



Original scientific paper

AI-Assisted Planning for Sustainable Urbanism: Mapping Urban Livability in a Contemporary American City through Tree Coverage

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ARTICLE INFO:

Article History:

Received: 16 June 2026
Revised 1: 6 September 2026
Revised 2: 17 September 2026
Accepted: 19 September 2026
Available online: 29 September 2026

Keywords:

Urban Livability
Tree Coverage
AI-assisted Planning
Spatial Analysis
Machine Learning
Environmental Resilience

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Publisher's Note:

The *Journal of Contemporary Urban Affairs* remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

ABSTRACT



This study explores the integration of artificial intelligence, spatial analysis, and urban design to evaluate and enhance urban livability while addressing socio-economic and environmental vulnerabilities in contemporary cities. Using Austin, Texas, as a case study, the research combines ArcGIS-based spatial analysis with AI-assisted modeling to examine environmental, socio-economic, and infrastructural datasets, with urban tree canopy coverage serving as a key indicator of neighborhood health and equity. A hexagonal tessellation grid is developed to break down census tract data into standardized spatial units. This allows vulnerability scores to be calculated and correlated with tree coverage. Machine-learning techniques, including regression-based predictive modeling, are applied to identify patterns of vulnerability and forecast future urban conditions using survey-based and real-time data inputs. The findings demonstrate that an integrated GIS–AI workflow effectively reveals socio-spatial disparities in urban livability, paving the way for sustainable urban design, scientific zoning strategies, and informed form-based coding interventions.

JOURNAL OF CONTEMPORARY URBAN AFFAIRS (2026), 10(2), 386-403.

<https://doi.org/10.25034/jcua.2026.v10n2-5>

www.jcua.com

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Highlights:

- A GIS–ML workflow integrates ten indicators across four domains of vulnerabilities.
- Flexible tree-canopy weighting sharpens localized vulnerability patterns.
- Hexagonal tessellation reduces administrative-boundary mapping bias.
- Zoning overlays translate vulnerability scores into planning priorities.

Contribution to the field statement:

This study advances vulnerability assessment by using tree canopy as a flexible variable within a multidomain composite index. By combining GIS, machine learning, hexagonal mapping, and zoning overlays, the model turns open data into spatially precise, reproducible evidence for land-use reform and green-infrastructure investment fostering economic equity and environmental resilience.

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How to cite this article? (APA Style)

Shah, K., & Flores, E. (2026). AI-assisted planning for sustainable urbanism: Mapping urban livability in a contemporary American city through tree coverage. *Journal of Contemporary Urban Affairs*, 10(2), 386-403. <https://doi.org/10.25034/jcua.2026.v10n2-5>

1. Introduction

1.1 Background and Context

Cities across the globe are increasingly confronted with the compounding pressures of rapid urbanization, climate change, and growing socio-spatial inequality (UN-Habitat, 2016). These pressures converge to produce urban vulnerability, a multi-dimensional concept encompassing environmental, social, economic, and spatial dimensions (Kaczmarek, Świąder, Heldak, & Prezioso, 2025, p. 2), which in turn deepens economic disparities in living conditions across urban neighborhoods. Historically, this vulnerability has accrued at a disproportionate rate: low-income and marginalized communities bear a greater share of environmental risk while receiving comparatively fewer of the economic investments needed to sustain healthy, resilient neighborhoods (Wolch, Byrne, & Newell, 2014).

Austin, Texas exemplifies this tension. As one of the fastest-growing metropolitan areas in the United States over the past decade, Austin added more than 250,000 residents between 2020 and 2024, a surge driven by post-COVID migration and expanding investment in the technology sector. This growth is unfolding across a landscape shaped by a long history of inequitable planning. Austin's 1928 City Plan designated East Avenue—today Interstate 35—as a racial boundary that physically separated Black and Latino communities from public investment and infrastructure. That divide persists in the city's present-day geography of environmental risk and socioeconomic disadvantage, making Austin a compelling case study for vulnerability-informed planning.

This paper presents an artificial intelligence (AI)-assisted methodology that applies machine learning (ML) algorithms to identify and validate urban livability and vulnerability in Austin, Texas across four domains: environmental, health, socioeconomic, and infrastructural. Building on this composite assessment, the study introduces an additional, flexible indicator—tree canopy coverage (TCC)—to refine future planning policy. Using ArcGIS for spatial data integration and KNIME to construct a Composite and Weighted Scoring Index, the study develops an ML-spatial analytical framework intended to be both accessible and adaptable for other rapidly growing cities navigating future development decisions.

1.2 Literature Review

The uneven distribution of urban livability is well established in planning and environmental justice scholarship, which offers several entry points for tracking vulnerability empirically. Soja (2010), for instance, argues that low-income and minority areas disproportionately face environmental stressors stemming from deficient green infrastructure, services, and built resiliency. Within Texas specifically, Bixler and Yang (2019) have examined “social vulnerability linked to policy considerations and resilience planning throughout the state” (p. 4), demonstrating that increased resiliency corresponds with reduced vulnerability. Although vulnerability remains a broad and contested construct, it becomes operationally tractable once anchored to a measurable, relatable factor.

TCC is a particularly salient factor given its documented ecosystem returns. As a fundamental component of urban environmental infrastructure, TCC functions both to mitigate environmental stressors and to signal patterns of urban inequality at the neighborhood scale. Beyond its environmental function, TCC has been shown by Schwarz et al. (2015) to exhibit “a positive and significant relationship between urban tree canopy cover and median household income” (p. 8), underscoring the close relationship between access to urban greenery and socioeconomic status.

Concurrently, advances in geospatial technology and artificial intelligence have substantially expanded the analytical toolkit available to planners. AI-assisted spatial analysis enables the integration of large, multidimensional datasets to reveal patterns across urban systems that conventional methods cannot readily detect (Janowicz, Gao, McKenzie, Hu, & Bhaduri, 2020). Building on this capability, ML models can be trained on historical spatial and environmental data to forecast future trends, evaluate the impact of policy interventions, and inform long-term planning strategies (Roy, Abdullah, & Siddique, 2024). Integrating planning expertise with these technologies thus offers more than a visual medium; it provides a directive analytical input for decision-making at the urban scale.

1.3 Problem Statement and Research Gap

Although considerable progress has been made in recent years in conducting urban vulnerability assessments, methodological gaps in index construction continue to present challenges and unresolved skepticism. Chief among these is the lack of consensus on what constitutes “vulnerable,” as reliance on the same categories across studies can yield substantially divergent vulnerability estimates depending on the constructed method (Eriksen & Kelly, 2007, as cited in Reckien, 2018, p. 2). Such inconsistencies can ultimately undermine the utility of vulnerability assessments and misdirect intervention efforts.

Incorporating TCC as a weighted variable introduces additional methodological challenges. The measurement of tree coverage can appear arbitrary, and no clear causal or mitigating relationship with urban vulnerability has been firmly established. Moreover, weighted approaches more broadly have been critiqued for the reason that they “often [lack] robust criteria and replicable quantitative empirical evidence” (Sullivan & Meigh, 2005, as cited in Reckien, 2018, p. 2). This gap is especially consequential for a city experiencing growth at the pace of Austin, where the pressure to accelerate development heightens the need for rigorous, adaptable analytical tools.

1.4 Objectives and Hypotheses

This paper presents an AI-assisted methodology for mapping urban livability and vulnerability in Austin, Texas, with tree canopy coverage serving as a central, flexible indicator (Figure 1). The study pursues three primary objectives. First, it constructs a Composite Urban Vulnerability Index by integrating variables across four domains—environmental, health, socioeconomic, and infrastructural—drawing on data from the City of Austin, the CDC 500 Cities database, and the U.S. Census Bureau's 2022 American Community Survey. Second, it develops a Weighted Vulnerability Index that incorporates tree canopy coverage as a flexible variable reflecting the study's central planning question. Third, it establishes the reliability of the framework through ML processes, applying a K-Means algorithm to identify and spatially characterize clusters of high vulnerability across Austin's neighborhoods, and a Random Forest algorithm to assess the reproducibility of the spatial framework in support of future planning and zoning decisions.

