Title
Remapping California's wildland urban interface: A property-level time-space framework, 2000−2020

Journal
Applied Geography, 167

ISSN
0143-6228

Authors
Berg, Aleksander K
Connor, Dylan S
Kedron, Peter
et al.

Publication Date
2024-06-01

DOI
10.1016/j.apgeog.2024.103271

Peer reviewed

Applied Geography 167 (2024) 103271

Contents lists available at ScienceDirect

Applied Geography

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

Remapping California's wildland urban interface: A property-level time-space framework, 2000–2020

Aleksander K Berg[a,b], Dylan S. Connor[a,*], Peter Kedron[c], Amy E. Frazier[c]

[a] School of Geographical Sciences & Urban Planning, Arizona State University, Tempe, AZ, 85281, USA
[b] Department of Geography, University of Colorado Boulder, Boulder, CO, 80309, USA
[c] Department of Geography, University of California Santa Barbara, Santa Barbara, CA, 93106, USA

A R T I C L E I N F O

Keywords:
Wildfire
Wildland urban interface
ZTRAX
Building footprint
land use land cover change

A B S T R A C T

Wildland fire poses a significant risk to property and people, and these risks tend to be highest in places where flammable, wildland vegetation abuts urban development. Traditionally, efforts to map these areas of intersection, known as the Wildland Urban Interface (WUI), have relied on satellite-derived land cover and census data. While these types of data are valuable for broadly delineating WUI areas, they are constrained in their ability to specifically identify at-risk residential properties and their characteristics over time. This article addresses these challenges through a multi-time-step, property-level framework that enhances current approaches based on moving window mapping, the Time Step Moving Window (TSMW) framework. We implement this framework on approximately 10 million geo-located property records from Zillow's Transaction and Assessment Database for California. Using this framework, we generate estimates of California's WUI from 2000 to 2020 and find that our time stepped building scale maps have allowed us to classify residential homes at-risk to burns with greater accuracy compared to time stepped Census polygon based maps. Based on these maps, we further estimate that approximately $1.34 Trillion, or 40%, of California's improved residential property value is situated within the WUI. Our approach provides a high-precision strategy for delineating at-risk residences and calculating localized financial costs associated with future hazard events.

1. Introduction

Extreme heat and drought, exacerbated by climate change, are increasing wildland fire danger and raising the chances that urban settlements will experience catastrophic burns. In the United States, the frequency and magnitude of wildland fires has increased for several decades, and the total area burned has quadrupled since 1985 (Burke et al., 2021). Larger and more frequent fires have also brought on greater economic costs, with U.S. taxpayers contributing $30.7 billion USD to wildfire suppression between 2001 and 2019 (NIFC, 2022). Many of these financial resources are devoted to settlements and land within the Wildland Urban Interface (WUI), an area that is particularly prone to fire due to concentrated interaction of flammable vegetation and human-driven ignition sources (Mell et al., 2010; Platt, 2010). An estimated 50 million homes in the United States are situated within the WUI (Anu Kramer et al., 2018), with this number having risen by over 350, 000 homes annually from 2000 to 2020 (Burke et al., 2021). Moreover, recent findings indicate that these homes within the WUI are disproportionately occupied by vulnerable populations, notably elderly residents living in rural areas (Winkler & Mockrin, 2024).

Despite the importance of the WUI to wildfire suppression and risk mitigation, there remains an ongoing debate about how to best measure and map these areas (Bento-Gonçalves & Vieira, 2020; Platt, 2010). Some WUI mapping methodologies have explored the use of models, including machine learning models that utilize wildfire exposure and other environmental factors (e.g., built and vegetated land) to define WUI areas (Miranda et al., 2020; Whitman et al., 2013). Though, across the primary measures, the WUI is defined along three dimensions: the density of the built environment, the location and density of wildland vegetation, and a buffer of impact that aims to capture potential 'neighborhood effects' (Stewart et al., 2007). However, these factors are incorporated differently into the two dominant approaches to measuring the WUI, which are described below.

First, Radeloff et al. (2005, 2018, 2022) advocate for a zonal approach to mapping the WUI that relies on census blocks and density thresholds for vegetation and developed land that are derived from satellite-based

* Corresponding author.
E-mail address: d.c@asu.edu (D.S. Connor).

https://doi.org/10.1016/j.apgeog.2024.103271
Received 11 November 2023; Received in revised form 4 April 2024; Accepted 10 April 2024
Available online 27 April 2024

land cover maps and census data. This classification method, which we term the block areal (BA) method due to the computation of areal measures within census blocks, is straightforward and can be applied nationwide and in countries with similar census data. The BA method has been the national standard for mapping and defining the WUI, and it is utilized by the U.S. Fire Administration and the U.S. Department of Agriculture Forest Service for identifying community risk to wildfire and emergency management (U.S. Fire Administration, 2022; Martinuzzi et al., 2015). However, because the BA method uses census-defined areas as its basic spatial units, mapping outputs must follow the boundaries of these areas, potentially misestimating WUI area. The BA is thus particularly susceptible to the modifiable areal unit problem (MAUP) (Openshaw & Taylor, 1981). Additionally, the full population of the United States is only enumerated every ten years, limiting the value of such data for measuring intradecadal spatial population change.

Second, an alternative to the BA method is to use a moving window approach, which centers a search window on each pixel in the study area and classifies whether that pixel is located within the WUI by applying the same building and vegetation density thresholds as the BA method to the area immediately surrounding that pixel (Bar-Massada et al., 2013). The moving window method can more precisely map the WUI at finer spatial granularity compared to the BA method and better capture the continuous nature of development (Bar-Massada, 2021). It has been applied to map the WUI at a higher granularity at local, state, and national, and global scales (Bar-Massada, 2021; Bar-Massada et al., 2023; Carlson et al., 2022; Schug et al., 2023).

The moving window method offers the advantage of higher resolution than the BA method, but acquiring geospatial data on built structures and their characteristics is a key challenge limiting its implementation. Information on built structures, including building type, size, and assessed value, is sometimes made available through local government agencies, for example Los Angeles County Office of the Assessor (2023), but piecing together fragmented and inconsistently enumerated data for the purposes of mapping can be onerous for researchers. To help overcome these issues, building footprint datasets have recently been made available by organizations including the Federal Emergency Management Agency (FEMA, 2022) and Microsoft (Microsoft, 2018). These datasets are being used to generate fine-scale population estimates (Depsky et al., 2022; Leyk et al., 2020), assess flooding impacts (Durst et al., 2021), and better understand the configuration of the built environment (Allen et al., 2020). However, the available large-scale building footprint datasets have limited building- or parcel-level attribute information (e.g., year built, assessed property value, etc.). Without this information, it is challenging to (1) differentiate residential from non-residential land uses, (2) identify when buildings were constructed in order to map changes in the WUI over time, and (3) quantify the risks to property and life within the WUI. While some of these limitations may be remedied through improvements in remotely-sensed data products, linking structure locations to attributes derived from large scale real estate databases provides a direct alternative, with long-term promise.

This study therefore leverages the fine-scale building- and parcel-level information from Zillow's ZTRAX (Zillow Transaction and Assessment Dataset) database to improve WUI mapping and investigate economic and social conditions in the WUI. ZTRAX is a large building and property data set based on existing cadastral data sources that comprises millions of records of built-up properties including characteristics such as size, age, land use type, and value (Uhl et al., 2021b). We utilize these data to make four important contributions. First, we build on the existing moving window method for mapping the WUI by developing a multiple time step extension that integrates building- and parcel-level attribute information, including building type and year built. These integrated data allow us to precisely map the WUI in a manner that can be updated at incremental time steps to understand changes over time. We term this approach the Time Step Moving Window (TSMW). Second, we use the TSMW framework to perform a multi-temporal analysis of the WUI in California to track two decades of change between 2000 and 2020. Third, we assess the efficacy of the TSMW framwork by measuring its accuracy in classifying residential structures in the WUI that were later exposed to wildland fire burns. Finally, we leverage building- and parcel-level attributes to generate a profile of housing in the WUI, including home type and assessed property value, and compare this profile to homes outside of the WUI to better understand the distinctive characteristics of the WUI in California. By incorporating high resolution property level data into the mapping of these high-risk areas, our approach is a step forward from other moving window WUI mapping techniques that typically see the WUI as temporally static and stationary. We have made the WUI maps that underlie this analysis publicly available to facilitate applied research and validation against alternative estimates.

The ZTRAX database has provided a valuable scientific opportunity to assess the potential value of such data for future research. Unfortunately, the partnership program that provided access to these data has ended. However, many new data products measuring the built environment at fine spatial, temporal, and attribute scales have already become available or are at an advanced stage of development. The most notable of these new products are the FEMA-developed USA Structures Database and parcel aggregation datasets such as ReGrid. Databases such as these will continue to be enhanced and are poised to redefine the field of risk mapping. We view these cutting-edge approaches and data sources as being highly complementary to traditional WUI mapping based on satellite-derived data. The analysis that follows is thus not circumscribed by the availability of ZTRAX but instead makes more general contributions to (1) demonstrating the public good of large property databases to support future access, and (2) establishing foundational knowledge that can be utilized in the latest generations of property, structure, and parcel databases.

