Evaluating Hays County Communities for Wildfire Evacuation Vulnerability | Project Proposal

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1 Problem Statement

The fastest growing land use type in the US is the Wildland-Urban Interface (WUI)-loosely defined as the area where houses meet or intermingle with undeveloped wildland vegetation (Radeloff et al. 2005). This growth presents a challenge to urban and emergency planners because of land use types, the WUI poses the greatest risk of wildfire due to the adjacency of human development and flammable vegetation (Radeloff et al. 2005, Radeloff et al. 2018). This argument is not without support, between 1990 and 2009, 7075 buildings were destroyed by wildfire in the California WUI, and wildfires in the Colorado Front Range continue to set annual records in terms of number of structures burned (Calkin et al. 2014, Kramer et al. 2021). Much of the expansion of the WUI has been attributed to amenity-driven growth outside of metropolitan areas, the general de-concentration of population and housing, and population shifts to the West and Southeast (Hammer, Stewart, and Radeloff 2009). This growth is expected to continue and may be exacerbated by the retirement of the baby boomer generation (Hammer, Stewart, and Radeloff 2009). Coupled with the increasing risk due to expansion of the WUI is the added risk that comes from climate change. It is projected that the WUI will experience 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 (Jolly et al. 2015, Schoennagel et al. 2017).

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. Communities are being developed with a high ratio of houses to community road-network exits and in some cases, residential developments are being built with upwards of 500 households to one exit (Cova 2005, Cova et al. 2013). This creates a 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 (Cova 2005). Together, the risk of wildfire and the lack of road infrastructure in the expanding WUI create a potentially disastrous situation.

To address this concern, this research project aims to develop a method for and then to locate communities (streets, blocks, subdivisions, etc.) within the fire-prone Hays County Wildland-Urban Interface that are at risk of difficult evacuations due to a high ratio of households to community exits. Wildfire potential varies within the WUI itself, and differing communities will have a range of household-to-exit ratios. The goal is to quantify the compound risk of wildfire and constrained evacuation potential for each neighborhood in the WUI, and to then identify which communities are at the highest risk of potential disaster. In addition to identifying at-risk communities, this project seeks to adapt existing methods for determining community household-to-exit ratios such that they can be completed within a traditional GIS and will thus be more accessible to planners and emergency managers.

Specifically, my research asks: within the fire-prone Hays County Wildland-Urban Interface, which communities face the highest potential of disaster due to the compound risk of wildfire and constrained evacuation? To answer this question, I employ GIS spatial overlay and spatial analysis techniques. I adapt and simplify methods developed by Cova and Church such that this process can be completed within a traditional GIS and with datasets readily available to planners and emergency managers. I use road and address point datasets available from the Capital Area Council of Governments (CAPCOG) to find the household-to-exit ratio for communities in the WUI, and I assess the wildfire hazard by making use of existing wildfire potential and WUI datasets available from the Texas A&M Forest Service (Church and Cova 2000).

My tentative arguments are that rapid development in the WUI surrounding major cities such as Dripping Springs, Kyle, and San Marcos, have created communities that are at a high risk of both wildfire and constrained evacuation. I expect to find communities with a considerable portion of their area within high or very high wildfire risk zones as defined by the Texas A&M Forest Service. I further expect to find some communities with an egress ratio of more than 200 households-per-exit, which has been used as a threshold for defining at-risk neighborhoods (Cova et al. 2013, Texas A&M Forest Service 2022b).

Answering this question will contribute to the literatures of wildfire risk in the growing WUI and to the limited literature on the risk of constrained egress from small communities. This project has a broad impact for urban planning and emergency management, and a more direct impact on the policy makers in Hays County. To help the Hays County planners and emergency managers understand these risks, an executive summary will be created and disseminated through personal connections.

