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Determination of Individual Building Performance Targets to Achieve Community-Level Social and Economic Resilience Metrics

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ABSTRACT:

The retrofit of wood-frame residential buildings is a relatively effective strategy to mitigate damage caused by windstorms. However, little is known about the effect of modifying building performance for intense events such as a tornado, and the subsequent social and economic impacts that result at the community level following an event. This paper presents a method that enables a community to select residential building performance levels representative of either retrofitting or adopting a new design code that computes target community metrics for the effects on the economy and population. Although not a full risk analysis, a series of generic tornado scenarios for different Enhanced Fujita (EF) ratings are simulated, and five resilience metrics are assigned to represent community goals based on economic and population stability. To accomplish this, the functionality

of the buildings following the simulated tornado is used as input to a computable general equilibrium (CGE) economics model that predicts household income, employment, and domestic supply at the community level. Population dislocation as a function of building damage and detailed socio-demographic U.S. census-based data is also predicted and serves as a core community resilience metric. Finally, this proposed methodology demonstrates how the metrics can help meet community-level resilience objectives for decision support, based on a level of design code improvement or retrofit level. The method is demonstrated for Joplin, MO. All analyses and data have been developed and made available on the open-source IN-CORE modeling environment. The proposed multi-disciplinary methodology requires continued research to characterize the uncertainty in the decision support results.

KEYWORDS: Community resilience; community goals; IN-CORE; multi-disciplinary; performance targets; retrofit; tornado

INTRODUCTION

The performance of civil infrastructure systems supports community resilience but has been primarily controlled by probability-based limit states design over the last several decades (e.g., ASCE 7-16). In 2015, the U.S. National Institute of Standards and Technology (NIST) proposed a general framework to help communities develop resilience plans for building clusters (a group of buildings that support a community function such as education) and infrastructure associated with social and economic systems (NIST 2015). Since then, an increasing number of researchers have focused on physical infrastructure systems and related distributed networks to quantitatively assess community-level resilience with multi-disciplinary measurements (e.g., Doorn et al. 2019, Wei et al. 2020, Wang et al. 2021, Roohi et al. 2020). According to McAllister (2016), engineering outcomes can be quantitatively coupled with socio-economic performance, providing more flexible and informative support for risk-informed decision-making with the public interest in mind. Advancements in community resilience modeling can help accelerate the development of building codes and standards to meet the requirements of community-wide resilience goals of the broader built environment at a higher level, consistent with performance objectives of individual buildings throughout their service lives (e.g., Ellingwood et al. 2017, Masoomi and van de Lindt 2019). For example, in the United States, building codes and standards (e.g., ASCE 2016) have focused on life safety goals, but the role of the individual building performance in fulfilling community resilience goals is unknown (Ellingwood et al. 2017). In order to address this grand challenge over the next decade, there is a need to link resilience design objectives with individual building performance levels (Wang et al. 2018). Physical performance of buildings has been quantitatively linked to community-wide social and economic outcomes in only one study by Roohi et al. (2020), without focusing on achieving community-level goals. Therefore, in this paper a systematic community-level analysis of linked physical, social, and economic systems is proposed to de-aggregate performance targets of buildings to enable the community to achieve pre-defined socio-economic community-wide resilience goals. The performance targets can be expressed in terms of individual building fragilities to further guide the performance-based engineering design of structural components given specific design features.

Community resilience goals mainly focus on robustness and rapidity (NIST 2015). The robustness goals emphasize improvements in the performance of building components, and the rapidity goals are devoted to allocating limited resources and creating organizational guidelines to ensure community recovery is implemented effectively and efficiently (Wang et al. 2018, Wang and van de Lindt 2021). The NIST Community Resilience Planning Guide, the San Francisco Planning and Urban Research Association, and the Oregon Resilience Plan provided examples of specifying the desired time-to-recovery as performance goals for building clusters at different functional levels (NIST 2015, NIST 2020, OSSPAC 2013, Poland 2009). Schultz and Smith (2016) developed rapidity resilience objectives for housing, utility systems, and transportation individually when the community is exposed to flood events at different return periods. However, only a few studies focused on examining the achievement of robustness goals. Chang and Shinozuka (2004) set a reliability goal of 95% likelihood of being able to meet the objectives for water systems (e.g., major pump station loses function) in given seismic events. Kameshwar et al. (2019) estimated the likelihood of achieving robustness performance goals (i.e., the performance of infrastructure systems from 0% to 100%) for the coastal town of Seaside, Oregon, subjected to combined seismic and tsunami hazards. Wang et al. (2018) used the Direct Loss Ratio (DLR) and Un-Inhabitable Ratio (UIR) as the resilience goals for measuring the robustness of a residential building cluster under tornado hazards, with the damage values linked to direct loss and un-inhabitability as defined from the HAZUS-MH MR4 technical manual for consistency.

In order to measure socio-economic aspects of community resilience, researchers have proposed metrics that can be potentially considered as indicators of community resilience. Potential indicators of economic resilience include the unemployment rate, income equality (e.g., based on gender, race/ethnicity), and business diversity (e.g., ratio of large to small businesses). Social resilience metrics reflect individual human and social needs, which can be represented in population changes and the distribution of socio-demographic characteristics (e.g., age, race, education levels) over time (Burton 2015, Cutter et al. 2014), access to social services and networks, and quality of life assessments. Some metrics can reflect the multifaceted socio-economic indicators of resilience. For example, temporary and permanent population dislocation following a disaster is a complex social and economic process jointly impacted by the functionality loss of physical systems and the socio-demographic characteristics (Wang et al. 2018). The effects of population dislocation can ripple through the local economy, social institutions, and building inventory. For example, local businesses may lose both employees and customers, and therefore, decide to close permanently and relocate. As residents and businesses leave and relocate, tax revenue for local government shrinks, forcing layoffs that can induce more residents to leave (Mieler et al. 2015) as well as shrinking resources for restoring and maintaining physical infrastructure.

In the present study, building functionality, employment, domestic supply, household income, and housing unit and population dislocation are used as physical and socio-economic resilience metrics in the context of a disaster. This is the first study in the literature where structural performance goals selected for buildings (or any physical system) are based on the ability to achieve both social and economic goals at the community scale. This is accomplished by chaining the performance of the built environment to a computable general equilibrium (CGE) model for economic metrics (i.e., household income, employment, domestic supply) and an existing population dislocation algorithm for sociological metrics (i.e., household/population dislocation), and ultimately determining the de-aggregated performance targets for individual buildings to meet a specified goal. The proposed methodology provides a structured but flexible approach to support resilience decision-making by helping stakeholders develop integrative implementation strategies to improve their resilience. Note that the proposed multi-disciplinary methodology builds on and integrates previous work (Wang et al. 2021), and continued research is needed to characterize uncertainty in the final decision support results.

DE-AGGREGATION OF COMMUNITY RESILIENCE GOALS

Fig. 1A summarizes the methodology used in this study to develop individual residential building performance targets to achieve community-level resilience goals in terms of physical, social, and economic metrics. The approach starts by articulating community resilience goals such as *less than an x% increase in unemployment immediately after an EF-3 tornado occurring anywhere in the community*. The preliminary design for individual residential buildings shown in Fig. 1A refers to structural combinations such as roof covering and is controlled by fragility functions. Please refer to the section on Wind Design to Achieve Community Resilience for more details about the design. Fig. 1B depicts the sequencing of analyses for a given community and its physical, social, and economic attributes), damage and functionality models, computable general equilibrium economic model, and the population dislocation algorithm, which is introduced in later subsections of this paper, to evaluate the hazard impacts and support community resilience planning. The percentage of residential buildings that were assigned the specified retrofit were analyzed using values ranging from 0% to 100%, in intervals of 10%, for the community. The objective is to determine the percentage of buildings that should be retrofitted such that the community-wide building performance metrics and socio-economic metrics calculated in the resilience analysis meet the community resilience goals. Note that community resilience goals would typically be community defined and could be adjusted based on community-specific needs, but illustrative values are utilized in this study.

Fig. 1A

Fig. 1B.