2. Data and methodology

2.1. Study area

The analysis focuses on the state of California (Fig. 1), where climatic conditions and urban development are intersecting in ways that are increasing the risk of destructive fire events. Wildland fire is a natural component of ecological cycles in California that predate human activity (Pigati et al., 2014), but in recent decades, more frequent and larger fires are occurring following a century of fire suppression and changes in climate, vegetation conditions, and human activity (Li & Banerjee, 2021; Williams et al., 2019). California's vegetation, adapted to arid and semi-arid biomes, is highly susceptible to fire (van Wagtendonk et al., 2018), and as the climate becomes warmer and drier, the magnitude of fires is increasing (Westerling & Bryant, 2008). Coupled with this environmental change is the expansion of urban developments, notably residential home constructions, in proximity to wildlands (Hansen, 2022; Pitt, 2022).

The expansion of housing into fire-prone areas in California is related to broader trends in U.S. housing markets. Housing demand in exurban locations is driven, in part, by population growth and rising home prices in core metropolitan areas. Recent decades have also seen sharp increases in amenity-driven migration as home buyers have increasingly sought access to open spaces and outdoor amenities, such as hiking and skiing, which tend to intermix or abut wildland vegetation (Villines, 2019). Residences in these locations therefore situate people in areas of high risk for wildland fire. While such trends are particularly pronounced in California, they are not unique to the state. High amenity rural and exurban places nationwide have experienced a doubling of their populations from 1975 to 2000 (McGranahan, 1999).

Fig. 1. Map of the project study area. Counties included in the study are shown in white. Due to data limitations, three counties were omitted from analysis: Del Norte, Imperial, and Mendocino, shown in black.

This study is therefore concerned with an important region over a key period with respect to wildland fires. Over the period of analysis from 2000 to 2020, 78,000 km^2 of Californian vegetated wildland burned, making these two decades the highest on record in terms of burned area in the state (CalFire, 2022). Economic costs for fire suppression in California in 2018 alone were estimated to be $148.5 Billion USD, or about 1.5% of the state's gross domestic product (Wang et al., 2020). It is thus more important than ever to describe and understand the changing nature of urban development with respect to fire risk in California.

2.2. Data pre-processing

Mapping and analysis relies on the integration of four datasets: land cover and vegetation, burn perimeters, building footprints, and the functional and economic characteristics of those buildings. We extract this information from four data streams: (1) land cover data from the National Land Cover Database (NLCD), (2) historical burn perimeters for California from the Monitoring Trends in Burn Severity (MTBS) dataset, (3) residential building footprints from the Federal Emergency Management Agency (FEMA), and (4) building and parcel-level attributes from the Zillow ZTRAX database. The details of each dataset as well as the pre-processing steps are detailed below (Fig. 2). The observations that we draw from these data sources focus on three approximate time slices of 2000, 2010, and 2020.

First, the land cover and vegetation data used in this study are derived from the NLCD. The NLCD is developed through a consortium of federal agencies that are concerned with the production of nationally consistent land cover data. The NLCD is based on 30 m resolution Landsat imagery and distinguishes between forest, shrubland, and grassland vegetation (Homer et al., 2004). While other, high resolution land cover products are available such as those derived from LIDAR data (Badia & Gisbert, 2020), we used the NLCD to permit direct comparisons with other WUI mapping products (Bar-Massada et al., 2013; Radeloff et al., 2005).

We extracted land cover data from three NLCD epochs (2001, 2011, and 2019) (Dewitz, J. and U.S. Geological Survey, 2021) to align with our three study years 2000, 2010, and 2020. We transformed the three epochs into binary rasters of wildland vegetation (NCLD classes: 41: "Deciduous Forest", 42: "Evergreen Forest", 43: "Mixed Forest", 52: "Shrub/Scrub", & 71: "Grassland/Herbaceous") and all other classes (Fig. 2). We also generated binary rasters of water and non-water area (Fig. 2). These data were then ultimately used to map the extent of the WUI (discussed below)[1].

Second, we constructed a database of burn perimeters from the Monitoring Trends in Burn Severity Dataset (MTBS) (Eidenshink et al., 2007; Picotte et al., 2020) for the years 2000 to 2020 (Fig. 2). This dataset comprises burns greater than 1000 acres (404 ha) in the U.S. from 1984 to present. The MTBS dataset was then subsetted to the study area, and burns flagged as prescribed were omitted.[2] These data are used to assess the exposure of homes mapped in and outside the WUI to wildland fire.

Third, building footprints were obtained from the USA Structures database, prepared by the Federal Emergency Management Agency (FEMA, 2022). USA Structures is the first comprehensive inventory of all structures larger than 450 square feet (41.8 m^2) in the United States designed for hazard analysis and emergency planning. The USA Structures dataset is based on detailed remotely sensed imagery and LIDAR data and has been shown to better represent the residential built environment compared to the widely-used Microsoft Building Footprints Dataset (Wan et al., 2023). We rely on the December 2021 iteration of the database, which contains 10,931,401 structures in California. While the USA Structures database is an excellent resource for identifying structure locations and size, it is less comprehensive with respect to other attributes such as the building type and valuation.

Fourth, to describe the characteristics of these structures, we use Zillow's Transaction and Assessment Dataset (ZTRAX) (Zillow, 2018). ZTRAX is one of the largest databases containing U.S. real estate data and has been made available free of charge through an application process to a set of academic research teams and institutions. The complete database includes more than 400 million public records across approximately 2750 U.S. counties. The data underlying ZTRAX have been assembled from a variety sources, including county assessor records. Although Zillow has ended their ZTRAX academic data sharing program, a set of derivative products have been made available for future use through the HISDAC-US compilation (Leyk & Uhl, 2018; Mc Shane et al., 2022). Likewise, similar parcel data that can be, and have been, linked to building data can be acquired through individual county assessor offices or via parcel aggregator services such as ReGrid and Attom. The ZTRAX data have already had a significant impact on the social science of urbanization, housing, and hazards. ZTRAX is being used to advance the frontiers in spatial data science by enabling analysis of long-term housing and urban development dynamics (Connor et al., 2020; Leyk et al., 2020; Uhl et al., 2021a, 2023). They have also been used specifically within the context of hazards to examine the changing nature of risk and exposure to wildland fire events (Baylis & Boomhower, 2021; Mietkiewicz et al., 2020), as well as flooding and storm surge (Braswell et al., 2021). We extracted records for 9,592,170

[1] Raster pre-processing was conducted using ArcGIS Pro version 3.0

[2] While the MTBS fire type of "unknown" includes some prescribed burns, we decided to keep the MTBS category as these records are overwhelmingly situated in the Eastern U.S. and should not greatly impact results in California.

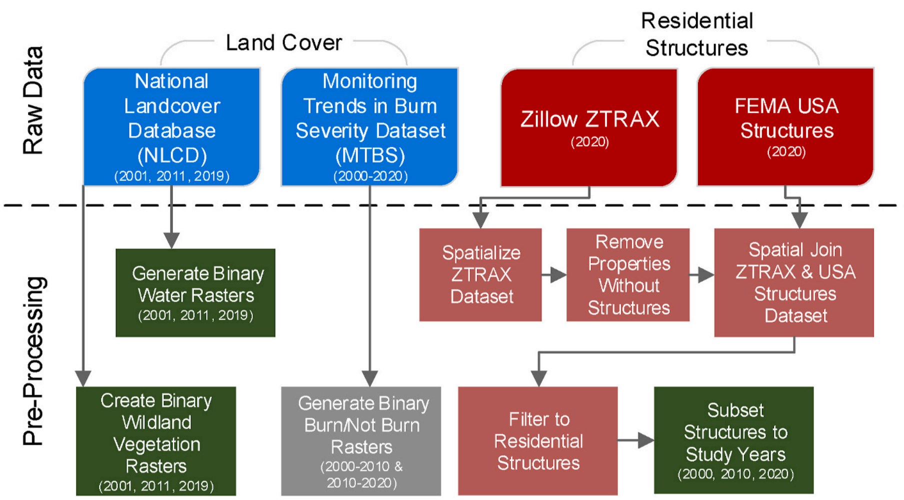

Fig. 2. Data and pre-processing steps for the land cover (blue) and structures (red) data streams used in the analysis. Green outputs are used to map the WUI and grey outputs are used for secondary analysis.