Accordingly, this study investigates two research questions: (1) whether spatially identifiable clusters of vulnerability in Austin reflect not only deficient TCC but broader patterns of environmental inequality, and (2) whether incorporating TCC as a weighted index yields greater planning relevance than a generalized vulnerability index.

1.5 Significance and Structure of the Paper

The significance of this research lies in its dual contribution to planning methodology and planning practice. Methodologically, it demonstrates how open-source GIS platforms and AI-driven ML can be integrated into a transparent, reproducible workflow for urban vulnerability assessment. Practically, it provides Austin—and, by extension, other rapidly growing cities globally—with a socioeconomic evidence base to support more equitable, canopy-sensitive planning decisions.

The remainder of this paper is organized as follows. Section 2 reviews the conceptual foundations of urban vulnerability and the role of flexible variables in composite index construction. Section 3 details the study area, data sources, and methodological process. Section 4 presents the spatial results of the vulnerability mapping and cluster analysis. Section 5 discusses the planning implications of the findings and offers conclusions and directions for future research. Taken together, this integrated GIS-ML workflow is intended to constitute a replicable method for cities experiencing rapid growth that seek to mitigate vulnerability through more informed, evidence-based planning.

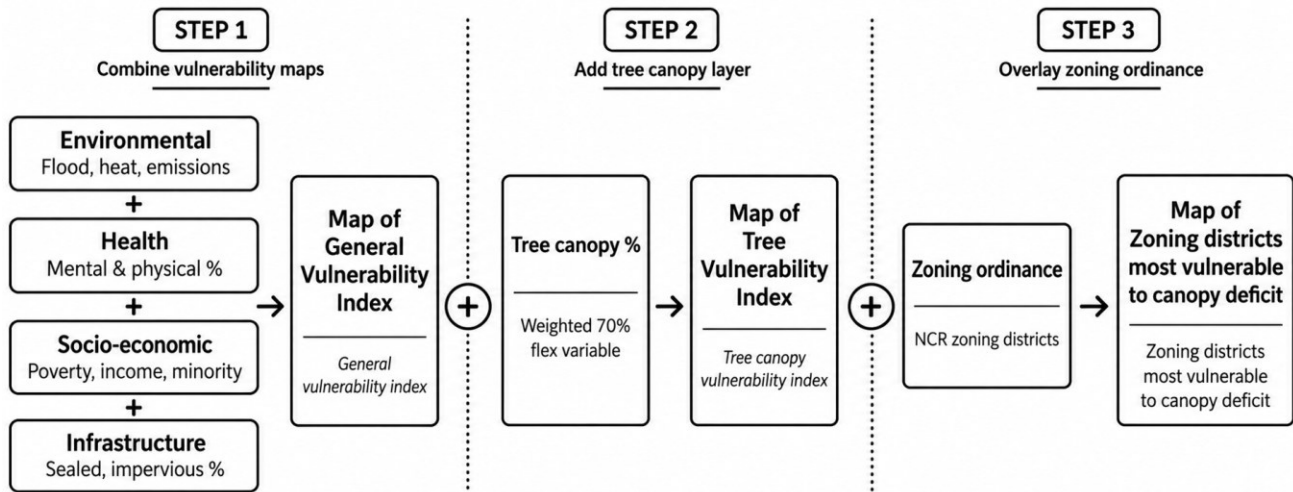


Figure 1. Structure of the Study.

2. Framework Discussion

2.1 Vulnerability Discussion

Urban centers have increasingly emphasized identifying vulnerabilities in order to support preparedness and, in some cases, to inform future mitigation strategies. However, the study of urban vulnerability need not remain confined to a pre-determined, disaster-scaled framework; it can instead function as an index of urban elements that contribute to residents' livelihoods and inform urban planning reform. As Xiu et al. (2011) define it, vulnerability “is rooted in the interaction between system and its environment” (p. 2) and draws on a set of variables that “combines socio-demographic and socio-economic characteristics influencing both the susceptibility and sensitivity of urban areas” (Kaczmarek, Świąder, Heldak, & Prezioso, 2025, p. 2).

These variables are understood as “numerous sets of indicators aimed at providing a picture of different risk components” (Galderisi & Limongi, 2021, p. 3). The intent is to translate a numeric set of risk variables into a composite picture of vulnerability that serves a pivotal role in index development. However, this type of analysis carries the risk of “focusing on specific ‘facets’ of vulnerability, overlooking its original multidimensional intent” (Galderisi & Limongi, 2021, p. 3). Compounding this challenge, the constraints of analysis are often bound by administrative jurisdiction, as committing to any single framing of vulnerability remains inherently arbitrary. Studying urban vulnerability further contends with datasets that lack current information, disproportionate regional scales, and inconsistent reliability (Galderisi & Limongi, 2021). This places planners in a difficult position when attempting to revise zoning laws and land use policy, often delaying necessary intervention.

Nevertheless, despite these limitations in scope, such analyses still capture multiple “facets” of vulnerability and generate a specialized body of data and information (Galderisi & Limongi, 2021, p. 3). This, in turn, produces multiple choropleth maps that spatially represent the outcomes of the scaled index. From a planning standpoint, as urban population growth continues to climb, Kaczmarek, Świąder, Heldak, and Prezioso (2025) observe a growing effort to identify vulnerabilities through territorial approaches, “supporting policymakers in providing tailored responses suited to varying geographical scopes and scales” (p. 3). Anchoring the analysis to a defined location therefore narrows and sharpens the process of identifying vulnerabilities, particularly in rapidly growing urban centers.

2.2 Identifying and Measuring Vulnerability Variables

Calculating urban vulnerability typically relies on constructing an index, which “can help to reduce complexity, to compare and rank results, and to communicate and present scientific outputs” (Reckien, 2018, p. 2). Building on the premise of interrelated components (Xiu et al., 2011), this study examines vulnerability across four domains: environmental, health, socioeconomic, and infrastructural. Many studies pursue this comprehensive approach by developing sets of indicators that serve as “proxy[ies] of the different groups of variables” (Brunetta & Salata, 2019, p. 2) to capture the spatial distribution

of vulnerability within a system. Other studies, such as Xofi et al. (2022), instead direct this approach toward composing a risk assessment of hazard levels related to seismic intensity, peak ground acceleration, and ground and soil conditions (p. 3). What these studies share is a process of identifying vulnerability within a given context and assigning it the most relevant measurable factors; through this spatial contribution, the system can be translated into a set of proxy indicators integrated into GIS, while accounting for the associated limitations (Brunetta & Salata, 2019, p. 2), which helps surface issues directly.

Despite these reasonable limitations, identifying the correct indicators remains essential to constructing a successful index. Much of this study's foundation draws on prior research, with additional context informed by the Imagine Austin Comprehensive Plan (IACP). This plan, characterized as a “proactive response to the challenges posed by rapid urbanization” (Zhao, Weng, & He, 2024, p. 3), established guiding principles for various programs and departments over a 30-year horizon. The plan envisioned addressing “the challenges of accommodating a growing population and safeguard[ing] the environment” (Zhao, Weng, & He, 2024, p. 3), encompassing a series of priorities that inform the development of a vulnerability index.

2.2.1 Environmental

Environmental factors, when insufficiently mitigated, tend to bear the greatest weight among vulnerable indicators in urban areas, particularly amid rising concerns over climate change. Comprising much of the urban landscape, environmental hazards and stressors are shaped by social, economic, and political forces (Pugh, 1996). A weak environmental system can compound other vulnerability indicators, notably heat islands, flooding, and air pollution. Historically, however, evolving thinking on sustainability and the relationship between development and the environment has carried increasing relevance (Pugh, 1996), driving greater interest in improved strategies going forward.

2.2.2 Health

Urbanization significantly influences health behaviors, often amplifying disparities among socioeconomic groups (Cacciatore et al., 2025, p. 8). As a central component of urban vulnerability, health shapes coping mechanisms that can become embedded in an individual's routine behavior. Measuring these responsive behaviors also brings mental health conditions into focus. Additionally, identifying physical capabilities helps assess debilitating conditions that, while not necessarily tied to the surrounding environment, remain impactful sources of vulnerability. These disparities are especially pronounced “among socioeconomically disadvantaged groups, [underscoring the need] to reduce health disparities and decrease the burden of chronic diseases in cities” (Cacciatore et al., 2025, p. 3).

