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The wildland–urban interface in the United States based on 125 million building locations

Amanda R. Carlson[1] | **David P. Helmers**[1] | **Todd J. Hawbaker**[2] | **Miranda H. Mockrin**[3] | **Volker C. Radeloff**[1]

[1]SILVIS Lab, Department of Forest and Wildlife Ecology, University of Wisconsin-Madison, Madison, Wisconsin, USA

[2]U.S. Geological Survey, Geosciences and Environmental Change Science Center, Denver, Colorado, USA

[3]Northern Research Station, U.S. Department of Agriculture Forest Service, Baltimore, Maryland, USA

Correspondence
Amanda R. Carlson
Email: carlson28@wisc.edu

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Abstract

The wildland–urban interface (WUI) is the focus of many important land management issues, such as wildfire, habitat fragmentation, invasive species, and human–wildlife conflicts. Wildfire is an especially critical issue, because housing growth in the WUI increases wildfire ignitions and the number of homes at risk. Identifying the WUI is important for assessing and mitigating impacts of development on wildlands and for protecting homes from natural hazards, but data on housing development for large areas are often coarse. We created new WUI maps for the conterminous United States based on 125 million individual building locations, offering higher spatial precision compared to existing maps based on U.S. census housing data. Building point locations were based on a building footprint data set from Microsoft. We classified WUI across the conterminous United States at 30-m resolution using a circular neighborhood mapping algorithm with a variable radius to determine thresholds of housing density and vegetation cover. We used our maps to (1) determine the total area of the WUI and number of buildings included, (2) assess the sensitivity of WUI area included and spatial pattern of WUI maps to choice of neighborhood size, (3) assess regional differences between building-based WUI maps and census-based WUI maps, and (4) determine how building location accuracy affected WUI map accuracy. Our building-based WUI maps identified 5.6%–18.8% of the conterminous United States as being in the WUI, with larger neighborhoods increasing WUI area but excluding isolated building clusters. Building-based maps identified more WUI area relative to census-based maps for all but the smallest neighborhoods, particularly in the north-central states, and large differences were attributable to high numbers of non-housing structures in rural areas. Overall WUI classification accuracy was 98.0%. For wildfire risk mapping and for general purposes, WUI maps based on the 500-m neighborhood represent the original Federal Register definition of the WUI; these maps include clusters of buildings in and adjacent to wildlands and exclude remote, isolated buildings. Our approach for mapping the WUI offers flexibility and high spatial detail and can be widely applied to take advantage of the growing availability of high-resolution building footprint data sets and classification methods.

KEYWORDS
exurban development, fragmentation, housing, human–wildlife conflict, rural development, urbanization, wildland fire

INTRODUCTION

The wildland–urban interface (WUI), or the area where housing intermingles with or abuts wildland vegetation, is a priority area for conservation and land management (Stewart et al., 2007). WUI areas in the United States have expanded considerably since 1990, reflecting a growing desire to build homes near natural amenities (Radeloff et al., 2018). Wildfire management in the WUI is a major concern globally as many countries are experiencing increases in annual burned areas and fire suppression costs (Chuvieco et al., 2016; Krawchuk et al., 2009; NIFC, 2020). The WUI is a major source of ignitions (Balch et al., 2017; Mietkiewicz et al., 2020) and is also where homes face the greatest risk from wildfires (Alexandre et al., 2016; Calkin et al., 2014). WUI growth also raises concerns for conservation because housing in close proximity to wildlands contributes to habitat fragmentation (Gonzalez-Abraham et al., 2007) and increases potential for human–wildlife conflicts (Bar-Massada et al., 2014; Davis, 1990). Understanding patterns of development in the WUI is therefore important for protecting human communities and for achieving conservation goals.

WUI maps are valuable tools for identifying areas with high potential for wildfire hazards or high impacts on wildlife and ecosystems. In the United States, WUI classifications are based on Federal Register definitions for minimum housing density and vegetation cover, allowing WUI areas to be derived from land cover and housing data (Radeloff et al., 2005; USDA & USDI, 2001). These definitions distinguish between two types of WUI: the intermix, where housing and vegetation intermingle; and the interface, where housing is adjacent to vegetation. WUI maps for the United States have been widely used for allocating firefighting and fuel treatment resources (Bento-Gonçalves & Vieira, 2020), assessing the spread of exotic species (Gavier-Pizarro et al., 2010), identifying high-risk areas for zoonotic disease transmissions (Larsen et al., 2014), and assessing effects of housing development on wildlife populations (Kreling et al., 2019; Loss et al., 2013; Pidgeon et al., 2007). A challenge in developing general-purpose WUI maps, however, is that relating fine-scale ecological processes to the WUI depends on mapping at relevant scales in terms of resolution and extent (Whitman et al., 2013).

Mapping the WUI over large areas has typically relied on aggregated housing density estimates, which are coarse in scale. In the United States, national WUI maps are based on U.S. Census Bureau block-level data (Martinuzzi et al., 2015; Radeloff et al., 2005). The census is updated every 10 years, allowing for decadal assessments of WUI growth (Radeloff et al., 2018). A limitation of these maps, however, is that block polygon sizes are variable and, in some rural areas, a single block can be up to several hundred square kilometers in area. This can lead both to errors of omission, where a block is not mapped as WUI even though housing density is high enough to qualify in a portion of the block, and errors of commission, where areas that are void of houses are included if a high-density housing cluster causes the entire block area to exceed the housing density threshold. These inconsistencies most affect rural areas where census blocks tend to be large and can be a concern for identifying WUI areas at risk of wildfire in the western United States, where maps are used to allocate fuel treatment and firefighting resources (Calkin et al., 2014). Because the precise locations of buildings within blocks are unknown, census-based WUI maps have limits for research and management questions focused on interactions between housing and wildlands at fine spatial scales.

An alternative to mapping the WUI using census block polygons is to derive housing density from individual building locations. The advantage of this approach is that it allows for a more consistent method for aggregating building densities, while also identifying the precise locations where buildings interact with wildlands. Bar-Massada et al. (2013) developed an algorithm for determining building densities and vegetation-cover thresholds based on building point locations, using a circular neighborhood approach with a user-defined radius. This offers greater flexibility in how building densities are determined compared to predefined census block neighborhoods, but selecting an appropriate radius may be challenging. This method is sensitive to the choice of radius, and there is no straightforward method to determine the "best" neighborhood size (Bar-Massada, 2021; Bar-Massada et al., 2013). Varying neighborhood size affects the patterns of the maps in predictable ways, however. Smaller radii include more buildings and offer higher precision around building locations, which can be advantageous for a number of wildfire hazard mapping applications. For example, identifying defensible space around homes at risk of wildfire may only consider a radius of 100 m or less (NFPA, 2018). Mapping wildfire threats to homes may involve larger scales of analysis, however, because firebrand travel can create hazards within several kilometers of a wildfire front (Braziunas et al., 2020; Calkin et al., 2014; Caton et al., 2017). Similarly, wildlife interaction studies may be affected by mismatches between the scale of WUI maps and scales of travel and habitat selection for species of interest (Blecha et al., 2018; Pidgeon et al., 2014). Mapping the WUI using individual building locations therefore requires careful consideration of how various neighborhood sizes may affect WUI classifications and subsequent analyses.

Building locations have not previously been used to produce national-scale WUI maps because acquiring these data across large spatial extents is challenging. The building-based approach has only been applied over small areas for which individual houses were manually digitized (Argañaraz et al., 2017; Lampin-Maillet et al., 2010; Lowell et al., 2009) or for which cadastral data were available (Bar-Massada et al., 2013). Advances in high-resolution satellite imagery collection and classification have made it more feasible to map all building locations over large regions using extensive image libraries and efficient segmentation algorithms (Postadjian et al., 2017). For example, Microsoft has released a freely available product providing footprints of nearly 125 million individual buildings across the conterminous United States, based on convolutional neural network segmentation of Bing Maps imagery (Bing Maps Team, 2018). Microsoft building footprints have been previously used in national-scale wildfire risk assessment tools to identify assets at risk (USDA Forest Service Wildfire Risk to Communities portal; https://wildfirerisk.org/), but individual building locations have not been used to evaluate building densities in relation to thresholds for WUI classification. Building locations can also be determined from real estate and cadastral databases, and commercial data products have been produced by Zillow, CoreLogic, and Landgrid. These data sets have been used to assess development patterns and histories at national scales (Leyk & Uhl, 2018), but the spatial and temporal completeness of these data sets is limited due to differences in cadastral records among counties. The cost of accessing these proprietary data can also be prohibitive. Building locations derived from satellite imagery are a suitable data source for developing WUI maps because they provide consistent spatial coverage across large extents.