Damage and functionality model

Eq. (1) determines the building damage probability (P_{damage}) using fragility functions for each building, which can be grouped by each building archetype, and have been fit to lognormal cumulative distribution functions (CDF) controlled by two parameters (median, λ, and standard deviation, ξ). The fragility functions (Fr_{DS}) represent the probability of exceeding damage state *i* (i.e., slight, moderate, extensive, complete) for each building as a function of the intensity measure (e.g., 3-s gust wind speed, spectral acceleration). For each Monte Carlo realization of a tornado event, a uniformly distributed random variable, R_j, between 0 and 1, is generated and compared to the building damage probabilities corresponding to the four damage states. As shown in Eq. (2), if the realization experiences the *moderate* damage state or greater, then the building is assumed to lose functionality in this study. The moderate damage state in tornado damage assessment means the building has moderate damage to window/doors and roof covering, but the building itself can be occupied and repaired (Memari et al. 2018). For business, it would not be possible to have an operational business in the moderate damage state, thus the building would be deemed nonfunctional in the CGE analysis. The building functionality status ($I^k_{fun,j}$) of Eq. (2) is either functional (1) or non-functional (0) for each realization. The index *j* is representative of each realization of the Monte Carlo simulation (*j* = *1* to *N*) for each building *k*. Subsequently, the building functionality probability (P_{fun}) can be approximated using Eq. (3).

$$P^k_{Damage,i} = Fr^k_{DSi}(IM = x) \tag{1}$$

$$I^k_{fun,j} = \begin{cases} 1 & R_j > Fr_{DS2} \\ 0 & R_j \leq Fr_{DS2} \end{cases} \tag{2}$$

$$P^k_{fun} \approx \frac{N^k_{fun}}{N} = \frac{\sum_{j=1}^{N}(I^k_{fun,j}=1)}{N} \tag{3}$$

After the MCS building damage analysis, the results are passed to the CGE economic analysis, where the building is considered nonfunctional if the probability of being in or exceeding DS2 (moderate damage) is greater than 0.5. The CGE is only run once after the structural analysis and this full sequence shown in Fig.1A is completed for each tornado scenario to develop a suite of scenarios.

Computable general equilibrium (CGE) model

The design or retrofit of infrastructure systems can be quantitively related to community-level economic resilience metrics through a dynamic economic impact model. In this study, the CGE model served as the economic impact model to quantitatively evaluate the varying impacts of natural disasters on the local economy. The section below provides a brief summary of the CGE model and its data. The implementation of the CGE model in this study is consistent with that of Wang et al. (2021); for further details on the CGE model, or its data and assumptions, please refer to Cutler et al. (2016) and Attary et al. (2020).

CGE model description

CGE models assume that firms maximize profits and households maximize welfare as a guide to making economic decisions. CGE models are data driven models that provide descriptions of how households, firms, and the local government interact to produce goods and services for an economy. In recent years, CGE models have become a particularly effective tool when applied to regional impact analysis of external shocks that are assimilated from other fields (e.g., Rose and Guha 2004, Rose and Liao 2005, Cutler et al. 2016, Attary et al. 2020). As such, financial shocks, health consequences of pollution, climate change, and, as this study conveys, natural hazards, can all be linked with a CGE model to simulate economic outcomes. Prior to the extensive use of CGE models, Input-Output (I-O) economic models were commonly used to model the impact of natural hazards (e.g., Rose and Liao 2005). While I-O models adequately simulate demand-side shocks they have been limited in their ability to determine impacts to the supply-side such as the loss of buildings and lifeline systems (Koliou et al. 2020). Since the CGE model can address both demand and supply side factors, it is the tool of choice to examine the impact of natural disasters.

A social accounting matrix (SAM) organizes data for three entities, households, firms, and the local government, that represent the flow of resources in an economy at a point in time. A SAM is a method to organize the data in a consistent way for modeling the interactions between all three entities. The SAM, along with input from other matrices, such as tax revenue, are input data to the CGE model. See Schwarm and Cutler (2003) for an extensive description of a SAM. The SAM used in this study is based on data from the Bureau of Labor Statistics, Bureau of Economic Analysis, and the U.S. Census Bureau. In addition, county tax assessor's data is used to obtain parcel-level physical characteristics of residential homes and business buildings. The buildings from this data set are merged with building specific archetypes to summarize the impact of a tornado on the functionality of these buildings.

CGE models are based on a range of fundamental microeconomic principles that include (1) utility-maximizing households that supply labor and capital, and use the proceeds to pay for goods and services and taxes; (2) the production sector is based on perfectly competitive firms that choose profit-maximizing amounts of intermediate inputs, capital, land, and labor to produce goods and services for both domestic consumption and export; (3) the government sector collects taxes and uses tax revenues in order to finance the provision of public services; and (4) local economy trades with the rest of the world. These principles help to formulate the CGE model, which consists of a series of equations and is calibrated when those equations exactly reproduce the data in the SAM.

The CGE model can then be used to simulate the outcomes from a wide range of exogenous shocks such as from a tornado.

Linking the building functionality model and the CGE model

Capital stock within a community is the key variable of interest linking the functionality model to the CGE model. The market values of commercial and residential buildings were aggregated into a Goods, Trade, and Other commercial sectors, and three housing services sectors (HS1, HS2, HS3). The Goods, Trade, and Other are themselves aggregations of the NAICS (North American Industry Classification System) sectors. Goods represent large manufacturing industries, Trade is mostly retail, and Other is a combination of industries including services, health and finance. This study focuses on residential buildings, where HS1 is lower-value homes, HS2 is higher-value homes, and HS3 is rented residential buildings.

Tornado damage to buildings, and their reduced functionality, is modeled as negative "shocks" in the CGE model. These shocks are the connection point between engineering outputs and the CGE model. Eq. (4) calculates the sector shocks (γ_s) as a percentage of capital stock remaining, where C represents the capital stock of each building k attributed to each sector s.

$$\gamma_s = \frac{\sum_{k=1}^{n} C_s^k \times P_{fun,s}^k}{\sum_{k=1}^{n} C_s^k} \tag{4}$$

Incorporating the output from the engineering models into external shocks enables the CGE model to estimate a range of post-hazard economic losses such as employment effects and domestic supply by sectors (Cutler et al. 2016). Furthermore, retrofit strategies that mitigate damage to residential properties will attenuate the shock to capital stock in the housing services sector and thus tend to reduce overall economic loss.

Population dislocation algorithm

The population dislocation algorithm, which has input from the building damage analysis, and detailed socio-demographic data, predicts the probability of dislocation immediately following the event (Girard and Peacock 1997, Peacock et al. 1997, Rosenheim et al. 2019). Eq. (5) uses a logistic regression model with five constants, c_1 to c_5, to estimate population dislocation probabilities (P_{dis}) for each damage state *i* based on property value loss (*ploss*) and building types (single-family or multi-family, *dsf*) for each building, *k*, and neighborhood characteristics (percent of black, *pblack,* and Hispanic populations, *phisp*) by each census group, *m*. The variable *dsf* is set to 1 if the number of estimated housing units was 1. The variable is 0 if the number of estimated housing units is greater than 1. The logistic regression constants were not changed for this specific community, but the variables such as the percent of the black and Hispanic population were updated based on the Census Bureau's data. Eq. (6) sums the dislocation probabilities for each damage state ($P^k_{dis,i,m}$). Damage state 1 (slight or no damage) is evaluated separately from damage states 2 to 4, consistent with the building functionality evaluations, to determine the dislocation probability of each building *k* in each census group *m* ($P^k_{dis,\mathrm{m}}$). For each Monte Carlo realization, the population dislocation algorithm can help predict whether the households leave their housing unit immediately after a hazard event. For more details on the population dislocation algorithm and the logistic regression model, please see Rosenheim et al. (2019) and Lin et al. (2008).

$$P^k_{dis,i,m} = \frac{1}{1+e^{-(c_1+c_2 ploss^k_{i,m}+c_3 dsf^k_m+c_4 pblack_m+c_5 phisp_m)}} \tag{5}$$

$$P^k_{dis,m} = P^k_{dis,1,m} \times P^k_{damage,1} + \sum_{i=2}^{4} P^k_{dis,i,m} \times (P^k_{damage,i} - P^k_{damage,i-1}) \tag{6}$$

ILLUSTRATIVE EXAMPLE FOR TORNADO HAZARDS

In this study simulated tornado wind fields defined as a peak three-second gust were used. Joplin was selected as the testbed to perform resilience assessments for tornado-induced events due to its history with a large double vortex Enhanced Fujita 5 (EF5) tornado in May of 2011. The purpose of the illustrative example was to determine the minimum percentage of wood-frame residential buildings that need to be retrofitted for the community to meet their resilience goals. These community-level resilience goals were defined in terms of building functionality, social, and economic metrics, using the proposed methodology. All analyses and data were performed and are available in the open-source IN-CORE modeling environment (https://incore.ncsa.illinois.edu/doc/incore/notebooks/Joplin_testbed). Please refer to Wang et al. (2020) for more details regarding the manual, datasets, and example notebooks for the IN-CORE modeling environment and visit http://resilience.colostate.edu/in_core/. Note that this example focuses on the resilience assessment at the community level specific to tornado events since tornadoes only strike a small footprint area within a community. The resilience model and the retrofit can be applied to a large urban area for other natural hazards such as earthquake events (e.g., Roohi et al. 2020).

