities in the context of post-hazard recovery and mitigation evaluation. Detailed information regarding the review and selection rationale of indicators related to the community social fabric concept is elaborated in the Methodology - SoFI Index Model section.

### *2.3. Composite index construction*

For most community resilience and vulnerability indices, the construction process begins with a theoretical analysis, which identifies critical systems that may be affected by disaster or are expected to play crucial roles in recovery [40]. Next community vulnerability or resilience indicators are selected to represent the identified systems. Such indicators include voter participation [41], percent of the land used for agriculture [32], and per capita income [30].

Although these indices are constructed using formally similar processes, there are myriad options at each step in the process in which normative judgment is applied, without a disciplinary consensus for identifying and weighting critical systems, selecting indicators, or acquiring and analyzing data, to reduce it to a single dimension. This contributes to the confusion and contestation around vulnerability and resilience assessments [18,40]. For instance, some studies identified three critical systems [42], while others identified four [35,43–45] or even five [46–49]. Even where the number of categories is the same, their composition can vary significantly [46] found that ten indicators appeared in 40% of studies, which may provide a starting point for establishing standards. Still, the

60% of studies without these indicators illustrate the magnitude of the challenge [40] developed a classification scheme and searching framework to accelerate identifying, selecting, and applying indicators associated with various aspects of social vulnerability. They identified a series of over 550 indicators and metrics of sustainable community resilience, which exhibit similar problems of specification and redundancy.

Another significant challenge for constructing indices lies in using correlation analyses to address redundancy among indicators. For a typical index, more than 20 relevant indicators are chosen. Dimension-reduction methods, such as PCA, are used to generate a smaller number of uncorrelated indicators that effectively summarize the original set [30,41,50]. Using coordinate rotations, such as varimax, with PCA makes the connections between the original indicators and the principal components clearer and easier to interpret [30]. However, this analysis framework does not yield a unique index from a set of primary indicators: choices in the analysis procedure can lead to different indices with varying groupings of primary indicators [48,51]. Another approach is Confirmatory Factor Analysis (CFA), which was used in the Communities Advancing Resilience Toolkit (CART) [52,53]. [54] also applied a CFA methodology to integrate a series of resilience dimensions in metropolitan areas of South Korea [55] used CFA to assess how well a method developed in Israel (the Conjoint Community Resiliency Assessment Measurement, CCRAM) performed in China [56] applied CFA to assess the reliability of an index for measuring resilience to economic structural change.

### *2.4. Uncertainty and global sensitivity analysis*

Any model output's usefulness depends on its output's accuracy and reliability. Nonetheless, since all models are eventually a form of abstraction of reality, not only the precise input data are rare in this case, and the modeling process is also subject to imprecision, leading to imperfect model output. As a result, the final model product is always associated with certain levels of uncertainties and imprecisions, which need to be assessed, interpreted, and visualized. Sensitivity and uncertainty analysis are great tools to investigate the imprecisions of the model outputs for users to be more confident when implementing activities associated with the model's results. The difference between the two approaches lies in that uncertainty analysis only evaluates and represents the uncertainty in model outputs that derives from uncertainty in inputs, while sensitivity analysis focuses on evaluating the contributions of the uncertain inputs to the total uncertainty in analysis outcomes.

Uncertainty analysis (UA) is an important process to assess the entire set of possible outcomes associated with their probabilities of occurrence. The uncertainty of model output values results from modest changes in model input values as well as different model configurations. The goal of uncertainty analysis in models of complex systems is to produce output metrics with greater precision, transparency, and credibility, with an underlying aim of improving user's confidence in implementing activities associated with model output. Uncertainty performance has been widely studied in model predictions of sea level rise [57], hurricane paths [58], and communities' social vulnerability [59]. Two general forms of uncertainty have been well understood: aleatoric and epistemic. Aleatoric uncertainty occurs because of heterogeneity or intrinsic model randomness. Epistemic uncertainty arises from things that cannot be known but could be measured from our measurement's limited accuracy and precision [60]. For example, in terms of social index research, aleatoric uncertainty affects the input data used for social indexes, but epistemic uncertainty accompanies every stage of the index construction process that can include conceptual framework development, selection of indicators, collection of data, consideration of measurement error, data transformation, weighting, and aggregation [59]. As modeling decisions during the development of the index proceed, epistemic uncertainty associated with each step propagates and potentially interacts with that from previous steps [59]. Uncertainty and sensitivity analysis are usually combined to quantitatively validate the social index, where uncertainty analysis help evaluate the robustness of index values. Sensitivity analysis decomposes the uncertainty to determine which index construction decisions have the most significant influence on the output rank variability.

Unlike the uncertainty analysis, sensitivity analysis (SA) attempts to determine the change in model output values that sources from modest changes in the model input value. While the context of the sensitivity analysis could be complex, the term SA often refers to a 'what-if' analysis where the model parameterization or the process configuration are varied one at a time [61]. SA also tells how the uncertainties (aleatoric and epistemic) in the independent variables affect the accuracy of our model's predictions of the dependent variables. Sensitivity analysis has been widely studied in human-environmental models such as weather and climate forecasts and simulations [62,63], sea level rise [64], projection of hurricane losses [65], evaluation of river water quality [66], multizone air flow evaluation [67] and communities' social vulnerability [68]. Besides, some emerging trends in sensitivity analysis have been found that the application of SA can be used to analyze the impact of non-numerical uncertain factors like model spatial resolution or structure [69].

[68] examined the sensitivity of quantitative features underlying the SoVI approach [30] to changes in its construction, the scale at which it is applied, the set of variables used, and various geographic contexts. Specifically, multiple aggregation levels in the State of South Carolina and different subsets of the original variables were used to determine the impact of scalar and variable changes on the SoVI construction process. For example, to assess the effect of changing the level of aggregation on the social vulnerability analysis, they constructed SoVI and applied the principal component analysis (PCA) on three different spatial scales: the county level that was the original SoVI scale adopted in Ref. [30]; census tract level scale, and a manually created intermediate level of aggregation [68]. They uncovered that as the level of aggregation at which the principal component analysis (PCA) was conducted decreased, the variance explained per component also decreased, and the number of components selected using the Kaiser criterion thus increased, echoing the result found by Ref. [70]. This is because with increasing level of aggregation, more and more spatial frequencies may be lost, and fewer numbers of independent variables can model the same amount of important information. Besides, they also tested the sensitivity of the algorithm to changes in construction and determined if that sensitivity was constant in various geographic contexts [68]. Regarding SoVI construction algorithm sensitivity analysis, they first identified three categories: PCA component selection, PCA rotation, and the weighting scheme used to combine the components to create the final index [68]. Several options were considered

within each of the three different index construction categories. For instance, in terms of PCA component selection, they considered the Kaiser criterion, percentage variance explained, the Horn's parallel analysis as different methods [68]. For PCA rotation methods, they accounted four rotation strategies which are the unrotated solution, varimax rotation, quartimax rotation, and promax rotation [68]. For weighting schemes, three approaches were considered: sum the component scores, the first component only, and weighted sum using explainable variance from PCA to weigh each component [68]. Factorial analysis with partial ("Type III") sums of squares approach was conducted to assess the impact of changes in the algorithm construction on the index values and found that the algorithm is robust to minor changes in variable composition and scale but is sensitive to changes in its quantitative construction such as weighting scheme [68]. Their sensitivity analysis plays a critical role in understanding the impacts of changes in index construction as well as the scale on the final index representation and increasing users' confidence in metrics designed to represent the highly complex phenomenon of social vulnerability [68].

