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Neighborhood-Scale Wildfire Evacuation Vulnerability in Hays County, TX

Chad Ramos and Yihong Yuan *

Department of Geography and Environmental Studies, Texas State University, San Marcos, TX 78666, USA; cgr50@txstate.edu
* Correspondence: yuan@txstate.edu

Abstract: Despite increasing wildfire severity and range, rapid development in the fire-prone Wildland–Urban Interface (WUI) has continued, and many neighborhoods are at risk of a constrained wildfire evacuation due to a high ratio of houses to community road-network exits. In Texas, Hays County is prone to fire, and rapid population growth has created a substantial WUI. Despite this, there is not sufficient research addressing neighborhood-level evacuation risks. The goal of this research, then, is to search Hays County for neighborhoods that face the highest combined risk of wildfire and potential evacuation difficulty. This research provides a limited use case wherein local decision-makers can quantify the combined risk of wildfire and constrained evacuation at the neighborhood scale by making use of standard spatial analysis techniques and publicly available datasets. The results show an alarming trend of low-egress neighborhoods in fire-prone areas within Hays County which carry the risk of a very difficult evacuation in cases when wildfire warning time is short. By using publicly available datasets and standard techniques, this research provides methods for local decision-makers across the state to identify these at-risk neighborhoods within their own jurisdictions which may aid in emergency planning and mitigation.

Keywords: wildfires; wildland–urban interface (WUI); risk assessment; geographic information science (GIS); hazards; evacuation

Citation: Ramos, C.; Yuan, Y. Neighborhood-Scale Wildfire Evacuation Vulnerability in Hays County, TX. *Geographies* **2024**, *4*, 481–499. https://doi.org/10.3390/geographies4030026

Academic Editors: Xu Chen and Luca Salvati

Received: 13 June 2024
Revised: 18 July 2024
Accepted: 24 July 2024
Published: 31 July 2024

1. Introduction

Wildfires in the United States have increased in severity, range, and seasonal duration, particularly in the west and southwest [1–3]. Both the total number of large fires and total area burned has increased significantly across a range of vegetation types in recent decades, and this increase in fire activity has led to a similar increase in the number of impacted structures [2,4,5]. By some estimates, at least 17,000 buildings were destroyed by large wildfires across the U.S. between 2000 and 2013, and other estimates suggest more than 3000 buildings were destroyed each year during this time period [6,7]. Wildfires in the Colorado Front Range continue to set annual records in terms of the number of structures burned, and some of the costliest wildfires in US history have occurred in the last 5 years, namely the 2018 Camp Fire that destroyed 14,000 structures in the town of Paradise, CA, and the 2021 Marshall fire that destroyed more than 1000 homes and displaced 40,000 people in Boulder County, CO [4,8–10].

Wildfire activity outside the U.S. has also been a growing threat. The 2009 Black Saturday bushfires were some of the most destructive in Australia's history, burning more than 450,000 hectares over the course of a month and resulting in 173 casualties [11]. Record-breaking temperatures coupled with severe fire conditions led to the 2017 Sir Ivan Fire in New South Wales which was so intense that it affected local weather conditions and created its own pyrocumulonimbus cloud, which strengthened the winds and caused additional lightning strikes ahead of the stormfront [12,13]. In Greece, the total area burned by wildfires each year has grown rapidly over the last four decades, including a spike in yearly wildfires after a 1998 policy change in fire management strategy [14]. The 2007 Greece mega-fires burned more than 180,000 hectares in one week and overwhelmed the firefighting capabilities of the country, despite an unprecedented amount of resources offered by many other countries [14]. The 2017 Pedrógão Grande fire in Portugal caused 65 deaths, destroyed hundreds of structures, and similar to the Sir Ivan Fire, created its own pyrocumulonimbus system [15]. Late-season fire occurrences during the winter of 2021/2022 have some considering whether climate variability is changing the fire regime in Portugal [16].

Despite the increase in wildfire activity, development in and around fire-prone areas, an area known as the Wildland–Urban Interface (WUI), has outpaced the growth of any other land use type [17–19]. This growth has increased wildfire ignition rates and placed more people and property at risk each year [1,18]. The WUI is defined as the area where houses meet or intermingle with undeveloped wildland vegetation [20,21]. It is the fastest-growing land use type in the U.S., and this growth presents a challenge to urban planners and emergency managers [18,22,23]. It is estimated that more than 46 million homes across 70,000 U.S. communities lie within the WUI, putting them at risk of an interface fire [7].

Much of the expansion of the WUI has been attributed to three factors: amenity-driven growth outside of metropolitan areas, the general de-concentration of population and housing, and population shifts to the west and southeast [24]. This growth is expected to continue and may be exacerbated by the retirement of the baby boomer generation [24]. Coupled with the wildfire risk due to the expansion of the WUI is the added risk that comes from climate change. It is projected that the WUI will experience a substantially higher risk of climate-driven fires in the coming decades due to the increased severity and frequency of drought and the lengthening of the fire season [25,26].

From the standpoint of urban planners and emergency managers, the risk of wildfire in the WUI is compounded by a lack of adequate road infrastructure to accompany the rapid growth of housing [4,23,27,28]. Communities in the WUI are being developed with little if any upgrades to existing road infrastructure, which can result in a high ratio of houses to community road-network exits and an increased evacuation time [28–30]. In some cases, residential developments are being built with upwards of 500 households to one exit [30]. This creates the risk of difficult evacuation and may have contributed to some of the most devastating WUI fires such as the Tunnel (Oakland–Berkeley) Fire of 1991. This community of 337 homes shared four exits, two of which were blocked within the first half hour of the fire leaving only two sparsely used community exits for evacuation [22,31]. The Tunnel Fire is far from the only example of a constrained wildfire evacuation, and together the risk of wildfire and the lack of road infrastructure in the expanding WUI create a potentially disastrous situation [32].

Studies have found many such neighborhoods across the western US, but that research does not extend to Texas [29,30]. Like many areas outside of the western US, Texas has seen an increase in wildfires in recent decades [33–35]. Hays County is one of the most fire-prone regions in the state, and rapid population growth has contributed to a substantial WUI in the county [36]. The state forest service provides many resources for understanding wildfire in Texas; however, despite several recent fires that have threatened WUI neighborhoods, there is little research on evacuation vulnerability. The primary question of this research, then, is which Hays County neighborhoods are at risk of a disastrous wildfire evacuation due to the combined threat of wildfire and potential evacuation difficulty? Answering this question can provide assistance to Hays County emergency managers as they seek to mitigate the threat of wildfire, and to municipal planners in the county by arming them with evidence and examples of dangerous developments should they seek to push for safer WUI building codes. Prior research by others combined heuristic models on road networks with wildfire hazard information from the LANDFIRE dataset to answer this question in other regions [30]. This research recognizes the necessity of being able to identify these neighborhoods at the local level, outside of research institutions, where planning and emergency management decisions are made. There is evidence to suggest that there are still organizational and technical barriers keeping GIS from widespread adaptation and exploitation [37,38]. Within the realm of public planning specifically, GIS is underutilized. Planners often use a GIS for superficial uses such as storing and accessing data, and creating simple maps for reports and public presentations, but it is rarely used to gain deeper insights from modeling or spatial analysis [38]. Even with the advent of web-based GIS and the increase in the availability of data, there are still calls being made for ease of use in geospatial technology [39]. As such, the secondary research question is, can prior methods be modified so that they are accessible to analysts and government employees not trained in network modeling and heuristic methods yet still adequately identify at-risk neighborhoods? In finding a solution to this question, this research becomes accessible to analysts trained only in standard spatial techniques, which can help to identify and mitigate against the risk in neighborhoods beyond the limited study area of this research. The general methodology used to identify at-risk neighborhoods presented here includes estimating the number of houses within each neighborhood, calculating the egress ratio of houses to community road-network exits, quantifying the wildfire risk at the neighborhood scale for each neighborhood, and then ranking the vulnerability of the neighborhoods based on their egress ratio and wildfire risk.