Our aim in this study was to evaluate the building-based approach to map the WUI in the conterminous United States. We created new maps of interface, intermix, and total WUI based on the Microsoft building footprints data set, which allowed us to precisely identify where buildings interact with wildland vegetation and address some of the limitations of coarse-scale maps based on census block-level housing densities. Our specific objectives were to (1) determine the total area of the building-based WUI in the conterminous United States and the number of WUI buildings, when mapped with varying neighborhood sizes, (2) assess the effect of various neighborhood sizes on the total area and spatial patterns of the WUI, (3) assess the differences between building-based WUI maps and census-based maps across the conterminous United States, and (4) assess the accuracy of Microsoft building location data and determine how errors affect the accuracy of resulting WUI maps.

METHODS

Study area

The conterminous United States has a total land area of 7.7 million km^2 and encompasses a wide range of housing patterns and wildland vegetation. The highest population densities and most extensive urbanization are east of the Mississippi River, where history of Euro-American settlement has been longest (Leyk & Uhl, 2018). The most extensive wildlands are in the 11 western states (California, Oregon, Washington, Idaho, Montana, Wyoming, Colorado, Utah, Nevada, Arizona, and New Mexico) where public lands make up 46% of total land area (USGS GAP, 2020). The central United States is heavily agricultural and therefore contains lower population densities and fewer public lands. Nationwide, housing growth since 1950 has been highest in suburban and rural areas in proximity to public lands, particularly in the South and West (Brown et al., 2005; Mockrin et al., 2022; Radeloff et al., 2010). There are also regional differences in wildland vegetation cover, with forests dominating the Eastern United States, the Upper Midwest, the Pacific Northwest, and high-elevation mountain regions in the West. At lower elevations, the western United States is dominated by deserts, grasslands, and shrublands. Wildland vegetation is relatively sparse in agricultural regions in the central United States. Previous census-based WUI mapping efforts have shown substantial regional differences in the amount of WUI, with eastern states having much higher proportions of their area in the WUI (up to 72%) than western or central states (Radeloff et al., 2005, 2018).

Data

The Microsoft data set (available at https://github.com/microsoft/USBuildingFootprints, accessed December 2019) contains 124,828,547 building footprints (polygon outlines) for the conterminous United States. Microsoft identified building footprints from high-resolution satellite images (0.3-m resolution) collected by Bing Maps, using a convolutional neural network semantic segmentation algorithm

(Bing Maps Team, 2018). Image collection dates are variable but are ca. 2015. Classification accuracies for individual building footprints were 93.5% recall and 99.3% precision based on 5 million training images. For our analysis, we converted all building footprints into points based on building centroids.

Our source for vegetation information was the 2016 National Land Cover Dataset (NLCD), a 30-m resolution satellite image classification (Yang, Jin, et al., 2018). We grouped NLCD classes into wildland vegetation and developed categories, using the same methodology previously used to develop census-based WUI maps. The wildland vegetation category combined all forest, shrub/scrub, grassland, and wetland classes, while the developed category combined all agricultural and urban classes. We excluded water, barren land, and snow/ice classes from the classification.

Building-based WUI maps

Our mapping approach used the definitions of interface and intermix WUI developed for previous census-based WUI mapping efforts based on U.S. Federal Register definitions (Radeloff et al., 2005; USDA & USDI, 2001). According to the definitions used for our building-based maps and for the census-based maps, WUI is where building density exceeds 6.17 units/km^2 and where land cover is either (1) at least 50% wildland vegetation (intermix) or (2) under 50% wildland vegetation but within 2.4 km (1.5 miles) of a patch of wildland vegetation at least 5 km^2 in area that contains at least 75% vegetation (interface). The distance selected for the interface definition is based on research from the California Fire Alliance suggesting that this is the average distance firebrands can travel from an active wildfire front (Stewart et al., 2007).

We mapped WUI across the conterminous United States at 30-m resolution using the NLCD as a template grid. We used the circular moving window algorithm developed by Bar-Massada et al. (2013) to classify each pixel as intermix, interface, or non-WUI using neighborhoods with six different radii: 100, 250, 500, 750, 1000, and 1500 m. We hereafter refer to different neighborhood sizes by their respective radius distances. For each neighborhood size, we calculated building density (units/km^2) for the focal pixel by counting the number of building centroids within the circular neighborhood (Figure 1a). We calculated the proportion of wildland vegetation pixels within the same neighborhoods, including those pixels for which a majority of the pixel area fell within the circular neighborhood window. Focal pixels with more than 6.17 buildings/km^2 and more than 50% wildland vegetation in surrounding neighborhoods were classified as intermix WUI. We then applied the interface WUI classification to all remaining pixels not classified as intermix during the initial classification step. We determined wildland proximity by first identifying patches of contiguous NLCD wildland vegetation pixels that met the criteria for interface vegetation, then generated 2.4-km buffers around the selected patches. Focal pixels that exceeded the building density threshold and that overlapped the wildland proximity layer were classified as interface WUI. Processing was carried out in Python 3.6 (Python Software Foundation, 2016) using the *arcpy* library in ArcGIS Pro 2.3 (ESRI, 2019).

We adjusted final intermix and interface WUI maps by removing groups of contiguous WUI pixels that did not contain any buildings. In some areas where buildings were sparse, pixels that were in between distinct clusters of buildings exceeded the building density threshold while pixels that were adjacent to the actual building locations did not (Figure 1b). This issue was more prominent when using larger neighborhood sizes. We removed these areas from the WUI classification in order to ensure that our maps represented areas of human-environment interactions, thus meeting the conceptual definition of the WUI.

Assessing the effect of neighborhood size

Because our classifications were based on a constant building density threshold of 6.17 units/km^2, the minimum number of buildings required to exceed the threshold for WUI classification varies predictably with the size of the circular moving neighborhood used in the classification algorithm. For our selected neighborhood sizes, the minimum number of buildings required to exceed the threshold ranges from 1 at the 100-m radius to 44 at the 1500-m radius (Table 1). The 500-m neighborhood requires groups of five or more buildings within neighborhoods that are ~80 ha in size. We determined that the neighborhood with a 500-m radius therefore most closely matches commonly accepted definitions of the WUI for wildfire resource allocation and planning based on communities rather than individual structures (Wildland Fire Executive Council, 2014), while still providing a high level of spatial detail around building locations. We focus on maps produced using this neighborhood size as our recommended products for wildfire planning and for general purposes. We present results for our full range of neighborhood sizes in order to demonstrate the flexibility of the building-based mapping approach, and to provide the data for specific applications where either smaller or larger neighborhood sizes are desirable.

As noted above, the neighborhood with a 100-m radius identifies all buildings that have sufficient neighboring vegetation to qualify as WUI, regardless of the