[59,71] investigated the uncertainty associated with the methods of the SoVI construction process, including decisions related to indicator selection, scale of analysis, measurement error, data transformation, normalization, and weighting. Each of these stages was imbued with uncertainty due to choices made by the index developer [59] to answer the research questions of how much uncertainty is associated with the SoVI, how does the index perform when alternative configurations are considered, and what is the relationship between vulnerability and uncertainty [59]. For example, in terms of the data transformation method, options of raw counts (none), population (percentage), and density (area) were applied [59]. For areas with low uncertainty, decision makers can implement vulnerability reduction strategies with greater confidence since the index representation is reliable [59]. His study applied Monte Carlo-based uncertainty analysis to assess and visualize uncertainty for a hierarchical SoVI [59]. During each run in the simulation, a single option within each stage of index development is selected and used to compute a social vulnerability index. The vulnerability ranks from that run are saved, and the process is repeated 7168 times [59]. In the uncertainty measurement and representation stage, three statistics of particular use to measure the uncertainty magnitude are the confidence levels (CIs), the median to evaluate bias, and the coefficient of variation (CV) to assess the index precision. They found that for areas with higher vulnerability, there tends to be greater index uncertainty, suggesting potential alternative use of the index not as an approach to identify high-vulnerability areas but as a screening tool to eliminate low-vulnerability areas from consideration [59]. They also suggested that the weighting stage that is the key driver of uncertainty for the hierarchical model [59]. Besides, they also concluded that the scale of analysis might be a manageable factor for an index explicitly designed for use at a particular administrative scale [59].

Thus, it is essential to conduct an uncertainty and sensitivity analysis for the proposed Social Fabric Index model developed in this study.

## 3. Methodology

In the method section below, we discuss the rationale for selecting relevant social fabric indicators and their approximations and the uncertainty and global sensitivity analysis framework.

### 3.1. SoFI index model

In this study, we aim to propose a Social Fabric Index (SoFI) Model to enable city planners and practitioners to track the change in the social fabric status of post-disaster communities in the context of natural hazards mitigation and recovery evaluation. The SoFI model proposed in this work is formalized as follows. The term "social fabric" refers to the degree of interpersonal connection and cohesion, and connection to place among community members. It embraces numerous interrelated phenomena, including demographic and economic factors, behavioral issues, social structures, social organizations, social networks, and relationships among people [72]. The demographic factors include population features of ethnicity, educational background, and religious affiliation. Economic factors include the monetary investment and activity associated with personal and enterprise entities within a community. Behavioral issues describe individuals' willingness to contribute to and participate in public affairs and shared activities. Finally, social structures, organizations, and networks all define the relationships between individuals, social groups, and families that closely relate to the social cohesion status of a community. Their relevance to the social fabric and the rationale for selecting relevant indicators for each dimension are elaborated in the following.

Different sociological perspectives profoundly influence the concept of the social fabric and its operationalization in a specific analysis method. Civil society and social fabric describe the ability of a geographic place "to nurture local spaces, facilitate micro-organizations that consist of people with similar beliefs and faith, and support the multiplicity of cultural matrixes consisting of different cultures along social dimensions to comprise civil society" [73].

In this study, we present a method for constructing a community Social Fabric Index that includes only physical or behavioral aspects of the community rather than their emotional effects. This decision makes it easy to apply the method using widely available public data without requiring difficult and expensive surveys of community members and their attitudes. We use metrics such as the churches' density and green public spaces as proxies for attachment to place.

In summary, we capture the social fabric concept from the following perspectives:

(1) Sociodemographic and economic factors, such as population and gender.
(2) Social institutions, such as family structure and composition.
(3) Social organizations, such as voluntary-based groups and churches.
(4) Social networks or relationships among people, such as community-wide events.
(5) A sense of belonging and identification with a particular social unit.
(6) A sense of social justice and equity, particularly in government policies, such as public hearings and elections.

(7) A willingness to participate in shared activities and possibly undertake voluntary work.
(8) A sense of life satisfaction, happiness, and positive future expectations.
(9) A sense of safety and security, such as fire stations and emergency rooms.

Different from traditional community indexes such as the Social Vulnerability Index (SoVI) [30], which mainly includes standard sociodemographic data from American Community Survey, the proposed SoFI model incorporates several new dimensions, including community cohesion and engagement, social organization, public facilities, and amenities that take people's relationship and connectivity within a community into consideration (Fig. 1).

Many studies have found a strong association between sociodemographic diversity and social cohesion. Sociodemographic diversity includes variables like education, migration background, ethnicity, and religious affiliation characteristics of the population within a community. Recent studies find that ethnic heterogeneity strengthens the social fabric, by promoting greater trust among members of different ethnic groups [74] and refute older studies that claimed that ethnic diversity might weaken social capital and social cohesion [75]. Thus, we included several ethnic indicators, such as the percentage of Asian, Hispanic, and Black populations, in the model. Education strengthens social cohesion by enabling new members to be engaged in social connections [76]. Additionally, education also promotes healthy lifestyles and social norms, reducing social inequalities [77]. Thus, the percentage of population with limited education was included in the model. Religion is another source of social cohesion through its role in strengthening shared values, creating a sense of unity, and fostering a sense of belonging [78]. Nonetheless, data on religious affiliation is not generally accessible, and its spatial distribution is not measured consistently in extant surveys [79]; therefore, we use the number of religion-related buildings as its approximations.

The family structure indicates the relationship structure of the individuals who live in a household and consider a family. Studies found that relationships between families play essential roles in community cohesion [80], and children are especially important to building inter-family connections in a neighborhood, at school, and in the greater community [81]. For many adults, retirement precipitates a changing relationship with the community [80]. In the past, adults who spent much of their adult life in the labor force, and their spouses, benefitted from pensions and other accumulated resources that could meet their retirement needs and allow for informal and formal charitable giving [80]. Retirees also have more time for volunteering formally or informally within the community [80]. Thus, households with seniors also have good potential to strengthen community cohesion and fabric. However, this may change as the majority of a new generation of retirees has not had access to defined-benefit pensions and has not been able to save adequately for retirement [82]. While recognizing the shortcomings of focusing on families, we nonetheless include demographic statistics on the fraction of single-parent and single-adult households, as these have been found to correlate negatively with social cohesion [83]. In addition, financial burdens, such as high cost of housing relative to household income, can discourage formation of new families [84,85]. Thus, the proportion of single-parent and single-adult households may reflect the social cohesion of a community, both


**Fig. 1.** Scoping diagram for communities' social fabric dimensions.

through the direct contribution of families to social cohesion and as an indirect measure of the economic health of the neighborhood [72,81,86].

Community engagement and place attachment are also core elements in promoting community identity and strengthening the social and cultural fabric [87]. In a cohesive and engaged community, people not only like to be surrounded by each other but also has a firm place attachment feeling to the place in which they live and never want to leave. Therefore, they are willing to participate in community public events like festival gatherings to hold aspirations for improving the community's common good [88]. Studies found that social cohesion can be significantly improved by engaging public organizations' work in social systems [89]. Residents are willing to participate in the responsive development of the community from an economic and social perspective since they strongly believe that they can possess their own future. A cohesive community also shares a common vision and a sense of belonging with each of its members. One significance is that it dramatically appreciates and values the opinions and thoughts of people from different backgrounds [90]. Participation in public affairs is particularly productive in enhancing community cohesion and engagement since people with variety of interests have a chance to reach an equilibrium so that the whole community can be seen as one interest entity [91]. Thus, we included several indicators associated with community public affairs engagement, and activities, such as the number of community events, elections, and hearings, as indicators in the model.