Early community evacuation research, which was instigated due to the perceived threat of nuclear power plants in the 1970s and later exacerbated by the accidents at Three Mile Island and Chernobyl, centered around estimating the time it would take to evacuate the area surrounding the threat [40,41]. Evacuation analysis on these large, community-wide areas began with determining the boundaries of the area that may need to be evacuated, which were deemed Emergency Planning Zones (EPZs) and were the basis for any large area evacuation analysis [29,40]. This approach of designating an EPZ around a known, static threat and then estimating how long it would take to evacuate the area became the framework for evacuation planning [42]. Researchers used this approach to consider how different evacuation variables such as population distribution, routing, network capacity, etc., would affect network clearance time [42].

A well-defined EPZ allows analysts to directly answer questions regarding how evacuations should proceed in the event of an emergency and how long it is likely to take, based on the existing threat. Cova and Church [29,43] argue that these advantages of forethought are lost in regions that are subject to certain types of hazards where a definite spatial extent does not exist, and therefore, a credible EPZ cannot be delineated. They argue that for hazards such as urban wildfire and toxic spills, the population to be evacuated cannot be determined in advance, and because of this, a special case of evacuation assessment is needed [29,43]. Others later refer to this problem as the difference between static and dynamic disasters and add that along with wildfires, hurricanes and certain floods can be considered dynamic [44,45]. In lieu of a credible EPZ, Church and Cova [29,43] reframe the problem as searching for neighborhoods that may be at risk of a difficult evacuation. With only being able to define an area that may be at threat from a dynamic hazard, such as a wildfire, they argue that the risk of a difficult evacuation itself is a threat [29,43].

Using this conceptualization of a potentially difficult evacuation as a threat, Church and Cova [29,43] develop and later modify a heuristically solved network modeling methodology for identifying neighborhoods that may face difficulties in the event of an evacuation—as measured by a high ratio of population to exit capacity. They call this method the Critical Cluster Model (CCM). In essence, the researchers define a neighborhood as the area (streets and intersections) encompassed by 'bottleneck' intersections [29,43]. Then the search for at-risk neighborhoods becomes that of finding neighborhoods with a high ratio of population to road-network exits.

Simplifications to the search for neighborhoods at risk of constrained evacuation can be made by moving away from computationally complex network analysis techniques which require a robust and highly detailed road network with network impedance values in the form of travel times or number of lanes [30]. There exists within the field of GIS and emergency management a growing trend of standardizing the data model of road networks and addressing points across government entities for the purpose of improving the handling and response to 9-1-1 calls [46]. Since 2014, this standardization has been fulfilled by the National Emergency Number Association (NENA) NG9-1-1 GIS data model for roads and address points [47]. The NG9-1-1 standard requires the attribute Neighborhood Community which is defined as, "The name of an unincorporated neighborhood, subdivision, or area, either within an incorporated municipality or in an unincorporated portion of a county or both, where the address is located" [47]. This attribute can be used to extract neighborhoods from the larger road network.

The approach presented in this research includes two changes that make the methods more broadly accessible than prior neighborhood-scale evacuation modeling methods. First, the road networks used in this research adhere to the National Emergency Number Association (NENA) NG9-1-1 data format that is required by many jurisdictions across the U.S., which makes the data widely available. Second, the methods use standard spatial analysis techniques as opposed to network modeling and heuristic methods in identifying low-egress neighborhoods and in assigning a wildfire risk to each neighborhood, which allows for the methods to be completed on a standard desktop GIS by technicians at the local level.

Hays County is one of the fastest-growing wildfire-prone counties in the state, and the results show an alarming trend of low-egress neighborhoods in fire-prone areas within the county. In total, 26 neighborhoods were identified as being at risk of a difficult WUI wildfire evacuation. There are likely other wildfire-prone areas with insufficient roadway infrastructure to accommodate evacuations and this broadly applicable methodology can help to guide planning and preparedness efforts across the state. The goals of this research are to systematically search Hays County neighborhoods to identify those that face the highest combined risk of wildfire and potential evacuation difficulty due to a high ratio of houses to community exits and second, to create a methodology that is accessible to planners and emergency managers at the local level, outside of research institutions, so that this analysis can be carried out by those making the planning decisions. Decisions that affect the vulnerability of WUI neighborhoods start at the development level, between developers and municipal or county planning offices. This research is innovative in bringing the assessment of neighborhood wildfire risk within the capabilities of local planning departments and therefore into these crucial conversations. By making use of these broadly applicable methods, emergency preparedness and mitigation in the WUI can become proactive rather than reactive. Section 2 provides a description of the study area and details the data and methodology used in the research. Section 3 presents the findings and provides a brief discussion on limitations and additional fire risks associated with WUI neighborhoods. We conclude this research in Section 4.

2. Data and Methods

The following section details the different parts of the research design including the study area, the data, and the analysis procedure. Section 2.3 includes a summary of the differences between this methodology and prior research, as well as a detailed description of the methods created here.

2.1. Study Area

Hays County is located in Central Texas along what is known as the I-35 corridor (Figure 1). The county is one of the fastest-growing regions in the U.S., with a population growth of 53% from 83,960 residents to 241,067 residents between 2010 and 2020 [48]. Much of this growth has occurred on the outskirts of metropolitan areas, resulting in an expansive WUI. It is estimated that 79.6% of Hays County residents live within the fire-prone WUI [36].