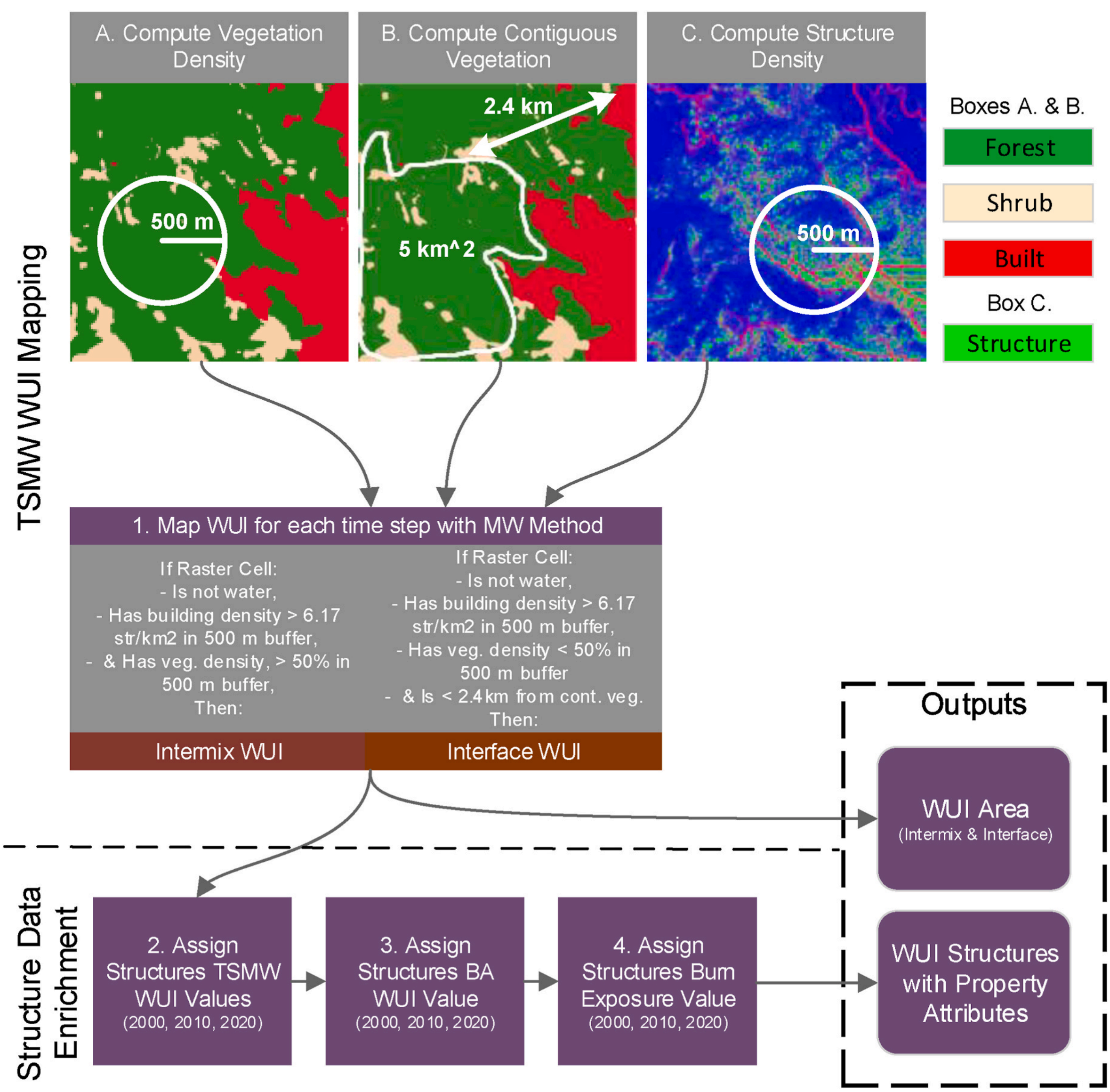

Fig. 3. Workflow for mapping the Intermix and Interface WUI using the Time Step Moving Window (TSMW) framework.

properties in California,[3] which include attributes such as land use codes (e.g., residential, commercial), building and property assessment values, and structural characteristics including built year and building quality (Fig. 2).

In order to accurately match the building footprints from the USA Structures database to the attribute information in the ZTRAX database, we developed a spatial integration strategy. The tabular ZTRAX data include coordinate information that was used to initially map a point for each property. The points are typically located in the geometric center of the parcel, so there can be considerable locational uncertainty in the degree to which these coordinates align with the location of the structure of interest (Uhl et al., 2021c). To rectify this issue, we spatially joined each ZTRAX location to the closest building within the USA Structures database. To ensure that improbable linkages are not made, any ZTRAX record not within 500m from a building footprint was removed. Initially, we attempted to join building footprints to ZTRAX data using a statewide parcel boundary file. Unfortunately, due to how ZTRAX addresses were geocoded, many entries were spatialized to the curb location of the property (outside the parcel). We therefore elected to use a consistent and computationally simpler spatial join process highlighted here.[4] The join process resulted in a database that retained all 10,931,401 FEMA USA Structure Footprints linked to ZTRAX attribute records. The majority of structures (75%) are located within 25 m (median distance = 8 m) of the closest ZTRAX centroids. This small median distance provides a high degree of confidence in our ability to match the USA Structures to the ZTRAX data. About 21% of residential ZTRAX records were attributed to more than one structure, with a maximum of 357 structures per record and an average of 1.4 structures per record .[5]

We next filtered the data to only include properties with residential land use codes (ZTRAX Standardized Land Use Codes beginning with RR and RI), which make up 91% of building footprints with complete ZTRAX records. To create temporal time slices, we further filtered the data based on retrospective year of construction to create separate datasets for structures existing in 2000 (8,656,012 structures), 2010 (9,706,713), and 2020 (9,974,034).[6] A complete record of the ZTRAX data are unavailable for three of California's 58 counties. As a result, our analysis does not include Del Norte, Mendocino, and Imperial counties. Taken together, these counties account for fewer than 1% of California's residents.

2.3. Time Step Moving Window mapping framework

The TSMW framework to mapping the WUI innovates on the widely-used moving window technique (Bar-Massada et al., 2013). Specifically, restricting the data solely to residential land uses enables mapping the WUI more precisely based only on residential structures, since these structures are of particular concern for capturing risk to life and personal property. This focus on residential structures aligns with prior conceptualizations of the WUI, which root risk of wildland fire to human-driven ignitions near homes. Precise building footprint locations along with property attribute data, particularly the year structures are built, permits a time stepped, high spatial resolution mapping of the WUI.

The methodology consists of three stages described below (Fig. 3): (1) high spatial resolution and time stepped mapping of the Intermix and Interface WUI using residential structures with attributes, (2) calculation of the structure-level attribute profile based on residential buildings mapped in the WUI, and (3) comparison of the area, structures, and structure profile between the TSMW approach and the BA method. These steps are described in detail below.

The moving window method (Bar-Massada et al., 2013) classifies WUI by placing a search window over every pixel in the study region and computing the density of buildings and wildland vegetation within the window to assign each pixel as either Interface WUI, Intermix WUI, or neither (Box 1, Fig. 3). Interface WUI denotes areas where there is a clear boundary between the built environment and wildland vegetation, while Intermix WUI denotes areas where structures are more dispersed and interspersed among the vegetation (USDA, 2001). In the BA method, the entire census block is classified as Intermix WUI if it satisfies the criteria of a minimum of one structure per 40 acres (6.17 structures/km^2 which is visualized in Box B. of Fig. 3) and 50% of the area is wildland vegetation. Or, it is classified as Interface WUI if a settled area has less than 50% wildland vegetation but lies within 2.4 km of a densely vegetated area that is at least 5 km^2 in size and at least 75% wildland vegetation (Bar-Massada et al., 2013; Glickman & Babbitt, 2001; Radeloff et al., 2005, 2018, 2022). We adopted these same thresholds and applied them using a circular moving window, as in the moving window method, instead of a census block to map the WUI at a pixel level.

The size of the moving window is determined by the researcher (Bar-Massada, 2021; Bar-Massada et al., 2013; Carlson et al., 2022). We used a 500 m diameter circular window, which approximates the area of the median size of census blocks in California. Moreover, earlier work using buffer-based mapping has tested the optimal size for capturing ignition sources and showed that 75% of human-driven wildfire ignitions happen within about 100–250 m of a structure (Conedera et al., 2015). Considering this, our selection of a 500 m window is more conservative while also enabling direct comparison to the census block-based BA method (visualized in boxes A & C of Fig. 3). Additionally, a 2.4 km buffer is generated around contiguous vegetation polygons that are at least 5 km^2 to assess the Interface WUI criteria of whether a pixel of interest is within that distance of a densely vegetated area. The MW algorithm was applied using an ArcGIS Pro 3.0 model (script) using the processed data described above (Box 1, Fig. 3). Three separate rasters were generated using the WUI algorithm for the three study years (2000, 2010, and 2020) using the respective data for each epoch ("WUI Area" in the Outputs section of Fig. 3). These final raster-based WUI maps have been deposited in a public archive.[7]

Summary statistics for the Intermix, Interface, and combined WUI are computed for each of the three study years (2000, 2010, and 2020). These statistics include the total area of WUI mapped in each category as well as the total change in land area classified as WUI from 2000 to 2010 and from 2010 to 2020. The residential structures used for mapping are also coded according to whether they were located in the Intermix WUI, Interface WUI, or outside the WUI[8] (Box 2. in Fig. 3). We computed summary statistics using R for the number of structures in the WUI in each time period, as well as the change over the two time periods.