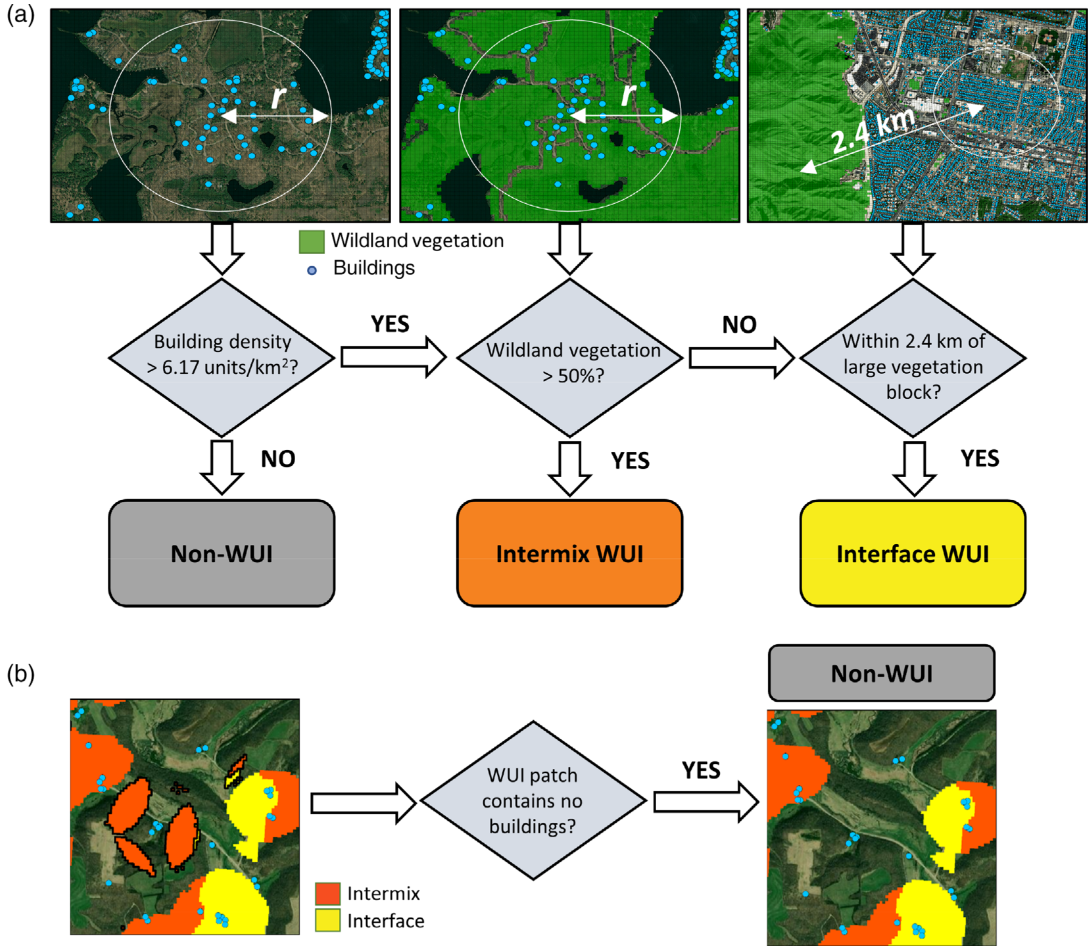

FIGURE 1 (a) Diagram of the algorithm used to classify intermix and interface wildland–urban interface (WUI) using building point locations, wildland vegetation (green pixels), and proximity to wildland vegetation surrounding the central pixel. Building density and percent wildland vegetation cover are calculated within circular moving-window neighborhoods with a variable radius distance *r*.
(b) Diagram of areas that were removed from final WUI maps (outlined in black), as a result of no buildings being present in contiguous WUI patches

TABLE 1 Neighborhood areas and minimum numbers of buildings required to exceed the neighborhood building density threshold (6.17 units/km^2) for wildland–urban interface (WUI) classification for each radius used to define circular moving neighborhoods to calculate building density and vegetation cover

Neighborhood radius (m)	Neighborhood area (km^2)	Minimum no. structures
100	0.0314	1
250	0.1963	2
500	0.7854	5
750	1.7671	11
1000	3.1416	20
1500	7.0686	44

number of neighboring buildings. We therefore aimed to determine how each larger neighborhood resulted in changes in area identified as WUI, using the 100-m neighborhood as a reference point. For each neighborhood size, we compared the total area mapped as either interface and intermix WUI across the conterminous United States and calculated mean patch size for contiguous WUI areas. We then combined the WUI maps produced using each radius to generate a single composite map indicating areas that are (1) WUI at all neighborhood sizes, (2) WUI only at smaller neighborhood sizes (i.e., that drop out of WUI as the radius increases beyond 100 m), or (3) WUI only at larger neighborhood sizes (i.e., that become WUI as the radius increases beyond 100 m). We used this composite map to visually examine how increasing neighborhood size affected patterns of WUI classifications at small spatial scales. We then calculated total WUI area gained versus lost with each increase in neighborhood size beyond the 100-m radius. These analyses were based on simple comparisons of total areas across the entirety of the conterminous United States.

We did not use statistical tests (e.g., *t* tests or analysis of variance) to compare the differences in area among neighborhood sizes because such tests are intended to compare mean differences among samples from a larger population, whereas our data represented complete enumerations of each WUI class across our area of interest.

Assessing differences between building-based and census-based WUI maps

We compared the building-based WUI with existing decennial census block-based WUI at the national scale. Census block-based WUI maps are available from the University of Wisconsin-Madison SILVIS lab (http://silvis.forest.wisc.edu/data/wui-change/) and are also archived by the USDA Forest Service (Radeloff et al., 2017). A key difference between the Microsoft building footprints and census data is that Microsoft footprints include non-housing structures while the census only reports housing units. The census also includes all housing units within apartment buildings and other multi-unit structures, while building footprints represent these as single structures. Furthermore, Microsoft building footprints can also be affected by classification errors, consisting of either false classification of features other than buildings or omission of buildings. It is possible, for example, that regions with dense forest cover may have higher rates of building omissions because tree canopies obscure buildings in satellite imagery. To assess how these differences may affect resulting WUI maps, we tallied the number of building centroids in the Microsoft data set within each census block and compared these numbers to census-reported housing units. We mapped the ratio of Microsoft building counts to census housing counts for all census blocks across the conterminous United States in order to assess geographic patterns. We expected that distinct patterns may result from geographic differences in density of non-housing structures (e.g., farm buildings, industrial or commercial buildings, structures associated with natural resource extraction), multi-unit housing (e.g., in dense urban areas), or forest cover.

We quantified the degree of similarity and areas of overlap between the final WUI maps based on the two approaches (census-based vs. building-based) to assess the overall effect of differences in building density definitions. We first computed Jaccard similarity indices between census-based WUI areas and buildings-based areas based on all six neighborhood sizes, comparing areas identified as intermix, interface, or total WUI areas (including either WUI type). The Jaccard index quantifies similarity by identifying areas of overlap between each pair of maps and dividing this by the area of union, or the total area encompassed by both maps. Values can range from 0 to 1, with 1 indicating a perfect spatial match. We also created confusion matrices depicting the area in each map category (non-WUI, intermix WUI, or interface WUI) that was classified as the same category by both mapping approaches, for each neighborhood size. Confusion matrices quantify the level of agreement between WUI areas in census-based maps and building-based maps, relative to the area identified by each approach. We additionally calculated differences in total WUI area for each neighborhood size, relative to the block-based area, and summarized these differences by state. Statewide summaries allowed us to identify broad regional differences in WUI patterns resulting from the differences between building footprint densities and census housing densities.

Influence of building location accuracy on WUI maps

We assessed the accuracy of the Microsoft buildings data set and its effect on building-based WUI classifications by manually inspecting 500 random sample locations across the conterminous United States. Our sample locations were circular areas with a 500-m radius, thus allowing us to assess the accuracy of the WUI map based on the 500-m neighborhood. For each sample area, we compared Microsoft building centroids to aerial imagery in ArcGIS Pro 2.3 (ESRI, 2019) and Google Earth Pro 7.3 (Google, 2020) to identify errors of omission, where buildings observed in the imagery were not included in the Microsoft data, and errors of commission, where a Microsoft building location corresponded to a non-building feature in the aerial imagery. We then determined whether adjusting for the errors caused the sample area to fall above or below the minimum number of buildings required to meet the building density threshold for inclusion as WUI (a minimum of five buildings for the 500-m neighborhood). If the sample area also met vegetation criteria for either intermix (the sample area contained at least 50% vegetation) or interface (the center pixel overlapped the vegetation proximity layer) WUI, then we recorded the sample as an error of omission or commission.

RESULTS

WUI area and number of buildings included

The building-based WUI classification resulted in 456,035–1,438,784 km^2, or 5.6%–18.8% of total land area in the conterminous United States, as being either intermix or interface WUI, depending on the size of neighborhood used in the mapping algorithm (Figure 2; Appendix S1: Table S1). Total WUI area substantially increased with increases in neighborhood size (Figure 3a). For example, total area roughly doubled from 456,035 km^2 to 893,321 km^2 using the 100-m versus the 250-m neighborhood, respectively, and increased to 1,242,840 km^2 using the 500-m neighborhood. Minimal changes in WUI area occurred with neighborhoods larger than the 500-m. The majority of WUI was in the eastern United States for all neighborhood sizes. Both intermix and interface WUI