2 Background

Hays County is located in Central Texas along the I-35 corridor (Figure 1). The county is one of the fastest growing regions in the US, with 53% population growth from 83,960 to 241,067 residents between 2010 and 2020 (Weilbacher 2021). Much of this growth has occurred on the outskirts of metropolitan areas, resulting in an expansive Wildland-Urban Interface (Texas A&M Forest Service 2022a, Texas A&M Forest Service 2022b). The Wildland-Urban Interface

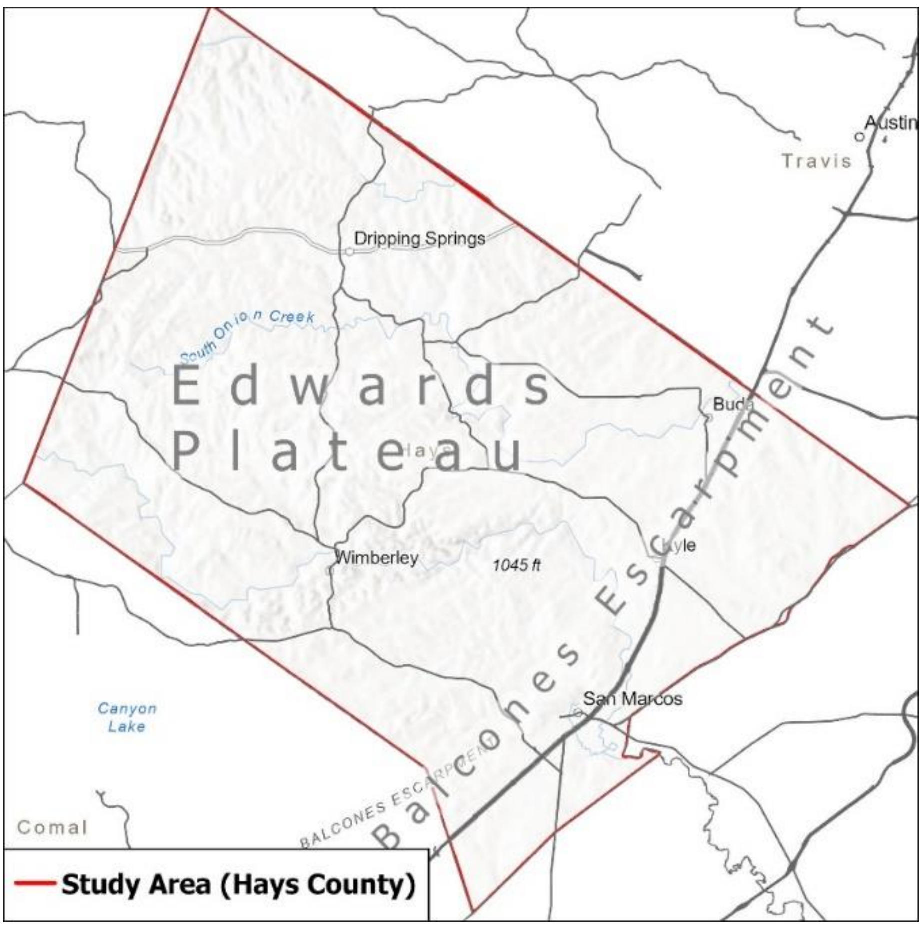

Figure 1 Study Area Overview
Author: Chad Ramos | Map Sources: TPWD, CONANP, Esri, HERE, Garmin, SafeGraphy, Meti/NASA, EPA, NPS, CAPCOG

land use type is defined as the area where houses meet or intermingle with undeveloped wildland vegetation, and is known to carry a significant wildfire risk (Radeloff et al. 2005). It is estimated that 79.6% of Hays County residents live within the fire-prone WUI (Figure 2a) (Texas A&M Forest Service 2022a).

The wildlands that the WUI is expanding into reside primarily on the Edwards Plateau physiographic province. The Edwards Plateau is characterized by rolling canyons, a mix of grasses, and woodlands made of both hardwoods and conifers (Swanson 1995, Texas A&M Forest Service 2022a). Canyons such as those found in on the Edwards Plateau can funnel air allowing fire to spread rapidly up-valley, adding to the risk (Hyndman and Hyndman 2017).