Community events include the initiatives of public socials by a Homeowners Association (HOA) or an apartment property management team in that all neighboring residents can participate to know each other better. Community elections include elections of volunteer representative residents for an HOA board by fellow neighbors. Community hearings are gatherings and events held by officials and residents in which residents are permitted to comment on public or political issues before the actions are taken. One example is the metro council meetings held by the Nashville city government in the David Scobey Council Chambers at the Historic Metro Courthouse located at One Public Square. Any public members wishing to speak at a public hearing can attend and express their opinions.

The level of reported crime in disadvantaged areas is related to low levels of social cohesion [92]. Study identified that crime rates are significantly lower than expected for those areas with high levels of social cohesion than those with low levels of social cohesion [92]. This correlation may be explained by the fact that social cohesion plays a critical role in reducing crime rates for a community [93,94].

However, collecting data on people's perception of community cohesion and attachment to place is challenging and time-consuming without conducting large-scale community surveys. Fortunately, important connections have been observed between place attachment and the practice of community participation and the planning process [87]. Thus, we used non-residential historical sites like monuments as a proxy to approximate place attachment [95]. Furthermore, it is believed that people who are associated with stronger feelings of place attachment and are more motivated in participating community public affairs [95].

Public facilities and amenities are essential in enhancing residents' social values by providing physical spaces for interaction and integration [96,97]. Thus, it is one of the most valuable aspects of the social fabric of a community. The study found that people tend to associate a community with their physical environment and the assets that the environment affords them [72]. In addition, the economic and social aspects of these infrastructures facilitate social connection, participation, integration, and improve social connectivity positively and negatively [72]. For example, schools serve as a physical medium where residents can communicate, help, and educate others. Restaurants and cafes provide valuable spaces for people to have meals with friends. They create more opportunities for people to have meals together and exchange opinions on cuisines and cultures, strengthening the social ties between individuals. As a result, in a community with sufficient public facilities, people can feel safe, secure, connected, and happy. We included a series of facilities and amenities, like the number of green spaces, barbers, supermarkets, universities, and fire stations, as indicators to reflect a community's capability to provide opportunities for its residents to exchange physical and spiritual resources in a common shared space.

The relationship between economic prosperity and the community's social fabric can be substantial [72]. Studies showed that people intend to strongly associate with affluent communities [72]. For example, people always want to go to communities with affluent choices of shopping centers and public green spaces that require the community's economic investment. People tend to believe that economic prosperity is essential for a solid social cohesive community to thrive [72]. Meanwhile, a high-quality economy also facilities the prosperity of local businesses such as pubs and restaurants so that people have more places to consume and interact with each other. This could readily lead to a virtuous circle in that a stronger economy strengthens the local tax base, thus enabling the potential of more public facilities investment to further allure more population to move in. Ideally, we want to describe a community's economic status from five perspectives: revenue, debt, investment, tax, and GDP. The revenue is the per capita monetary income of all people and local businesses within a community. The debt is the per capita debt of all people and local businesses within a community. The investment is the per capita financial investment from all people and businesses outside a community. The tax is the per capita monetary tax contributed by all people and businesses within a community. The GDP is the per capita gross domestic product of a community. However, since this information is tough to obtain from a public data source, we included some indicators that are publicly accessible to approximate the financial status of a community, like median gross income, unemployment rate, median gross rent, median house value, and the number of cafes/pubs per capita.

Voluntary, public supportive organizations are believed to significantly affect social cohesion levels [98]. Relevant studies suggested that active participation in voluntary and supportive organizations often leads to autonomous actions that are shaped and carried out for the common good [98]. [83] pointed out that the fundamental desire for recognition drives the satisfaction we obtain from being connected to others. Thus, active participation in a voluntary organization involves our need for human connectedness. The voluntary and supportive organizations can include national and international nonprofit/nongovernmental organizations (NGOs), including churches, charities, and lobbies, etc. Although they may serve different purposes and people with specific interests, they help unite people with similar faith and ideas to achieve common goals [98,99]. We used the number of churches, cathedral buildings, chapels, mosques, charities, temples, etc., as indicators to approximate the voluntary and supportive organizations.

Based on these social fabric literature reviews mentioned above, seven critical dimensions associated with community social fabric status were identified, and their corresponding indicators are displayed in Fig. 1. Dimension and related indicators description are summarized in Table 1. Complete information on these indicators is summarized in Appendix A Table A.1. These indicators were incorporated in the proposed SoFI. Data were derived from the American Community Survey (ACS) using the Census Data Engine for most demographic diversity and family composition indicators. For example, gender diversity was derived by calculating the difference between the male and female populations, and ethnic diversity was approximated by calculating the standard deviation of the ethnic group populations. For the identified public facilities and amenities indicators, data was manually derived from Google map, state-registered charities search engines, governmental crime activity maps, and open street map. Some social organization, community relationships, and community cohesion and engagement indicators were approximated by relevant physical facilities indicators.

After the selected indicators were collected, SoFI was constructed based on an inductive configuration since it begins with a large set of indicators [71]. Options of model's each construction stage were arbitrarily selected to serve as the baseline. We use italics in Table 2 to show the baseline options for each construction stage. Specifically, all selected indicators were normalized based on the corresponding census tract unit area and standardized using z-score standardization. Then, principal components analysis was performed on the normalized and standardized indicators. Following, the Kaiser criterion was adopted for principal component selection, and varimax rotation was adopted for principal component interpretation. Finally, a new summary index named "SoFI" was calculated by directly summing all the selected principal components based on Kaiser selection and varimax rotation interpretation results. All the calculation was implemented in the RStudio software. Then, the calculated data was exported to ArcGIS Pro to reveal the spatial distribution of the social fabric index.

**Table 1**
Social fabric dimension and indicators.

| Dimension | Description | Indicators |
|---|---|---|
| Sociodemographic Diversity | Differences among people in various forms including gender, ethnic, education attainment, etc. ***Sources:*** [39,74–77,100] | POP, MALE_POP, FEMALE_POP, ASIAN, RELIGIOUS_POP[a], BLACK, HISPANIC, WHITE, LIMIT_EDUCATION, LIMIT_ENGLISH |
| Community Cohesion and Engagement | Community people's participation in public policy affairs. ***Sources:*** [72,87–89,91,92,95,101] | COMMU_EVENT[a], COMMU_ELECTION[a], COMMU_HEARING[a], CRIME |
| Community Economy/Finances | Community's monetary and economic values ***Sources:*** [72] | COMMU_REVENUE[a], COMMU_DEBT[a], COMMU_INVEST[a], COMMU_GDP[a], COMMU_TAX[a], MEDIAN_INCOME, UNEMPLOYMENT, POVERTY, MEDIAN_HOUSE_VALUE, MEDIAN_GROSS_RENT |
| Family Composition/Structure | Differences among family structure within a community including single parent family, married couple family, etc. ***Sources:*** [102–104] | FAM_OWN_CHILD, SING_PARENT_FAM, SING_PERSON_HOSHD, MULTI_FAM_HOUS, SENIOR_HOUS, TOT_HOUSHD |
| Social Organization | The community-led non-profit organizations that can provide public and voluntary services to its people. ***Sources:*** [83,98,99] | SUP_GRP[a], VOL_GRP[a], CATHEDRAL, CHAPEL, MONSTERY, MOSQUE, RELIGION, TEMPLE, CHURCH, CHARITY |
| People's willingness to participate in shared activities (Relationships) | The public places density that enables people to participate shared activities to enhance their connections. ***Sources:*** [72,105,106] | RECREATION, PUB, MONUMENT, STADIUM, CAFÉ, RESTAURANT |
| Public Amenities and Facilities | The public physical amenities that create opportunities to nurture and organize people within a community. ***Sources:*** [95–97]; | FIRE_STATION, GROCERY, SUPERMARKET, EMERGENCY, HEALTHCARE, HOSPITALS, COLLEGE, KINDERGARTEN, LIBRARY, K-12_SCH, PUBLIC_SCH, PRIVATE_SCH, UNIVERSITY, BANK, BUS_STOP, GR[a]EEN, BARBER |

[a] Indicators are not available on ACS data source or are approximated by other indicators.