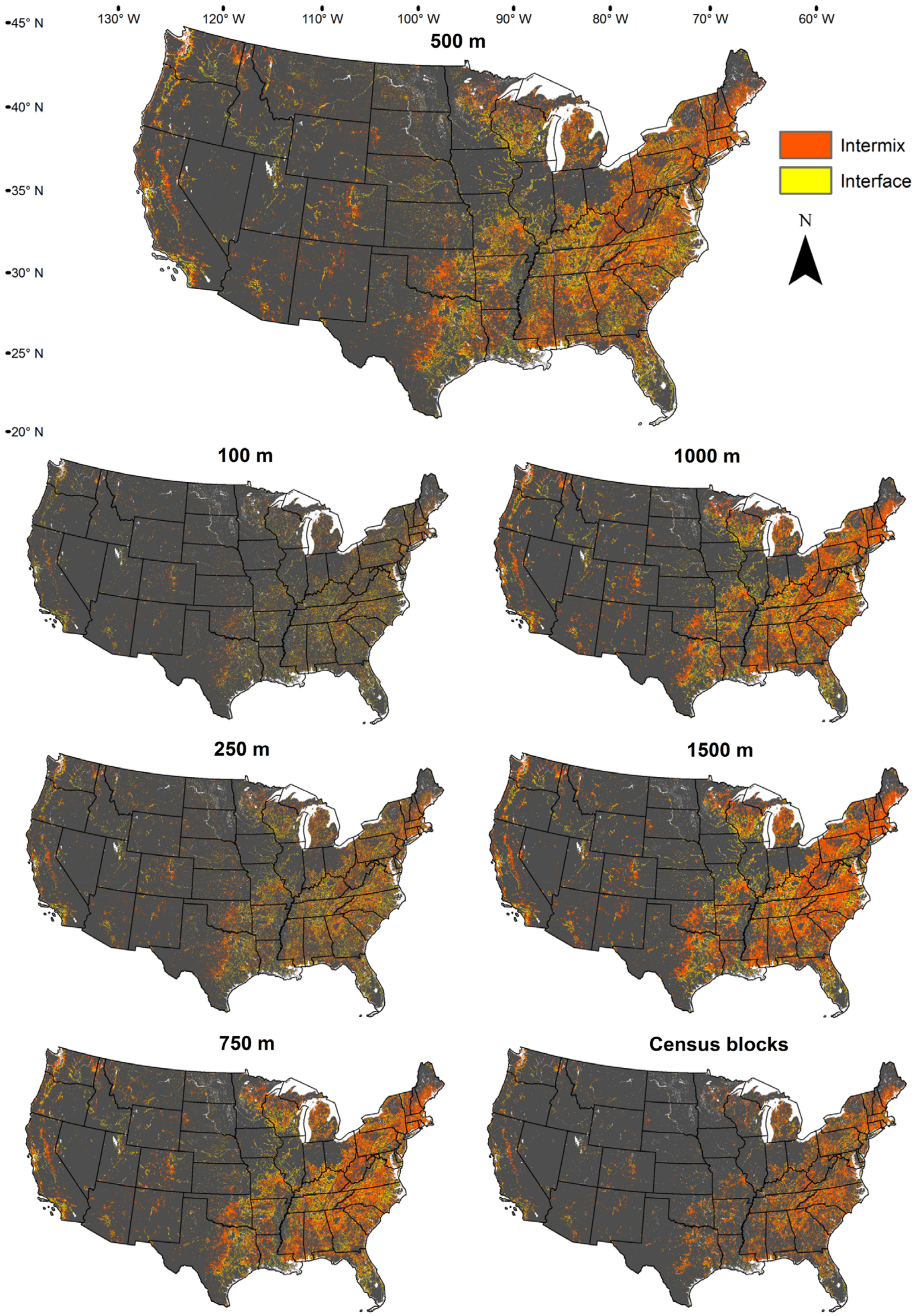

FIGURE 2 Maps of intermix and WUI produced by the building-based mapping algorithm using six circular neighborhood sizes (defined by the indicated radius distances) and by the census block-based mapping algorithm. The enlarged map based on the 500-m neighborhood is our recommended map for wildfire planning and for general purposes

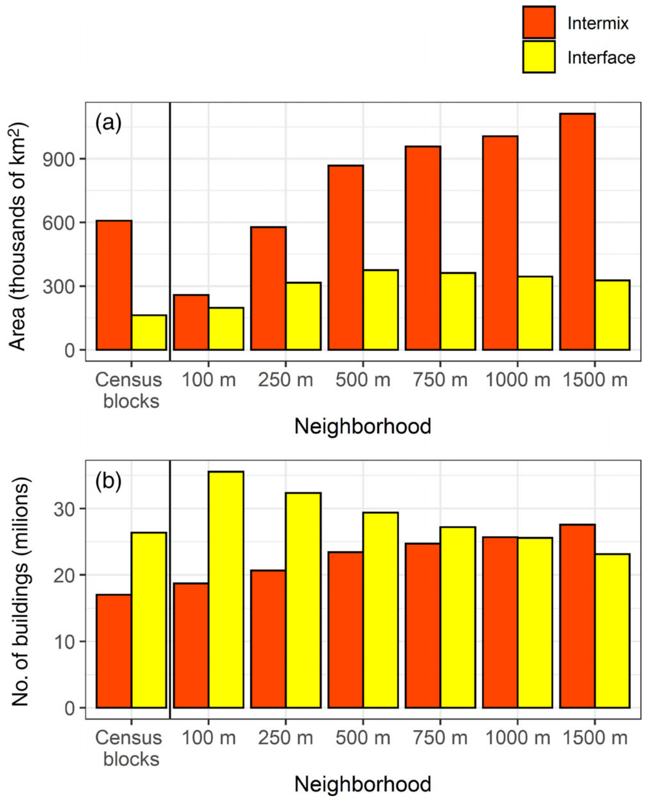

FIGURE 3 (a) Area mapped and (b) number of buildings included in WUI areas for the census-based map and for building-based maps based on six different circular neighborhood sizes (indicated by the radius distance), for intermix and interface WUI. Number of buildings for the census-based map is based on reported housing units within blocks classified as WUI; number of buildings for building-based maps are based on Microsoft building location counts within pixels mapped as WUI

classes were well dispersed throughout the eastern United States, but interface WUI was somewhat more concentrated around urban areas. WUI was less extensive in the western states, the Great Plains, and agricultural regions in the Midwest. In the western United States, WUI was concentrated around densely populated areas, particularly around mountain ranges.

Neighborhood size affected the relative proportion of WUI area classified as intermix versus interface WUI (Figure 3a). The area of intermix WUI exceeded interface for all neighborhood sizes, but differences in neighborhood size had a larger effect on the area mapped as intermix compared to area mapped as interface. For example, intermix WUI area increased from 257,962 km^2 (3.4% of the conterminous United States) to 1,111,682 km^2 (14.5% of the conterminous United States) as neighborhood size increased from 100 m to the 1500 m. The ratio of intermix to interface WUI was roughly equal (1.30) when using the 100-m neighborhood but increased to 3.40 with the 1500-m neighborhood.

In contrast to WUI area, the number of buildings in the WUI was relatively constant across the range of neighborhood sizes (Figure 3b). The 100-m neighborhood resulted in the largest number of WUI buildings at 54,276,242 (43.5% of all buildings in the Microsoft data), with the number of buildings declining slightly with increasing neighborhood size and falling to 50,703,297 (40.6% of all buildings) for the 1500-m neighborhood. The number of buildings within intermix WUI also increased with increasing neighborhood size but decreased for interface WUI, such that the percentage of buildings in intermix versus interface WUI increased from 34.5% for the 100-m neighborhood to 54.4% for the 1500-m neighborhood.

Effect of neighborhood size

As neighborhood size increased beyond 100 m, the amount of WUI area added was much greater than the area lost (Figure 4a). When comparing WUI areas for the 1500-m neighborhood to areas for the 100-m neighborhood, an area equivalent to 13.2% of the conterminous United States (1,008,687 km^2) became additional WUI while 1.1% (84,750 km^2) dropped out. The total area that was consistently mapped as WUI (either intermix or interface) across all neighborhood sizes was 338,415 km^2, which was 74.2% of the area classified as WUI using the 100-m neighborhood and 4.4% of the conterminous United States. Larger neighborhood sizes did not map WUI surrounding isolated buildings and small building clusters, resulting in maps with more WUI area but that encompassed fewer buildings (Figure 3). Larger neighborhoods also resulted in larger contiguous patches of WUI area (Figure 4b). Examining the fine-scale pattern of this effect, we found that larger neighborhoods resulted in fewer individual building clusters and larger buffer areas in surrounding wildland vegetation (Figure 5). Areas mapped using smaller neighborhoods more closely resembled patterns of actual building locations. The changes in WUI patterns resulting from increasing the neighborhood size were largely consistent in the western, central, and eastern United States (Figure 5).