[3] This number is smaller than the total number of structures presented below due to the spatial join process, which can capture multiple structures on a parcel. For example, the ZTRAX data, at the parcel scale, could be joined to the main home and an additional detached unit (ADU). Likewise, many apartment complexes are represented by a single ZTRAX entry even though there are multiple residences on the property.

[4] Structure processing completed using ArcGIS Pro version 3.0.

[5] We ran an additional set of robustness checks by remapping the WUI using the largest structure attached to a ZTRAX parcel. To do this we subsetted the 2020 structure dataset to the largest structure joined to a ZTRAX parcel, this subsetted dataset contained roughly 7 million structures. We then remapped the WUI using the same moving window method described below. These subsetted WUI maps were then compared to our original 2020 WUI map by extracting the percent WUI coverage per census block. We found that, on average, the original 2020 WUI maps covered 31% of each census block versus the subsetted maps covering 29%. To confirm the similarity between the two maps we ran a Pearson correlation between the two coverage values which showed a very strong correlation of 0.896.

[6] Filtering to included only residential structures was conducted in R.

[7] https://doi.org/10.5281/zenodo.10015378

[8] Completed using the 'Extract Values to Points' tool in ArcGIS Pro 3.0 with our structures dataset and the WUI raster maps.

Likewise, a profile of residential structures was generated to assess whether there are differences in the home type (single vs. multi-family homes), building size, year built, and the assessed value of the property improvements for structures inside versus outside the WUI.

For comparison, the same sets of statistics for WUI area and structures were generated for the same time periods using the BA method (Radeloff et al., 2018, 2022) (added to TSMW WUI structures in Box 3, Fig. 3). To assess and compare the efficacy of maps created using the TSMW framework and the BA method, we developed a confusion matrix of true positives, false negatives, false positives, and true negatives based on whether homes in and out of the WUI were exposed[9] to a wildland fire burn area (using structures enriched in Box 4, Fig. 3). The burn exposure data were derived from the MTBS dataset described above and joined with the structure points in ArcGIS Pro 3.0. We use the MTBS data as a benchmark for comparing the performance of WUI mapping methodology.

3. Results

3.1. Example case of TSMW mapping of the WUI

The main contributions of our multiple time step mapping approach using building-level data is in situating residential development and its effects on the WUI in both space and time. We begin our results by demonstrating this contribution through an exemplar case of how urban expansion redefines the WUI, as elucidated by the TSMW approach. Fig. 4 depicts the development of the 4000 acre (16 km^2) Ladera Ranch master-planned community in Orange County, California from 2000 to 2020. As of 2023, the Ladera Ranch community has single-family residences with valuations in excess of $5 million.

The map from the initial year, 2000, captures the region prior to the development of Ladera Ranch. In this period, the Intermix and Interface WUI occupies approximately 43% of the land area depicted in Fig. 4. The initial land area classified as WUI closely follows the perimeters of the pre-2000 structures (black) of San Juan Capistrano to the southwest and to the other surrounding settlements. The construction of the Ladera Ranch development, which was completed by 2010 (green dots in Fig. 4), greatly expands the area of interaction between housing and wildland vegetation. Based on the TSMW mapping approach, the land area classified as WUI increased by 35% over the period 2000 to 2010.

Over the following decade (2010 to 2020), we observe further residential development and expansion of the WUI. In 2013 and 2015, the Rancho Mission Viejo and Esencia communities opened to the east of Ladera Ranch (purple), again significantly expanding the WUI, this time by an additional 31% from the 2000 base level. This case thus provides a particularly strong illustration of the value of fine-scale analysis for studying where the WUI and its associated risks are being redefined over relatively short time horizons.

3.2. Summary statistics for TSMW- and BA-defined WUI

Having illustrated the localized insights provided by the TSMW approach, we return to the broader systematic evaluation and comparison of the TSMW and BA methods. Fig. 5 presents the spatial distribution of the 2020 WUI as calculated by the TSMW approach highlighting California's two most populous regions, The Bay Area (left pane of Fig. 5) and Southern California, (right pane of Fig. 5). Areas marked in dark orange are classified as Intermix WUI, which is where structures are surrounded by wildland vegetation. Areas marked in light orange are classified as Interface WUI, which is where structures, are near areas of contiguous vegetation. Both rural (i.e. Sierra Nevada Mountains in the top right corner of panel A. of Fig. 5) and dense urban areas (i.e. Los Angeles Basin in the bottom left of panel B. of Fig. 5) are captured in this WUI mapping.

The TSMW approach showed a 8.4% growth in the overall WUI area from 2000 to 2010, from 39,522 km^2 (10.4% of the study area) to 42,842 km^2 (11.2% of the study area), in the left most column of Table 1. WUI growth slowed to less than 0.9% over the next 10 years, with 43,205 km^2 (11.3% of the study area) in the WUI as of 2020. The number of structures within the TSMW WUI in California, similar to land area, increased 12.6% from 2000 to 2010 from 3,491,774 in 2000 to 3,933,305 in 2010. The number of structures in the WUI in California slightly increased, 1.5%, from 2010 to 2020, to a total of 3,992,030, middle left of Table 1.

In all three periods, the TSMW approach classifies approximately 50% more land area as WUI than the BA method. This difference has also increased over time. Specifically, the TSMW approach maps 14,785 km^2 more WUI than the BA method in 2000, 15,614 km^2 more in 2010, and 16,148 km^2 more by 2020. These discrepancies are due to the reliance of the BA method on an areal threshold of population density, which is often difficult to exceed in rural and remote regions where there might be development taking place.

The TSMW approach also classifies relatively high numbers of structures as being in the WUI. In 2000, the TSMW approach classifies 236,789 more structures in 2000 than the BA method, 93,133 more in 2010, and 22,661 more structures in 2020. The difference in WUI-classified structures between the two approaches has largely attenuated by 2020.

Across approaches, in terms of both land and structures there were differences and similarities in the growth rate of the WUI. From 2000 to 2020 the total area classified as WUI was very similar for the two approaches. The WUI area increased by 9.3% for TSMW approach and 9.4% for the BA. Interestingly, the count of structures classified within the WUI increased by 14.3% for TSMW and 21.9% for BA. The higher rate of growth within the BA-defined WUI might reflect the sensitivity of the TSMW to changes in the built and vegetated environment. As development into vegetated areas occurs, the WUI specified using the TSMW technique moves with it as areas that were once WUI get further from the building and vegetation boundary. Conversely, the static polygons of the BA method, as soon as they hit the WUI thresholds, get classified as a whole areal unit, adding more area in one go.

The TSMW and BA mapping approaches both show that the growth of the WUI has slowed considerably since 2010. For both approaches, the 2010–2020 growth rates for area and structures are only a fraction of their 2000 to 2010 levels. Nonetheless, despite the slowdown of growth relative to the 2000 to 2010 period, the WUI in California continues to expand.

The main differences across the TSMW and BA methods can largely be attributed to the type of land that is classified as WUI under the two approaches. Fig. 6 shows the delineation of the WUI by TSMW and BA for Millerton Lake, a region that is situated northeast of Fresno in the Sierra Nevada foothills. While much of this region is classified as WUI, there are strong deviations between the two approaches. The reliance of the BA method on block spatial units results in a WUI delineation that follows block boundaries, leading to less precision in terms of classification. The TSMW approach, in contrast, can more effectively classify finer intersections between housing and vegetation. The TSMW-defined WUI thus tends to be "patchier" and more inclusive of small and isolated residential-wildland interactions. These small patches, which are generally overlooked by the BA method, contribute to the large area-based differentials between the two classifications.

[9] It is important to note that being "exposed" does not mean the structure was destroyed in a fire as buildings can be in a burn perimeter and not be destroyed and inversely can be out of a burn perimeter and be destroyed. More detailed assessments of wildfire exposure in the WUI have been conducted like Ager et al. (2019) but these nuances remain out of the scope of our aim to remap the WUI through time using attribute rich property data.

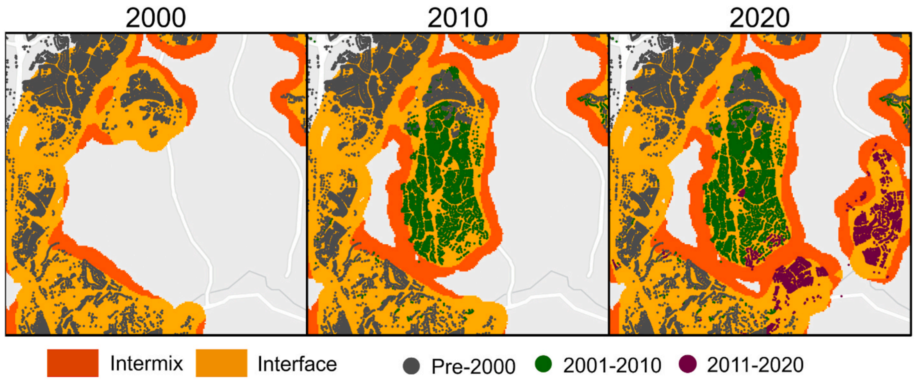

Fig. 4. Growth of the WUI over time using the Time Step Moving Window (TSMW) method. WUI extent and locations of residential buildings built before 2000 (left, black dots), before 2010 (center, green dots), and before 2020 (right, purple dots).