2.2.3 Socio-Economic

This analysis of marginalized communities focuses primarily on Black, Hispanic, and Asian populations to highlight the historical implications of systemic disenfranchisement. This pattern of marginalization reflects adverse conditions not only in the surrounding environment but also at the individual level, correlating closely with household income and unstable living conditions—an attribute that heightens the risk of falling below the poverty line. As other forms of vulnerability begin to intensify, socioeconomic status tends to decline in tandem.

2.2.4 Infrastructure

A city's infrastructural condition maintains a close relationship with its communities. Seamless integration enables fluid movement that residents can utilize to its full potential, functioning in some respects as “a constant and reciprocal relationship between desire and its fulfilment” (Borges, 2012, p. 4). This relationship, however, can falter. Shortcomings such as excessive impervious cover and inadequate street and roadway accessibility magnify existing issues, which can, in turn, exacerbate other vulnerability factors by generating instability and heightened exposure. In this way, infrastructure not only connects communities but can also disconnect, segregate, and isolate different parts of the city (Borges, 2012, p. 5).

2.3 Spotlighting Flexible Variables: Tree Canopy Coverage

Developing a flexible index requires much of the same foundational variables, supplemented by an additional indicator to guide planning coordination. Beyond its broader planning objectives, the IACP also established a “Compact and Connected” focus for urban planning and policy (Zhao, Weng, & He, 2024). In setting this baseline for urban growth, the plan is oriented “toward innovative towns and key centers instead of conventional low-density developments” (Zhao, Weng, & He, 2024, p. 3), enabling a broader study of urban vulnerability at the city scale.

The selection of tree canopy coverage as the additional indicator draws on Austin's Community Tree Priority dataset, which identifies potential project areas intended to “bring the benefits of trees to neighborhoods in need” (Fulton, Ries, & Riley, 2025, p. 3). Findings from this dataset reveal social and economic discrepancies in areas lacking tree canopy coverage. From a planning perspective, this creates a rationale for identifying potential zones for preservation strategies aimed at helping cities overcome “multiple forms of historical inequality and planning practices” (Zhou et al., 2021, p. 1765). Notably, this is not intended to assert a causal correlation between the two forms of vulnerability, but rather to highlight one as a contributing piece that helps expose the other.

2.4 Machine Learning Processes

Translating a spatial understanding of urban vulnerabilities and their variables into a viable planning solution often requires verification through replication. Given that much of current practice is moving in this direction, ML algorithms help establish a reliable predictive process. ML models offer a versatile capacity to calculate, assign, and model complex, interactive datasets and variables, extending beyond the restrictive assumptions often inherent to conventional planning approaches (Chaturvedi & Vries, 2021). As vulnerability is identified, it must be classified and, most importantly, supported by “a comprehensive geospatial database that is able to assess existing land use and model future changes” (Chaturvedi & Vries, 2021, p. 3).

Building on this database, the ML approach draws on multiple methods to support the index. The first, K-Means, is an unsupervised learning method in which unlabeled data is trained to “find hidden patterns, structures, or relationships without any guidance” (Mutambik, 2024, p. 5). This method serves as a critical tool for grouping vulnerabilities according to risk level and optimizing visual output. The second, Random Forest, is “an ensemble learning algorithm based on decision tree classifiers, bagging, and bootstrapping” (Chaturvedi & Vries, 2021, p. 4). This process trains a designated dataset to assess and report the success rate of its replicability, thereby verifying the structure of the index and clarifying the relative importance of its constituent variables.

2.5 Visual Return

The data required for this analysis were collected and analyzed as shapefiles (.shp) sourced from the City of Austin, the CDC 500 Cities database, and the U.S. Census Bureau's American Community Survey (ACS). These datasets were visualized at the 2022 Census Tract level, which offered the greatest consistency across the reporting cycles of these local and national agencies. This approach is particularly advantageous, as it improves clarity regarding the state of vulnerability while affirming that, although areas remain susceptible to risk, they also retain the capacity for recovery (Kaczmarek, Świąder, Heldak, & Prezioso, 2025), bridging qualitative and quantitative research in service of planning interventions.

2.5.1 Tessellations

Although visually consistent with common practice, analyzing vulnerability requires boundaries that remain as neutral as possible. Census tracts present a limitation in this regard, as they “present challenges due to their potential size disparities, leading to heterogeneity and potentially less accurate results” (Monzur, Tabassum, & Bashir, 2024, p. 3). To address this limitation, the study instead visualized the data using a hexagonal grid, whose spatial structure offers an advantage in uniformity that reduces ambiguity (Monzur, Tabassum, & Bashir, 2024, p. 2). This grid was shaped to conform to the municipal boundaries of Austin for study containment.



3. Searching for Urban Vulnerabilities – Influencing Zoning and Planning Measures

3.1 Study Area - Austin, Texas

Austin, Texas was selected as the study area given its rising prominence over the past decade. As the capital of Texas, Austin is the 11th-largest city and the 29th-largest metropolitan area in the United States, and it has become an established base for major technology companies—including Oracle, Google, Microsoft, and Tesla—within the 21st century. This shift has attracted substantial in- and out-of-state migration for employment opportunities and has helped establish a diversified tax base. Austin has additionally cultivated a reputation for sustainability and preservation practices, with a planning emphasis on compact development.

This growth, however, has intensified the need to meet rising demand. Austin carries a documented history of displacement affecting minority and underdeveloped neighborhoods, a pattern spatially reinforced by Interstate 35, which has long functioned as a physical barrier dividing the city into eastern and western sections. The city's eastern neighborhoods, in particular, have drawn growing development interest despite a persistent lack of adequate resources and unmet community needs, placing these residents in a heightened position of vulnerability. Beyond this underlying vulnerability, rezoning requests have become increasingly common across the city, seeking to convert single-family zoning into mixed-use designations permitting three- to five-story construction. However, many of these rezoning proposals fail to incorporate adequate preservation strategies to ensure that any resource deficits in these neighborhoods are addressed rather than compounded.

3.2 Accumulating Data and Transfers

Assessing the variables needed for vulnerability, they are built off the four clarified categories and branch off into 10 distinct variables to generate the index being gathered into ArcGIS Pro. Data for the index can be found via the aforementioned sources.

Table 1. List of Vulnerability Variables.

Categories	Year	Dataset	Variable	Alias	Unit of Measure
Environmental	2023	City of Austin	Flood %	PERCENT FL	%
	2023	City of Austin	CO2 Emissions	EMISSIONS	Number
	2023	City of Austin	Heat Island	HeatDisp 1	Number
Health	2022	CDC 500	Mental %	mhlth crud	%
	2022	CDC 500	Physical %	phlth crud	%
Socio-Economic	2023	US Census	Household Income	HHMedian 2	%
	2023	US Census	Below Poverty %	BelowPov 3	%
	2022	City of Austin	Minority Status	MINOR STAT	%
Infrastructure	2022	City of Austin	Pervious Cover %	PCT IMPERV	%
	2022	City of Austin	Sidewalk Conditions	SDWLK PCT	%
Flex Variable	2024	City of Austin	Tree Canopy%	CanopyDIFF	%

Downloading multiple datasets to conduct one study requires the need of a consolidated source to view all respective information to proceed. This involves sourcing from US Census Bureau's TIGER/Line® Shapefiles, more specifically, 2022 Census Tracts. Through a join by related attributes, in this case the aligned census tract ID from both sides, they stack into a single attribute table that spatially represents Austin. Once the tracts have been joined, a hexagonal tessellation is created based on the municipal boundary and created at an area of 100,000sqm each (Figure 2). As the two shapefiles are overlaid, a spatial join will merge the existing combined data from the tracts based on the biggest intersection with the hexagons. This results in the datasets now being represented through a Grid-ID (Table 2) and being a key for returning at the end of the process. From here, the hexagonal shapefile's dataset is exported as a Comma-Separated Value (.csv) table to be utilized at the machine learning level.