Community description

Joplin is a typical small to medium size community, located in southwest Missouri in the United States and spanning Jasper and Newton counties. In this illustrative example, a total of 19 archetype buildings (e.g., residential, business, healthcare, education) were used to represent the buildings within the community. Five typical wood-frame residential buildings from Masoomi et al (2018) with different footprint areas, roof structures, and number of stories were used to describe all the residential buildings. The electric power network is generally regarded as the most impacted infrastructure system by tornado (and most wind) events and was therefore also included herein to examine the dependency between the building infrastructure and electric power network. Transmission/distribution substations and wood poles are the two types of vulnerable components included in the electric power network. Other networks such as water, transportation, and telecommunication networks were not considered in this study, but could be modeled in future work as needed. It is acknowledged that the functionality of other network systems depends on the reliability of the electric power network (e.g., Unnikrishnan and van de Lindt 2016, Zou and Chen 2019). For example, water towers are vulnerable in that they need to be supplied with electric power (Masoomi and van de Lindt 2018), so may only last several days following a tornado if backup generators for pumps are not available/supplied. Additionally, damaged and/or fallen trees/poles can block the roads following tornadoes and cause adverse impacts on the transportation networks (e.g., Hou and Chen 2020, Hou et al. 2019).

Table 1 provides a summary of the built environment and social systems for the testbed and example in this study. The number of buildings and the number of housing units in Joplin is 28,152 and 23,261 (Note: multi-family will have multiple households in one building), respectively, and the building dataset was developed circa 2010 before the 2011 Joplin tornado. Note that non-residential buildings include 13 building types herein such as commercial buildings and social institutions, e.g., schools. The housing unit estimation was determined based on the 2010 Decennial Census data and an existing housing unit allocation algorithm (see Rosenheim et al. 2019 for details). The allocated housing units are also designated by race/ethnicity and household income, in addition to tenure status, as shown in Table 1. The number of workers employed in Joplin in 2010 was 39,831, and the total domestic supply was US$3.04 billion. Please refer to

Wang et al. (2021) for more details on the building inventory, electric power network, housing unit characteristics, and economy in Joplin.

Table 1.

Initial capital stock values come from the Newton and Jasper County Assessor's offices that encompass Joplin. It is important to note that the building level county assessor's data and the building level archetype data used in the functionality model are from different sources. Fortunately, both datasets had detailed geographic coordinate location information for every building. Therefore, in order to connect individual building level archetypes and functionality to economic sectors, the building level sector information from the county assessor's office was merged with the archetype datasets using a GIS spatial join algorithm. Building level data are then aggregated to the sector level.

Generic tornado models

A series of generic tornadoes based on the gradient technique (Standohar-Alfano and van de Lindt 2015) were used as the hazard models impacting the community, resulting in physical damage to buildings and the electric power network, and propagating economic losses, household disruption, and population dislocation. Tornados with different EF ratings (EF0 - EF5) are associated with different ranges of wind speeds. Fig. 2 shows the geometry of the gradient model for an EF2, EF3, and EF4 single tornado, respectively, where the width of the applied tornadoes is equal to the average of the historical tornado data for the Enhanced Fujita (EF) rating (Attary et al. 2018). The start points, end points, and the directions of all tornado scenarios were assigned randomly within the community boundaries. The NIST Community Resilience Planning Guide (NCRPG) encourages communities to use routine levels (i.e., hazard events that are more frequent with less consequential events that should not cause significant damage), design levels (i.e., hazard events used to design structures), and extreme levels (i.e., beyond design levels and likely to cause extensive damage) to address a range of potential damage and consequences (NIST 2020). This study examines the community resilience impacted by 100 random tornadoes for each different intensity level (i.e., EF2, EF3, EF4) individually in line with the concept encouraged in the NCRPG. It is worth noting that most tornadoes travel in paths from the southwest towards the northeast (Suckling and Ashley 2006). Additionally, it is important to mention that the building inventory was developed for Joplin exclusive of other nearby homes outside of the Joplin boundaries. Thus, some of the tornado scenarios might damage buildings outside of Joplin in the simulation but they are not included in the determination of physical damage and the associated socio-economic losses in this study.

The methodology presented herein is general and can be implemented for any hazard type. The socio-economic goals defined for the community, partially or wholly, do rely on a hazard-specific analysis. For example, earthquake events commonly impact the entire community, whereas a tornado directly impacts a relatively small geographic footprint within a community, but the impact can extend to the entire community in terms of social and economic impacts. Additionally, building functionality is highly related to tornado intensity, tornado path/width, and housing density (urban or rural).

Fig. 2

Multi-disciplinary community resilience goals

In this study, core resilience metrics inform three community stability areas, namely physical services, economic activity, and population stability. Physical services stability was estimated by determining building functionality two different ways: with and without the impact of the reliability of the electric power network. Percent changes in employment, domestic supply (e.g., food, care, security), and household income were used to jointly reflect the activity of the local economy. Population stability was calculated as the percent change in households being dislocated by housing unit (or population) following a disruptive event. Three community resilience goals (Goal A, Goal B, and Goal C) were targeted as routine level (EF2), design level (EF3), and extreme level (EF4) tornado events, respectively, as indicated in Table 2. The community resilience goals may be viewed as being modest, but reasonable because tornadoes typically strike a portion of the entire community, sometimes 5% to 10%. All residential and commercial buildings outside the tornado path were not physically damaged but may still lose electric power. Therefore, two types of physical service metrics related to building functionality were proposed herein: considering the dependency between buildings and the electric power network or neglecting the dependency of buildings on electric power.

It is important to mention that each community is unique with its own characteristics, and each will have its own specific resilience goals and potential solutions. In this study, having clearly defined resilience goals in terms of core metrics is intended to demonstrate how a community can change a physical design of a component within their infrastructure (buildings in this case) to affect change in their physical service, population, and economic stability areas if a natural hazard was to strike. For example, keeping the percentage of households dislocated below 5% is one of the social resilience goals identified for tornados at the extreme hazard level.

Table 2.

Wind design to achieve community resilience

Tornadoes are low-probability high-consequence events that often result in significant physical damage and socio-economic impacts but have not been considered in the structural design codes and standards (e.g., ASCE 7-16) so far. That will change soon since tornadoes are planned to be included for Risk Category 3 and 4 buildings (e.g., hospitals, emergency operations centers, etc.) beginning in 2022. Some challenges such as pressure deficit, vertical components of the tornadic winds, and windborne debris in tornadoes made it difficult to rationalize a design process for most buildings (e.g., Haan et al. 2010, van de Lindt et al. 2013, Masoomi and van de Lindt 2017). In this study, basic construction improvements were modeled using modified fragilities for individual building performance. Table 3 presents building fragility functions for typical and retrofitted residential buildings with a different structural combination of roof coverings, roof sheathing nailing patterns, and roof-to-wall connection types (Wang et al. 2021). The typical design would have regular asphalt shingles, 8d common nails spaced at 150/300 mm (6/12 inch) attaching roof sheathing panels to trusses, and two 16d toenails to connect the roof rafters over the vertical studs. The retrofit design used regular asphalt shingles, roof sheathing nails spaced at 150/150 mm (6/6 inch) and two H2.5 hurricane clips as roof-to-wall connections. A series of cases was examined, ranging from 10% of residential buildings in a community being retrofitted to 100%, to select how many residential buildings would need to be retrofitted to achieve the desired community resilience goals. Several of these scenarios are illustrated in Fig. 3. The damage fragility curves for a suite of 19 building archetypes incorporating 13 non-residential building types, each having four damage states (i.e., slight, moderate, extensive, and complete), are available to cover the entire range of wind speeds (Masoomi et al. 2018, Memari et al. 2018, Koliou et al. 2017, Masoomi and van de Lindt 2016).

Table 3.