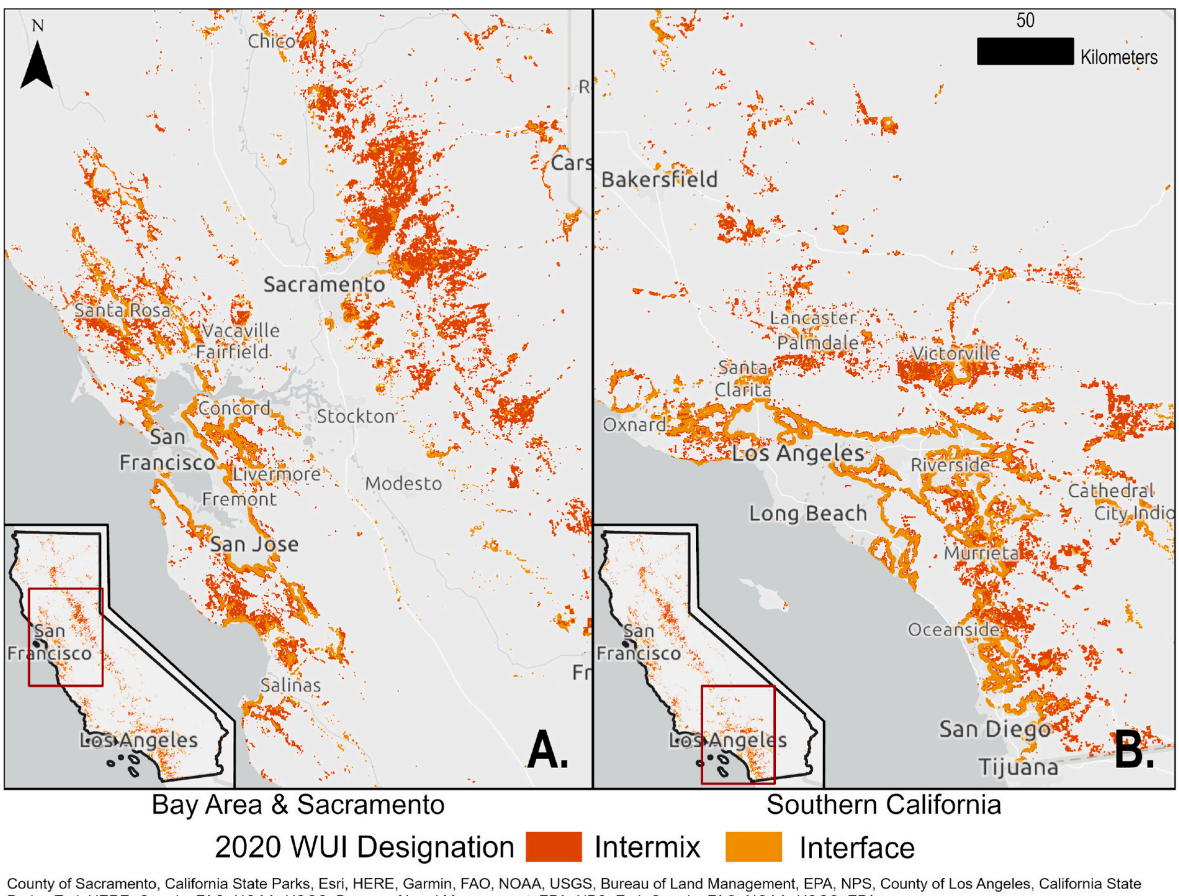

Fig. 5. Spatial Distribution of the 2020 WUI in the Bay Area and Southern California. WUI calculations made using the TSMW identify intermix (red) and interface areas (orange).

3.3. Classification performance of TSMW and BA

In Table 2, we present the classification performance of the TSMW approach and the BA method, as inferred from the probability that buildings exposed to wildland burns (defined by burn perimeter) were indeed located within the respective WUI definitions. In terms of burn exposure, the first two metrics of concern are the true positive and false negative rates. A true positive indicates a structure that was identified as within the WUI and subsequently exposed to wildland fire. A false negative indicates a structure that was identified as being outside of the WUI, but which was ultimately exposed to a wildland fire. If a WUI mapping technique is performing well, it should have a high true positive rate which and a low false negative rate. Across the 2000 to 2010 and 2010 to 2020 time periods, we find that the TSMW approach outperforms the BA method on both metrics (Table 2).

Between 2000 and 2010, there were 549 wildland fire incidents in the study area comprising 55,708 exposed structures over 24,524 km^2 of burned area. The TSMW approach accurately captured 88.2% of structures exposed to a wildland fire during that time period, while the BA method captured 82.1% of exposed structures. Similarly, between 2010 and 2020, 535 incidents occurred in the study area comprising 52,590 structures over 46,927 km^2 of burned area. The TSMW method

Table 1
WUI area and structure estimates for the Time Step Moving Window (TSMW) approach to Block Areal (BA) method for the three time periods (2000, 2010, and 2020) and the decadal changes between those periods. Percent of the study area's total land area is noted (#%) and the percent change in land area and structure counts is noted as (+/−#%).

Time Period	WUI Area		WUI Structures	
	TSMW	BA	TSMW	BA
2000	39,522 km^2 (10.4%)	24,737 km^2 (6.5%)	3,491,774	3,254,985
2010	42,842 km^2 (11.2%)	27,228 km^2 (7.1%)	3,933,305	3,840,172
2020	43,205 km^2 (11.3%)	27,057 km^2 (7.1%)	3,992,030	3,969,369
Δ 2000 to 2010	3320 km^2 (+8.4%)	2491 km^2 (+10.1%)	441,531 (+12.6%)	585,187 (+18.0%)
Δ 2010 to 2020	363 km^2 (+0.9%)	−171 km^2 (−0.7%)	58,725 (+1.5%)	129,197 (+3.4%)

accurately captured 94.6% of structures exposed to a burn as being in the WUI, while the BA method captured 87.2% of exposed structures. For both time periods, the TSMW method outperforms the BA method in terms of its efficacy for correctly classifying areas as WUI that were exposed to a wildland fire.

Importantly, the TSMW method also had a lower false negativity rate than the BA method, meaning that TSMW is less likely to classify burn-exposed structures as being outside of the WUI. From 2000 to 2010, 6582 (11.8%) of the residential structures that were exposed to a burn were classified as non-WUI by TSMW. In comparison, 9949 residential structures, or 17.9%, of structures that were exposed to a burn over this period were classified as being outside of the WUI by BA. The differential of 3400 structures implies that the false negativity rate of the TSMW approach is lower than that of the BA method (41% difference). Making the same comparison for the 2010 to 2020 period, the false negativity rate for TSMW is also lower than the BA method (58% difference).

This strong performance of the TSMW approach does come at some cost with respect to classification of structures outside of burn areas. The TSMW approach exhibits a higher implied false positivity rate, as inferred from structures that are WUI classified but which are never exposed to a burn. For 2000–2010 and 2010–2020, respectively, we find that the TSMW false positivity rate is 2.7 and 1.1 percentage points higher than that of the BA method. This implies a 2.67% to 6.7% difference in TSMW false positivity relative to BA. It should, however, be

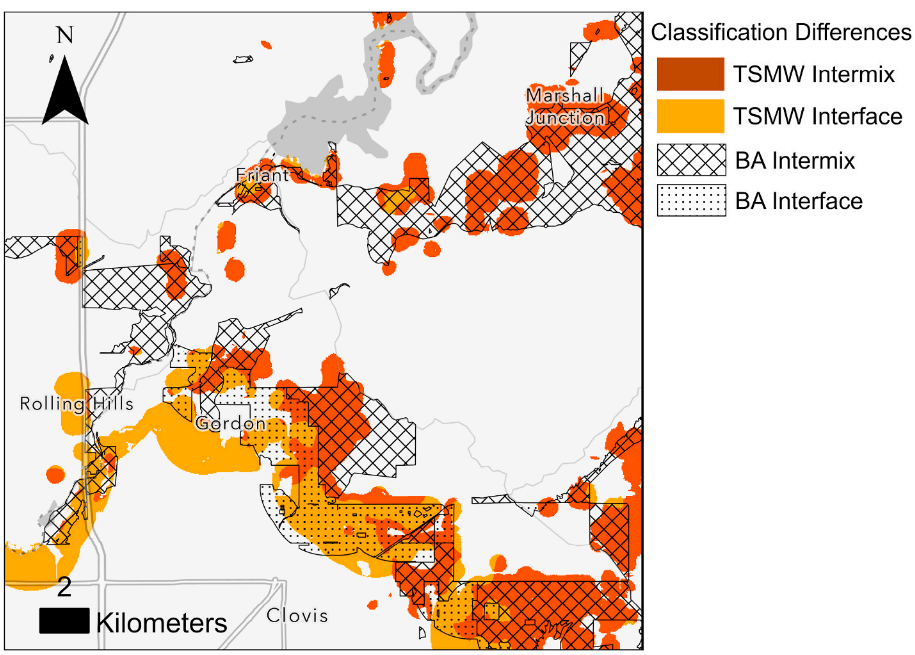

Fig. 6. Differences between the Time Step Moving Window (TSMW) and Block Areal (BA) method Radeloff et al. (2018) for the Wildland Urban Interface and Intermix based on 2010 data.