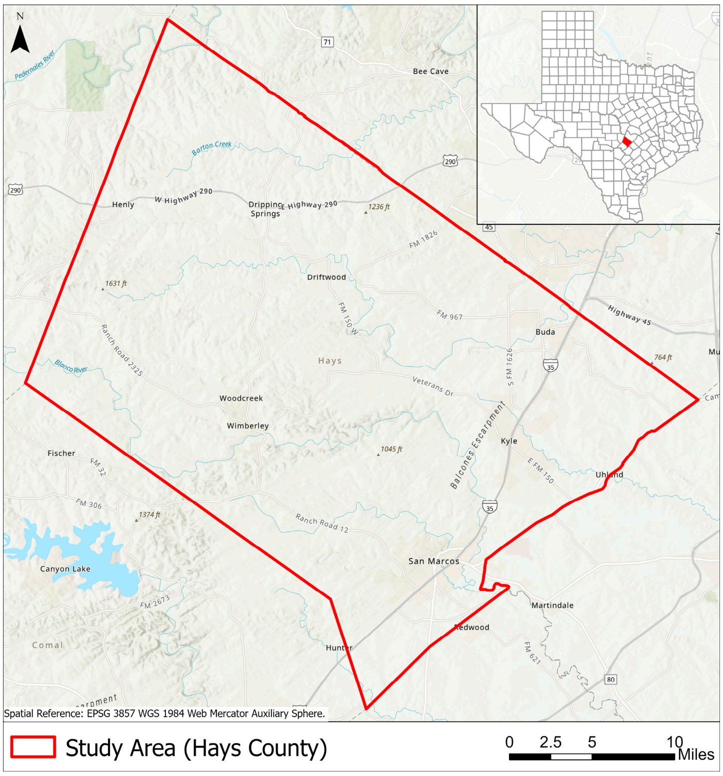


Figure 1. Hays County study area, located in central Texas, USA.

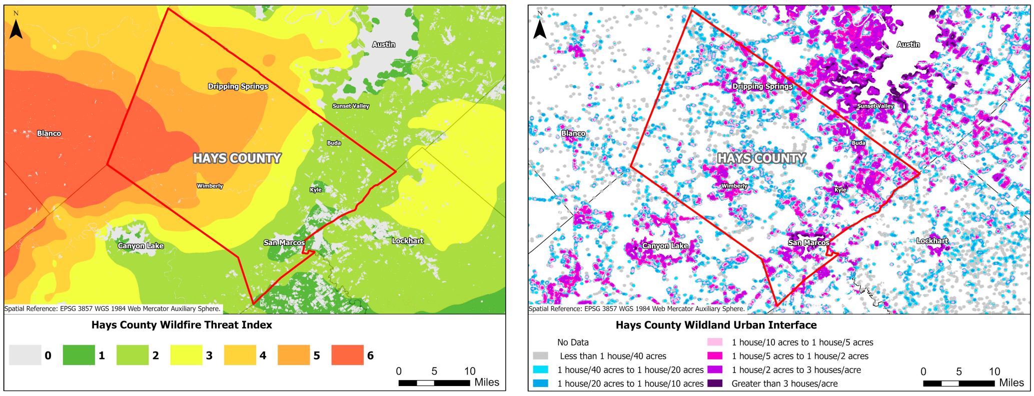
The wildlands that the WUI is expanding into consist primarily of the Edwards Plateau physiographic region. The Edwards Plateau is characterized by rolling canyons, a mix of grasses, and woodlands made of both hardwoods and conifers [36,49]. Canyons such as those found in the Edwards Plateau can funnel air allowing fire to spread rapidly up-valley, adding to the risk [50]. Along with these physical characteristics, climatological factors add to the fire risk in Hays County. Central Texas is prone to periodic drought to the extent that it is considered a normal condition, and drought severity is expected to increase in Texas due to climate change, further exacerbating the wildfire risk [51,52].

The combination of drought, exacerbated by climate change, and the vegetated canyons of the Edwards Plateau create conditions conducive to wildfire which is evidenced by the region's long history of fire [36,49,53]. Between 2005 and 2020, Hays County had 634 wildfires reported and 7118 acres burned [36]. Statewide, Texas has had multiple fire seasons with more than 1 million acres burned, and the 2011 fire season, which culminated in one of the most destructive wildfires in Texas history, saw 31,453 wildfires, 4 million acres burned, and nearly 3000 homes destroyed [54]. Finally, it is estimated that upwards of 80% of Texas wildfires occur within 2 miles of a community [36].

2.2. Data

Identifying Hays County neighborhoods at risk of a constrained evacuation in the face of an interface fire required datasets representing the road networks, the wildfire threat, address points, and the WUI. This research made use of publicly available datasets from the Capital Area Council of Governments (CAPCOG) and the Texas A&M Forest Service Texas Wildfire Risk Assessment (TWRA). The road network and address points used were the February 2022 Hays County Road Centerlines and Address Points datasets available through the Capital Area Council of Governments Open Data portal. The wildfire and WUI data used were the Wildfire Threat Index (WTI) and WUI datasets from the TWRA. The TWRA includes a set of GIS data relating to wildfires and wildfire risk in the state [36].

The specific fire hazard map from the TWRA used in this study was the Wildfire Threat Index (see Figure 2a) which describes the "likelihood of a wildfire occurring or burning into an area" and is derived from a combination of physical landscape characteristics such as surface and canopy fuel loads, historical fire occurrence, historical weather observations, and terrain characteristics [36]. The Wildfire Threat Index ranges from 1 being a low threat to 7 being a very high threat of wildfire, with a separate category for areas considered non-burnable [36]. The representation of the WUI used in this study was the TWRA WUI dataset for Hays County (Figure 2b).



(**a**) (**b**)

Figure 2. (**a**) Hays County Wildfire Threat Index as described by Texas A&M Forest Service [36]; (**b**) Hays County Wildland–Urban Interface as described by Texas A&M Forest Service [36].

These four datasets were used in combination with standard spatial techniques to compute neighborhood household-to-exit ratios and to quantify the wildfire risk level at the neighborhood scale. Next, these neighborhood characteristics—the household-to-exit ratio and the wildfire threat—were used to assess the combined risk of constrained evacuation and wildfire hazard in neighborhoods within the Hays County WUI.

2.3. Analysis

The general approach to identifying at-risk neighborhoods includes estimating the number of houses within each neighborhood, calculating the egress ratio of houses to community road-network exits, quantifying the wildfire risk at the neighborhood scale for each neighborhood, and then ranking the vulnerability of the neighborhoods based on their egress ratio and wildfire risk. The methodological approach presented here is derived from the methods of Cova et al. [30], with three crucial differences. First, prior methods require an input road network dataset with lane capacity or impedance values, paired with a computationally complex spatial optimization technique to define neighborhoods and exits. This prior methodology was among the first of its kind in recognizing the need to move away from earlier evacuation planning strategies that relied on a pre-defined Emergency Planning Zone (EPZ) related to specific, known hazards in favor of a methodology that could account for hazards like wildfires and hazardous material spills that do not have a pre-defined EPZ [29,30]. It has many advantages, including that it does not rely on a set of pre-defined neighborhoods. Instead, the model defines neighborhoods by searching a road network [29]. Any set of roads in the network that may represent a difficult small-scale evacuation will be identified, regardless of whether the roads represent a well-defined and designated neighborhood [29]. While it is advantageous, the computational complexity of the methods makes it difficult for local planners and emergency managers with limited resources to make use of the insights the research can provide. The research presented here deviates by making use of a public dataset of roads set to the NENA NG9-1-1 standard. The NG9-1-1 data model is a framework describing how roads and address points are to be represented inside a GIS. The data model serves to support the exchange of address and road information required for emergency 9-1-1 calls across government agencies. This GIS data structure includes the attribute Neighborhood Community, which is defined as, "The name of an unincorporated neighborhood, subdivision, or area, either within an incorporated municipality or in an unincorporated portion of a county or both, where the address is located" [47]. As public street data are created at the municipal or county level, technicians assign the Neighborhood Community attribute to streets within designated communities [46]. Using a roads layer set to the NG9-1-1 standard eliminates the need for the complex network analysis used by Cova et al. [30] to extract neighborhoods from a network and brings this analysis well within the capabilities of a desktop GIS, though only in the limited use cases where jurisdictions have adequately created their NG9-1-1 street centerline data. Using an NG9-1-1 standard roads layer has the additional benefit of adaptability in that methods created here can be used on public road datasets for any location, so long as they are set to the NG9-1-1 standard and the jurisdiction has sufficiently entered the Neighborhood Community information.