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 (Sansom, Armitano, and Wassenich 2008). Studies have shown that a 6 month to 1 year drought will occur somewhere in Texas more often than average precipitation over the same period (Sansom, Armitano, and Wassenich 2008). Drought severity is expected to increase in Texas due to climate change, further exacerbating the wildfire risk (Nielsen-Gammon et al. 2020).

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 (Texas A&M Forest Service 2022a., Swanson 1995, Nielsen-Gammon 2011). Between 2005 and 2020, Hays County had 634 wildfires reported and 7118 acres burned (Texas A&M Forest service 2022a). Statewide, Texas has had multiple fire seasons with more than 1 million acres burned and the 2011fire season, which culminated in the worst wildfire in Texas history, saw 31,453 wildfires, 4 million acres burned, and nearly 3000 homes destroyed (Jones, Saginor, and Smith 2013).

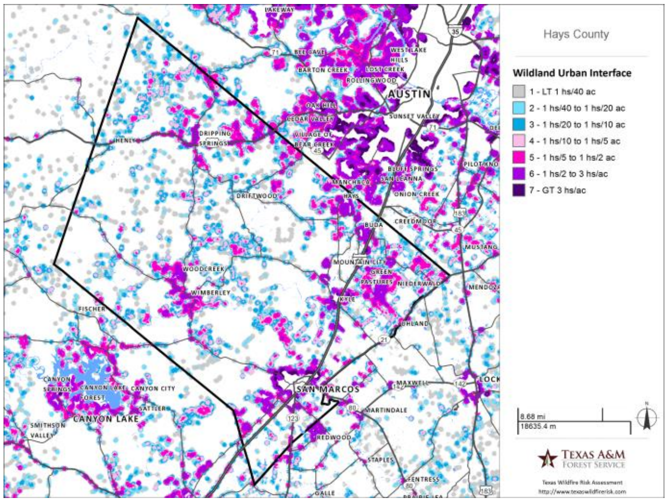

Figure 2a Hays County Wildland-Urban Interface
Source: Texas A&M Forest Service 2022a

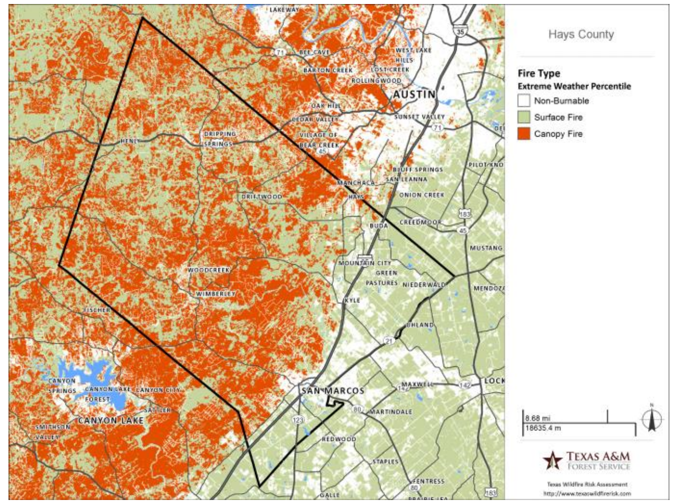

Figure 2b Hays County Potential Fire Type

Finally, it is estimated that upwards of 80% of Texas wildfires occur within 2 miles of a community and many of the communities in Hays County lie within the 174,823 acres identified by the Texas A&M Forest service as being at risk of very destructive canopy fires (see Figure 2b) (Texas A&M Forest Service 2022a).

3 Literature Review

My research draws upon and contributes to two scholarly bodies of literature: wildfire risk in the wildland-urban interface and community evacuation analysis. Wildfire risk in the wildland-urban interface describes both the rapid growth of the WUI land use type as communities expand beyond urban centers and into the wildlands, and the inherent wildfire risk carried by this land use type. I contribute to this literature by assessing the wildfire risk at a neighborhood scale for communities in Hays County. The literature on community evacuation modeling chronicles the development of evacuation modelling that treats the risk of a difficult evacuation from a community as a threat in and of itself. I contribute to this literature first by proposing a limited yet simplified method for assessing the risk of constrained neighborhood evacuation and second by evaluating neighborhoods in Hays County.