Fig. 3

Community resilience metrics

After combining the fragility functions for retrofitted residential buildings and the original fragility functions for other buildings in the community model, the community assessment was performed by chaining the algorithms as described earlier. Resilience metrics in terms of physical services, economic activity, and population stability were examined to explore the effect of wind mitigation retrofits on community resilience enhancement, i.e., to link resilience goals at the community level with the selection of a mitigation policy for building retrofit. Table 4 and Table 5 indicate some key findings for these core community resilience metrics in terms of the physical, economic, and social stability areas. The full suite of results for buildings retrofitted at each of the different percentages for the building stock under different scenarios are not shown herein for brevity. As an example, when the community was impacted by the idealized EF4 tornados, the number of non-functional buildings and the number of housing units dislocated can be reduced by 11.7% (1,187 to 1,048) and 11.0% (847 to 754), respectively, when 40% of residential buildings are retrofitted. The percentages shown in Table 4 are defined as the change in the metrics being measured (e.g., household dislocation) out of the total value that can be measured for that metric (e.g., households) for the community. Fig. 4 illustrates the histograms of typical metrics in terms of physical services stability and population stability from one hundred (100) EF2 tornado scenarios as an example. The reason for a few extreme values at the left end in the histograms is that the socio-economic losses caused by the tornado event are also highly related to the attributes of the area hit by the tornado, such as population density. In more rural areas, both population and building density is lower, and tornadoes striking these areas impact the local economy and cause household dislocation at a smaller scale compared to dense urban areas.

Workers employed at damaged or non-functional commercial buildings may face work interruption or job loss, leading to reduced household income and consumption expenditures. As part of the CGE simulation of this event, these values are calculated and represented in Table 5. Table 5 conveys that retrofitting played a significant role in mitigating economic impacts to domestic supply, especially employment and household income. From the lowest to highest retrofit application (from 0% to 100%) for EF2 and EF3, a more than 36% reduction (from \$3.9 million to \$2.5 million) in household income loss, and a 53.8% reduction (from 78 to 36) in employment loss, is observed.

Table 4.

Fig. 4

Table 5.

The minimum percentage of residential buildings retrofitted to achieve the community-level resilience goals can be determined for each tornado scenario (e.g., average of EF rating tornado striking anywhere in the community), as illustrated in Table 6 and Table 7. Note that the column fields shown in Table 6 and Table 7 are consistent with those representing each metric in Table 2. In order to meet all the multi-disciplinary community resilience goals for EF2 tornadoes (see Goal A in Table 2), the metrics for household dislocation controlled the retrofit level and at least 34.2% of residential buildings would need to be retrofitted. However, the employment metrics control the retrofit level for the EF3 and EF4 tornado scenarios. The fundamental contribution of this analysis methodology is the ability to essentially de-aggregate the community-level resilience goals in terms of physical, social, and economic metrics into building retrofit requirements. The goals themselves are flexible and can be adjusted by the analyst on a case-by-case basis. Additionally, it would also be possible to quantify the impact of a change in building code for new construction following a tornado or with some modification to the methodology and examine the effect of implementing new building code requirements over time as a community grows.

Table 6.

Table 7.

CONCLUSIONS

Community resilience assessments help the community determine what is needed to improve their performance, and long-term benefits relative to the 'do nothing' case. This study presents a methodology to determine building retrofit targets to achieve community-level physical, social, and economic resilience goals, in support of community resilience decision-making. A series of tornado scenarios at different intensity levels were simulated and applied to an illustrative community testbed. A set of core resilience metrics includes the percent of buildings that are analytically predicted to remain functional, the percent of households/population dislocated, and the percent change in the local economy (i.e., employment, domestic supply, household income). The mitigation focuses on residential buildings, and the objective is to determine the minimum percentage of residential buildings across a community that need to be retrofitted in order to achieve the multi-disciplinary community resilience goals. Based on the work presented herein, and recognizing that uncertainty in the results is not addressed, the following preliminary conclusions can be drawn:

- The percent of loss of functionality to buildings and the percent of household dislocation, as the key resilience metric in the study, may be reduced by approximately 11% when 40% of residential buildings are randomly retrofitted throughout the community for the assigned EF4 tornado scenario. For the EF2 and EF3 tornado scenarios, 40% of residential building retrofit may help mitigate the housing unit dislocation by approximately 14%.

- Building retrofits can play a significant role in reducing capital stock damage and further mitigating economic loss to domestic supply, employment, and household income. From the lowest (0%) to highest (100%) retrofit application for residential buildings for the EF2 and EF3 tornado scenarios, there would be more than a 35% reduction in unemployment, and more than a 50% reduction in household income loss.
- To meet all the multi-disciplinary resilience goals for tornadoes in the routine level intensity (EF2) defined in this study, the household dislocation metric controlled the retrofit level and at least 34.2% of residential buildings would need to be retrofitted. For the tornadoes at the design level hazard intensity (EF3) and extreme level hazard intensity (EF4), the employment metric controlled the retrofit level. The resilience goals are flexible and can be quantitively adjusted for different levels based on community input and the unique needs of a community. Clearly different multi-disciplinary metrics may control the retrofit requirements for different hazard intensities but are also specific to the resilience goals selected. This further underscores the need to consider goals across different community stability areas.

The study did not address budget constraints of the community and costs to retrofit, which would further limit selections of different retrofit strategies for different households. Note that communities have access to many funding sources outside of their own tax dollars for mitigation programs. The Federal Emergency Management Agency (FEMA) Building Resilient Infrastructure and Communities (BRIC) and Department of Housing and Urban Development (HUD) Community Development Block Grant–Disaster Recovery (CDBG-DR) programs are two examples.

The residential buildings were assumed to be retrofitted randomly without the consideration of the community retrofit priorities for residential buildings or individual capacity (e.g., high-income owners versus low-income renters).

Additionally, future studies will directly incorporate the CGE model and population dislocation algorithm into the analysis sequence to enable addressing uncertainty in the results. The results can then reflect the uncertainty of the socio-economic description specific for each hazard event.

Addressing the limitations above is beyond the scope of this study but future studies may include a risk-based cost-benefit analysis for the wind mitigation retrofits and the impact of insurance incentives and other policies, such as insurance companies offering a discount in annual insurance premiums for homeowners to encourage them to retrofit their houses.

In summary, the ability to de-aggregate community resilience goals to individual building performance targets can help accelerate the development of resilience-based building codes and standards that satisfy community-wide resilience goals of the broader built environment. The ability to achieve community-level resilience goals in terms of socio-economic metrics can provide community decision-making support for stakeholders and planners.

DATA AVAILABILITY STATEMENT

Some data and models involved in this study are available online in a Jupyter Notebook at https://incore.ncsa.illinois.edu, which allows users to reproduce this research with Python codes, data, and visualization.

ACKNOWLEDGEMENTS

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NOTATION

The following symbols are used in this paper:

C = The capital stock

c_1 - c_5 = Parameters for the logistic regression model

dsf = Building types (single-family or multi-family)

Fr_{DS} = Fragility functions

i = Damage states

$I_{fun,j}^{k}$ = The building functionality status

j = Each realization of the Monte Carlo simulation

k = Each building

m = Each census group

N = The total number of Monte Carlo simulation realizations

$pblack$ = Percent of black throughout the census group

P_{damage} = The building damage probability

P_{dis} = The population dislocation probability

$P^{k}_{dis,i,m}$ = The dislocation probabilities for each damage state

$P^{k}_{dis,\mathrm{m}}$ = The dislocation probability of each building in each census group

P_{fun} = The building functionality probability

phisp = Percent of Hispanic populations throughout the census group

ploss = The property value loss

R_j = Random variables between 0 and 1

s = Each sector

γ_s = Sector shocks

λ = Medians of fragility functions

ξ = Standard deviation of fragility functions

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Tables

Table 1. Built environment and human social system for Joplin testbed

Joplin testbed	Description	Values
Built environment		
Buildings	Residential	24,903
	Non-residential	3,249
	In total	28,152
Electric power network	Substations	18
	Poles	23,857
Human social system		
Housing units	Owner-occupied	11,344
	Renter-occupied	9,435
	Vacant	2,455
	Group quarters	22
	In total	23,261
Population	Owner-occupied	26,873
	Renter-occupied	20,949
	In total	49,810

Table 2. Community resilience goals based on core metrics

		Physical service metrics		Population stability metrics		Economic stability metrics		
Community goals	Tornado intensity (NCRPG hazard level)	% buildings remaining functional (due to damage)	% buildings remaining functional (due to damage + electrical power)	% households dislocated (unit: households)	% population dislocated (unit: people)	% change in employment	% change in domestic supply	% change in mean household income
Goal A	EF2 (Routine)	98%	95%	1%	1%	0.2	0.5	0.2
Goal B	EF3 (Design)	96%	89%	3%	3%	0.5	1.0	0.5
Goal C	EF4 (Extreme)	94%	83%	5%	5%	0.8	1.5	0.8