Building-based versus census-based WUI maps

Regional patterns of intermix and interface WUI in building-based maps were similar to those of census-based maps. Building-based maps resulted in greater total WUI areas compared to the census-based maps, however, for all neighborhood sizes except for the 100-m neighborhood

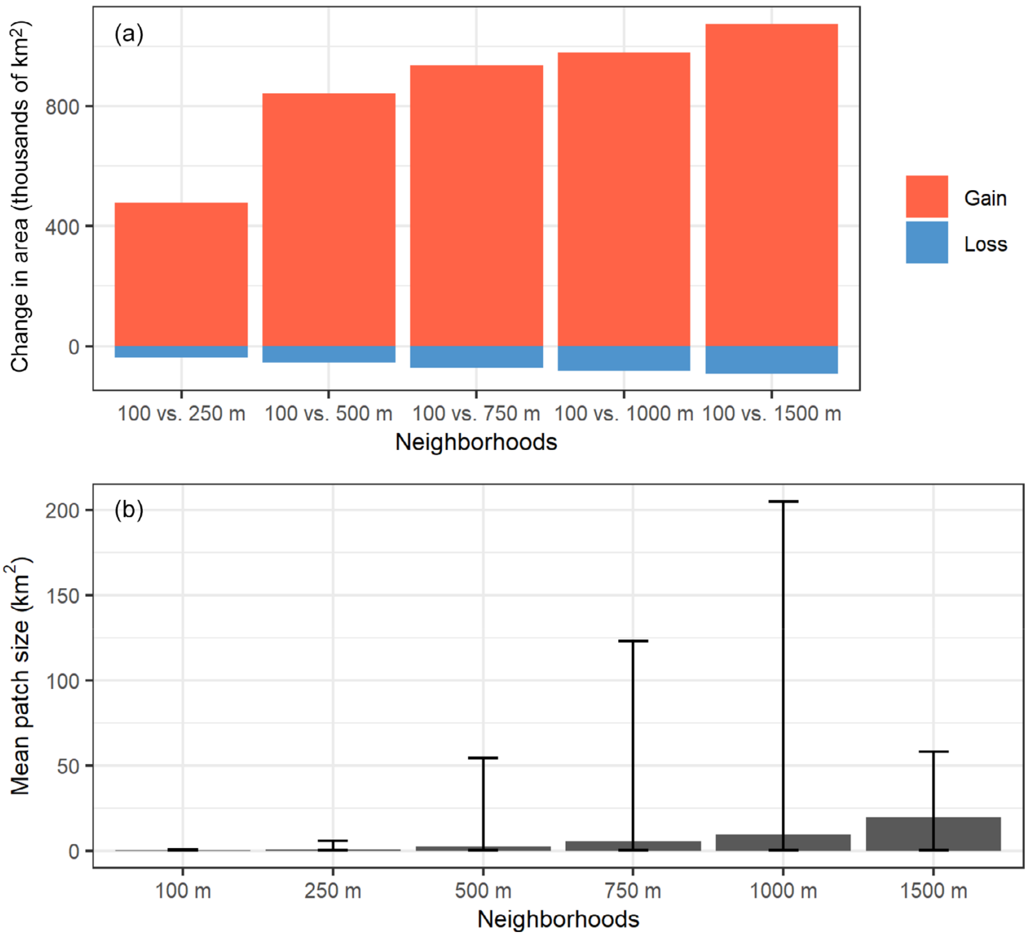

FIGURE 4 (a) Total wildland-urban interface (WUI) area gained and area lost across the conterminous U.S. with each increase in radius used to produce building-based maps, relative to maps produced with a 100-m radius. The 100-m radius identifies all buildings as potentially being in the WUI, given sufficient neighboring vegetation, regardless of the number of other buildings in the same neighborhood. (b) Mean size of WUI patches mapped across the conterminous U.S. for each radius, with bars indicating standard deviations

(Figure 3a; Appendix S1: Table S1). The building-based method using the 1500-m neighborhood mapped nearly twice as much total WUI area compared to the census-based method (1,438,784 vs. 770,298 km^2, respectively, or 18.8% vs. 10.1% of the conterminous United States). The 250-m neighborhood identified a total amount of WUI area closest to that of the census block-based WUI (893,321 km^2 or 11.7% of the conterminous United States), while proportions of intermix versus interface WUI were most similar to the census-based maps at the 1500-m neighborhood (Figure 3a; Appendix S1: Table S1).

Building-based maps resulted in greater numbers of buildings in the WUI (intermix and interface combined) compared to the census-based maps, for all neighborhood sizes. The total numbers of WUI buildings included in building-based WUI maps was 50,703,297–54,276,242, depending on neighborhood size (Figure 3b), compared to 43,434,112 census housing units included in the census-based maps. Building-based maps also included more buildings as a percentage of total buildings in the conterminous United States, with 40.6%–43.5% of all Microsoft building footprints being in the WUI compared to 33.2% of all census housing units). The share of buildings in the intermix versus interface was most similar to that of the census-based map when using the 250-m neighborhood (39.0% of WUI buildings in the intermix in the building-based map versus 39.3% of WUI housing units in the intermix in the census-based map).

Comparing Microsoft building counts to census block-level housing numbers revealed important regional patterns (Figure 6). Greater numbers of buildings relative to housing units were typical for agricultural regions in the Great Plains and Midwest and also for some public lands in the West. Fewer numbers of structures relative to census housing units were typical for urban areas with higher-density housing. Additionally, areas in the sparsely populated far northern parts of the Northeast had low proportions of buildings relative to housing units. This region of the United States is heavily forested, and low numbers of Microsoft building footprints may

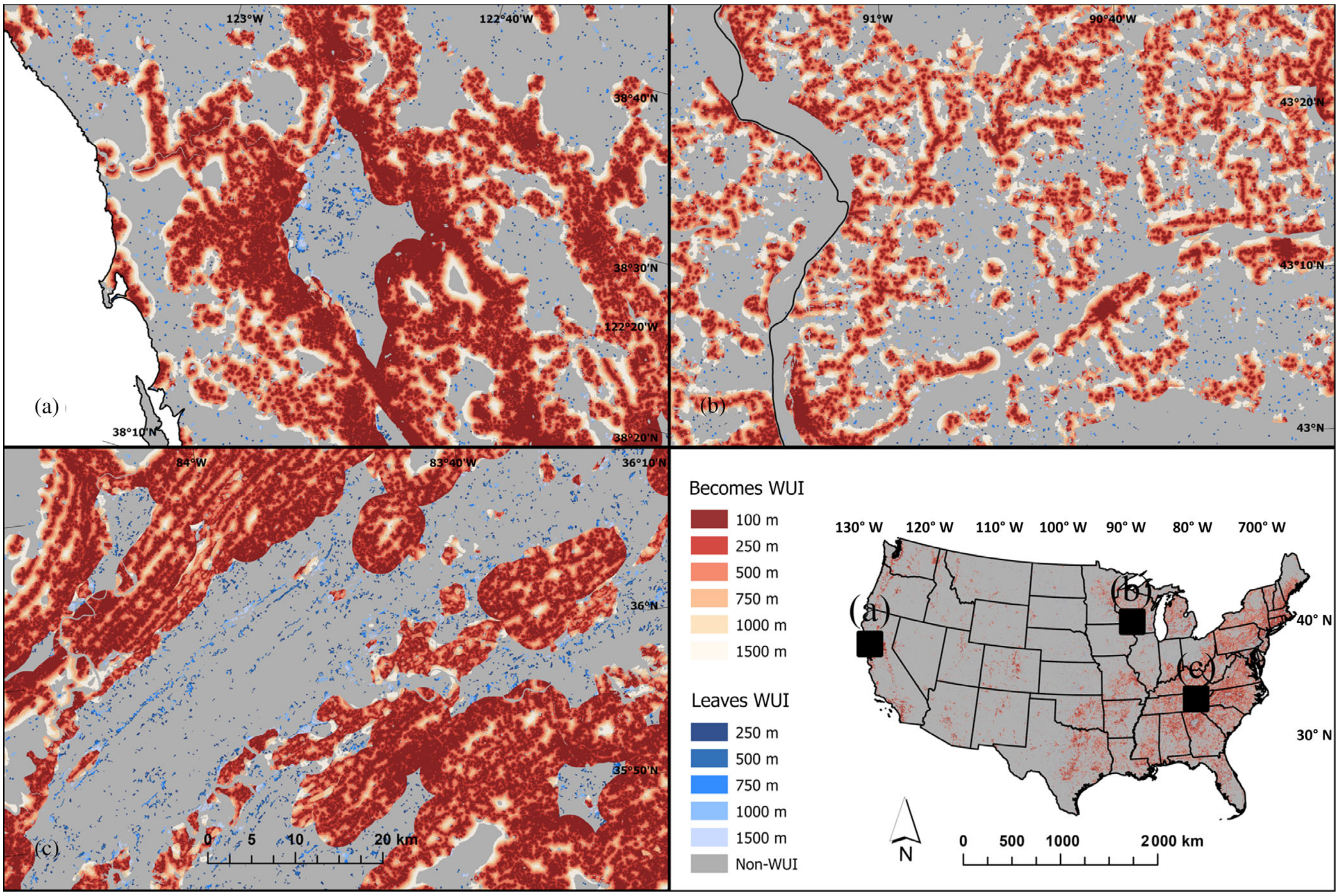

FIGURE 5 Composite maps depicting WUI areas included as either intermix or interface WUI with all circular neighborhood sizes (dark red), areas that become WUI as neighborhood radius increases from 100 m (yellow-orange shades), and areas that leave WUI as neighborhood radius increases from 100 m (blue shades) for three example areas: (a) Santa Rosa, California, (b) the Driftless Area, Wisconsin, and (c) Knoxville, Tennessee

reflect an undercounting of buildings that are obscured by tree canopies in satellite imagery.