Table 2
Sensitivity and specificity of the Time Step Moving Window (TSMW) and block areal (BA) methods for capturing residential structures (and %) exposed to wildland fire burns from 2000 to 2010 and 2010–2020.

Classification		Inside burn		Outside burn	
		WUI	Not WUI	WUI	Not WUI
		"True Positive"	"False Negative"	"False Positive"	"True Negative"
2000 to 2010	TSMW	49,126 (88.2%)	6582 (11.8%)	3,797,113 (41.2%)	5,411,837 (58.8%)
	BA	45,759 (82.1%)	9949 (17.9%)	3,550,042 (38.5%)	5,658,908 (61.5%)
2010 to 2020	TSMW	49,740 (94.6%)	2850 (5.4%)	3,890,552 (41.1%)	5,586,749 (58.9%)
	BA	45,839 (87.2%)	6751 (12.8%)	3,787,815 (40.0%)	5,689,486 (60.0%)

noted that wildland burns are probabilistic processes and therefore we would not expect all buildings inside to the WUI to have been exposed to a burn over our study period. It may be that the higher rate of false positivity in the TSMW classification reflects true but unrealized risk.

In summary, mapping the WUI with building- and parcel-level attribute information within the moving window framework results in a more attuned capture of the probability that a burn-exposed building is correctly classified as being inside the WUI. The TSMW classifies more buildings as being inside the WUI which impacts the rate of implied false positives.

3.4. Real estate profile within the TSMW-defined WUI

The building- and parcel-level information integrated into the TSMW approach also permit a deeper assessment of the types or characteristics of buildings that are mapped within the WUI compared to those outside the WUI (Table 3). Across California, there are just under 4 million residential buildings inside the WUI compared to just under 6 million outside the WUI.

We find discrepancies in the types of residences within the WUI, with single family homes comprising a greater percentage of the total structures inside (92%) than outside (85%) of the WUI. Houses in the WUI also tend to have been constructed more recently than those outside of the WUI (average year built of 1977 vs 1964, respectively). This difference reflects, in part, the role of newer housing developments beyond the traditional urban core expanding the frontier of the WUI.

Finally, there are also sizeable differences in terms of the total assessed value of the property improvements (e.g., buildings). Specifically, homes inside the WUI tend to have higher valuations than those outside. The median improvement assessed value for homes inside the WUI is $214,290 while for homes outside of the WUI it is only $152,653. Further, 74% of the buildings outside the WUI are located in the category with the lowest assessed values (Less than $250K), while this number is only 58% for residences inside the WUI. For the most part, WUI residences are more highly represented across almost all valuation categories above $250,000. The WUI is therefore not only a place of heightened fire risk but also disproportionately populated by higher value, single family homes. As of 2020, we estimate that residential structure in the WUI were valued at $1.34 Trillion USD or approximately 40% of the total improved property value in the state.

4. Discussion and conclusion

In this study, we used a detailed real estate database to produce the first structure-level WUI maps for California based on multiple time points, a methodology we call the Time Step Moving Window (TSMW) framework. Our approach enables a consistent mapping of the WUI over repeated time points, which facilitates the analysis of change in the spatial structure of the WUI through time, as well as related shifts in the profile of its residents and structures (as implied by property attributes). Specifically, we spatially matched building-level attribute information contained in the ZTRAX property database to building footprints delineated by the FEMA USA Structures database. This combined database was then integrated with land cover data to develop a temporally explicit version of the moving window method of WUI identification. Using these high resolution, property level data, we can filter the WUI based on a potentially large range of structure- and population-based characteristics. In our case, we make use of the official land use designations to restrict our analysis to residential structures. Our approach maintains the spatial granularity of the moving window technique, while enabling the classification of the WUI at more frequent time intervals compared to previous studies that depend on data from the decennial census. We demonstrate the value of this approach by examining the configuration and composition of the WUI in California, a location that is prone to fire and experiences escalated wildland fire risk.

In California, our TSMW framework identified a substantially larger area of land and quantity of buildings as located in the WUI compared to the BA method. We primarily attribute these differences to the reliance of the BA method on structure density thresholds that are typically measured for census-derived areal units (e.g., census blocks). These density thresholds can produce erroneous classifications for larger areal units that have small but spatially concentrated populations. If such areas fall below the inclusion threshold for population density, they will be classified as being outside of the WUI. Our property-level TSMW framework is far more sensitive to finer spatial variation in settlement density. More abstractly, these issues represent a specific instance of the Modifiable Areal Unit Problem (MAUP), which is a form of statistical bias that manifests when analytic outcomes exhibit sensitivity to the size and shape of underlying spatial units.

These issues can be illustrated through specific examples. Consider a densely populated but isolated housing development that is surrounded by potentially flammable vegetation. If this development is located within a large but mostly undeveloped census block, it is likely to be classified as non-WUI area by the BA method. This misclassification occurs because the extensive area suggests an absence of dense settlements. Essentially, the drawing of block boundaries (or other any spatial unit) can significantly influence the calculation of population density, which in turn affects WUI classification.

Conversely, census blocks may be classified as part of the WUI even if large portions of the block do not meet the density criteria for WUI classification. This over-classification can occur when, for example, a small area of the block is occupied by a small but densely populated suburban development. The BA method therefore simultaneously produces localized over counts and under counts of WUI area and structures. While the outcomes produced by moving window approaches, such as ours, may also exhibit sensitivity to the chosen size of the window, we contend (similar to other analyses of the moving window method), that researchers can rely on theory to define the size of the window and more effectively assess the potential bias. The moving window thus provides a more transparent basis for testing sensitivity and robustness compared to the BA method.

In our comparison of the BA method to our TSMW framework, we observed large differences in the classification of WUI land, but greater similarity between the approaches in terms of WUI-classified buildings. Regarding the built environment, the relative consistency between BA and TSMW raises the question as to whether these methods are in overall agreement in building classification. Our analysis indicates that, although the total enumerated buildings within the WUI is similar between the two approaches, they do not necessarily classify the same buildings as at risk. We document that the buildings classified as within the WUI by the TSMW approach were more likely to be exposed to wildfire later compared to those classified by the BA method. This observation provides preliminary evidence that the TSMW approach may result in fewer false positives in terms of fire risk. This distinction is particularly important for fire management, suggesting that the TSMW

Table 3
Structure level attributes within and outside of the TSMW WUI including residence type, year built, and improvement assessed value.

	WUI, N = 3,992,301	Not WUI, N = 5,982,041
Residence Type		
Single Family	3,672,508 (92%)	5,065,071 (85%)
Multi-Family	319,522 (8.0%)	916,933 (15%)
Year Built	1977 (23)	1964 (26)
Imp Assessed Value		
$250k or Less	2,333,115 (58%)	4,422,769 (74%)
$250k to $500k	1,183,763 (30%)	1,124,492 (19%)
$500k to $1m	360,422 (9.0%)	285,277 (4.8%)
$1m to $5m	103,110 (2.6%)	114,406 (1.9%)
$5m +	11,620[a] (0.3%)	35,060[a] (0.6%)
Median	$214,290	$152,653

[a] 9191 of the WUI $5 million + homes are multi-family & 32,468 of the non-WUI $5 million + homes are multi-family.

framework may offer a more accurate approach to identifying structures at genuine risk to wildfire burns.

The data integration and subsequent analyses performed in this paper open a number of new analytical pathways and areas of research. First, the integration of residential building attribute data into the study of the WUI allows for a detailed examination of the effects of the configuration and composition on the built environment on fire risk at multiple spatial and temporal scales. It is well established that the spread of wildland fire is determined by large scale (e.g., forest configuration, slope) and small scale (e.g., distances between homes) factors. With the integrated datasets used here, it is possible to measure the residential environment at both scales and begin to test over large areas how the residential landscape interacts with surrounding vegetation during fires. For example, the datasets used in this study makes it possible to examine how defensible space policies that change wildland configuration and composition around buildings may be moderated by the features of individual homes. Similarly, understanding when homes were built can shed light on their susceptibility to fire as different building materials are characteristic of different time periods. Identifying building-level predictors of policy adoption and susceptibility enriches our understanding of the WUI, which in prior conceptualizations defined WUI designated areas and zones of equivalent risk. Pursuing these research paths also has potential implications for policy administration and forecasting policy effectiveness. Understanding how susceptible different homes are to fire, how likely they are to spread fire, or take actions that reduce the chances of spread can be used to inform models of fire spread.