Table 3. Lognormal parameters for residential wood-frame building fragilities in this study

Building type	Building description	Damage states	Original fragility functions (m/s)		Retrofit design in terms of fragilities (m/s)	
			λ	ξ	λ	ξ
T1	Residential wood building, small rectangular plan, gable roof, 1 story	DS1	3.68	0.13	3.68	0.14
		DS2	3.56	0.14	3.85	0.12
		DS3	3.63	0.13	3.98	0.11
		DS4	3.68	0.14	4.16	0.13
T2	Residential wood building, small square plan, gable roof, 2 stories	DS1	3.60	0.13	3.60	0.13
		DS2	3.53	0.13	3.76	0.12
		DS3	3.59	0.13	3.91	0.11
		DS4	3.68	0.13	4.17	0.12
T3	Residential wood building, medium rectangular plan, gable roof, 1 story	DS1	3.61	0.13	3.61	0.13
		DS2	3.51	0.13	3.77	0.12
		DS3	3.57	0.13	3.92	0.11
		DS4	3.74	0.12	4.23	0.12
T4	Residential wood building, medium rectangular plan, hip roof, 2 stories	DS1	3.73	0.13	3.73	0.13
		DS2	3.65	0.13	3.87	0.12
		DS3	3.71	0.13	4.00	0.11
		DS4	3.76	0.13	4.28	0.12
T5	Residential wood building, large rectangular plan, gable roof, 2 stories	DS1	3.75	0.13	3.75	0.13
		DS2	3.65	0.13	3.88	0.12
		DS3	3.70	0.13	3.98	0.11
		DS4	3.64	0.15	4.06	0.14

Table 4. Community resilience metrics for physical and social systems that benefit from residential building retrofits (Mean values)

Residential building retrofits	Physical service metrics: The number of buildings non-functional (due to damage)	Physical service metrics: The number of buildings non-functional (due to damage + electrical power)	Population stability metrics: Housing unit dislocation (unit: housing units)	Population stability metrics: Population dislocation (unit: people)
EF2				
0%	315 (1.1%)	981 (3.5%)	231 (1.0%)	478 (1.0%)
40%	251 (0.9%)	971 (3.5%)	197 (0.9%)	409 (0.8%)
70%	200 (0.7%)	963 (3.4%)	169 (0.7%)	350 (0.7%)
100%	150 (0.5%)	955 (3.4%)	142 (0.6%)	295 (0.6%)
EF3				
0%	703 (2.5%)	1,387 (4.9%)	501 (2.2%)	1,021 (2.1%)
40%	601 (2.1%)	1,377 (4.9%)	436 (1.9%)	894 (1.8%)
70%	523 (1.9%)	1,368 (4.9%)	388 (1.7%)	796 (1.6%)
100%	443 (1.6%)	1,360 (4.8%)	339 (1.5%)	692 (1.4%)
EF4				
0%	1,187 (4.2%)	2,583 (9.2%)	847 (3.6%)	1,711 (3.4%)
40%	1,048 (3.7%)	2,570 (9.1%)	754 (3.2%)	1,532 (3.1%)
70%	939 (3.3%)	2,558 (9.1%)	685 (2.9%)	1,392 (2.8%)
100%	828 (2.9%)	2,547 (9.1%)	613 (2.7%)	1,231 (2.5%)

Table 5. Economic stability metrics given different levels of residential building retrofits and tornado scenarios (Mean values)

Residential building retrofits	Economic stability metrics		
	Employment loss (unit: person)	Domestic supply loss (unit: millions of $)	Household income loss (unit: millions of $)
EF2			
0%	78 (0.2%)	10.4 (0.3%)	2.0 (0.2%)
40%	62 (0.2%)	8.4 (0.3%)	1.6 (0.1%)
70%	49 (0.1%)	6.9 (0.2%)	1.3 (0.1%)
100%	36 (0.1%)	5.3 (0.2%)	0.9 (0.1%)
EF3			
0%	160 (0.4%)	22.0 (0.7%)	3.9 (0.3%)
40%	136 (0.4%)	19.2 (0.6%)	3.3 (0.3%)
70%	118 (0.3%)	17.0 (0.6%)	2.9 (0.3%)
100%	99 (0.3%)	14.7 (0.5%)	2.5 (0.2%)
EF4			
0%	270 (0.7%)	36.8 (1.2%)	6.7 (0.6%)
40%	236 (0.6%)	32.7 (1.1%)	5.9 (0.5%)
70%	211 (0.5%)	29.6 (1.0%)	5.3 (0.5%)
100%	182 (0.5%)	26.2 (0.9%)	4.6 (0.4%)

Table 6. Percentage of residential buildings requiring retrofit to achieve community resilience goals

Community goals	Physical service metrics		Population stability metrics	
	% buildings remaining functional (due to damage)	% buildings remaining functional (due to damage + electrical power)	% households dislocated (unit: households)	% population dislocated (unit: people)
Goal A	3.4%	12.0%	34.2%	33.3%
Goal B	8.0%	6.0%	17.5%	14.0%
Goal C	15.1%	16.0%	19.8%	15.4%

Table 7. Percentage of residential buildings requiring retrofit to achieve community resilience goals

Community goals	Economic stability metrics		
	% change in employment	% change in domestic supply	% change in mean household income
Goal A	28.7%	13.1%	19.4%
Goal B	21.5%	18.7%	11.6%
Goal C	29.0%	29.0%	18.0%

Figures Captions

Fig. 1 (a) The framework of the de-aggregation of community-level resilience goals; and (b) The sequence of analyses for community resilience assessment and metrics

Fig. 2. The geometry of generic tornado models for different EF ratings: (a) EF2; (b) EF3; (c) EF4

Fig. 3. Residential buildings retrofitted randomly assigned through the community: (a) 0% retrofitted; (b) 40% retrofitted; (c) 80% retrofitted

Fig. 4. Statistics of resilience metrics in terms of physical service and population stability: (a) building functionality without retrofit; (b) building functionality with 100% residential retrofit; (c) housing unit dislocation without retrofit; (d) housing unit dislocation with 100% residential retrofit

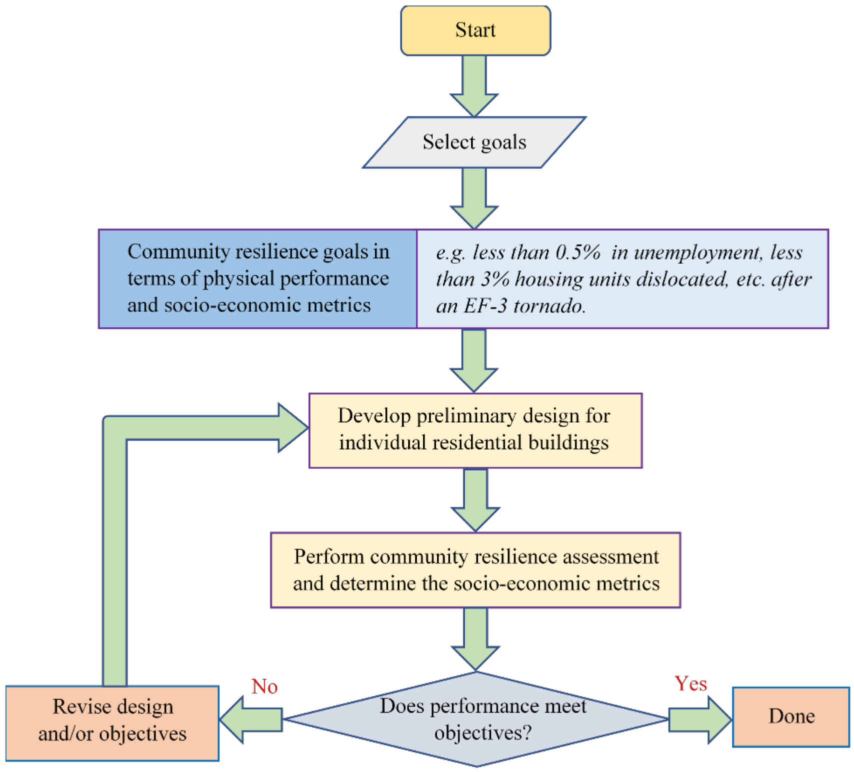

Start
Select goals
Community resilience goals in terms of physical performance and socio-economic metrics
e.g. less than 0.5% in unemployment, less than 3% housing units dislocated, etc. after an EF-3 tornado.
Develop preliminary design for individual residential buildings
Perform community resilience assessment and determine the socio-economic metrics
Does performance meet objectives?
No
Yes
Revise design and/or objectives
Done