The second adaptation from the methods used by Cova et al. [30] was in the way that households are counted. Li, Cova, and others [55] argue that population estimates using address points can improve upon estimates made using Census block-level population, or housing density data. The methodology of the 2013 research by Cova and others [30] uses the earlier approach of estimating population and households based on Census block level and other data. It has since become common practice for municipalities to create and publish address point datasets, and as such, the research presented here used the approach suggested by Li et al. [55] and utilized an address points layer from the same NG9-1-1 dataset as the roads layer to estimate the number of households in each neighborhood.

A third adaptation builds upon research comparing modern building evacuation codes to neighborhood evacuations, adjusting the number of neighborhood exits based on their orientation within the neighborhood. A modern building code requires that the outer exits of a building be spaced a certain minimum distance from each other to ensure the likelihood of at least one exit remaining viable during an evacuation and to reduce the number of occupants attempting to evacuate through each exit [22]. An analog to this was created for neighborhoods which suggests that any two neighborhood exits that are closer to each other than half the distance between the two furthest-spaced houses in a neighborhood do not constitute separate exits [22]. For example, if two neighborhood exits are oriented on the same side of a neighborhood, exit to the same road, and are only 100 m from each other while the maximum length of the neighborhood (and thus the evacuation distance for some occupants) is more than a kilometer, then these two exits do not truly represent separate exits. In instances like these, it is necessary to reduce the number of exits before calculating the egress ratio.

The complete analysis process consists of four general steps, which were performed entirely within ESRI's ArcGIS Pro software (version number 3.03):

1. Calculate the household-to-exit ratio;
2. Adjust the number of exits based on exit arrangement;
3. Quantify the risk of wildfire at the neighborhood scale;
4. Rank neighborhoods based on their combined risk of wildfire and constrained evacuation.

2.3.1. Calculate the Household-to-Exit Ratio

The initial step in the evaluation is to calculate the household-to-exit ratio for each neighborhood. This was conducted by first dissolving the NG9-1-1 roads layer by the Neighborhoods attribute. Every road in a network set to the NG9-1-1 standard either has or does not have a neighborhood name associated with it; therefore, by dissolving on this attribute, the road layer will effectively be separated into two subnetworks—one representing neighborhoods and one of non-neighborhood roads (c.f. Figure 3a,b, note that different road segment colors represent different neighborhoods). Next, the neighborhood subnetworks that did not intersect the WUI layer were removed from further analysis as they are not at high risk for wildfire. Neighborhood exits were then defined as the intersections between the neighborhood and non-neighborhood subnetworks (see Figure 3c).

These exits represent a change from low-capacity local roads to higher-capacity roads that can be used to evacuate the area.

Figure 3. (**a**) A subsection of the Hays County road network; (**b**) a subsection of the Hays County road network dissolved and stylized based on the Neighborhoods attribute, such that each neighborhood is represented by a different color and non-neighborhood roads are represented in black; (**c**) a subsection of the Hays County road network with exits illustrated at the intersections of neighborhood and non-neighborhood roads; (**d**) neighborhood roads buffered by 100 ft with address points used to estimate the number of households in each neighborhood.

The second part of estimating the household-to-exit ratio was to estimate the number of houses within each neighborhood. To do so, the neighborhood roads subnetwork centerlines were buffered by 100 ft, and the resulting buffer polygon was used to count the address points within each neighborhood (see Figure 3d) [56–58]. We chose the buffer parameters based on the commonly used thresholds in local zoning regulations [56–58]. A value of 100 ft. represents the conservative estimate of the distance between the road centerlines and the adjacent address points. Neighborhood rights-of-way are generally 50 ft to 60 ft wide, maximum setbacks are generally 40 ft, and address points are centered on structures [56–58]. The sum of the street width (between the centerline and the edge of the right-of-way) and the maximum setback distance is 70 ft, which leaves 30 ft to account for variation in the placement of the address point on the households. Finally, the crucial households-to-exit ratio was calculated for each neighborhood from the estimated exit and household counts for each neighborhood.

2.3.2. Adjust the Number of Exits Based on the Exit Arrangement

In addition to the total number of exits in each neighborhood, it is important to consider the arrangement of the exits before determining the egress ratio. Two exits that are close to each other in comparison to the overall length of the neighborhood may not truly constitute separate exits. Research comparing neighborhood evacuations to research on building evacuations suggests that any two exits that are nearer each other than one-half the maximum length of the neighborhood should not be considered separate exits [22]. To account for this, the maximum length of each neighborhood and the distances between each possible exit pair were measured. The maximum neighborhood length was calculated by measuring the largest distance between any two points in each neighborhood convex hull polygon. For each neighborhood, the distances between each exit pair were compared to the maximum neighborhood length to assess whether any two exits were closer to each other than the critical distance of one-half of the maximum length. Finally, the arrangements of the exit pairs that failed to meet the distance requirement were assessed, and the number of exits was adjusted. This allowed for the calculation of the adjusted exit ratio.

2.3.3. Quantify the Risk of Wildfire at the Neighborhood Scale

The third step in the analysis was to assess the wildfire risk at the neighborhood scale for each of the Hays County neighborhoods within the WUI. This was conducted by performing an overlay analysis between the neighborhoods and the TWRA Wildfire Threat Index layer. To do so, a minimum bounding geometry polygon was created from each of the 100 ft. neighborhood buffer polygons (see Figure 4a). These resulting polygons were used to represent the full spatial extent of each neighborhood.

(**a**) (**b**)

Figure 4. (**a**) The TWRA Wildfire Threat Index dataset overlayed on neighborhood polygons; (**b**) the Wildfire Threat Index apportioned to neighborhood polygons as the percent of overlap between the neighborhoods and the levels of wildfire threats.

Next, an overlay analysis was performed between these neighborhood polygons and the TWRA Wildfire Threat Index layer such that the percent of each index level overlying a neighborhood was calculated and assigned to the underlying neighborhood (c.f. Figure 4a,b). Overlaying the Wildfire Threat Index layer onto the neighborhood polygons and then assigning to each neighborhood the portion of each threat level that overlies the neighborhoods provided the second characteristic necessary to assess the combined risk of wildfire and constrained evacuation.