**Table 2**
Experiment design of uncertainty and sensitivity analysis.

| | Uncertainty Analysis | | Sensitivity Analysis |
|---|---|---|---|
| N | $2^9$ | **Estimator** | First order: "saltelli" [107], |
| K | 5 | | Total order: "jansen" [108], |
| Model evaluation | $N(k+2) = (5+2) \times 2^9 = 3584$ | **Matrices** | c ("**A**", "**B**", "$\mathbf{A}_{\mathrm{B}}^{(i)}$") |
| Input Factor PDF | Uniform Discrete | **Sample Algorithm** | Quasi-Random sampling |

### 3.2. Global sensitivity and uncertainty analysis on the SoFI model

Before applying such a model that could have significant policy implications, it is critical to understand the limitations and how individual factors that go into the SoFI may drive outcomes. Two general forms of uncertainty are associated with models, including aleatoric and epistemic. Aleatoric is caused by the model's heterogeneity and the inherent randomness of input parameters and processes [109]. The epistemic uncertainty is caused by an incomplete and imprecise understanding of model parameters [110].

Traditionally, every stage of the SoVI construction step is arbitrarily selected, ignoring any epistemic uncertainties accompanying every step of the index construction process. However, epistemic uncertainty could interact with previous steps and propagate with the proceed of modeling decisions during the index development process.

Thus, we performed an uncertainty and global sensitivity analysis on the SoFI model to answer the following research questions: (a) How much uncertainty is associated with the SoFI model? (b) What is the relationship between the SoFI model and uncertainty? (c) Which modeling decision contributes the most to variability in the SoFI model? To answer these questions, model alternatives for an inductive SoFI for Davidson County, Nashville, were subjected to an uncertainty analysis using Quasi-Monte Carlo simulation and variance-based global sensitivity analysis. The uncertain model decisions evaluated are summarized in Fig. 2.

In terms of variance-based global sensitivity analysis, we adopted two sensitivity indices to evaluate the contribution of a construction factor to the model's output variability. The first-order sensitivity index measures the effect of varying a single construction factor alone. The total order sensitivity index measures the contribution to the model's output variance not only of the uncertain factor but also with all variances caused by its interactions with other uncertain factors. To calculate global sensitivity indices, we adopted the estimator of [107] to calculate the first order of the sensitivity index $S_i$ that unconditionally contributes to the total output variances:

$$S_i = \frac{\frac{1}{N}\sum_{v=1}^{N} f(\boldsymbol{B})_v \left[ f\left(\boldsymbol{A}_B^{(i)}\right)_v - f(\boldsymbol{A})_v \right]}{V(y)} \tag{1}$$

Please see Ref. [107] for more detailed mathematical derivation.

The method of [108] was used to calculate the total order of sensitivity index $S_{Ti}$ that accounts for interaction effects among input factors, following the best practices identified in the sensitivity analysis [107,111]:

$$S_{Ti} = \frac{\frac{1}{2N}\sum_{v=1}^{N} \left[ f(\boldsymbol{A})_v - f\left(\boldsymbol{A}_B^{(i)}\right)_v \right]^2}{V(y)} \tag{2}$$

where any sampling point in either **A** or **B** sampling matrix can be indicated as $x_{vi}$, where $v$ and $i$ respectively index the row and the column. Please see Ref. [108] for more detailed mathematical derivation. Estimators for both $S_i$ and $S_{Ti}$ were reviewed in Ref. [112].

Sobol's [113] method of Quasi-Random sampling was used as the sampling algorithm for selecting the input factors since it fills the input space quicker and more evenly, leaving smaller unexplored volumes. To compute the pair ($S_i$,$S_{Ti}$) values, 2 $N$ simulations are

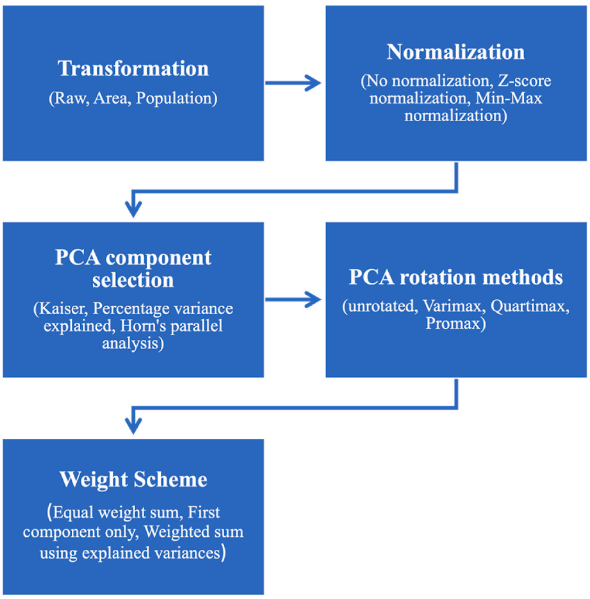


**Fig. 2.** Diagram of uncertain construction factors associated with social fabric index (SoFI) composition process.

needed for computing model output $Y$ corresponding to matrices **A**, **B**, while $kN$ simulations are required to compute $Y$ from $\mathbf{A}_{\mathbf{B}}^{(i)}$. Thus, the sensitivity indices pair gives a good description of the model sensitivities at a reasonable cost with a $N(k+2)$ model evaluations, where $N$ represents the sample size of **A** or **B** matrices that is required to approximate the multidimensional integration implicit in an equation to a plain sum [114]. $N$ typically varies in the 100–1000 range. All the sensitivity computation processes were conducted in the R package sensobol [115]. The computation of uncertainty and global sensitivity analysis was conducted in the RStudio software. The detailed experiment design is summarized in Table 2.

Detailed information regarding the mathematical approach and derivation of variance-based global sensitivity analysis is elaborated in the supplemental material.

### 3.3. Case study: Davidson County, Nashville, TN, USA

Davidson County (Nashville), Tennessee, in the U.S. is selected as the case study area for investigating the social fabric index and its uncertainty and sensitivity analysis (Fig. 3). Located in the heart of Tennessee, Davidson County consists of primarily urban areas spanning over 1300 square kilometers [116]. In a recent 2020 survey, the population was approximately 715,884, with 54.05% being non-Hispanic White [116]. One of the most significant natural disasters in Nashville was flooding in May 2010. The area was severely affected, with more than \$2.3 billion in property damages. The home buyout program that has been in use in Nashville for nearly thirty years was carried out as a mitigation strategy to motivate affected people to move to non-affected places aftermath of the 2010 flood, leading to potential heterogeneous influences on the social fabric status across space [11]. So far, it is reported that over 400 homes were bought out prior to and after the 2010 flood disaster. Thus, we selected Davidson County, Nashville, as our study area. All demographic variables used in the SoFI construction were collected from the 2018 ACS source.