Figure 1a

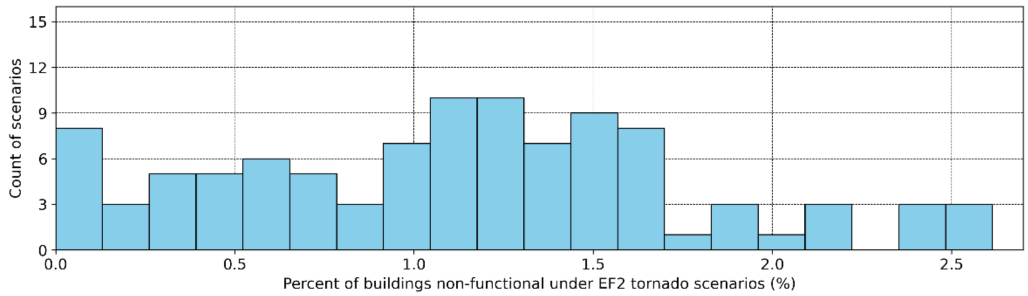


Figure 4a

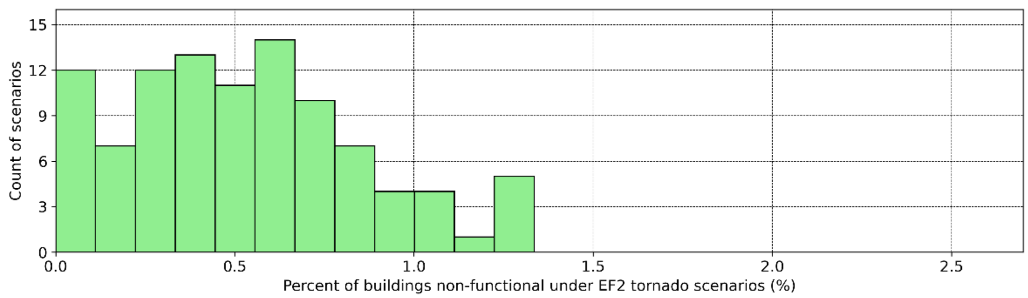


Figure 4b

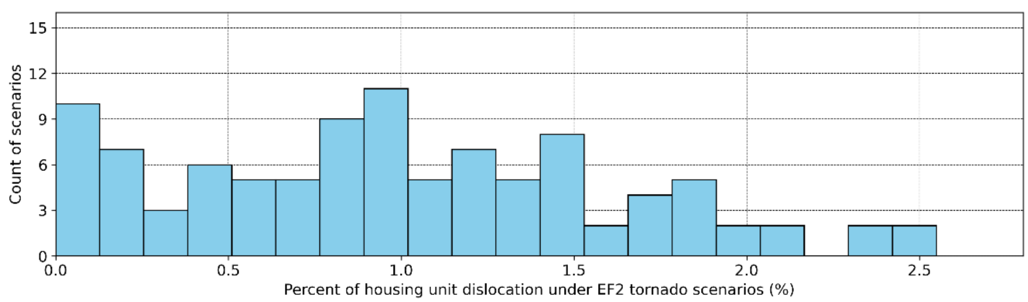


Figure 4c

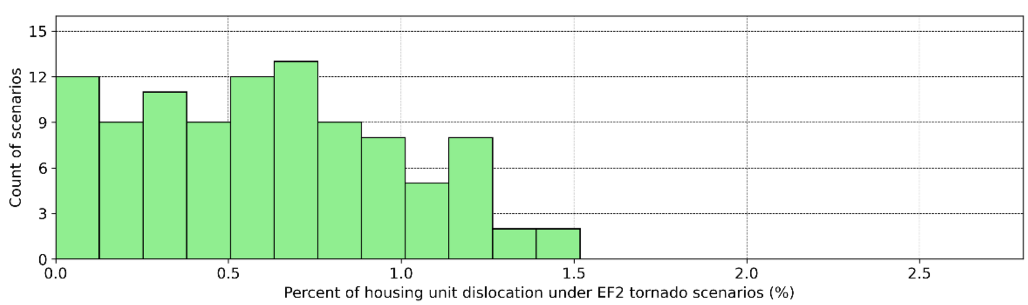


Fig 4d

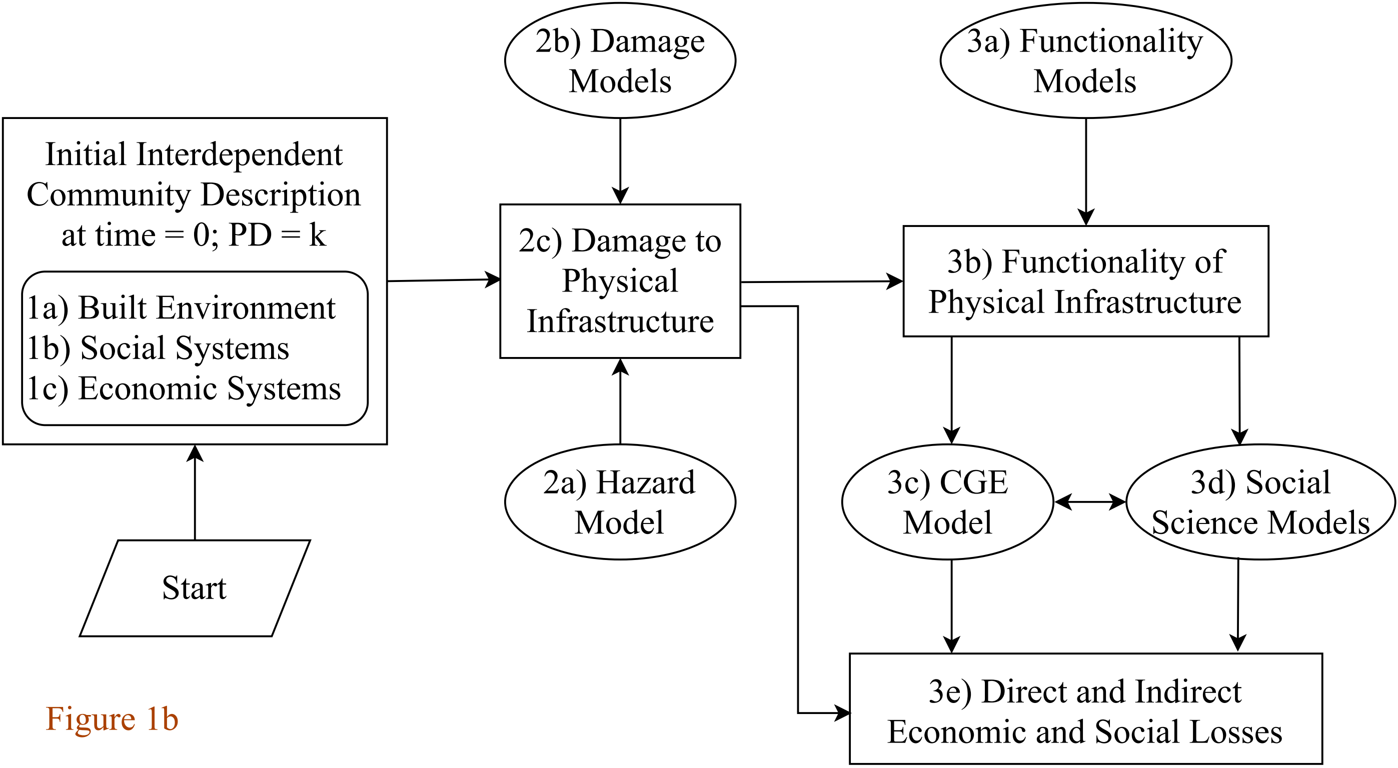

2b) Damage Models
3a) Functionality Models
Initial Interdependent Community Description at time = 0; PD = k
1a) Built Environment
1b) Social Systems
1c) Economic Systems
2c) Damage to Physical Infrastructure
3b) Functionality of Physical Infrastructure
2a) Hazard Model
3c) CGE Model
3d) Social Science Models
Start
3e) Direct and Indirect Economic and Social Losses