Differences between the building footprint and census housing data sets resulted in regional patterns in differences in WUI areas between the two mapping approaches, with the building-based method resulting in considerably more WUI area (intermix and interface combined) in a few states in the Great Plains, Midwest, and West (Figure 7). This difference occurred for all neighborhood sizes in these states, even though building-based WUI area across the conterminous United States was less than census-based WUI area for the 100-m neighborhood. Building-based WUI area was greater than census WUI area in all states for all neighborhoods except for the 100-m neighborhood. Differences between building-based and block-based WUI areas were much lower for states east of the Mississippi River (Figure 7).

Spatial similarity between census-based and buildings-based maps was low according to the Jaccard indices, with a maximum similarity of 0.43 between census-based total WUI area and building-based total WUI area using the 1000-m neighborhood (Table 2). Agreement between census-based and building-based maps was fairly high when distinguishing between WUI and non-WUI classes, with >89% agreement of non-WUI pixels in census-based maps also being classified as non-WUI by building-based maps (corresponding to >93% agreement relative to building-based maps; Table 3). For interface WUI, similarity between the census-based and building-based maps was 0.19–0.21 for all neighborhood sizes despite the census-based total area being close to the building-based area using the 100-m neighborhood (Figure 3a). This dissimilarity indicates substantial differences between the precise areas identified as interface WUI by each method. Roughly 50%–60% of census-based interface area matched building-based interface area at all neighborhood sizes except the 100-m neighborhood, where agreement was only 37.9% (Table 3). Because the building-based method identified more interface WUI area, these areas of overlap represented only 31.1% or less of building-based area. For intermix WUI, Jaccard similarity between the two approaches was lowest when using the 100-m neighborhood (0.18) and highest when using the 1000-m

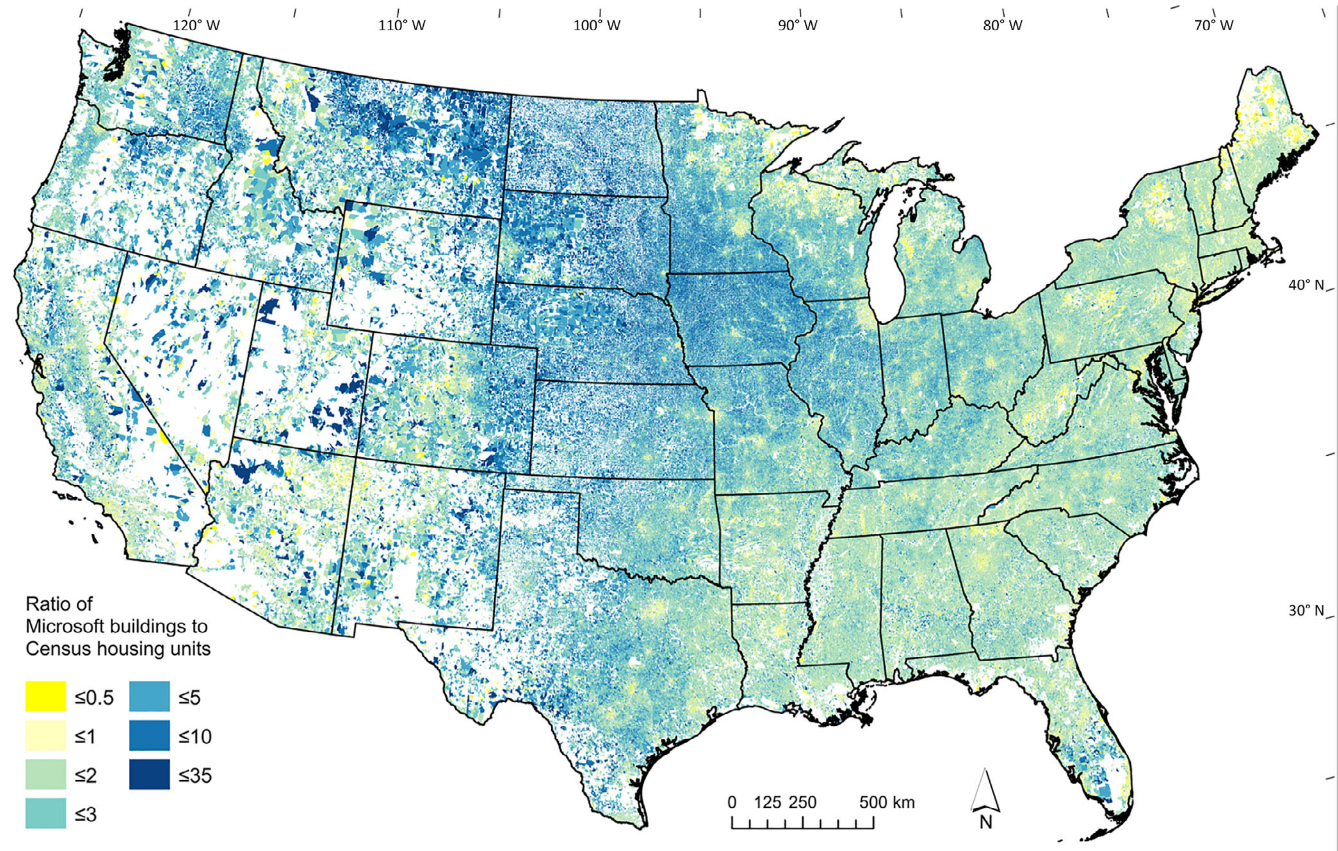

FIGURE 6 Ratios of Microsoft building counts to census-reported housing units for U.S. census blocks. Ratios >1 indicate more Microsoft building footprints than census-reported housing units

neighborhood (0.40). Because larger neighborhoods increased the total area of intermix WUI, they also resulted in more building-based intermix area overlapping with census-based WUI area, with a maximum of 79.4% agreement relative to the census-based area when using the 1500-m neighborhood (Table 3). Larger neighborhoods also increased the amount of building-based intermix WUI relative to census-based area, such that agreement was only 43.4% relative to the building-based map using the 1500-m neighborhood.

Influence of building location accuracy on WUI maps

We identified errors of omission or commission in the Microsoft buildings data in 125 of our 500 samples (25%). Out of 6714 Microsoft building footprints included in the sampled areas, we identified 671 errors of omission, where buildings seen in aerial imagery were missing in the Microsoft data, and 75 errors of commission, where Microsoft building footprints were falsely identified (e.g., a feature such as a boulder or pond was incorrectly classified as a building). Adjusting for the errors only affected building density threshold exceedance in 13 samples, however. Of these, 12 samples exceeded the building density threshold for WUI classification (a minimum of five buildings in the sample area) only after adding buildings that were omission errors, and one fell below the threshold after removing buildings that were commission errors. Ten of those 12 samples with omission errors also exceeded the vegetation density threshold for intermix WUI ($n = 0$) or were within the vegetation proximity buffer for interface WUI ($n = 1$), resulting in a WUI omission error rate of 2.0%. The single sample with a commission error in building density did not meet either intermix or interface vegetation criteria, resulting in a WUI commission error rate of 0.0%. Some commission errors likely exist in un-sampled areas of the WUI maps, but our results indicate a very low rate of occurrence.