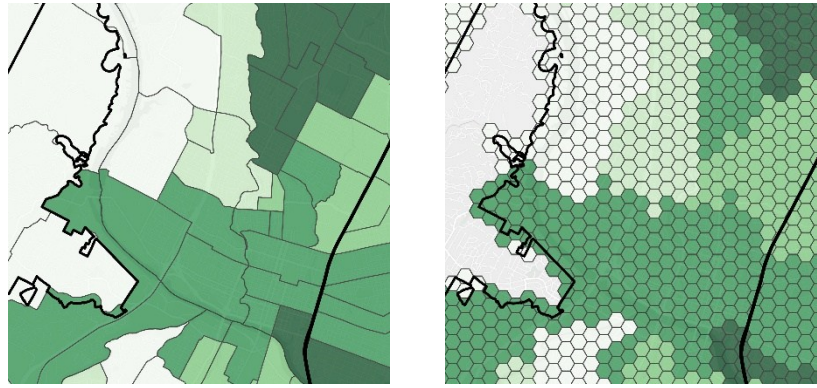


Figure 2. Visual Comparison (Tracts to Hexagons).

Table 2. Example of Exported Table.

Grid_ID	Name	PERCENT_FL	mhlth_crud	phlth_crud	BelowPov_3	EMISSIONS
BB-148	Census Tract 109.23	12.41985767	17.2	12.2	5.03729437	9179.001217
BB-147	Census Tract 109.23	12.41985767	17.2	12.2	5.03729437	9179.001217
BC-147	Census Tract 24.34	12.41985767	19.6	17.2	15.13924051	9179.001217
BA-146	Census Tract 109.23	12.41985767	17.2	12.2	5.03729437	9179.001217

3.3 KNIME Production Workflow

The analytical process of machine learning is done through KNIME, a database visual workflow that involves a variety of statistical models to generate outputs, much of it relating to a coding structure. Here, the table is inserted and applied to the vulnerability workflow (Figure 3) that will generate not only the necessary indexes to identify the general and flex vulnerability scores, but a series of additional procedures for cluster visual return through a K-Means method and a verification regression scheme through a Random Forest Algorithm.

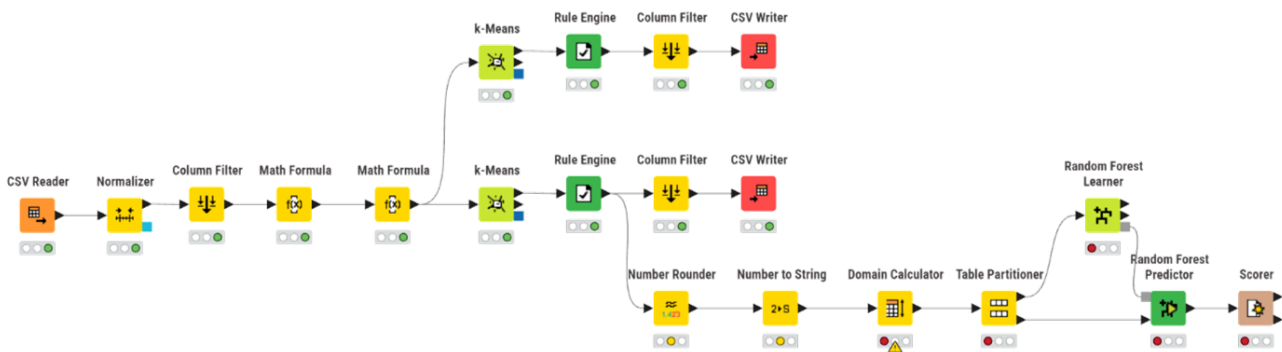


Figure 3. KNIME Workflow.

3.3.1 Normalization and Scoring

The variables come from diverse ranges and units which initially lacks cohesive structure for an index. Using the normalizer node, it streamlines all variables, including the flex, utilising the min-max method. This stabilizes the value between the minimum value of 0 and the maximum value of 1 (Equation 1).

$$\frac{X_{org} - X_{min}}{X_{max} - X_{min}} = Norm.$$

Equation 1. Normalization Equation.

Involving this output of normalized values, the workflow follows through a column filtration scheme that removes any excess columns that were missed from the initial .csv export. This ensures a removal of oversaturated data for the export process. Once this is covered, the next step involves the first index:

general vulnerability. This is calculated through the Math Formula Node which runs the applied equation (Equation 2) and results in a % output value. This equation involves the normalized values from the four categories and averages them out to their respective group. Once these four categories are averaged out, each average will be summed together, with the resulting sum divided by the number of categories, in this case four, to be the first of the two indexes created. This index is appended as a new column for future reference as “VulScore”.

$$\frac{(AvgV_1 + AvgV_2 + AvgV_3 + AvgV_4)}{4} = \% \text{ Vulnerability}$$

Equation 2. General Vulnerability.

3.3.2 Applying Weights

Similarly, the application of the flex vulnerability follows after the resulting general vulnerability with a second Math Formula Node. The first index is an overview of what is considered vulnerable accumulated together with the established categories, but the flex vulnerability works as an extension to that equation, involving a fifth category that serves the function of determining areas of TCC. Through a weighted process, the equation is split between two sections: one holding the *VulScore*, and the other holding the flex variable (Equation 3). For the subject of the study, this variable will be the TCC %. The weights according to their respective scores are based on their importance of influence on the index outcome, resulting in an application of a 0.3 weight to *VulScore* and a 0.7 weight to the flex. Because the calculation is aimed at identifying areas lacking in TCC, it garners a higher weight towards the index. After this calculation is met it appends to new column referenced as “*VulScore_wTree%*”.

$$\left(0.3 \times \frac{V_1 + V_2 + V_3 + V_4}{4}\right) + (V_5 \times 0.7) = \% \text{ Tree Vulnerability}$$

Equation 3. Weighted Vulnerability Index.

3.3.3 K-Means Method

Once both scores have been calculated, the workflow branches off into the K-Means node to create a series of clusters in identifying the levels of vulnerability that are being faced within the Austin area. What this node will do is take the range of both “*VulScore*” and “*VulScore_wTree%*” separately and evenly distributes into 5 distinct clusters according to their ranges, 0.21-0.69 and 0.06-0.84 respectively.

The 5 clusters are identified as levels of severity in the succeeding node, Rule Engine. It works to label and identify the risk levels as the output from the K-Means only identified as Clusters 1-5. Here, the risk levels are identified in order: Low Risk, Compact Risk, Medium Risk, Considerable Risk, and High Risk. By categorising their respective index scores, the outputs can be spatially reflective into ArcGIS Pro as a suitable visual. Afterwards, the dataset is exported through a .csv writer which will relay back to ArcGIS Pro (Table 3).

Table 3. Exported Table.

Grid_ID	VulSCR_Cluster	VulScore	VulFLEX_Cluster	VulScore_wTree%
BB-148	High Risk	0.66	High Risk	0.81
EA-199	Compact Risk	0.35	Medium Risk	0.44
CG-431	Medium Risk	0.53	Considerable Risk	0.71
VA-88	Low Risk	0.22	Low Risk	0.17

3.3.4 Random Forest Method

The second branch in this workflow analyzes the success of reproducibility utilizing a Random Forest Algorithm. With a set of indexes created through a composite and weighted structure, the return value needs to be analyzed via success rate. Meaning replicating the process from a sample set of the same

data and ensuring the return is as accurate as perceived and provide evidence of the reliance of these variables.

Entering the table partitioner node, it takes the relative % size, in this case 70%, and runs through a series of stratified sampling according to the two indexes, “*VulScore*” & “*VulScore_wTree%*”. After their process is ran, it enters a Random Forest Learner node which will consider the targeted index and run it through the 10 variables that were used, of which it will run 100 “trees” to verify the reliability of the calculation. Which leads into the Random Forest Predictor and Scorer nodes, creating a new column dedicated to this resulting count and scoring the success rate of the two indexes. For the “*VulScore*”, it came out to a 97.33% replicability rate with an error of 2.67% while the “*VulScore_wTree%*”, resulted in a 98.32% replicability rate with an error of 1.678%.