Figure 1b

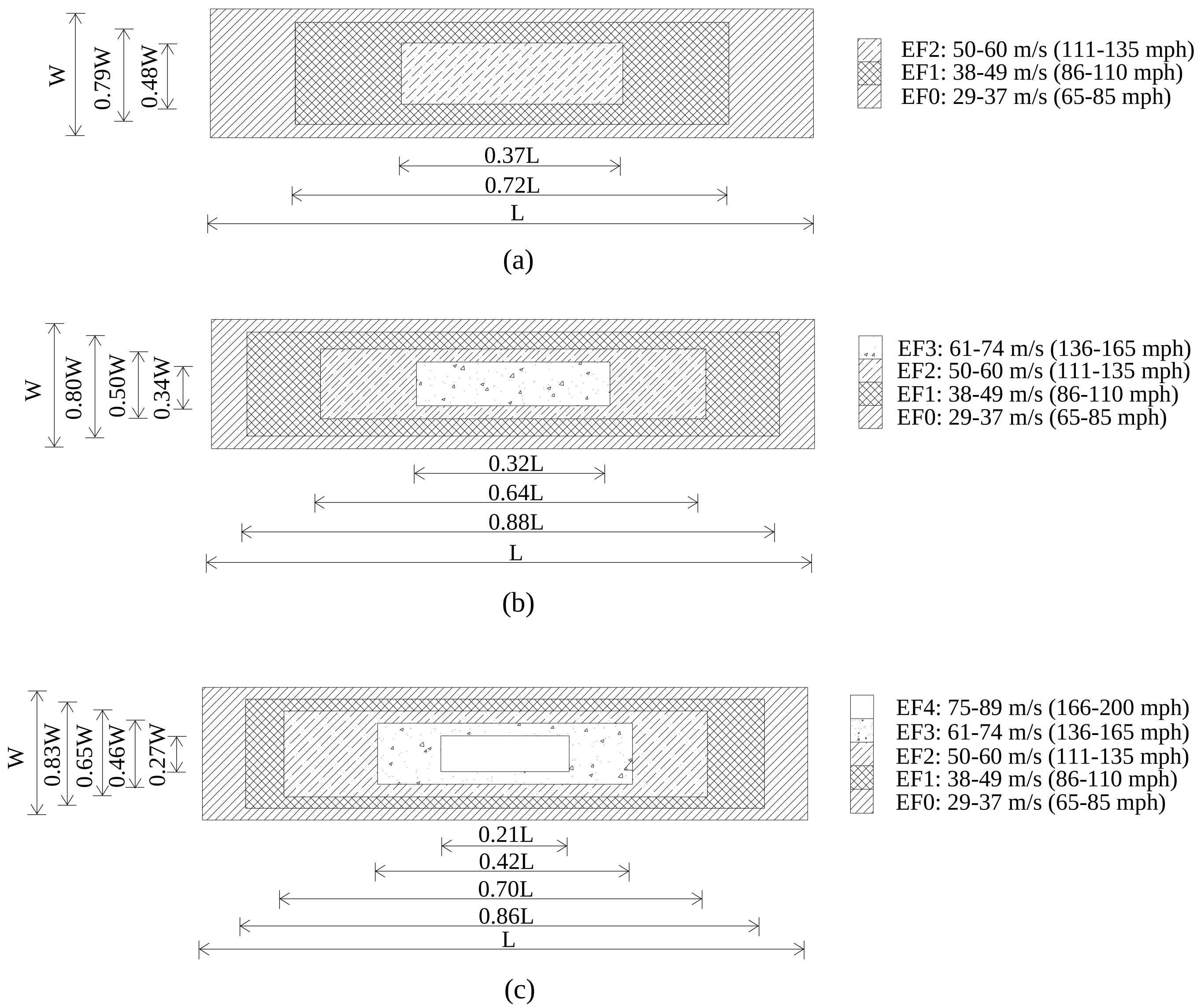
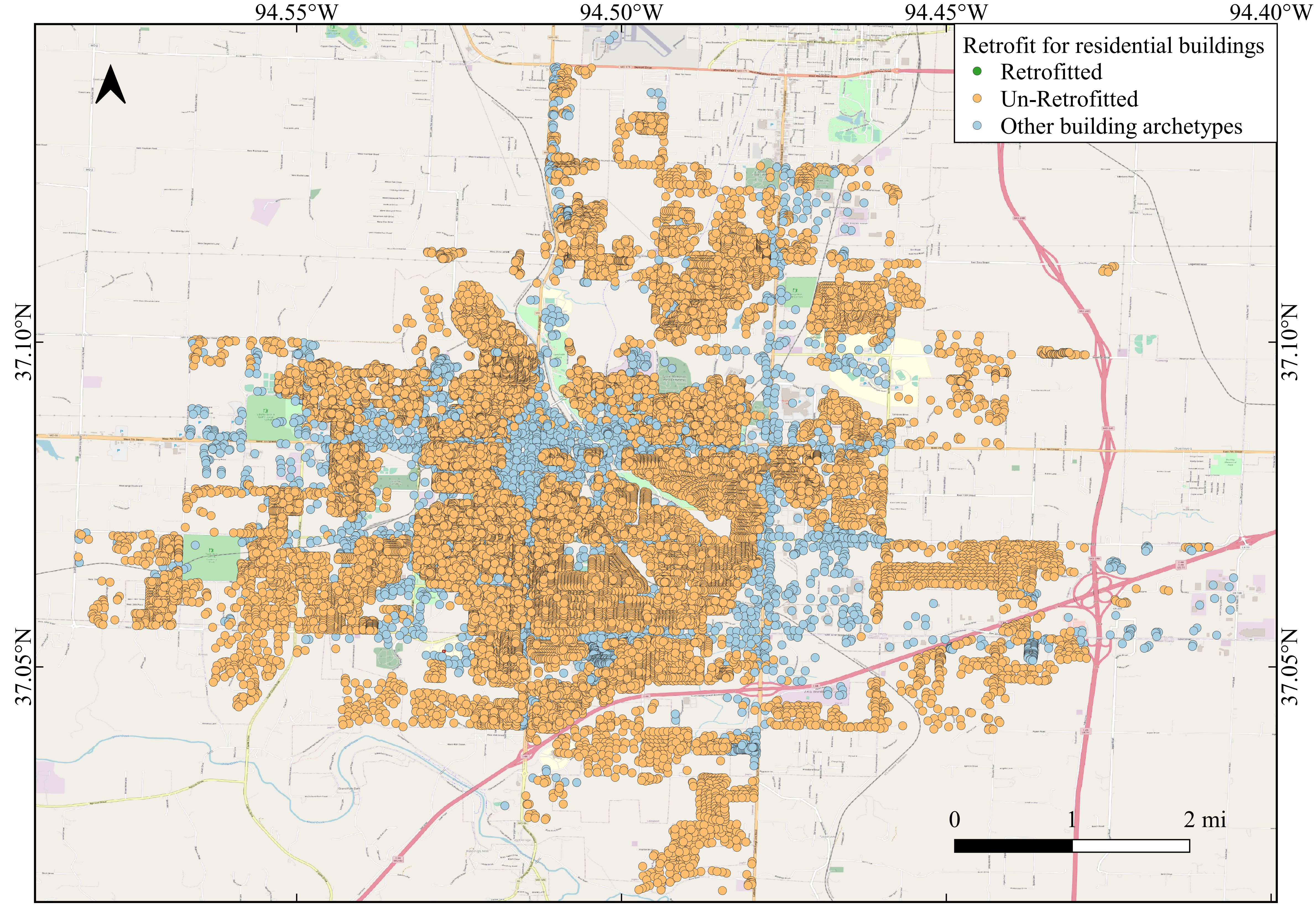
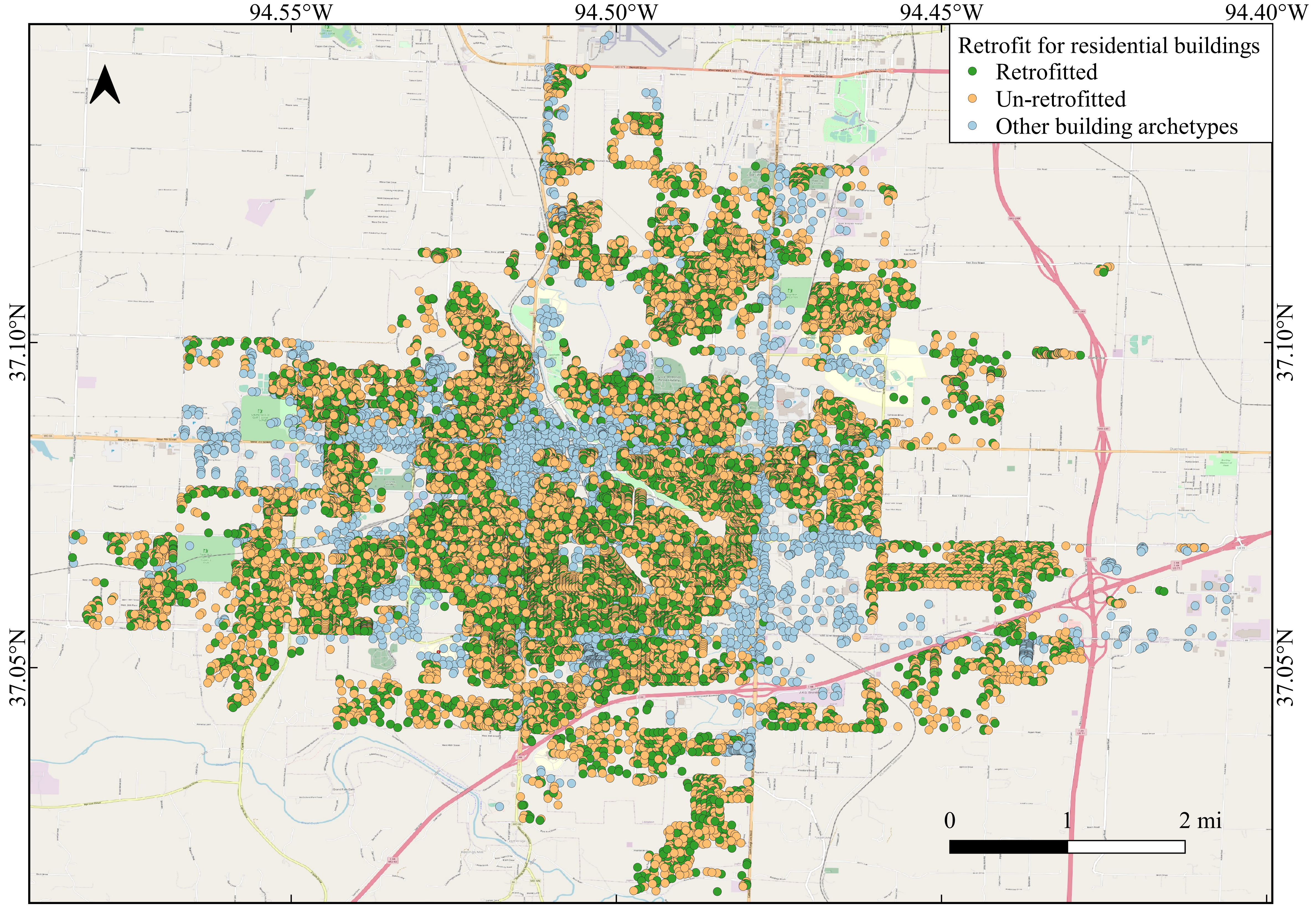