The Davidson County, Nashville area's baseline SoFI was mapped for each tract. Then, the Monte Carlo simulation was conducted with a discrete uniform probability density function (PDF) for each index construction stage. The baseline SoFI mapping was applied in the analysis because a reference baseline index value is a vital precursor to conducting robustness analysis [117]. The median and variance were the two vital statistics indicators of the simulation results. The median is an approximate measure of baseline ranking accuracy when considering uncertain alternative construction approaches. Since measuring the true social fabric is a challenge in the real world, the median can serve as an unbiased estimator of central tendency to be considered an approximation to the 'true' index value [71]. Therefore, uncertainty increases as the deviation between the median and baseline deviation increases [71]. The coefficient of variation (CV) and 95% confidence interval (CI) were computed as descriptive metrics to show the SoFI variance for each

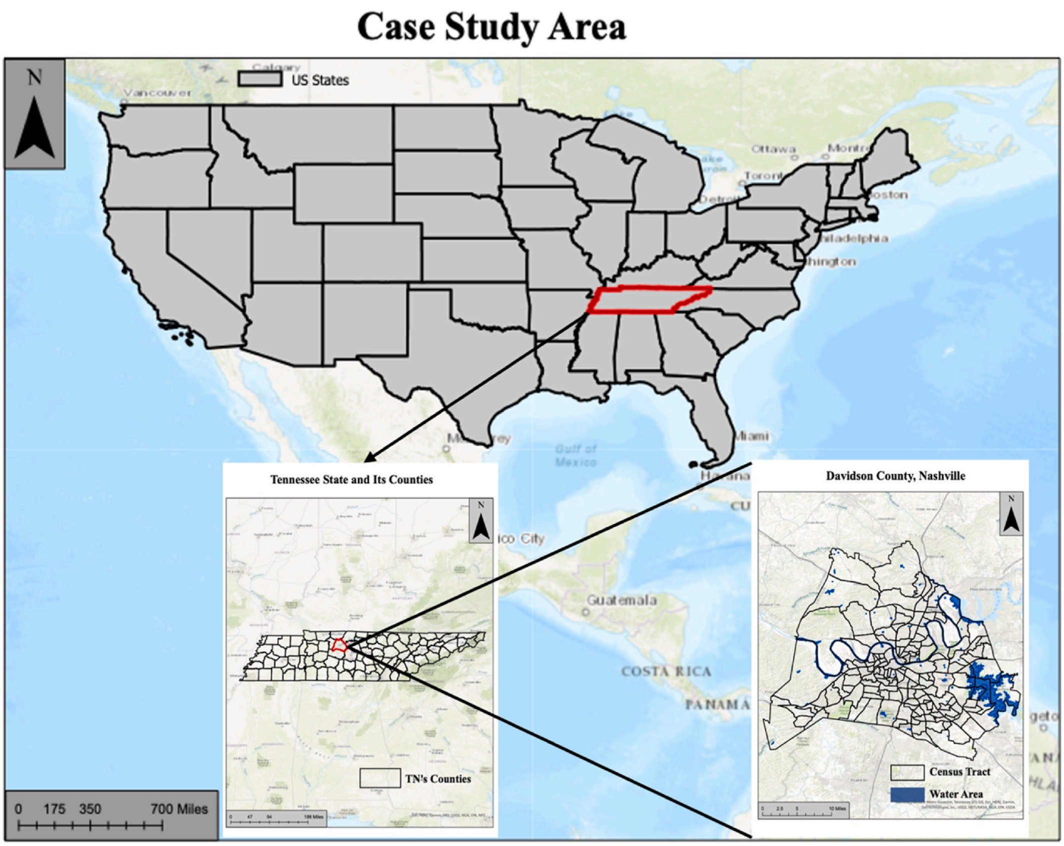


**Fig. 3.** Case study area: the Davidson County, Nashville, Tennessee, USA.

tract. The coefficient of variation is computed as the standard deviation divided by the mean to represent the uncertainty of a tract's social fabric level. Additionally, the confidence interval serves as an interval estimate of the 'uncertainty' parameter for a tract's SoFI rank value. These two uncertainty descriptive metrics were verified to be appropriate to differentiate the uncertainty estimates for the index model between census tracts [59]. For global sensitivity analysis, the first and total order of the sensitivity index associated with each construction stage were calculated for each tract. The average of the two sensitivity indices was computed across all tracts within Davidson County to evaluate the fractional contribution of each model index construction stage to the model's output total uncertainty. The detailed results are elaborated on in the Results section.

## 4. Results and discussions

Fig. 4(d) presents the baseline index for the inductive SoFI model for tracts in Davidson County. Census tracts identified with better social cohesion status represent larger rankings of the baseline shown in dark blue colors, while smaller rankings of the baseline index signify worse social cohesion shown in red colors, with the remaining 30% of tracts assigned moderate social cohesion rankings shown in orange and yellow colors. A clear pattern is identified that social cohesion is generally better in rural communities rather than in urban areas, echoing the findings from previous studies [118]. Tracts with lower social cohesion are found to be clustered in the downtown area, which highly correlates with the low-income population density distribution pattern. Groupings of higher social cohesive census tracts are identified along the northwestern part of the county, where fewer crimes exist. These findings support our hypothesis that social fabric can be represented by a socially cohesive population and its associational relationship with places, where rural areas can take advantage of every social fabric dimension, including sociodemographic diversity, physical infrastructure, green and public spaces, and social engagement. Nonetheless, urban areas lack these elements to pursue a cohesive