3.4 Returning Visuals

Returning to ArcGIS, with the .csv table exported from KNIME, it is imported back into the file for rejoining. The hexagonal tessellation is once again selected and chosen to join with the imported table. The Grid-ID would then reunite to ensure a smooth transition of data. Once this join is complete, the hexagons will now be able to reflect the resulted calculated indexes from the KNIME ML Process.

3.4.1 Zoning Map

Additionally, the City of Austin’s zoning map was imported and overlayed onto the new hexagons. Through a selective overlay process, the hexagons of anything considerable or high risk were identified. Here the zones are exported and set as their own shapefile to isolate from their original accumulating into three spatial zones.

4. Discussion

4.1 Interpretation of Key Findings

Taken together, the three maps produced in this study offer a clear and spatially legible reading of urban vulnerability across Austin. The General, Tree Canopy, and Zoning outputs converge on a coherent spatial structure: vulnerability is concentrated, patterned, and geographically aligned with the divisions long associated with the 1928 City Plan and the Interstate 35 corridor. This convergence is the central strength of the approach, as a single, reproducible workflow renders a complex, multi-domain condition into an interpretable spatial form that planners can read directly. The maps describe spatial association rather than causation, a distinction that sharpens rather than diminishes their value: by showing precisely where the four domains of vulnerability coincide with historically underinvested geographies, they supply the evidence base that planning most needs. The interpretation below reads each map through the machine-learning procedure that produced it, K-means clustering for spatial classification and a Random Forest learner for validation, so that the spatial narrative remains anchored in analytical output.

4.1.1 General Urban Vulnerability Index

Figure 4 establishes the baseline spatial picture. The K-means procedure resolves the composite score into five clearly differentiated severity classes, producing a map in which lower-vulnerability units fall predominantly in the western and northwestern city and higher-vulnerability units concentrate in central and eastern Austin, extending toward the southeast. The most informative feature of this result is its spatial contiguity: high-vulnerability units cluster into defined, coherent zones rather than scattering, demonstrating that neighborhoods carrying deficits across flood exposure, physical health, poverty, and sidewalk condition tend to occupy the same ground. This compounding of burdens is precisely the condition composite indices are designed to surface, and the clustering makes it visible at a glance. Representing the continuous vulnerability surface through five interpretable tiers communicates these gradients clearly to planning audiences, and the east-west structure it reveals aligns with the differential investment history discussed in Section 3, giving that history a measurable present-day spatial signature.

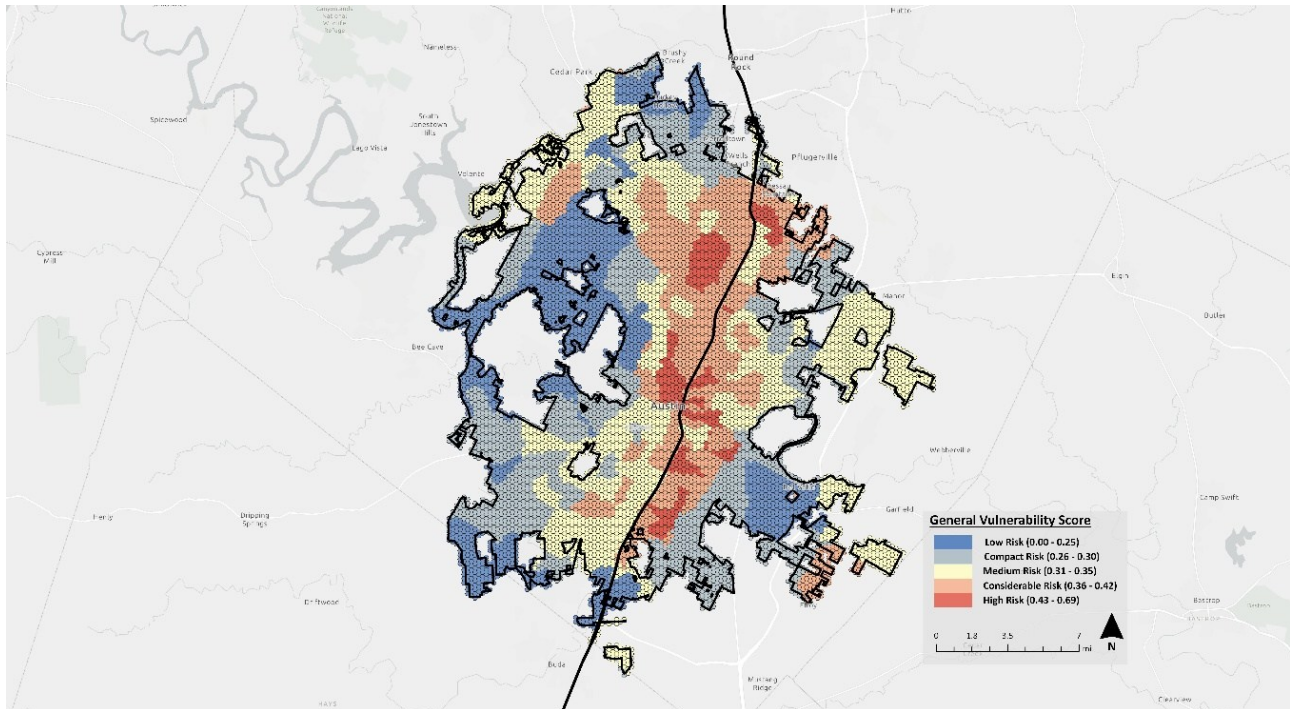


Figure 4. Resulting Composite Vulnerability Index Analysis.

4.1.2 Tree Canopy Vulnerability Index

Figure 5 demonstrates the methodological core of this study: the treatment of tree canopy as a weighted flexible variable within the composite index. Weighting canopy at 70 percent of the score sharpens the map on the specific planning question at hand, and the result is a meaningful intensification and geographic expansion of high-vulnerability zones across east and southeast Austin, while western areas with established canopy retain their lower scores. This responsiveness is the intended behavior of the flexible-variable design: the index re-points toward the priority under examination while retaining its multi-domain foundation. The resulting map is therefore not a general vulnerability picture but a purpose-built one, answering directly where canopy deficit and accumulated vulnerability coincide most acutely.

This spatial coincidence resonates strongly with the environmental-justice literature. According to Locke et al. (2021), they documented substantially lower present-day canopy in formerly low-graded neighborhoods, and Austin’s canopy-poor eastern and southeastern zones map onto the same areas identified in Section 3, a correspondence that lends external credibility to the local finding. This literature also shows that the canopy-disadvantage relationship is shaped by local factors such as housing age, density, and climate rather than following a single universal proportion, and the present study contributes a finer-grained, city-specific reading to that broader picture. Positioned this way, Austin’s maps add a spatially explicit case to a well-established body of evidence.

The canopy signal also illuminates why these zones matter. Reduced canopy is well documented as a contributor to heat exposure, so the areas the weighted index flags are those where environmental, health, and infrastructural stressors are most likely to reinforce one another. The 70/30 weighting was selected deliberately to foreground this dynamic, and it performed as designed, surfacing the canopy-specific geography without overriding the multi-domain baseline. Calibrating this weight empirically across a range of values is a natural next step that would further strengthen an already effective design, as discussed in the strengths and limitations below.