W
0.79W
0.48W
EF2: 50-60 m/s (111-135 mph)
EF1: 38-49 m/s (86-110 mph)
EF0: 29-37 m/s (65-85 mph)
0.37L
0.72L
L
(a)
W
0.80W
0.50W
0.34W
EF3: 61-74 m/s (136-165 mph)
EF2: 50-60 m/s (111-135 mph)
EF1: 38-49 m/s (86-110 mph)
EF0: 29-37 m/s (65-85 mph)
0.32L
0.64L
0.88L
L
(b)
W
0.83W
0.65W
0.46W
0.27W
EF4: 75-89 m/s (166-200 mph)
EF3: 61-74 m/s (136-165 mph)
EF2: 50-60 m/s (111-135 mph)
EF1: 38-49 m/s (86-110 mph)
EF0: 29-37 m/s (65-85 mph)
0.21L
0.42L
0.70L
0.86L
L
(c)

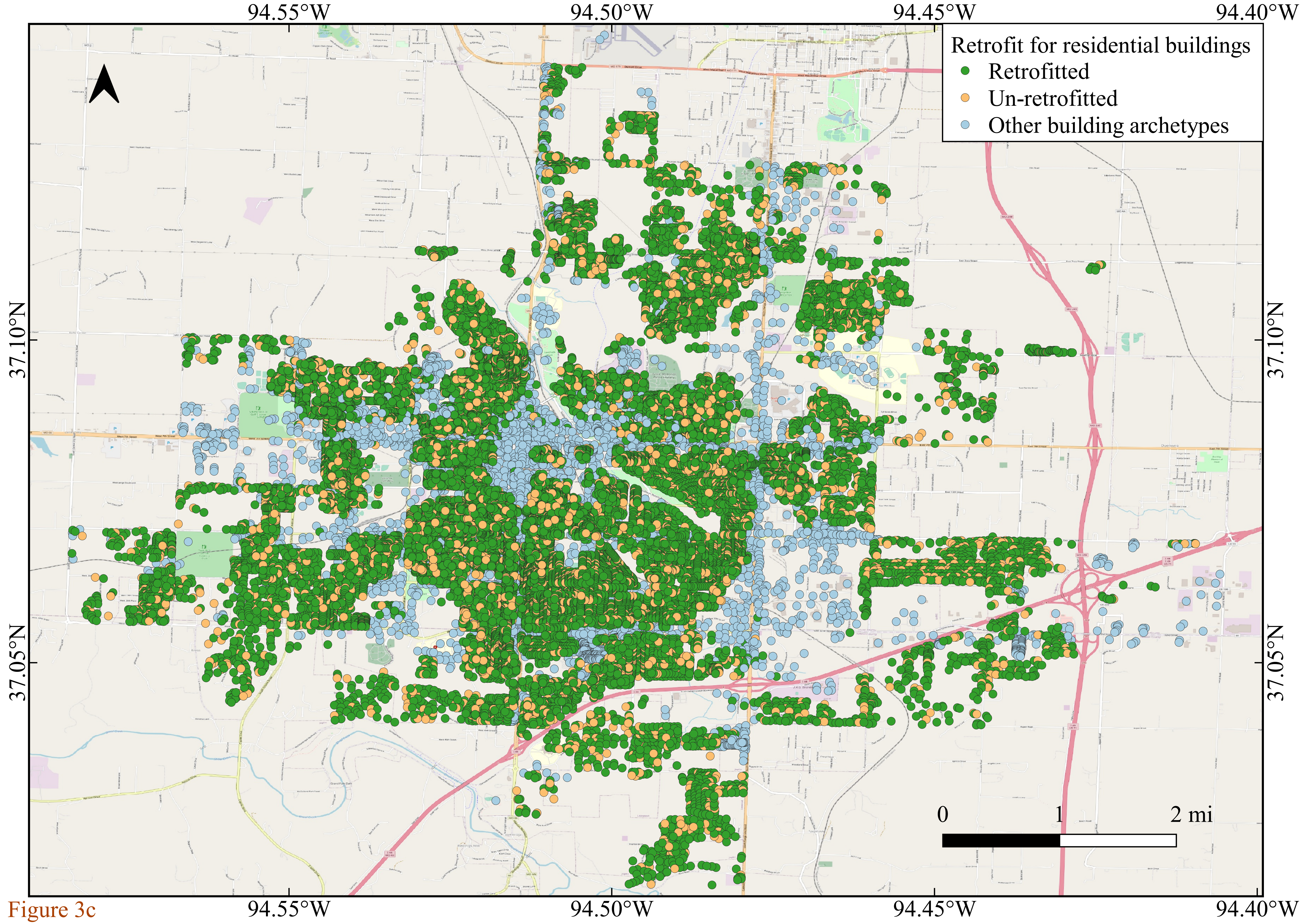
Figure 2



94.55°W
94.50°W
94.45°W
94.40°W
37.10°N
37.05°N
Retrofit for residential buildings
Retrofitted
Un-Retrofitted
Other building archetypes
0
1
2 mi

Figure 3a


Retrofit for residential buildings
Retrofitted
Un-retrofitted
Other building archetypes
94.55°W
94.50°W
94.45°W
94.40°W
37.10°N
37.05°N
0
1
2 mi
Figure 3b



94.55°W
94.50°W
94.45°W
94.40°W
37.10°N
37.05°N
Retrofit for residential buildings
Retrofitted
Un-retrofitted
Other building archetypes
0
1
2 mi

Figure 3c