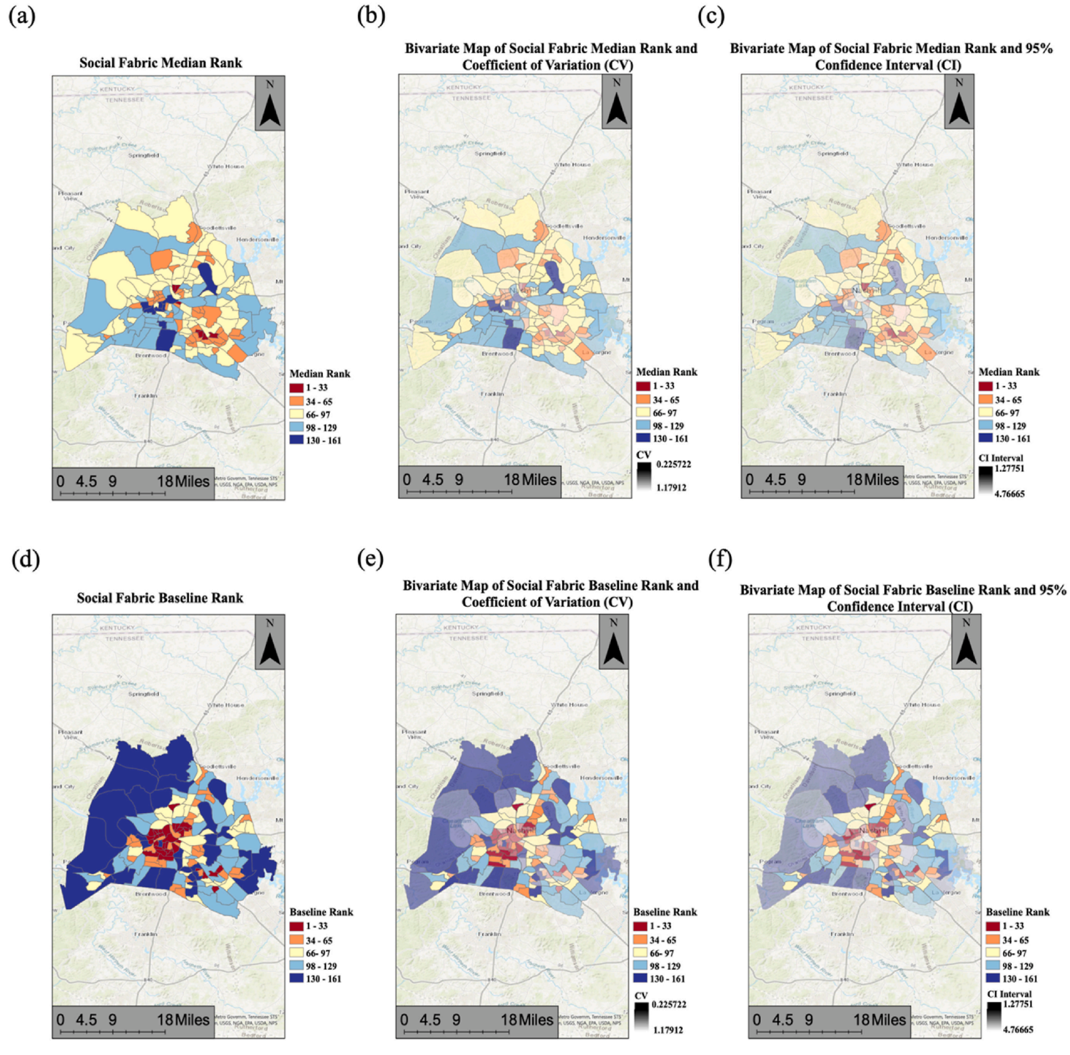


**Fig. 4.** SoFI and its uncertainty visualizations: (a) SoFI median ranking for tracts in the Davidson County; (b) SoFI median ranking and CV for tracts; (c) SoFI median ranking and 95% CI for tracts; (d) SoFI baseline ranking for tracts; (e) SoFI baseline ranking and CV for tracts; (f) SoFI baseline ranking and 95% CI for tracts.

environment though they provide vitality to attract diverse population groups from different cultural backgrounds. Study found that although the high density of neighborhood and land use mix might indicate a higher urban vitality, they might cause damage to social cohesion since strained relations, mass population migration movements, and possibly high crime rates could lead to social fragmentation [119]. This points out the importance of efficiently evaluating the effects of flood mitigation strategies like home buyouts on those inland waterway communities. Take the city of Nashville as an example, home buyouts usually take place in those downtown communities close to inland Cumberland River waterways after the 2010 flood. The buyouts could accelerate the population movement and migration, further worsening the social fabric status of these originally fragmented communities.

The Monte Carlo simulation produced a distribution of the SoFI rankings for each tract, providing a means to evaluate uncertainty in the index rank model. Fig. 4(a) presents the social fabric median ranking for each tract based on the simulation results, which we consider as a rough approximation to the 'true' index value. Comparing Fig. 4(a) and (d), we identify similarities between baseline and median ranking for most tracts, suggesting that our baseline index can successfully capture the social fabric information of the area with adequate accuracy. Specifically, both indices illustrate the trend of a worse social cohesive status for those tracts around the downtown area and a better social fabric structure for those tracts along the northwestern rural communities of the county. However, certain discrepancies can be found between the median and baseline index, especially for those small tracts in the heart of the county, where baseline rank identified those tracts as socially fragmented areas, median rank seems to miscategorize these tracts into the socially cohesive category since median value tends to enlarge the index rank. This stresses the importance of performing uncertainty analysis of the model. To better quantify and visualize the relationship between uncertainty and SoFI ranking associated with each tract, we used a bivariate map to visualize the index ranking value and its descriptive uncertainty metrics in the same plot (Fig. 4(b)–(c), (e) - (f)).

Here, we used transparency to present uncertainty metrics where alpha was set to 1 (fully opaque) to represent tracts with the lowest uncertainty, and alpha was set to 0 (fully transparent) to represent the largest uncertainty. Fig. 4(b) and (c) are the spatial representation of the SoFI model uncertainty, showing that tracts with worse social fabric status tend to have a more extensive CV and a wider CI. Clear visualization of some missing tracts in both Fig. 4(b) and (c) suggests that the SoFI model needs to be more certain about its judgment of the social fabric status of these tracts, including those tracts in the southeastern part of the county mentioned above. Compared with Fig. 4(a), we found that the SoFI model is better at determining moderate social fabric tracts than those with higher or lower social fabric status, especially for those with lower social cohesion. The visualization of the baseline rank bivariate map suggests similar findings (Fig. 4(d)and(e)). Tracts with moderate social fabric status are opaquer than those with a higher or lower degree of social cohesion, supporting the conclusion from the median rank model.

Fig. 5(a) and (c) reveal the relationship between median and baseline social fabric rank and index variability from CV perspectives, respectively. A negative correlation between social fabric rank and index variability is revealed that the index variability and uncertainty increase with the decrease of the social cohesion level. This relationship is also identified in Fig. 4 and again verified by

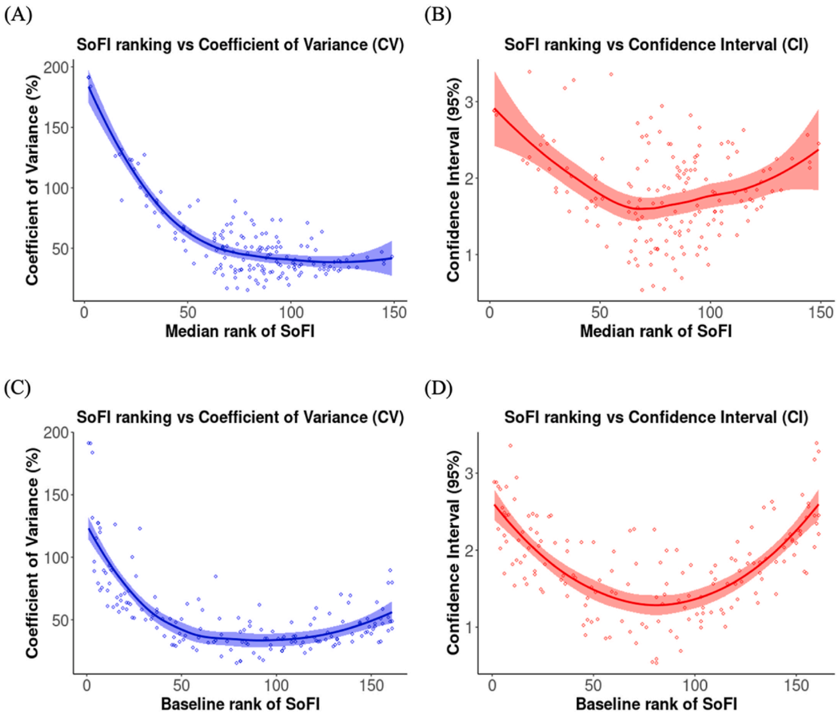


**Fig. 5.** The relationship between SoFI rankings and uncertainty descriptive metrics: (A) median ranking with CV; (B) median ranking with CI; (C) baseline ranking with CV; (D) baseline ranking with CI.

previous studies [59]. The relationship between CI and social fabric rank shown in Fig. 5(b) and (d) also exhibits a similar trend compared to CV results. The difference is that not only for weak social cohesive tracts, CI also suggests a larger uncertainty with the increase of social fabric index (Fig. 5(b), (d)). As SoFI is aimed to identify socially fragmented areas with lower social cohesion status, this indicates that the index model is better at filtering moderate socially cohesive areas rather than identifying communities with higher or lower levels of social fabric status. However, the SoFI model can serve as a guide to capture the general trend of social fabric status from rural to urban communities.