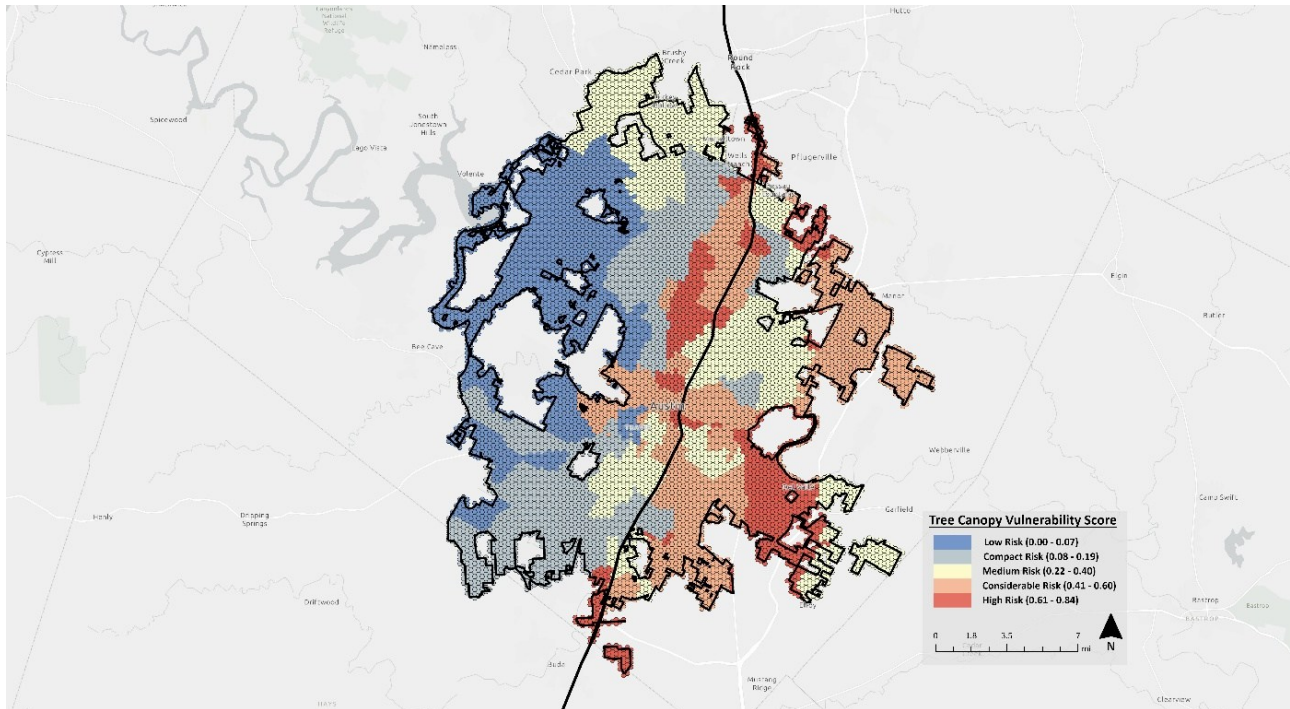


Figure 5. Resulting Tree Canopy Vulnerability Index Analysis.

4.1.3 Zoning Vulnerability Index

Figure 6 extends the analysis from diagnosis to planning application by overlaying the scored hexagonal grid onto Austin's zoning ordinance. This is where the methodology delivers its most directly actionable output: it identifies the three zoning categories, Industrial, Commercial, and Planned Unit Development, that carry the highest concentration of high-vulnerability units, clustered in the southeastern quadrant. Rather than pointing to broad areas of concern, the overlay resolves the vulnerability surface to specific, named zoning districts, translating spatial analysis into the categories through which planning operates.

This pattern aligns with a substantial literature on the historical siting of industrial and commercial land uses in lower-income and minority neighborhoods (American Planning Association, 2021), and the overlay gives that well-documented dynamic a precise, contemporary spatial expression in Austin. Reading the overlay alongside the land-use variables that inform the index keeps the relationship between zoning and score transparent and interpretable.

The overlay's precision is its practical payoff. By locating where high vulnerability and permissive land-use classifications intersect, it gives planners a defensible, evidence-based starting point for prioritizing attention, with the southeastern Industrial and Commercial clusters emerging as clear candidates for canopy and green-infrastructure focus. These are also areas under active development pressure, which makes the timing of the analysis especially useful: the map identifies where evidence-informed intervention could be directed before growth locks existing disparities into place.

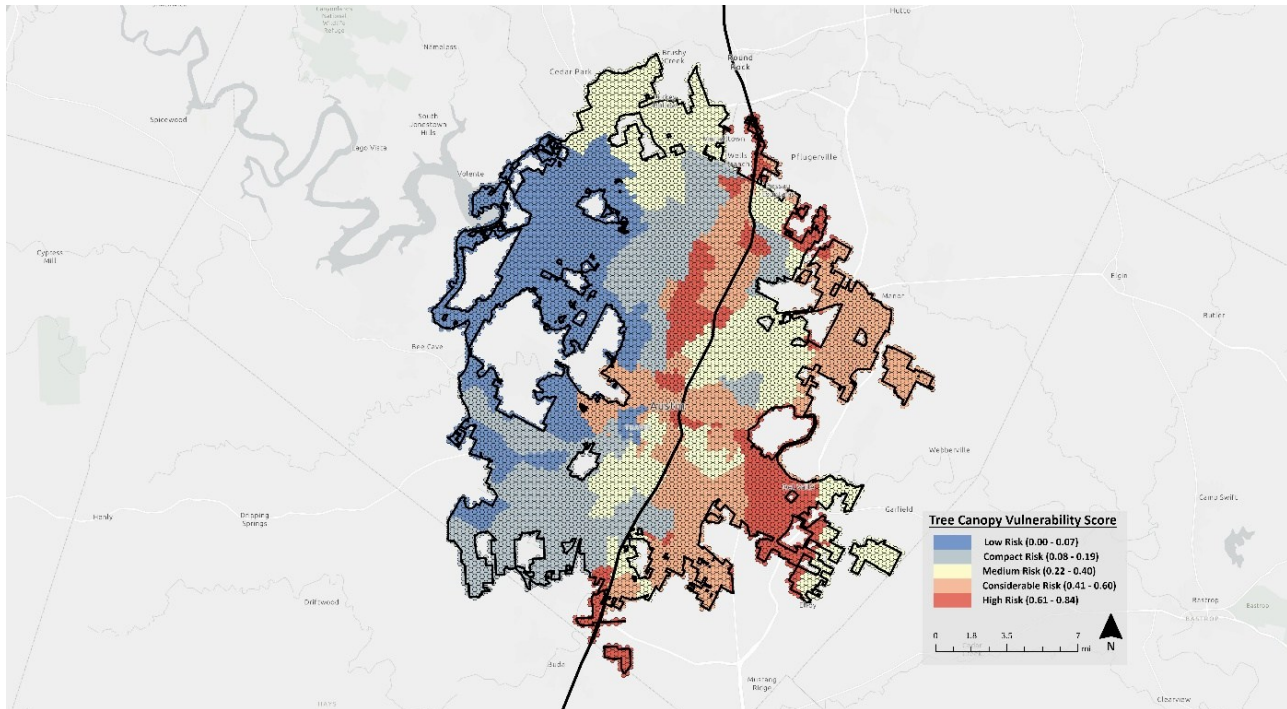


Figure 6. Resulting Zoning Vulnerability Index.

4.2 Comparison with Previous Studies

The findings sit comfortably within, and extend, the established research on urban canopy, socioeconomic status, and environmental justice. Schwarz et al. (2015) found canopy coverage positively associated with median household income across several American cities, and Locke et al. (2021) tied historical redlining to present canopy deficits. Austin’s maps reproduce these relationships at a finer spatial resolution, with canopy deficits concentrated in the same zones where poverty, minority population share, and environmental risk are highest, and the alignment of the local results with multi-city findings strengthens confidence in the workflow’s validity.

The literature also shows that the canopy–disadvantage relationship is more complex than a simple gradient. Schwarz et al. (2015), the same study that establishes the income–canopy correlation, found that the negative association between race and canopy coverage largely disappears once multivariate models incorporate controls for housing age, population density, and education, suggesting that canopy distribution is shaped by a suite of interacting variables rather than income or race alone. This study complements rather than contradicts that finding by resolving the relationship within a single city at hexagonal resolution, it captures the local, compounded texture that broad city-to-city comparisons necessarily smooth over. The Austin case is therefore best read as fine-grained, place-specific evidence that sits within a wider body of research still working out the relative weight of each contributing factor. Methodologically, the use of hexagonal tessellation is a deliberate strength of the approach. Unlike census tracts, which follow administrative rather than social or ecological logic, the hexagonal grid supplies a uniform, neutral unit of analysis that reduces boundary effects and the perceptual distortion common to choropleth mapping. Research in spatial ecology supports hexagonal grids for exactly these properties (Birch, Oom, & Beecham, 2007), and their use here produces a spatially coherent surface that communicates vulnerability gradients more faithfully than tract-based mapping would.