DISCUSSION

Our new WUI maps demonstrate the potential for using individual building locations to map the WUI at a continental scale. The building-based mapping approach resulted in patterns of WUI in the conterminous United States that

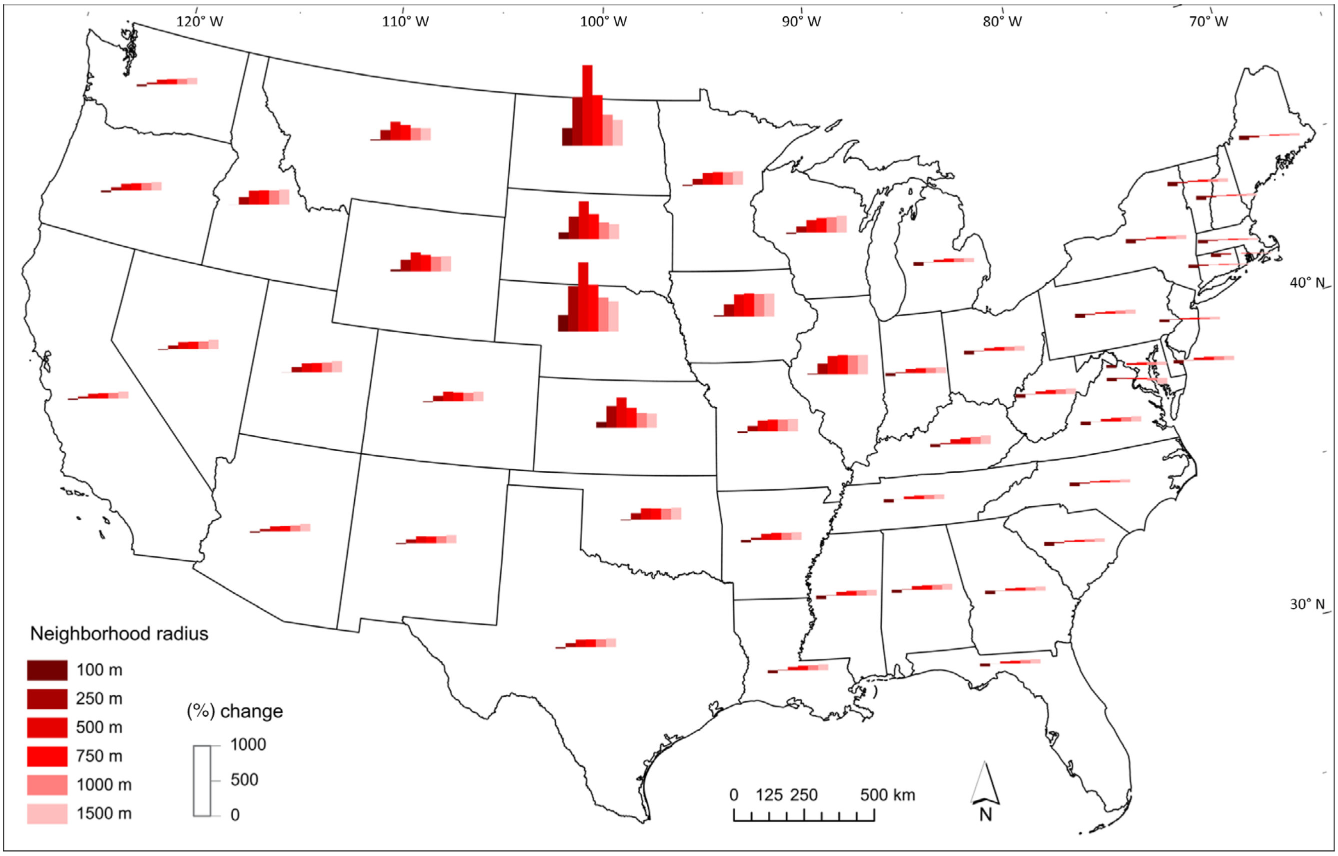

FIGURE 7 Change in total WUI area (intermix and interface combined) mapped by the building-based method relative to census block-based WUI area, as percent difference, for each circular neighborhood size used to aggregate building locations and vegetation. Results are plotted by state to show important geographic patterns in the differences between the building-based and census-based approaches, in which the building-based approach resulted in the greatest increases in WUI area in the north-central states

TABLE 2 Jaccard similarity indices indicating the amount of spatial overlap between census-based wildland–urban interface (WUI) areas and buildings-based areas, calculated using circular neighborhoods with variable radii

Neighborhood radius (m)	Total WUI	Intermix	Interface
100	0.27	0.18	0.21
250	0.36	0.30	0.21
500	0.40	0.36	0.21
750	0.42	0.39	0.21
1000	0.43	0.40	0.21
1500	0.42	0.39	0.19

Note: Similarity was determined for intermix and interface WUI, as well as for total area of either WUI type.

were generally consistent with maps based on the 2010 census. The majority of WUI areas were identified in the eastern United States; WUI areas in the western United States were more concentrated around urban centers and on the edges of public lands; and the central United States contained relatively little WUI overall. Maps based on actual building locations, however, are more spatially precise compared with maps based on coarse-scale census blocks. This precision offers a major advantage for wildfire management, where the spatial configuration of buildings at fine scales can have a large effect on the risk of building loss (Syphard et al., 2012) and for representing complex spatial patterns of human–wildlife interactions (Kertson et al., 2011). Furthermore, the buildings-based approach allows for flexibility selecting the neighborhood size when mapping the WUI, which influences the spatial pattern of resulting WUI maps. With the growing availability of building location data sets and classification algorithms, our methodology can be widely applied to generate WUI maps in the United States and elsewhere in the world.

Using smaller neighborhoods to map the WUI means that a greater number of buildings are included and that the areas mapped as WUI have a spatial pattern that resembles actual building locations. For instance, in the extreme case of the neighborhood with a 100-m radius, only a single building is required to qualify as WUI as long as there is sufficient neighboring vegetation.

TABLE 3 Confusion matrices comparing pixels identified in each wildland–urban interface (WUI) class (non-WUI, intermix, or interface) in census-based maps versus building-based maps, using variable radius distances to define circular neighborhoods for determining building density and vegetation cover

Census blocks	Non-WUI	Intermix	Interface	Agreement
100-m				
Non-WUI	7112	111	88	97.3%
Intermix	426	133	49	21.9%
Interface	87	14	62	37.9%
Agreement	93.3%	51.7%	31.1%	…
250-m				
Non-WUI	6860	278	173	93.8%
Intermix	273	275	59	45.3%
Interface	54	24	84	51.5%
Agreement	95.4%	47.7%	26.5%	…
500-m				
Non-WUI	6639	440	230	90.8%
Intermix	162	393	52	64.7%
Interface	36	34	93	57.0%
Agreement	97.1%	45.3%	24.7%	…
750-m				
Non-WUI	6608	476	226	90.4%
Intermix	122	440	45	72.4%
Interface	31	41	91	55.9%
Agreement	97.7%	46.0%	25.1%	…
1000-m				
Non-WUI	6597	497	216	90.2%
Intermix	105	462	41	76.0%
Interface	29	47	87	53.4%
Agreement	98.0%	45.9%	25.2%	…
1500-m				
Non-WUI	6526	570	214	89.3%
Intermix	89	482	37	79.4%
Interface	27	59	77	47.2%
Agreement	98.3%	43.4%	23.5%	…

Notes: Cell values are areas of overlap in thousands of square kilometers. Row percentages represent the amount of agreement between the two approaches for each category relative to the census-based area, calculated by dividing area of overlap by the row sum; column percentages represent agreement relative to the buildings-based area, calculated by dividing area of overlap by the column sum.

This may be advantageous for identifying buildings at risk from wildfires because more structures are mapped, and also for identifying areas for fuel treatments because WUI area is restricted to the defensible space around actual structure locations (Braziunas et al., 2021; Syphard et al., 2014). Past work has indicated that about 30% of buildings destroyed by fire are in census blocks not classified as WUI due to low building densities (Kramer et al., 2018), suggesting that more inclusive mapping approaches could be useful for targeting outreach and education. Small neighborhoods can also be useful for identifying areas of interaction between humans and animals if individual buildings, or small groups of buildings, can affect species of concern. For example, it has been demonstrated that individual buildings have the greatest effect on bird species composition within a range of 180 m in most of the United States (Glennon & Kretser, 2013). Spatial precision offered by building location data can therefore be desirable for assessing human–environment interactions when there is not a need to prioritize areas based on building numbers.