The median and variance are essential measurements to exhibit the reliability and robustness of the index model designs. However, which model parameters are the main drivers of those uncertainties remains unknown. Global sensitivity analysis provides a diagnostic tool to produce sensitivity indices that can evaluate the behavior of model parameters in terms of both first-order and interactive total-order effects perspectives. The sensitivity indices for the model are shown in Table 3 and Fig. 7. The first-order index values are vital to determine highly effective construction alternatives, and the total-order effect index values provide a comprehensive view of the total influences brought by each construction stage, including its own and interactions with others.

For this inductive SoFI model, the transformation and PCA selection are the two essential construction parameters with high first-order and total-order effects of sensitivity indices (Fig. 7). Taken together, the first-order effects account for 0.44 of the total variances, indicating that significant interactions are involved between these parameters. We identified the most important output variance contributor for each tract by comparing the first-order and the total-order sensitivity index value of each construction step for each tract and mapped the dominant factors that have the largest sensitivity index value of the SoFI rank model on the tracts of the Davidson County, Nashville (Fig. 6). Fig. 6 suggests that indicator transformation parameters tend to contribute more uncertainties to those tracts with higher or lower areas, while the weighting scheme plays more critical roles in those tracts with smaller sizes. PCA selection dominates uncertainty contributions for certain amounts of tracts since it highly correlates with the following rotation and weighting scheme stages, overriding some of the uncertainty contributions from the following construction steps. Thus, the roadmap to reducing the uncertainty in the SoFI is clear: focus more on choosing the appropriate transformation approach when the mapping units are highly heterogenous and the combination of PCA selection, rotation, and weighting scheme when mapping standard homogenous units that best represent model's principals. For instance, the sensitivity analysis results enable city planners and practitioners to have more confidence in choosing raw indicator values when mapping on a homogeneous spatial/population unit and in determining population or area-weighted indicator values based on the observation of population and spatial units' area distribution when mapping on a heterogeneous spatial/population unit application.

## 5. Challenge and future work

The present study uses standard sociodemographic data to develop a numeric spatial index model to evaluate a community's social fabric status across space. However, previous studies find that sufficiently deriving social, behavioral, and psychological variables like social fabric through standard available demographic and land use measures is always challenging. While proxy indicators based on sociodemographic information and physical infrastructure data can provide adequate measures that relate to the community's real or behavioral aspects, important emotional effects of the social capital are likely to be missed from the proposed indicator-based index model. For instance, the study identified important connections between the environmental and community psychology on place attachment and community participation and engagement [87]. It is believed that overlooking emotional connections to place could lead to failure to adequately measure community participation and engagement motivation, an important dimension of the social fabric [87]. Additionally, community psychologists have researched many attitudes, emotions, and perceptions of the social fabric, including the sense of community (SOC) [120]. A primary benefit of SOC is social support from the community, which depends on the quality of one's emotional relationship with community members [120]. Thus, genuinely community-level measures of SOC are recommended to be included to describe a community's social fabric status comprehensively.

The future study aims to incorporate indicators of emotional and psychological effects of the social fabric into the current SoFI model. A community survey can be considered an adequate approach to obtain solid emotional and psychological constructs of a community's social fabric, like place attachment and sense of community. Finally, we recommend establishing a community database of emotional and psychological variables to enable a broader application of the model.

## 6. Model implementation for mitigation policy evaluation

The SoFI model developed in this study is a core element in assessing communities' social fabric in the post-hazard recovery process. Nonetheless, effectively implementing the SoFI model in real-world applications must address two additional challenges: Modifiable Areal Unit Problem (MAUP) and database quality. Here, we demonstrate a potential application example of the SoFI model implementation for post-hazard mitigation policy evaluation (Fig. 8). Additionally, we briefly illustrate the other two challenges to improve the overall quality of the future community post-hazard social fabric evaluation framework.

**Table 3**
Summary of sensitivity analysis results.

| Sensitivity Index/Construction Stage | Transformation | Normalization | PCA Selection | PCA Rotation | Weighting Scheme |
|---|---|---|---|---|---|
| First-order | 0 | 0.24 | 0.12 | 0.07 | 0.012 |
| Total effect | 0 | 0.85 | 0.47 | 0.38 | 0.3 |

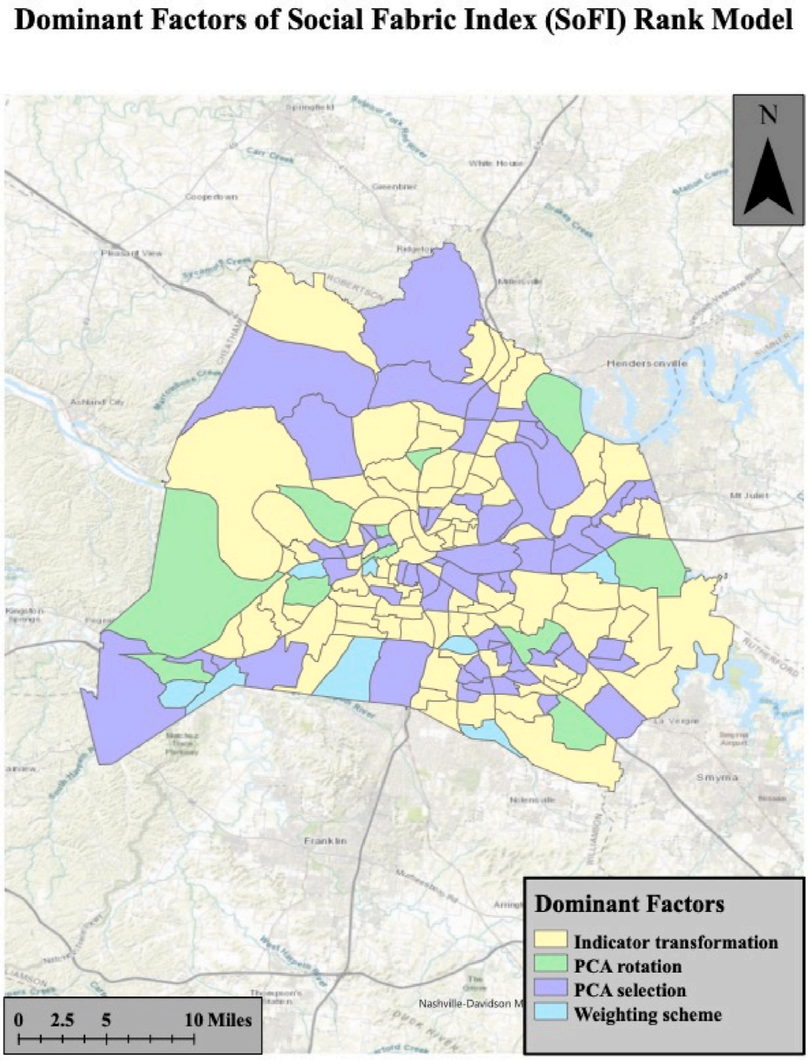


**Fig. 6.** Identified dominating factors of SoFI ranking model for each tract of the Davidson County, Nashville.

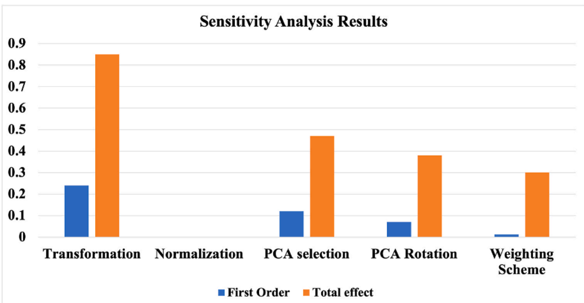


**Fig. 7.** Sensitivity analysis results.

Fig. 8 shows an application example of the SoFI model implementation on tracking the social fabric status of the flood-affected community in the recovery process. Suppose a future flood like the 2010 Nashville catastrophic flood hits the community. Mitigation policies like home buyouts can be applied to the flood-affected area to move the affected population to places without being flooded. With the progress of home buyouts, city planners and practitioners can create time-dependent social fabric maps to track the change in the social fabric status of those affected communities in the post-recovery process. These time-dependent social fabric maps can enable the policymakers better understand how mitigation policies like home buyouts may impact the community's