Second, the building attributes contained in the integrated data used here also make it possible to examine how broader social and economic forces may be shaping wildland fire risk. In this paper, we identified differences in the residential type, age, and assessed value of homes located inside and outside of California's WUI. This descriptive analysis is a first step toward developing richer analyses of the economic drivers of WUI expansion and the creation of fire risk. For example, the temporal dimension of these data could be used to link the spatial expansion of the WUI, or increased human activity in the WUI, to specific economic and social events such as the COVID-19 pandemic. Integrated with postal data tracking temporary change of addresses or rental records, maps generated using the TSMW framework could shed light on how migration patterns are shifting wildland fire risk.

Third, we view our work as a forerunner to the next phase of data science in support of the management of risk, response, and recovery to wildland fires and other hazardous events. The ongoing enhancements to the FEMA-supported USA Structures database may prove to be a particularly critical advancement at the intersection of data and emergency management. FEMA has already populated USA structures with building occupancy data for nine US states and intends to expand coverage to the entire United States. This database could be further enriched with the types of additional information described in this paper (e.g., property valuation, year of construction, hazard exposure and risk). A nationally harmonized and representative structure-level database of this form, enriched with detailed attribute information, could redefine the possibilities for both emergency management and hazards research, including the spatial optimization of emergency management infrastructure and damage assessment (Helderop & Grubesic, 2022; Murray et al., 2012, pp. 109–122).

Despite Zillow's decision to end their academic data sharing program, USA Structures and other complementary data sources will continue to drive new research and raise new questions. Although this study used ZTRAX, there are many other suitable alternative parcel databases (e.g., ReGrid and Attom). These parcel data are also available through county assessor offices, much of the time at no cost. However, it remains unclear what the advantages and disadvantages of different data sources are for different management tasks, or how to best integrate any given source with the USA Structures dataset. Conducting studies that resolve this question and address the open issue of how to best match data across data sources will be key to further progress. While we rely on a supervised spatial-matching approach to rectify the disassociation between parcel centroids based data and building footprints, there are persisting question of how to best resolve location dislocations between parcels and buildings, particularly when local cadastral data is not available or difficult to access.

Our use of the National Land Cover Database (NLCD) is limited in its spatial and temporal resolution. With high resolution satellite imagery collected daily becoming readily available though the likes of Planet Labs and new rapidly updated land cover datasets, like Google's and the World Resource Institute's Dynamic World, future work could utilize TSMW like integration techniques to map the WUI at more frequent intervals. These new data streams can be integrated to better understand the dynamics of the wildland urban interface and other hazards at the human environmental intersection. Maps, models, and projections based on these new data streams will serve to better inform people and policy makers on the hazards our communities face.

New data streams come with challenges of accuracy and efficacy, particularly human generated social and economic data. While there has already been some evaluation of the data sources used here (i.e. ZTRAX and USA Structures), more work is needed to investigate the strengths and weaknesses of these data sources (Uhl et al., 2021b; Wan et al., 2023). Further investigation into the scales of analysis of hazards, socio-economic drivers of urban growth into high risk areas, and how to best measure vulnerability would be particularly valuable.

Collectively, this work contributes to the ongoing development of methods to map the WUI, and to track and analyze fire risk in the United States. This study also sets a path for further data integration efforts related to the WUI and serves as a potential model for others seeking to link similar building-level data to the USA Structures dataset. Further research that builds on our work may provide new insights into how the composition and spatial configuration of the residential landscape inside the WUI may shape fire risk and impacts in those areas. The TSMW framework provides a more nuanced way to look at how the human environment engages with fire prone landscapes. Together, these efforts can help enable individuals, communities, policy makers, and developers in making better decisions in preparing for wildland fire hazards.

CRediT authorship contribution statement

Aleksander K Berg: Writing – review & editing, Writing – original draft, Visualization, Software, Funding acquisition, Formal analysis, Conceptualization. **Dylan S. Connor:** Validation, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Peter Kedron:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Amy E. Frazier:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Acknowledgements

We thank our reviewers and editors for helping us to improve the manuscript. We gratefully acknowledge access to the Zillow Transaction and Assessment Dataset (ZTRAX) through a data use agreement between the University of Colorado Boulder, Arizona State University, and Zillow Group, Inc. More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group. Support by Zillow Group Inc. is acknowledged. We thank Johannes Uhl and Stefan Leyk for their great work in preparing the original dataset. For feedback and comments, we also thank Billie Lee Turner II, Sharmistha Bagchi-Sen, and participants at the 2022 Global Conference on Economic Geography, the 2022 Young Economic Geographers Network meeting, and the 2023 annual meeting of the American Association of Geographers. Funding for our work has been provided by Arizona State University's

Institute of Social Science Research (ISSR) Seed Grant Initiative. Additional funding was provided through the Humans, Disasters, and the Built Environment program of the National Science Foundation, Award Number 1924670 to the University of Colorado Boulder, the Institute of Behavioral Science, Earth Lab, the Cooperative Institute for Research in Environmental Sciences, the Grand Challenge Initiative and the Innovative Seed Grant program at the University of Colorado Boulder as well as the Eunice Kennedy Shriver National Institute of Child Health & Human Development of the National Institutes of Health under Award Numbers R21 HD098717 01A1 and P2CHD066613.