2.3.4. Rank Neighborhoods Based on Their Combined Risk of Wildfire and Constrained Evacuation

Having quantified the adjusted household-to-exit ratios and having assessed the risk of wildfire at the neighborhood scale, the final ranking of Hays County neighborhoods was made. This was carried out in two steps. First, the neighborhoods were assessed based on their wildfire potential by grouping the neighborhoods according to their primary level of wildfire threat, as calculated by the overlay of the TWRA Wildfire Threat Index layer from a class 7 "Very High" threat to a class 1 "Low" threat [36]. The WTI is derived from a combination of physical landscape characteristics including surface and canopy fuel loads, historical fire occurrence, historical weather observations, potential resultant fire spread rate, and local terrain characteristics such as slope, aspect, and elevation [30].

It is calculated consistently across the state such that a given level of threat in one area of the state is equivalent to the same threat level in another part of the state allowing for comparisons across regions [30]. The analytical output values derived from the combination of landscape, historical fire, and historic weather patterns are categorized into 7 classes and given general descriptions to "aid in the use of Wildfire Threat for planning activities" according to the state forest service [30]. In this way, the neighborhoods that share a similar potential of "a wildfire occurring or burning into" the area were grouped together [36]. Next, the neighborhoods in each of the 7 wildfire threat groupings were ranked in descending order by their egress ratio of households per community exit. Finally, all neighborhoods that did not meet the 200 households-to-exit threshold set by Cova et al. [30] were removed, as neighborhoods below this threshold are at a lower risk of a constrained evacuation.

By ranking the neighborhoods in this way, the most at-risk neighborhoods are defined as those that achieve the following: 1. Represent the highest risk of a wildfire occurring within the neighborhood based on landscape characteristics such as fuel load, historical fire and weather patterns, and terrain conditions. 2. Meet the threshold for, and have the highest value of, being at risk of a constrained evacuation. By this ranking, the theoretical highest-risk neighborhoods are those primarily within the Wildfire Threat level 7 that have the highest egress ratio.

3. Results and Discussion

In total, the methods created here successfully identified 57 Hays County neighborhoods as being at risk of a difficult evacuation based on the 200 households-per-exit criteria (see Table 1). Of these, 26 are in wildfire threat zone 3 or higher, indicating a combined risk of wildfire and constrained evacuation (see Figure 5). The highest exit ratios are well above the 200 households-per-community-exit threshold, and the highest estimated exit ratio is 1614 houses per community exit, found in the Woodcreek neighborhood (located in level 5 wildfire threat west of Wimberly, see Figure 5). There are 12 neighborhoods with an estimated exit ratio above 500, and 6 of these are in high-risk wildfire threat levels 5 or 6 (see Table 1, Figure 5). To put these 6 neighborhoods with both an exit ratio above 500 and a high level of wildfire risk in perspective, similar research searching the 11 westernmost US states found only 31 neighborhoods in total with both an exit ratio above 500 and a wildfire risk, though this research took place more than 10 years prior and there are likely many more neighborhoods in the west that meet this threshold now [30].

Table 1. Data for the 57 Hays County WUI neighborhoods with an egress ratio above 200 houses per community road-network exit, grouped by their level of wildfire risk and ranked in descending order by egress ratio.

Rank	Name	House Count	Adjusted Exits	Egress Ratio	Fire Risk Level	LON	LAT
1	WOODCREEK	3228	2	1614	5	−98.141	30.035
2	HIGHPOINTE	1041	1	1041	5	−97.996	30.169
3	CALTERRA	515	1	515	5	−98.099	30.173
4	WOODCREEK GOLF	1618	4	404	5	−98.113	30.021
5	LA VENTANA WEST	290	1	290	5	−98.045	30.095
6	CEDAR OAKS MESA	249	1	249	5	−98.131	29.974
7	S SUNSET CANYON	246	1	246	5	−98.021	30.182
8	SHADY VALLEY	203	1	203	5	−98.220	30.209
9	BELTERRA	2041	2	1020	4	−97.985	30.191
10	DEER CREEK	1327	2	664	4	−98.049	30.275
11	REUNION RANCH	534	1	534	4	−97.937	30.155
12	ARROWHEAD RANCH	422	1	422	4	−98.123	30.197
13	N SUNSET CANYON	1253	3	418	4	−98.038	30.208
14	BIG SKY RANCH	746	2	373	4	−98.079	30.204
15	WEST CAVE ESTATES	323	1	323	4	−98.060	30.277

Table 1. *Cont.*

Rank	Name	House Count	Adjusted Exits	Egress Ratio	Fire Risk Level	LON	LAT
16	GOLDENWOOD	938	3	313	4	−97.974	30.137
17	BUSH RANCH	247	1	247	4	−97.980	30.210
18	ROLLING OAKS	245	1	245	4	−98.022	30.064
19	ESCARPMENT	467	2	234	4	−97.917	30.171
20	BUNKER RANCH	221	1	221	4	−98.129	30.196
21	HERITAGE OAKS	216	1	216	4	−97.990	30.212
22	SPRINGLAKE	201	1	201	4	−98.099	30.220
23	SW TERRITORY	463	1	463	3	−97.884	30.139
24	ELLIOTT RANCH	637	2	318	3	−97.895	30.112
25	RUBY RANCH	310	1	310	3	−97.920	30.073
26	LA CIMA	268	1	268	3	−97.999	29.895
27	SUNFIELD	3210	3	1070	2	−97.802	30.079
28	SHADOW CREEK	1837	3	612	2	−97.814	30.041
29	BLANCO VISTA	1606	3	535	2	−97.894	29.949
30	WATERLEAF	1037	2	518	2	−97.844	29.967
31	CROSSWINDS	503	1	503	2	−97.816	30.024
32	WHISPERING HOLLOW	1497	3	499	2	−97.862	30.090
33	TRACE	498	1	498	2	−97.990	29.807
34	KISSING TREE	780	2	390	2	−97.993	29.845
35	CIMARRON	1145	3	382	2	−97.861	30.113
36	SOUTHLAKE RANCH	365	1	365	2	−97.845	29.999
37	KINGSWOOD	362	1	362	2	−98.019	29.841
38	COTTONWOOD CREEK	693	2	346	2	−97.938	29.817
39	CYPRESS FOREST	1021	3	340	2	−97.899	30.000
40	CULLEN COUNTRY	1015	3	338	2	−97.860	30.097
41	SUNSET RIDGE	334	1	334	2	−97.851	29.971
42	KENSINGTON TRAILS	667	2	334	2	−97.837	30.010
43	PURPLE MARTIN AVE	319	1	319	2	−97.835	30.035
44	AMBERWOOD	944	3	315	2	−97.841	30.027
45	HOMETOWN KYLE	910	3	303	2	−97.891	30.001
46	BISHOP CROSSING	569	2	284	2	−97.969	29.889
47	GREEN PASTURES	851	3	284	2	−97.809	30.004
48	LAUREL ESTATES	838	3	279	2	−97.982	29.863
49	POST OAK	814	3	271	2	−97.865	29.971
50	THE RAILYARD	525	2	262	2	−97.804	29.995
51	MOUNTAIN CITY	241	1	241	2	−97.892	30.039
52	HIGHLANDS	466	2	233	2	−97.819	29.967
53	STONERIDGE	921	4	230	2	−97.825	30.064
54	ANTHEM	221	1	221	2	−97.905	30.026
55	EL CAMINO REAL	410	2	205	2	−97.934	29.836
56	MEADOW PARK	205	1	205	2	−97.819	30.072
57	BUNTON CREEK	1058	2	529	0	−97.838	29.980