The study’s principal methodological advance is the operationalization of tree canopy as a weighted, flexible variable within a composite index, rather than as a standalone or equally weighted indicator. This design lets a single framework be re-pointed at different planning questions simply by changing the flexible variable, so the index can reflect general vulnerability conditions and simultaneously amplify a specific policy focus. This flexibility is a genuine contribution to the growing literature on

AI-assisted urban vulnerability assessment, offering a template that is both analytically grounded and directly adaptable to the questions individual cities need to ask.

4.3 Strengths and Limitations

The framework's strengths are substantial. It integrates ten variables across four domains, drawn from verified open data sources, into a single normalized, spatially comparable surface through a workflow that is transparent and fully reproducible with widely available tools. Its reliability is tested rather than merely asserted: across fifty runs on a 70/30 train-test split, a Random Forest learner reproduced the composite index at 85.3 percent and the weighted index at 79.1 percent, confirming that the index structure is internally consistent and that its scores follow robustly from the input variables. The flexible-variable design adds genuine adaptability, allowing the index to be reweighted or re-pointed without disturbing its underlying structure, and the hexagonal tessellation further strengthens the output by neutralizing the irregular geometry of administrative boundaries.

As with any composite spatial model, a set of boundary conditions defines the framework's scope and points toward its refinement. Because the vulnerability score depends on the currency and completeness of its inputs, quantifying and propagating data uncertainty would let future outputs carry explicit confidence information. The 70 percent weighting reflects a deliberate analytical choice, and a sensitivity analysis across alternative weights would formalize the design's flexibility and clarify how much of the weighted pattern derives from the canopy signal itself. Testing multiple hexagon sizes would further characterize the framework's sensitivity to the modifiable areal unit problem inherent to any areal aggregation. These are refinements to a demonstrated and effective method rather than obstacles to it, each a well-defined path to sharpening an approach that already produces coherent, actionable results.

4.4 Implications and Future Directions

The planning implications of these findings are direct and actionable. The zoning vulnerability overlay gives planners a spatially explicit, evidence-based foundation for prioritizing canopy investment and land-use reform, and it connects the analysis to a central concern of planning theory: the equitable distribution of environmental goods and the reading of present inequities as the accumulated outcome of past land-use decisions. The Industrial, Commercial, and PUD districts of southeast Austin that score worst on the combined index represent priority areas where instruments such as form-based codes, green-infrastructure overlays, and canopy-coverage minimums tied to development permits are well positioned to make a measurable difference, and where the pressure of active development makes timely action especially valuable.

More broadly, the study points toward a mode of vulnerability-informed planning in which open-data pipelines, AI-assisted scoring, and flexible index design combine into living, updatable planning tools rather than static assessments. Within this framework the machine-learning methods do focus, dependable work, classifying the vulnerability surface, validating its structure, and rendering it spatially, and as open-data ecosystems expand, the same workflow provides a foundation on which predictive and longitudinal extensions can be built.

Future research can build directly on this foundation. The most immediate opportunities strengthen the framework itself, through calibrating the flexible-variable weighting, adding spatial-autocorrelation and multi-scale diagnostics, and propagating data uncertainty into the outputs, while the natural extensions broaden its reach: applying the methodology comparatively across other rapidly growing cities to test transferability, incorporating longitudinal data to track vulnerability over time, and integrating participatory, community-level input to ground the spatial outputs in lived experience. Together these directions would carry a proven diagnostic workflow toward an even more powerful predictive and prospective planning instrument.

5. Conclusion

5.1 Summary of Key Findings

This study developed and demonstrated an AI-assisted methodology for mapping urban livability and vulnerability in Austin, Texas, using tree canopy coverage as a weighted flexible indicator within a

composite spatial index. Its central contribution is a transparent, reproducible workflow that renders a complex, multi-domain condition into a spatially legible form and, through the zoning overlay, into directly actionable planning intelligence. Demonstrated here on 2022 data for Austin, the framework establishes a foundation designed for extension to other cities and time periods.

The General Urban Vulnerability Index revealed a clear east-west gradient, with high-vulnerability zones concentrated in central and east Austin and lower vulnerability across the western and northwestern city. This spatial pattern aligns closely with the geography institutionalized by Austin's 1928 City Plan and the construction of Interstate 35, giving a well-known history a concrete, measurable expression in the present-day urban landscape.

The Tree Canopy Vulnerability Index sharpened and extended this pattern. Weighting canopy at 70 percent of the composite score expanded the reach and intensity of high-vulnerability zones across east and southeast Austin, demonstrating the flexible-variable design's ability to re-focus the index on a specific planning priority. The result supports the study's central proposition, that canopy deficit and broader vulnerability concentrate together, and identifies canopy coverage as a powerful spatial marker of accumulated disadvantage.

The Zoning Vulnerability Overlay translated these findings into planning-actionable intelligence, identifying the Industrial, Commercial, and Planned Unit Development districts of the southeastern corridor as the clearest priorities for planning investment, policy reform, and green-infrastructure attention.

5.2 Implications of the Findings

The findings carry implications for how cities approach vulnerability assessment and equitable economic development. First, they show that a composite index combining environmental, health, socioeconomic, and infrastructural variables with a context-specific flexible variable produces more planning-relevant spatial outputs than single-domain or equally weighted assessments. This flexibility lets planners pose targeted questions, here where tree canopy deficits concentrate vulnerability, while retaining the breadth of a multi-domain view.

Second, the zoning overlay makes a direct, practical case for integrating vulnerability mapping into zoning and land-use processes. By resolving vulnerability to specific zoning districts, it gives planners a concrete and defensible basis for prioritizing canopy-sensitive reforms, green-infrastructure requirements, and targeted investment, precision that matters especially in a fast-growing city like Austin, where development pressure is intense and the risk of displacing vulnerable communities through greening initiatives is real.

Third, the study affirms the value of AI-assisted spatial analysis as a planning-support tool. The pairing of ArcGIS for spatial integration and tessellation with KNIME for normalization, scoring, and clustering produced a workflow that is transparent, reproducible, and accessible to planning practitioners without advanced data-science training, and whose reliability the Random Forest validation directly supports.

5.3 Limitations of the Study

Several considerations define the scope of the study and frame its next stage. As with any data-driven index, output quality depends on input quality, and quantifying and propagating data uncertainty would allow future maps to carry explicit confidence information. The 70 percent weighting reflects an analytical judgment tuned to this study's canopy focus; a sensitivity analysis across weights would formalize the flexible design and clarify how much of the weighted pattern derives from the canopy signal itself. Testing multiple hexagon sizes would characterize the framework's behavior across scales and its exposure to the modifiable areal unit problem. Finally, the analysis captures a single 2022 snapshot, and longitudinal application would add the temporal dimension that tracks how vulnerability evolves as development proceeds.

5.4 Recommendations for Future Research

Future research can extend this work along several complementary lines. The most immediate refined the framework itself, calibrating the flexible-variable weighting through sensitivity analysis, adding spatial-autocorrelation and multi-scale diagnostics, and propagating uncertainty into the final scores,

each sharpening a method that already delivers coherent, actionable results. Building outward, comparative application across other rapidly growing cities would test and demonstrate the framework's transferability; longitudinal application using annual datasets would let planners track vulnerability over time and evaluate the impact of interventions; participatory data collection would enrich the quantitative index with community-level insight; and a predictive modeling layer, using the index as a baseline, would project vulnerability under alternative development scenarios and move the framework from descriptive to prospective.

Urban planning in rapidly growing cities cannot afford to remain reactive. The methodology developed in this study offers a proactive, spatially precise, and equitable approach to understanding where vulnerability concentrates, what drives it, and where intervention will matter most, and a reproducible foundation on which more powerful predictive tools can be built.