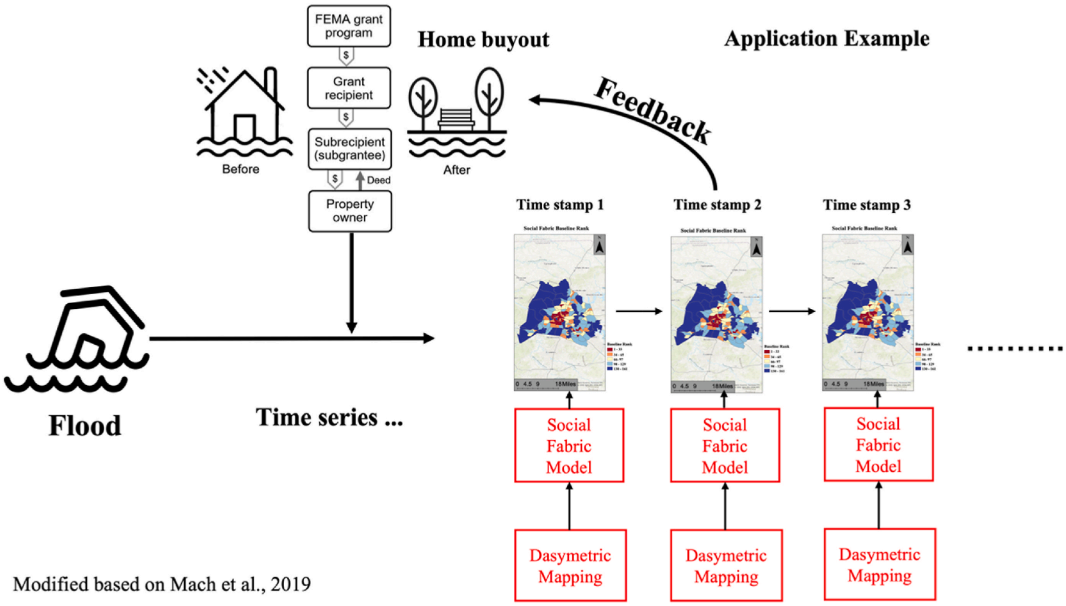


**Fig. 8.** Application example of model implementation for hazards mitigation policy evaluation.

long-term social fabric stability, thus providing valuable feedback on the design of the next-generation mitigation policy strategies (Fig. 8).

However, effectively tracking the social fabric status change in the post-disaster recovery process requires synthesizing the social fabric index model in an appropriate spatial resolution that is usually finer than the publicly available and accessible database, such as the census tract. In post-disaster social vulnerability evaluation and planning, one of the biggest challenges is the mismatch between the publicly accessible spatially aggregated data and the spatial data corresponding to the area or the spatial unit of interest that is usually finer than the public aggregated data. This challenge is often referred to as the modifiable areal unit problem (MAUP). For example, flood usually occurs at the spatial scale of census tracts, counties, or even metro cities. However, home buyouts typically happen at a much finer spatial scale, such as census blocks or tax parcel scale. As a result, while the effects of flood and home buyouts can cause different disruptions to communities within the census tract, producing a census tract social fabric map might fail to reveal the information in this scenario. Thus, in this case, it is essential to build the social fabric index map on a spatial scale finer than the census tract to reveal the micro-change of the social fabric status of communities within the census tract. This enables analysts to accurately track the social fabric status change of affected areas where buyouts occur, thus providing policymakers with sufficient information and insights. Previous studies have demonstrated a hybrid approach incorporating a dasymetric mapping to spatially disaggregate coarser social vulnerability distribution information to a finer one [121]. While it is beyond our topic in this study, the combination of the SoFI model, and a spatial disaggregation dasymetric mapping model also enables the production of valuable social fabric information of hazard-affected communities in the mitigation and recovery process (Fig. 8).

Additionally, the database quality also serves as an important aspect to ensure the accuracy of the SoFI model application. For instance, the frequently updated spatial data points of public facilities and infrastructures enable the SoFI index model to represent the change of economic prosperity and place attachment in the community more reliably. Thus, building a high-quality, frequently updated public facilities, amenities, and infrastructures database is crucial to improve the accuracy of the SoFI model for assessing communities' post-disaster recovery status.

## 7. Conclusion

The recent growing recognition that natural hazard mitigation efforts need to include social fabric dimensions if they hope to be effective motivates the development of a numeric index tool to quantitatively measure community's social fabric status across space. Meanwhile, the transition from a theoretical construct to real-world decision support tool makes it critical to evaluate if the indices model is robust. In this article, we adopted an inductive model structure to incorporate a series of indicates related to tangible and behavioral aspects of the community social fabric concept to compute a quantitative social fabric index model. Using this proposed model, we produced a tract-level social fabric map of Davidson County, Nashville, as a case study. To validate the model's robustness, we have conducted internal uncertainty and global sensitivity analysis to systematically assess the construction alternatives associated with model configurations. Here, we summarize the main findings and recommendations as follows.

The quantification and evaluation of the community social fabric is an essential and complicated addition to the current hazard mitigation planning process. A physical indicator-based social fabric index is a starting point to uncover the influences of hazard mitigation strategies like home buyouts on a community's social capital and cohesion, which is often overlooked by previous studies. Our proposed SoFI model presents a high-quality social fabric map highly correlated to the community's urban and rural characteristics.

However, although the SoFI can provide valuable information about a community's social fabric status from a physical and behavioral perspective, the current model might neglect the emotional and psychological attachment to the places. As such, the effects of the emotional and psychological indicators on the model remain unknown. Thus, incorporating sub-indices of emotional and psychological constructs into the current model is strongly recommended in future work.

The goal of this research also includes applying the uncertainty and global sensitivity analysis to evaluate and visualize the social fabric index model's uncertainty. Five sources of epistemic uncertainty were incorporated in a Monte Carlo simulation experiment, including indicator normalization, indicator transformation, PCA selection, PCA rotation, and weighting scheme. Overall, the simulation results suggest a larger uncertainty in areas of a worse social fabric, indicating proper use of the SoFI model as a screener to filter out the moderate and high social cohesive areas from the consideration. Thus, further investigations can accelerate the recognize of those vulnerable social cohesive areas. Meanwhile, the global sensitivity analysis results indicate that only part of the index construction stages is potential sources of output uncertainty. The indicator transformation and PCA selection are crucial uncertainty contributors in all the construction stages. Additionally, the uncertainty contributions decrease with the order of the model construction step. The preceding step tends to absorb the uncertainty contributions of the following steps through interactions between steps. Besides, different model parameters contribute differently under different circumstances. For instance, the SoFI model focused on mapping social fabric status on a heterogenous scale is less sensitive to the weighting scheme stage than mapping on a standard homogeneous spatial scale. Likewise, the transformation might not contribute significant uncertainties to the SoFI model's output for application at a particular homogeneous spatial scale. Future work aims to validate this hypothesis by applying the SoFI model to more case study areas with various community social characteristics.

## Funding

This work was supported by the U.S. Department of Transportation Maritime Transportation Research and Education Center (MarTREC) University Transportation Center.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2023.103913.

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