The prevalence of low-egress neighborhoods in Hays County is likely due to the rapid growth of the Austin metropolitan area in recent decades and the nationwide push for large, amenity-rich neighborhoods outside of metropolitan areas [24]. As the metroplex expands into the once-rural counties surrounding Austin, developers are able to purchase large tracts of formerly agricultural land for development. Because neither Hays County nor the municipalities within the county have any WUI-specific code restrictions on neighborhood size, the number of houses per exit, etc. that are present in other wildfire-prone areas, developers can build large, unrestricted neighborhoods, which is likely the most cost-effective strategy.

While there are many low-egress WUI neighborhoods in the county, the results include 31 with a low wildfire risk. Typically, WUI neighborhoods face the highest threat of wildfire but in Hays County, the majority of all neighborhoods are within the WUI. This is somewhat atypical and again is likely due to the rapid growth within the county. In keeping pace with the population growth of the greater Austin area and the need for housing, developers are creating residential neighborhoods on the boundaries of the few municipal areas in the county faster than commercial development can expand the inner cities. Once commercial development and the municipal annexation process catch up to the residential development, these 30 or so lower-risk WUI neighborhoods will likely no longer be within the WUI, which will better reflect their designation as low wildfire risk.

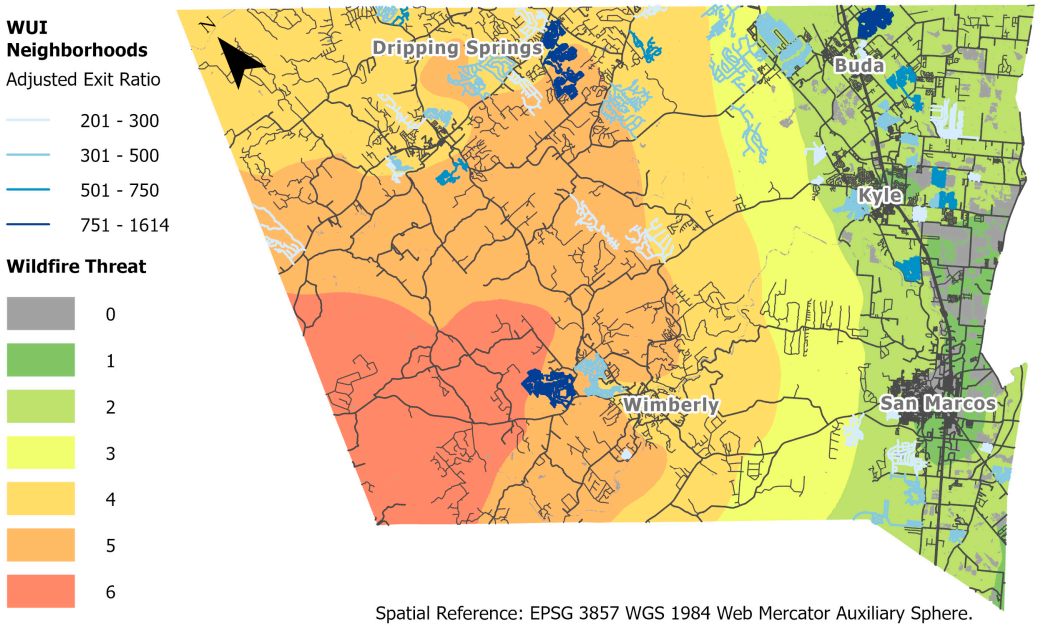


Figure 5. Hays County WUI neighborhoods with an egress ratio above 200 houses per community exit and the Wildfire Threat Index.

Finally, these results also include many neighborhoods with exits arranged such that they do not meet the requirements to be considered separate exits. In total, 37 of the 57 identified Hays County at-risk neighborhoods have exits that are too close to each other to constitute separate exits, which further exemplifies that residential neighborhoods simply are not designed for complete evacuation.

3.1. Additional Risk Factors

Beyond the metrics used to identify at-risk neighborhoods within this research (exit ratio, wildfire risk, and exit arrangement), there are several other wildfire threat characteristics that can affect the decisions of both residents living in WUI neighborhoods and planners and emergency managers involved in preparedness efforts. These include the potential intensity of a fire due to adjacent fuel and landscape characteristics, the structure density and vegetation density within the neighborhoods, and the vegetation and fuel buildup along roadways and along egress arteries. These additional risk factors are discussed here using the Woodcreek neighborhood as an example. The Woodcreek neighborhood, located just west of the city of Woodcreek, is the most at-risk neighborhood identified by this research. This neighborhood has an estimated adjusted exit ratio of 1614 houses per community exit, which is more than 8x the threshold value [30].

In addition to the high exit ratio and wildfire threat, the abundance of wildlands surrounding each neighborhood and the intensity of a potential fire predicted by the characteristics of these wildlands can affect mitigation and preparedness efforts. As seen in Figure 6, there are thousands of acres of wildlands bordering the Woodcreek community. This includes approximately 2000 acres of wildlands characterized according to the state forest service's Fire Intensity Scale (FIS) as having the potential to produce a high- to very high-intensity wildfire (see Figure 6) [36]. The FIS provides a standard scale to measure potential wildfire intensity and is similar to the Richter scale for earthquakes in that the order of magnitude in severity between each of the 5 classes is ten-fold [36]. Approximately 2000 acres of the wildlands surrounding Woodcreek rank 4.5 on the FIS (See Figure 6), indicating a potential fire characterized by common short-range and possible medium-range spotting, significant potential for harm or damage, large flame lengths, and creating fires where "direct attack by trained firefighters, engines, and dozers is generally ineffective, indirect attack may be effective" [36]. Unlike the TWRA Wildfire Threat Index, which describes the likelihood of a fire starting or burning in an area, the FIS describes the potential intensity of a fire should one occur at a particular location. In addition to the compound risk of wildfire occurrence and constrained evacuation, WUI neighborhoods like Woodcreek may need to consider the additional factor of potential wildfire intensity.