3.1 Wildfire Risk in the Growing Wildland-Urban Interface

The Wildland-Urban Interface (WUI) land-use type has many definitions, some conceptual and some defined more precisely by measurable characteristics. A common definition describes the WUI as "the area where houses meet or intermingle with undeveloped wildland vegetation (Radeloff et al. 2005). The 2015 International Wildland-Urban Interface Code, a set of fire-safety minded building code standards which have been adapted by many cities in fire prone areas, defines the wildland as, "an area in which development is essentially nonexistent, except for roads, railroads, power lines and similar facilities". The code gives a definition of the WUI that encompasses more than just houses as, "that geographical area where structures and other human development meets or intermingles with wildland or vegetative fuels" (International Code Council 2014, Schoennagel et al. 2017). More technical definitions of the WUI vary by region but in many cases are similar to the City of Austin's requirements for adaptation of the aforementioned 2015 ICC building codes. The city defines three risk levels based on three characteristics: proximity to 40+ acres of wildland, estimated fuel load of adjacent wildlands, and the slope of the land at the building location (Baker 2019).

As is implied in the definitions, there is an inherent risk of wildfire in the WUI and of land use types, the WUI poses the greatest risk of wildfire disaster due to the adjacency of human development and flammable vegetation (Radeloff et al. 2018). Recent wildfires in California notwithstanding, it has been shown that wildfire frequently burns buildings within the WUI. Between 1990 and 2009, 7075 buildings were destroyed by wildfire in the California WUI, and Colorado Front Range wildfires continue to set annual records in terms of number of structures burned (Calkin et al. 2014, Kramer et al. 2021).

Given the fire potential, residential development in the WUI is a growing problem for land use and emergency planners. The WUI within the US has grown rapidly in recent decades and shows no signs of slowing. Between 1990 and 2010 the WUI grew in terms of new houses (30.8 million to 43.4 million) and in land area (581,00 km^2 to 770,000 km^2) which makes it the fastest growing land-use type in the US (Radeloff et al. 2018). Furthermore, there has been significant growth in housing built within the perimeter of previous wildfires occurring between 1990 and 2015, indicating that prior wildfire occurrence is not a deterrent to new growth (Radeloff et al. 2018). While population growth can account for some of this expansion, the majority can be attributed to amenity-driven growth outside of metropolitan areas, the general de-concentration of population and housing, and population shifts to the West and Southeast (Hammer, Stewart, and Radeloff 2009). This growth may be exacerbated by the coming retirement of the baby boom generation (Hammer, Stewart, and Radeloff 2009). Coupled with the increasing risk due to expansion of the WUI is the added risk that comes from climate change. In the coming decades, the WUI is expected to experience substantially higher risk of climate-driven fires (Schoennagel et al. 2017). This projection is attributed to the increased severity and frequency of drought brought about by climate change, as well as the lengthening of the fire season, particularly in the West (Jolly et al. 2015, Schoennagel et al. 2017).

Texas is also at risk of worsening wildfire (Texas A&M Forest Service 2022a). Just as in the West, climate change is expected to increase frequency and severity of droughts in Texas (Nielsen-Gammon 2011). The drought of 2011 led to the one of the most active and destructive wildfire seasons in Texas history and created the conditions for the Bastrop Complex Fire, which burned 32,000 acres and destroyed more than 1600 homes (Jones, Saginor, and Smith 2013). Institutional mitigation measures have been taken in the City of Austin-the adaptation of fire-minded building codes for structures in the WUI-but other cities and counties have been slower to adapt (Baker 2019).

My research draws upon and contributes to the literature of wildfire risk in the WUI by assessing and quantifying wildfire risk within the WUI at the scale of individual neighborhoods. I build upon current statewide wildfire risk assessments and attempt to locate neighborhoods that are at risk of both wildfire and constrained evacuation in Hays County.