References

Ager, A. A., Palaiologou, P., Evers, C. R., Day, M. A., Ringo, C., & Short, K. (2019). Wildfire exposure to the wildland urban interface in the western US. *Applied Geography, 111*, Article 102059.
Allen, M., Gillespie-Marthaler, L., Abkowitz, M., & Camp, J. (2020). Evaluating flood resilience in rural communities: A case-based assessment of dyer county, Tennessee. *Natural Hazards, 101*, 173–194.
Anu Kramer, H., Mockrin, M. H., Alexandre, P. M., Stewart, S. I., & Radeloff, V. C. (2018). Where wildfires destroy buildings in the US relative to the wildland–urban interface and national fire outreach programs. *International Journal of Wildland Fire, 27*, 329–341.
Badia, A., & Gisbert, M. (2020). LiDAR technology to map forest continuity: A municipality tool to prevent forest fires in a wildland–urban interface. *Applied Geography, 114*, Article 102134.
Bar-Massada, A. (2021). A comparative analysis of two major approaches for mapping the wildland-urban interface: A case study in California. *Land, 10*, 679.
Bar-Massada, A., Alcasena, F., Schug, F., & Radeloff, V. C. (2023). The wildland – urban interface in europe: Spatial patterns and associations with socioeconomic and demographic variables. *Landscape and Urban Planning, 235*, Article 104759.
Bar-Massada, A., Stewart, S. I., Hammer, R. B., Mockrin, M. H., & Radeloff, V. C. (2013). Using structure locations as a basis for mapping the wildland urban interface. *Journal of Environmental Management, 128*, 540–547.
Baylis, P. W., & Boomhower, J. (2021). *Mandated vs. voluntary adaptation to natural disasters: The case of U.S. wildfires*.
Bento-Gonçalves, A., & Vieira, A. (2020). Wildfires in the wildland-urban interface: Key concepts and evaluation methodologies. *Science of the Total Environment, 707*, Article 135592.
Braswell, A., Leyk, S., Connor, D., Uhl, J., & Others. (2021). Creeping disaster along the US coastline: Understanding exposure to sea level rise and hurri-canes through historical development. *Technical report*. Center for Open Science.
Burke, M., Driscoll, A., Heft-Neal, S., Xue, J., Burney, J., & Wara, M. (2021). The changing risk and burden of wildfire in the United States. *Proceedings of the National Academy of Sciences of the United States of America, 118*.
CalFire. (2022). Stats and events. https://www.fire.ca.gov/stats-events/. (Accessed 26 September 2022).
Carlson, A. R., Helmers, D. P., Hawbaker, T. J., Mockrin, M. H., & Radeloff, V. C. (2022). The wildland-urban interface in the United States based on 125 million building locations. *Ecological Applications, 32*, Article e2597.
Conedera, M., Tonini, M., Oleggini, L., Vega Orozco, C., Leuenberger, M., & Pezzatti, G. B. (2015). Geospatial approach for defining the Wildland-Urban interface in the alpine environment. *Computers, Environment and Urban Systems, 52*, 10–20.
Connor, D. S., Gutmann, M. P., Cunningham, A. R., Clement, K. K., & Leyk, S. (2020). How entrenched is the spatial structure of inequality in cities? Evidence from the integration of census and housing data for denver from 1940 to 2016. *Annals of the Association of American Geographers, 110*, 1022–1039.
Depsky, N. J., Cushing, L., & Morello-Frosch, R. (2022). High-resolution gridded estimates of population sociodemographics from the 2020 census in California. *PLoS One, 17*, Article e0270746.
Dewitz, J., & Geological Survey, U. S. (2021). *National land cover database (NLCD) 2019 products (ver. 2.0, june 2021)*.
Durst, N. J., Sullivan, E., Huang, H., & Park, H. (2021). Building footprint-derived landscape metrics for the identification of informal subdivisions and manufactured home communities: A pilot application in hidalgo county, Texas. *Land Use Policy, 101*, Article 105158.
Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z. L., Quayle, B., & Howard, S. (2007). A project for monitoring trends in burn severity. *Fire Ecol, 3*, 3–21.
FEMA. (2022). USA structures. https://gis-fema.hub.arcgis.com/pages/usa-structures. (Accessed 21 June 2022).
Glickman, D., & Babbitt, B. (2001). Urban wildland interface communities within the vicinity of federal lands that are at high risk from wildfire. *Federal Register, 66*, 751–777.
Hansen, G. C. (2022). *San francisco - landscape*.
Helderop, E., & Grubesic, T. H. (2022). Hurricane storm surge: Toward a normalized damage index for coastal regions. *Natural Hazards: Journal of the International Society for the Prevention and Mitigation of Natural Hazards, 110*, 1179–1197.
Homer, C., Huang, C., Yang, L., Wylie, B., & Coan, M. (2004). Development of a 2001 national Land-Cover database for the United States. *Photogrammetric Engineering & Remote Sensing, 70*, 829–840.
Leyk, S., & Uhl, J. H. (2018). HISDAC-US, historical settlement data compilation for the conterminous United States over 200 years. *Scientific Data, 5*, 1–14.
Leyk, S., Uhl, J. H., Connor, D. S., Braswell, A. E., Mietkiewicz, N., Balch, J. K., & Gutmann, M. (2020). Two centuries of settlement and urban development in the United States. *Science Advances, 6*, Article eaba2937.
Li, S., & Banerjee, T. (2021). Spatial and temporal pattern of wildfires in California from 2000 to 2019. *Scientific Reports, 11*, 8779.
Martinuzzi, S., Stewart, S. I., Helmers, D. P., Mockrin, M. H., Hammer, R. B., & Radeloff, V. C. (2015). *The 2010 wildland-urban interface of the conterminous United StatesResearch Map NRS-8* (pp. 1–124). Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station.
Mc Shane, C., Uhl, J. H., & Leyk, S. (2022). Gridded land use data for the conterminous United States 1940–2015. *Scientific Data, 9*, 1–18.
McGranahan, D. A. (1999). *Natural amenities drive rural population change* (pp. 1–24). Food and Rural Economics Division, Economic Research Service, U.S. Department of Agriculture. Agricultural Economic Report No. 781.
Mell, W. E., Manzello, S. L., Maranghides, A., Butry, D., & Rehm, R. G. (2010). The wildland–urban interface fire problem–current approaches and research needs. *International Journal of Wildland Fire, 19*, 238–251.
Microsoft. (2018). *Microsoft building footprints*. https://hub.arcgis.com/datasets/esri::microsoft-building-footprints-features/about. (Accessed 4 October 2022).
Mietkiewicz, N., Balch, J. K., Schoennagel, T., Leyk, S., St Denis, L. A., & Bradley, B. A. (2020). In the line of fire: Consequences of Human-Ignited wildfires to homes in the U.S. (1992–2015). *Fire, 3*, 50.
Miranda, A., Carrasco, J., González, M., Pais, C., Lara, A., Altamirano, A., Weintraub, A., & Syphard, A. D. (2020). Evidence-based mapping of the wildland-urban interface to better identify human communities threatened by wildfires. *Environmental Research Letters, 15*, Article 094069.
Murray, A. T., Tong, D., & Grubesic, T. H. (2012). *Spatial optimization: Expanding emergency services to address regional growth and development*. Chapters.
NIFC. (2022). Suppression costs. https://www.nifc.gov/fire-information/statistics/suppression-costs. (Accessed 21 September 2022).
Office of the Assessor. (2023). Los angeles county assessor portal. https://portal.assessor.lacounty.gov/ (NA-NA-NA).
Openshaw, S., & Taylor, P. J. (1981). The modifiable areal unit problem. In N. Wrigley, & R. J. Bennett (Eds.), *Quantitative geography: A British view* (pp. 60–69). Routledge & Kegan Paul.
Picotte, J. J., Bhattarai, K., Howard, D., Lecker, J., Epting, J., Quayle, B., Benson, N., & Nelson, K. (2020). Changes to the monitoring trends in burn severity program mapping production procedures and data products. *Fire Ecology, 16*, 1–12.
Pigati, J. S., McGeehin, J. P., Skipp, G. L., & Muhs, D. R. (2014). Evidence of repeated wildfires prior to human occupation on san nicolas island, California. *Mwna, 7*, 35–47.
Pitt, L. M. (2022). *Los Angeles*.
Platt, R. V. (2010). The Wildland–Urban interface: Evaluating the definition effect. *Journal of Forecasting, 108*, 9–15.
Radeloff, V. C., Hammer, R. B., Stewart, S. I., Fried, J. S., Holcomb, S. S., & McKeefry, J. F. (2005). The wildland–urban interface in the United States. *Ecological Applications, 15*, 799–805.
Radeloff, V. C., Helmers, D. P., Kramer, H. A., Mockrin, M. H., Alexandre, P. M., Bar-Massada, A., Butsic, V., Hawbaker, T. J., Martinuzzi, S., Syphard, A. D., & Stewart, S. I. (2018). Rapid growth of the US wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences of the United States of America, 115*, 3314–3319.
Radeloff, V. C., Helmers, D. P., Mockrin, M. H., Carlson, A. R., Hawbaker, T. J., & Martinuzzi, S. (2022). *The 1990-2020 wildland-urban interface of the conterminous United States - geospatial data* (3rd ed.).
Schug, F., Bar-Massada, A., Carlson, A. R., Cox, H., Hawbaker, T. J., Helmers, D., Hostert, P., Kaim, D., Kasraee, N. K., Martinuzzi, S., Mockrin, M. H., Pfoch, K. A., & Radeloff, V. C. (2023). The global wildland-urban interface. *Nature, 621*, 94–99.
Stewart, S. I., Radeloff, V. C., Hammer, R. B., & Hawbaker, T. J. (2007). Defining the wildland–urban interface. *Journal of Forecasting, 105*, 201–207.
Uhl, J. H., Connor, D. S., Leyk, S., & Braswell, A. E. (2021a). A century of decoupling size and structure of urban spaces in the United States. *Commun Earth Environ, 2*.
Uhl, J. H., Hunter, L. M., Leyk, S., Connor, D. S., Nieves, J. J., Hester, C., Talbot, C., & Gutmann, M. (2023). Place-level urban–rural indices for the United States from 1930 to 2018. *Landscape and Urban Planning, 236*, Article 104762.
Uhl, J. H., Leyk, S., McShane, C. M., Braswell, A. E., Connor, D. S., & Balk, D. (2021b). Fine-grained, spatiotemporal datasets measuring 200 years of land development in the United States. *Earth System Science Data, 13*, 119–153.
Uhl, J. H., Leyk, S., McShane, C. M., Braswell, A. E., Connor, D. S., & Balk, D. (2021c). Fine-grained, spatiotemporal datasets measuring 200 years of land development in the United States. *Earth System Science Data, 13*, 119–153.
USDA. (2001). Urban wildland interface communities within the vicinity of federal lands that are at high risk from wildfire. In *Technical report 01-52. Forest service, USDA; bureau of Indian affairs, bureau of land management, fish and wildlife service, and national park service*.
U.S. Fire Administration. (2022). Wildland urban interface (WUI). https://www.usfa.fema.gov/wui/. (Accessed 6 October 2022).
van Wagtendonk, J. W., Sugihara, N. G., Stephens, S. L., Thode, A. E., Shaffer, K. E., Fites-Kaufman, J. A., & Agee, J. K. (Eds.). (2018). *Fire in California's ecosystems 2nd Edition. Fire in California's Ecosystems*. University of California Press.
Villines, C. (2019). The California ski boom: Tourism, urban growth, environmentalism, and social diversity in sierra Nevada ski areas, 1960-1980. *Footnote: Journalism History, 3*, 92–118.

Wan, H., Ganguli, S., Jain, M., Anderson, D., Mohankumar, N. M., & Wilson, K. (2023). Areal interpolation of population projections consistent with different SSPs from 1-km resolution to block level based on USA structures dataset. *Computers, Environment and Urban Systems, 105*, Article 102024.
Wang, D., Guan, D., Zhu, S., Kinnon, M. M., Geng, G., Zhang, Q., Zheng, H., Lei, T., Shao, S., Gong, P., & Davis, S. J. (2020). Economic footprint of California wildfires in 2018. *Nature Sustainability, 4*, 252–260.
Westerling, A. L., & Bryant, B. P. (2008). Climate change and wildfire in California. *Climate Change, 87*, 231–249.
Whitman, E., Rapaport, E., & Sherren, K. (2013). Modeling fire susceptibility to delineate wildland-urban interface for municipal-scale fire risk management. *Environmental Management, 52*, 1427–1439.
Williams, A. P., Abatzoglou, J. T., Gershunov, A., Guzman-Morales, J., Bishop, D. A., Balch, J. K., & Lettenmaier, D. P. (2019). Observed impacts of anthropogenic climate change on wildfire in California. *Earth's Future, 7*, 892–910.
Winkler, R. L., & Mockrin, M. (2024). Aging and wildfire risk in the USA. In *Population association of America's applied demography conference*.
Zillow. (2018). *Zillow's transaction and assessment database (ZTRAX)*.