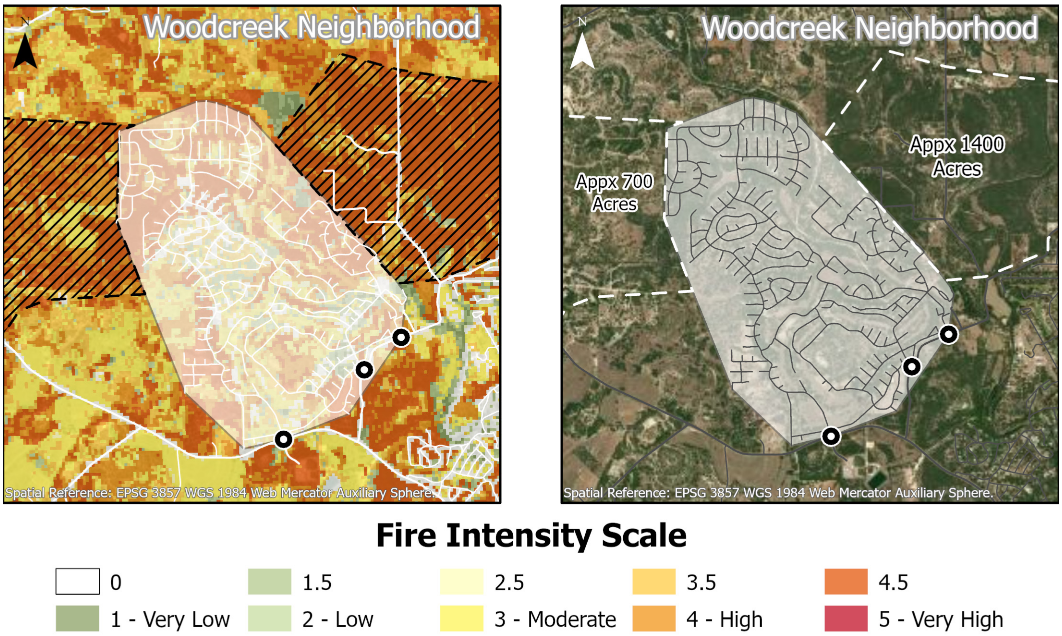


Figure 6. The Woodcreek neighborhood and the fire intensity potential of the surrounding wildlands. Note the black and white dots which represent the only road network exits from the community.

A second factor to consider beyond those used in this research is the density of houses and trees in the neighborhood. A case study of the 2018 Camp Fire in Paradise, California—the most destructive and deadly wildfire in California history—revealed several pre-fire characteristics of the community that catalyzed the fire's destructiveness [59]. Some of these characteristics can be used in assessing other WUI neighborhoods. It was described of Paradise that it "...was a community built in the forest, and the distinction between wildland vegetation and residential vegetation can be ambiguous" [59]. The vegetative density on residential parcels was identified as one of the four factors that "most significantly influenced overall fire losses" and combined with the structural density, significantly influenced the destructiveness of the Camp Fire [59]. Woodcreek shares a similarly high vegetative density, as can be seen in Figure 7, and the effective structural density of 2.6 structures per acre in the developed clusters of Paradise matches that of Woodcreek at 2.7 structures per acre [59]. While the type of vegetation is quite different in Woodcreek, the vegetative and structural densities are alarmingly similar.

Further insight into the structure and vegetation density can be drawn from WUI defensible space recommendations. Homes can be made defensible which may allow them to provide occupants sufficient safety in a passing wildfire; however, this requires at the very least the ability for the homeowner to control the space surrounding the household [22]. Research shows that even in the most severe cases, wildfire radiative and convective heat will not ignite wood structures at a distance greater than 40 m, which suggests that 40 m of space devoid of fuel and other vegetation may be sufficient to protect homes and structures from flame fronts during a wildfire [60]. The International Code Council WUI

Building Code, recently adopted by the City of Austin, requires 50 feet of defensible space for homes at the median hazard severity level [61]. Even at the lower threshold of 50 ft, many of the homes in Woodcreek fail in this defensible space requirement because one home's defensible space overlaps the neighboring space (see Figure 8) which would require neighbors to work in concert to create a defensible space. Furthermore, many of the houses in Woodcreek are themselves within 50 ft of one another, meaning that even devoid of vegetation, some houses cannot sufficiently clear an area for defensible space (see Figure 8).

Figure 7. A subsection of the Woodcreek neighborhood exemplifying the density of both houses and trees. Note that the white triangles represent address points. The structure density in these compact subsections is approximately 2.7 structures per acre.

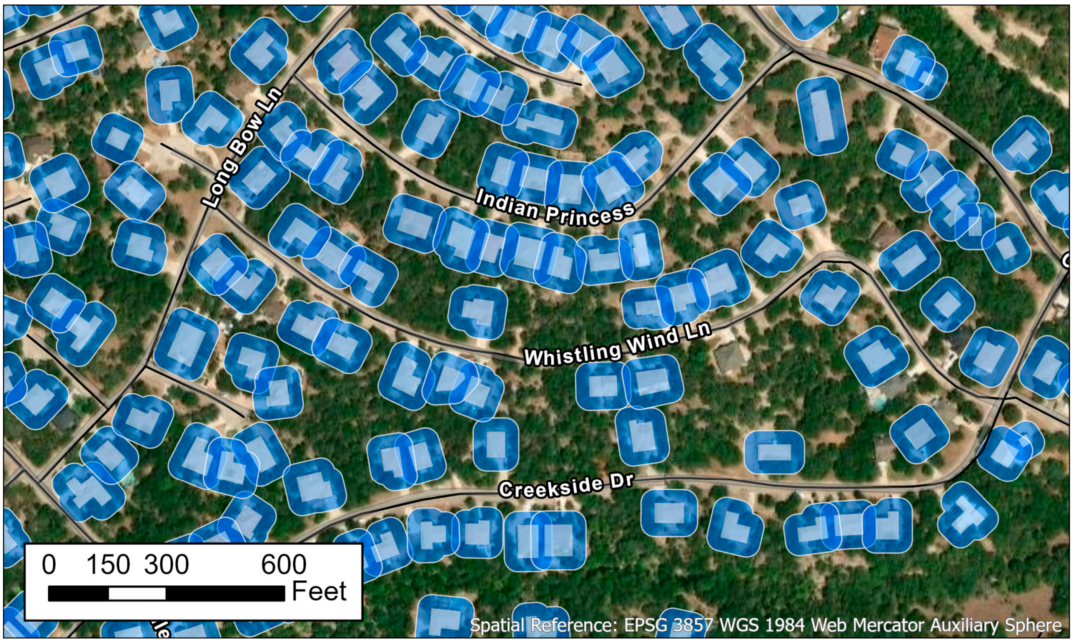


Figure 8. A subsection of the Woodcreek neighborhood with house footprints and a 50 ft buffer representing the minimum defensible space recommendations. Note the overlap in defensible spaces between houses.