Acknowledgements

We would like to acknowledge Julio Carrillo, AICP, LEED Fellow, for his guidance and support throughout the development of this research. His insights and feedback contributed meaningfully to the direction of the study. We would also like to thank Alan Halter (Geospatial Analyst with the City of Austin) for his insight into calculating vulnerable processes and statistical outputs.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflicts of Interest

The authors declare no conflicts of interest.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Institutional Review Board Statement

Not applicable.

Credit author statement

Kunth Shah: Conceptualization, Methodology, Formal analysis, Visualization, Writing-original draft, Project, Administration, Resources, Software

Edwin Flores: Data Curation, Formal analysis, Methodology, Validation, Visualization, Writing-Review and Editing, Resources, Software

All authors have reviewed and approved the final version of the manuscript.

References

- American Planning Association. (2021). Environmental justice and zoning reform (PAS Report). *American Planning Association*. <https://www.planning.org/publications/report/9295614/>
- Birch, C. P. D., Oom, S. P., & Beecham, J. A. (2007). Rectangular and hexagonal grids used for observation, experiment and simulation in ecology. *Ecological Modelling*, 206(3–4), 347–359. <https://doi.org/10.1016/j.ecolmodel.2007.03.041>
- Bixler, R. P., & Yang, E. (2019). *Social vulnerability in Texas: Implications for resilience, equity, and climate policy* (pp. 1–21). Planet Texas 2050, The University of Texas at Austin. <https://tmo.utexas.edu/sites/default/files/Texas%20Social%20Vulnerability%20Report.V4.pdf>
- Borges, H. F. (2012). Connecting infrastructure and urbanism (pp. 1–16). Universitat Politècnica de València.



- Brunetta, G., & Salata, S. (2019). Mapping Urban Resilience for Spatial Planning-A First Attempt to Measure the Vulnerability of the System. *Sustainability*, 11(8), 1-24. <https://doi.org/10.3390/su11082331>
- Cacciatore, S., Mao, S., Nuñez, M. V., Massaro, C., Spadafora, L., Bernardi, M., Perone, F., Sabouret, P., Biondi-Zoccai, G., Banach, M., Calvani, R., Matteo Tosato, Marzetti, E., & Landi, F. (2025). Urban health inequities and healthy longevity: traditional and emerging risk factors across the cities and policy implications. *Aging Clinical and Experimental Research*, 37(1), 1-16. <https://doi.org/10.1007/s40520-025-03052-1>
- Chaturvedi, V., & de Vries, W. T. (2021). Machine Learning Algorithms for Urban Land Use Planning: A Review. *Urban Science*, 5(3), 68, 1-16. <https://doi.org/10.3390/urbansci5030068>
- Fulton, A. J., Ries, P. D., & Riley, G. E. (2025). Where Are the Benefits of Trees Needed Most? A Comparison of Equity-Based Mapping Tools in Austin, Texas. *Arboriculture & Urban Forestry*, 1-26. <https://doi.org/10.48044/jauf.2025.020>
- Galderisi, A., & Limongi, G. (2021). A Comprehensive Assessment of Exposure and Vulnerabilities in Multi-Hazard Urban Environments: A Key Tool for Risk-Informed Planning Strategies. *Sustainability*, 13(16), 9055, 1-19. <https://doi.org/10.3390/su13169055>
- Janowicz, K., Gao, S., McKenzie, G., Hu, Y., & Bhaduri, B. (2020). GeoAI: Spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. *International Journal of Geographical Information Science*, 34(4), 625–636. <https://doi.org/10.1080/13658816.2019.1684500>
- Kaczmarek, I., Świąder, M., Heldak, M., & Prezioso, M. (2025). Addressing Urban Vulnerability: A Comprehensive Approach. *Land*, 14(8), 1527, 1-28. <https://doi.org/10.3390/land14081527>
- Locke, D. H., Hall, B., Grove, J. M., Pickett, S. T. A., Ogden, L. A., Aoki, C., Boone, C. G., & O'Neil-Dunne, J. P. M. (2021). Residential housing segregation and urban tree canopy in 37 US cities. *npj Urban Sustainability*, 1(1), 15, 1-9. <https://doi.org/10.1038/s42949-021-00022-0>
- Monzur, T., Tabassum, T., & Bashir, N. (2024). Alternative Tessellations for the Identification of Urban Employment Subcenters: A Comparison of Triangles, Squares, and Hexagons. *Journal of Geovisualization and Spatial Analysis*, 8(2), 1-23. <https://doi.org/10.1007/s41651-024-00200-5>
- Mutambik, I. (2024). Assessing Urban Vulnerability to Emergencies: A Spatiotemporal Approach Using K-Means Clustering. *Land*, 13(11), 1744, 1-22. <https://doi.org/10.3390/land13111744>
- Pugh, C. D. J. (1996). *Sustainability, the environment and urbanization*. Earthscan.
- Reckien, D. (2018). What is in an index? Construction method, data metric, and weighting scheme determine the outcome of composite social vulnerability indices in New York City. *Regional Environmental Change*, 18(5), 1439–1451. <https://doi.org/10.1007/s10113-017-1273-7>
- Roy, P., Abdullah, M., & Siddique, I. (n.d.). Machine learning empowered geographic information systems: Advancing Spatial analysis and decision making. *World Journal of Advanced Research and Reviews*, 2024(01), 1387–1397. <https://doi.org/10.30574/wjarr.2024.22.1.1200>
- Schwarz, K., Fragkias, M., Boone, C. G., Zhou, W., McHale, M., Grove, J. M., O'Neil-Dunne, J., McFadden, J. P., Buckley, G. L., Childers, D., Ogden, L., Pincetl, S., Pataki, D., Whitmer, A., & Cadenasso, M. L. (2015). Trees grow on money: Urban tree canopy cover and environmental justice. *PLOS ONE*, 10(4), e0122051, 1-17. <https://doi.org/10.1371/journal.pone.0122051>
- Soja, E. W. (2010). *Seeking spatial justice*. University of Minnesota Press.
- UN-Habitat. (2016). World cities report 2016: Urbanization and development — Emerging futures. *United Nations Human Settlements Programme*. <https://unhabitat.org/world-cities-report-2016>
- Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities just green enough. *Landscape and Urban Planning*, 125, 234–244. <https://doi.org/10.1016/j.landurbplan.2014.01.017>
- Xiu, C., Cheng, L., Song, W., & Wu, W. (2011). Vulnerability of large city and its implication in urban planning: A perspective of intra-urban structure. *Chinese Geographical Science*, 21(2), 204–210. <https://doi.org/10.1007/s11769-011-0451-7>



- Xofi, M., Domingues, J. C., Santos, P. P., Pereira, S., Oliveira, S. C., Reis, E., José Luís Zêzere, Ricardo, Lourenço, P. B., & Ferreira, T. M. (2022). Exposure and physical vulnerability indicators to assess seismic risk in urban areas: a step towards a multi-hazard risk analysis. *Geomatics Natural Hazards and Risk*, 13(1), 1154–1177. <https://doi.org/10.1080/19475705.2022.2068457>
- Zhao, C., Weng, Q., & He, Z. (2024). Spatiotemporal analysis of underlying factors in urban transformations: Quantifying the importance of urban plan intentions in the Austin Metropolitan Area, Texas. *Land Use Policy*, 149, 1–12. Sciencedirect. <https://doi.org/10.1016/j.landusepol.2024.107415>
- Zhou, W., Huang, G., Pickett, S. T. A., Wang, J., Cadenasso, M. L., McPhearson, T., Grove, J. M., & Wang, J. (2021). Urban tree canopy has greater cooling effects in socially vulnerable communities in the US. *One Earth*, 4(12), 1764–1775. <https://doi.org/10.1016/j.oneear.2021.11.010>



How to cite this article? (APA Style)

Shah, K., & Flores, E. (2026). AI-assisted planning for sustainable urbanism: Mapping urban livability in a contemporary American city through tree coverage. *Journal of Contemporary Urban Affairs*, 10(2), 386–403. <https://doi.org/10.25034/jjcua.2026.v10n2-5>