3.2 Community Evacuation Modeling

Early community evacuation research, which was instigated due to the perceived threat of nuclear power plants in the 1970's 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 (Sorensen, Vogt, and Mileti 1987, NRC 1980). Research on large scale evacuations grew to include not just the area surrounding nuclear power facilities, but also the areal limits given by the 100-year floodplain, and at-risk coastal areas that are subject to hurricane land fall (Sorensen, Vogt, and Mileti 1987). Evacuation analysis on these large, community-wide areas began with determining the boundaries of the area that may need to be evacuated (Sorensen, Vogt, and Mileti 1987). These boundaries were deemed Emergency Planning Zones (EPZ) and were the basis for any large area evacuation analysis (Church and Cova 2000, Sorensen, Vogt, and Mileti 1987). 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 (Southworth 1991). Researchers used this approach to consider how different evacuation variables such as population distribution, routing, network capacity, etc., would affect network clearance time (Southworth 1991).

Initially, the estimates of evacuation time were modelled in a linear fashion and based on static disasters (Manliguez et al. 2017). These practices have since been replaced by a number of modelling strategies that take advantage modern computing abilities (Manliguez et al. 2017). Modern evacuation routing methods can be separated into three categories: simulation, network flow, and heuristic methods (Manliguez et al. 2017). Simulation methods are those that attempt to virtually simulate an emergency event related to a known hazard. Simulation models tend to focus on the role of the individual in an evacuation, attempting to predict the individual's choices, movements, and interactions (Manliguez et al. 2017). For example agent-based modelling, a subcategory of simulation, treats individuals as units called agents. A set of rules guiding agent behavior is established and the simulation attempts to visualize how constituent agents interact with each other, providing insight into how the collective behavior of the group may affect evacuation times (Chen & Zhan 2008). Network flow methods focus not on the individual but on the network itself in modelling evacuation time (Manliguez et al. 2017).

Network flow methods treat the evacuation network, usually a road network, as a network graph. A maximum estimated egress time is assigned to each link in the network and the problem is defined as a minimum cost network flow problem and solved by relevant algorithms (Manliguez et al. 2017). Finally Heuristic methods are those that make use of a heuristic algorithm in solving the evacuation routing problem. Many real-world urban evacuation scenarios are too computationally complex to solve in a timely manner and thus a heuristic algorithm, which attempts to solve a problem in an in-exact yet computationally optimal manner, must be used (Cova and Church 1997, Shekhar et al. 2012).

There is a common defining characteristic to many of these models, that of the EPZ. Cova and Church suggest that the establishment of an EPZ about a known threat which has a definite spatial extent is key to a model's ability the answer the pertinent questions of who needs to be evacuated where they need to be routed to (1997). A well-defined EPZ allows analysts to move directly to 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 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 (Cova and Church 1997, Church and Cova 2000). The researchers call this problem the Indeterminable Evacuation Planning Zone (IEPZ) and state it as, "How can an evacuation assessment be performed when the population to evacuate is an unknown (i.e., when a credible EPZ cannot be established in advance)?" (Cova and Church 1997). 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 (Shababi 2015, Manliguez et al. 2017). In lieu of a credible EPZ, Church and Cova 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 (Cova and Church 1997, Church and Cova 2000).

Using this conceptualization of a potentially difficult evacuation as a threat, Church and Cova develop and later modify a heuristically solved network modelling methodology for identifying neighborhoods that may face transportation 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).** Without an EPZ to define the hazard risk boundaries the difficulty then becomes defining a neighborhood from a network. The researchers define a neighborhood as the set of nodes and arcs (intersections and streets) surrounding a *critical node*, "which has the highest *cte* or *bld* value", with cte being the clearance time, or time it would take to clear the network and bld being the bulk lane demand, a reworking of cte which uses lane capacity instead of flow rate to estimate evacuation time (Cova and Church 1997, Church and Cova 2000). In essence, the researchers define a neighborhood as the area (streets and intersections) surrounding a 'bottleneck' intersection-an intersection that represents the highest possible value of population per intersection (Cova and Church 1997, Church and Cova 2000). And the search for at-risk neighborhoods becomes that of finding neighborhoods with a high ratio of population to road-network exits.