A final additional risk that may need to be considered for Hays County WUI neighborhoods is the presence of vegetation along community exit roadways. This concept was put forth in research comparing modern building codes to neighborhood codes in terms of evacuation [22]. In this research, it is suggested that roads along community exits be given a 30-foot buffer zone clear of trees and other fuel that could block a roadway during a fire [22]. This hazard became a reality during the Camp Fire. During the evacuation, spot fires impacted egress arteries through smoke, fire, ember exposures, burned and fallen trees, poles, and other debris [9]. Because of this, the four major egress arteries were closed and reopened intermittently during the evacuation. In total, two of the four arteries were closed simultaneously for 68% of the main six-hour evacuation window [9]. This was also an issue during the 1991 Tunnel fire. A substantial amount of fuel along the exit roadways caused the two main neighborhood exits to be closed within the first half hour of the fire [31]. Woodcreek is at risk of a similar risk of road closures from spot fires. Many of the roadways are very close in proximity to the tree line, and even house-lined streets have substantial vegetation growing very near the roadway.

3.2. Limitations

The primary limitation of this research relates to the determination of the neighborhood household-to-exit ratio. Other models do not rely on a set of pre-defined neighborhoods, and the models define neighborhoods by searching a road network [29]. Any set of roads in the network that may represent a difficult evacuation will be identified, regardless of whether the roads represent a well-defined neighborhood. The methods presented here can only identify neighborhoods that have been pre-defined, and that have been named such that the Neighborhood attribute within the NG9-1-1 data standard can be populated. This means that only planned neighborhoods will be considered, and even colloquially well-known neighborhoods whose name is not official or whose extent is not formal enough for it to be given the Neighborhood attribute will be missed.

With regard to the input data themselves, the methods presented here rely heavily on the accuracy of the road networks and the Neighborhood attribute in publicly available datasets. This presents additional data challenges as the road datasets require thorough data cleaning before processing, which adds a considerable amount of time to the application of the methods and reduces the broad applicability. Data inaccuracies can lead to results that differ significantly from reality. For example, a missing road segment in the GIS data could cause a two-exit neighborhood to appear as a one-exit neighborhood, doubling the exit ratio. There are many sources of potential errors in the publicly available road network data that limit the accuracy of the results. Furthermore, not all jurisdictions have sufficiently populated the Neighborhood Community attribute in the NENA NG9-1-1 data structure upon which this methodology relies.

Further, it is possible that some neighborhoods will be erroneously removed from the analysis if the neighborhoods are built after the creation of the WUI dataset but before the creation of the roads and address points datasets. In this case, the neighborhood might not intersect the WUI dataset and would therefore be removed from the analysis with other non-WUI neighborhoods, even if it would otherwise qualify as being a WUI neighborhood. If it is suspected that the WUI dataset is out of date compared to the input roads and address points, the problem could be alleviated by adding an additional analysis step of calculating the WUI rather than relying on publicly available datasets.

Similarly, although the road widths, setbacks, and other planning-related regulations affecting the neighborhood characteristics are consistent across the study area, and although many of these planning regulations stem from statewide regulations, there are likely variations across the state and in regions beyond Texas. It may be necessary to evaluate the housing count for select neighborhoods to validate the accuracy in regions beyond the study area. However, as this methodology is designed to be performed by local planners and emergency managers making assessments of their own regions, it is likely they will be the most knowledgeable about regional differences in regulations that may affect the counting of houses in each neighborhood.

Finally, there are limitations that stem from the wildfire data. The Wildfire Threat Index from the Texas A&M Forest Service provides a meaningful and convenient way to rank neighborhoods based on their susceptibility to wildfire. These data, however, are limited to Texas counties. There may be analogs for regions outside of Texas, but unlike the input road data, there is no standard for wildfire data across government agencies which limits the applicability of this research.

Many of the limitations of this methodology stem from either data quality within regions or potential data inconsistency across regions. Even though the NG9-1-1 data model is required by counties in Texas and in many regions across the U.S., the municipal planning process results in individual jurisdictions creating and managing their own data. One county may have highly accurate data and a fully populated Neighborhood Community field in the GIS road network dataset while another may have only populated the field for a select few neighborhoods. These inaccuracies and omissions result in extensive data cleaning prior to analysis, which adds considerable analysis time. Because of this, a more accurate and consistent nationwide dataset of roads and address points is needed. Such datasets exist, but not with the crucial Neighborhood Community field from the NG9-1-1 data model. Future research could perhaps make use of a road network dataset with road classifications as an analog to the Neighborhood Community attribute. One such dataset is the Open Street Maps street network, which is both nationwide and able to classify roads into separate categories including residential. If a methodology could be adapted to make use of the road classifications in lieu of the Neighborhood Community attribute, this could solve the issues of omitting neighborhoods without a well-defined boundary or official name, issues with inconsistencies across regions, etc., while still maintaining an ease of use that would allow local planners and emergency managers working outside of research institutions to perform their own analyses in their own regions.

4. Conclusions

The rapidly expanding WUI land-use type is a growing problem for urban planners and emergency managers due to the risk of wildfire created by the adjacency of human development and flammable vegetation. This risk is compounded by the lack of adequate road infrastructure to accompany the rapid housing growth. The goal of this research was to systematically search Hays County communities for fire-prone, low-egress neighborhoods using techniques that would be available to local planners and emergency managers, outside of research institutions. In total, 26 fire-prone WUI neighborhoods were identified with an exit ratio of more than 200 households per community exit, including 6 such neighborhoods with an exit ratio greater than 500. These neighborhoods carry a risk of a very difficult evacuation in cases when wildfire warning time is short such as was the case in the 1991 Tunnel Fire and at a much larger scale, the 2018 Camp Fire in Paradise, CA. While the ranking here identifies the most at-risk neighborhoods in terms of wildfire threat and egress ratios, more work is needed to incorporate additional wildfire, landscape, and road infrastructure characteristics in identifying at-risk neighborhoods. This research provides a starting point in wildfire evacuation hazard identification in Hays County and exemplifies the need for targeted emergency planning as well as local government and community public safety outreach. Hays County emergency managers can use the ranking here to guide targeted emergency planning, and municipal planners can use the examples provided as evidence for the need to adopt WUI-specific development codes should they wish to push for their implementation. Further, having successfully identified at-risk neighborhoods without the need for more complex spatial techniques, the methods created here may allow similar research to be undertaken for the many other high-wildfire-risk counties across the state by analysts outside of research institutions. Also, this study focuses on demonstrating a method that can be widely accessible to policy-makers, rather than comparing efficacy. Future studies with different research goals may conduct a multi-model analysis to compare the pros and cons of various methods. Climate change is expected to increase both drought and wildfires in Texas, and coupled with continual population growth, the need for targeted wildfire mitigation efforts cannot be understated.

Author Contributions: Conceptualization, C.R. and Y.Y.; methodology, C.R. and Y.Y.; software, C.R.; formal analysis, C.R.; investigation, C.R.; data curation, C.R.; writing—original draft preparation, C.R.; writing—review and editing, Y.Y.; visualization, C.R.; project administration, Y.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Restrictions apply to the availability of these data. Data were obtained from The Texas A&M Forest Service through the Texas Wildfire Risk Explorer and are available at https://wrap.texaswildfirerisk.com/Map/Public/#whats-your-risk (accessed on 13 March 2022) with the permission of The Texas A&M Forest Service.

Conflicts of Interest: The authors declare no conflict of interest.

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