Mapping the WUI with larger neighborhood sizes results in maps that more closely match conceptual definitions of the WUI based around aggregated housing densities (Radeloff et al., 2005; Stewart et al., 2007) rather than identifying all individual buildings that intermingle with or abut vegetation. We found that larger neighborhood sizes added more WUI area by including more vegetated areas, but that more isolated WUI areas became excluded, reducing the total number of WUI buildings. These excluded areas were either individual or small groups of buildings in a wildland vegetation matrix, or buildings adjacent to small patches of vegetation in a developed matrix. This more conservative method of identifying buildings in the WUI may be desirable for allocating limited resources for fuels treatment and suppression and may better represent the zone of hazard where buildings face a high likelihood of destruction from a wildfire front (up to ~850 m from vegetation; Caggiano et al., 2020). Furthermore, larger neighborhoods can identify where wildlife is affected by high building density within a given distance, rather than by building presence alone (Theobald et al., 1997). Ultimately, applications of WUI maps will likely focus on a variety of ecological processes such as invasive species spread, zoonotic disease transmission, and many types of human–wildlife interactions (Bar-Massada et al., 2014), in addition to wildfire applications, which may use different neighborhood sizes to best capture appropriate scales of interaction. Assessing WUI impacts on wildlife abundance and diversity, for example, may require the selection of a neighborhood size that represents the distance over which ecological impacts can be detected. The magnitude of the effect at any given distance may vary substantially over ranges up to several kilometers and may also depend heavily on the species of interest (Benítez-López et al., 2010). Our composite WUI maps (Figure 5) therefore can be particularly useful for assessing patterns at multiple scales.

We found that overall spatial agreement between the census-based and buildings-based maps was fairly low according to Jaccard indices. Bar-Massada (2021) explored factors contributing to the dissimilarity between the two approaches in California, finding that dissimilarity was highest in areas where census blocks were larger and where buildings were more spatially clustered. This finding supports our assumption that the buildings-based approach identified WUI with more precision than the census-based approach and therefore has the greatest value in rural areas where census blocks are large and where fine-scale housing density is variable within blocks. This helps to explain why we saw the greatest increases in WUI relative to census-based area in regions of the United States with high agricultural land cover, because farm buildings tend to be highly clustered. The precision of the buildings-based approach may also identify WUI areas more accurately in the western United States, which includes many desert and mountain areas where buildings are sparse and may be clustered in valleys or near water sources. Buildings-based maps did not increase the amount of WUI area in the western states relative to census-based maps as substantially as in the central-northern states, but identifying WUI area more precisely and consistently in the West could be highly valuable for assessing wildfire risk. Wildfire exposure in the western United States tends to be highly concentrated in rural areas bordering public lands, where large fires tend to originate and spread (Ager et al., 2019), and it is therefore important to identify the precise locations of buildings at risk.

Differences between census-based WUI maps and maps based on Microsoft data can also be attributed to the different buildings included in each data set. A key difference is that the census reports numbers of housing units only, while the Microsoft data set does not differentiate between housing and non-housing structures. The growth of the WUI in the United States has been largely attributed to deconcentrated housing development near protected areas and other natural amenities (Hammer et al., 2009; Radeloff et al., 2018), but national-scale WUI maps in the United States have not previously included areas where wildlands interact with non-housing development (although this has been done in Canada; Johnston & Flannigan, 2018). Our building-based maps therefore provide an advantage over maps that exclude these areas, because industrial or commercial buildings, farm buildings, or structures associated with natural resource extraction also have impacts on natural environments. Oil and gas wells, for example, fragment natural habitats and substantially impact wildlife (Brittingham et al., 2014), and agricultural landscapes are often important areas of human–wildlife conflict (König et al., 2020; McInturff et al., 2020). Furthermore, these types of structures face risk from wildfire but are often not included in wildfire risk assessments based on WUI maps. The lack of differentiation between housing and other types of structures may be a limitation in some cases, however, for example, it may be desirable to prioritize residential homes only when planning evacuation routes for wildfire events (Cova et al., 2013), or when identifying threats to wildlife from domestic pets. An additional difference between the two data sources is the classification of multi-unit housing as single building footprints versus multiple housing units. For this reason, we observed large differences between Microsoft building footprints and census housing counts in high-density urban areas where there are likely high numbers of apartment buildings and condominiums. Users of either the census-based or building-based maps should therefore carefully consider these differences and evaluate the strengths and weaknesses for intended applications of the maps.

Satellite-derived building location data are a valuable resource for identifying WUI areas but are not without errors that may affect resultant maps. Our accuracy assessment revealed that building classification errors occurred frequently in the Microsoft data, but that WUI pixels were classified correctly 98.0% of the time despite these errors. Omission errors, where buildings are not detected in the Microsoft data set, may be more likely to occur where buildings are obscured by tree canopy cover (Khoshboresh-Masouleh et al., 2020), and this source of error may have reduced WUI areas and building numbers in some regions. We found that this may be a concern in parts of the Northeast where there is heavy forest cover and low-density housing. Buildings may also be undercounted in high-density urban areas (Yang et al., 2019). This is less of a concern for WUI mapping, however, because the building density threshold will be exceeded in dense urban areas regardless, and because high-density urban areas are unlikely to meet vegetation thresholds for WUI. While we found that overall rates of error in the WUI maps were low, users of the maps should use caution in verifying that WUI areas correspond to true locations of buildings. This is especially true when using maps based on neighborhoods with radii smaller than 500 m, because these neighborhoods require fewer buildings to exceed the density threshold for WUI classification. We did not separately assess accuracy for maps based on these smaller neighborhoods, but we expect that their error rates are higher than those for the 500-m neighborhood maps because building density exceedances are more likely to be affected by a single misclassified building.

In the future, updating building-based WUI maps will depend on up-to-date building location data and vegetation maps. Presently, the Microsoft buildings data set is only available for one time period (ca. 2015), and further classification of high-resolution satellite imagery is required to assess WUI growth. However, such updates are possible and could be made frequently, whereas updates to the U.S. census are only available every 10 years. As new satellite images are recorded, building locations can be mapped with building classification algorithms such as convolutional neural networks (Yang, Yuan, et al., 2018). Although it would require considerable effort to update WUI maps regularly for the conterminous United States, and unlike the census, these updates are not required to occur at regular intervals, the potential for frequent updates offers an advantage for equipping communities and land managers with up-to-date information to mitigate negative impacts of WUI development. More frequent updates are feasible for smaller areas and could be used to assess WUI growth at local scales. Furthermore, this methodology could be of great benefit outside the United States in countries where fine-resolution census data are not publicly available or are not regularly updated.

Our WUI maps for all neighborhood sizes and for the composite of neighborhood sizes is freely available for download from the USGS Science Base Catalog (Carlson et al., 2021). Users of these maps should select the neighborhood radius used to determine housing density and vegetation cover that is most appropriate for capturing the scales of human–environment interactions about which they are most concerned, with consideration for how different neighborhoods capture isolated groups of buildings versus larger clusters. In the absence of strong rationale for selecting a particular neighborhood size, using maps based on 500-m or larger neighborhoods represents commonly accepted definitions of the WUI that focus on groups of buildings (i.e., "urban" or "suburban" settings). We found that there is little advantage in considering larger neighborhoods than the 500-m because changes in WUI area and number of WUI buildings were minimal, and because smaller neighborhoods offer greater precision around building locations. The maps based on the 500-m neighborhood therefore are most ideal for general purposes. These maps identified WUI over 16.2% of the conterminous United States (1,242,840 km^2) and include 52,816,394 buildings (42.3% of all Microsoft building footprints).

CONCLUSIONS

National-scale data sets representing locations of individual buildings offer a novel opportunity to classify the WUI at a fine level of spatial detail. Our building-based maps improve on existing census-block-based maps by identifying precise structure locations within the WUI and by offering a spatially consistent and flexible method to select neighborhoods of analysis to match relevant scales of ecological processes. Compared to census-based WUI maps, we identified a greater amount of WUI area in some rural regions in the north-central United States where large numbers of buildings are associated with agricultural or natural resource extraction and low housing densities. Our national-scale maps offer insights into how non-housing structures contribute to the WUI. Furthermore, our work demonstrates the potential of developing building-based WUI maps for countries where census data is not publicly available or is not regularly updated, and for utilizing the growing availability of high-resolution satellite data sets and building classification algorithms to make more frequent updates to WUI maps.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Underlying data for this research were based on publicly available data sets. Building locations were derived from Microsoft building footprints (Bing Maps Team, 2018). Wildland vegetation cover data was based on the 2016 National Land Cover Dataset (Yang, Jin, et al., 2018). Processing code and output maps (Carlson et al., 2021) are available through the USGS ScienceBase catalog: https://doi.org/10.5066/P94BT6Q7.

ORCID

Amanda R. Carlson https://orcid.org/0000-0002-0450-2636

Todd J. Hawbaker https://orcid.org/0000-0003-0930-9154

Miranda H. Mockrin https://orcid.org/0000-0002-1158-3833

Volker C. Radeloff https://orcid.org/0000-0001-9004-221X

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

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