They later modify this method and apply it to searching for at-risk neighborhoods within the fire prone wildland-urban interface (Cova 2005, Cova et al. 2013). In applying the method to the WUI, Cova and colleagues limit the search to the road network within the WUI, arguing that the disaster risk of wildfire is most prevalent in the growing WUI land-use type (Cova et al. 2013). This later research still uses the Critical Cluster Model in defining neighborhoods at risk of constrained evacuation. **However, by limiting the search within the WUI, I argue that the researchers are moving away from the earlier defined IEPZ and are moving back towards the EPZ.** The risk of wildfire is still a dynamic threat compared to that of a nuclear facility, dam, or other static threat, however by delimiting the search for at-risk neighborhoods to those within the high risk WUI, the researchers are establishing a credible EPZ, albeit a very large one. The researchers do not frame the problem in this way, they are still using the CCM which works independent of an EPZ. They state that it is computationally necessary as they are searching 11 US states for neighborhoods at risk of constrained evacuation (Cova et al. 2013). **I argue that by limiting the search to road networks within the WUI they are creating an EPZ because by doing so they are also moving the methodology one step closer to being able to be run within a GIS.** As it stands, the computational complexity of the model and the spatial extent of the networks likely to be used requires the process to be run outside of a GIS, albeit with the help of a GIS in creating the network itself. By limiting the network to that within the WUI-by using the WUI *as* an EPZ- they are reducing both the complexity of the constrained evacuation problem and the extent of the networks to be searched. Part of the simplicity of an EPZ is that an *exit* is defined by the outer boundary of the EPZ (Sorensen, Vogt, and Mileti 1987). In using the WUI as the EPZ, the search for neighborhoods at risk of constrained evacuation is greatly simplified, so long as it is understood that the underlying threat in the WUI is urban wildfire.

Further simplifications to search for neighborhoods at risk of constrained evacuation can be made by moving away from network analysis techniques. These techniques require a robust and highly detailed road network with network edge attributes corresponding to impedance in the form of travel times and number of lanes (Cova et al. 2013). There exists within the field of GIS and emergency management a growing trend of standardizing the data model of road networks and address points across government entities for the purpose of improving the handling and response to 9-1-1 calls (URISA 2021). Aside from improved 9-1-1 response, Li, Cova, and others argue that such a national address database would improve wildfire evacuation warnings, wildfire evacuation traffic simulation, and wildfire damage assessment (Li et al. 2019). Since 2014, this standardization has been fulfilled by the National Emergency Number Association NG9-1-1 GIS data model for roads and address points (NENA Data Structures Committee 2020, URISA 2021). I assert that public road and address data set to this standard can be used in place of more complex road networks for the purpose of identifying at-risk neighborhoods. 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" (NENA Data Structures Committee 2020). This attribute can be used to separate the network into roads within a neighborhood and roads outside of a neighborhood, removing the need for network analysis to define neighborhoods.

In sum my research draws upon and contributes to the literature of community evacuation modelling on the dynamic threat of urban wildfire by adapting the methods created by Cova and Church such that they can be completed within a modern GIS. I follow the goal of locating neighborhoods at risk of constrained evacuation, and I do so using the same metric as the 2013 research– a high ratio of households per community exit (Cova et al. 2013). I follow the concepts presented in the CCM, but I apply the WUI as an EPZ to reduce both the complexity and extent of the search for at-risk neighborhoods. I further simplify the methods by making use of public road networks set to the NENA NG9-1-1 data standard, which requires the designation of neighborhood roads.

4 Methods

The rapidly expanding Wildland-Urban Interface land-use type is a growing problem for urban and emergency planners due to the risk of wildfire created by the adjacency of human development and flammable vegetation (Radeloff et al. 2005, Radeloff et al. 2018). The risk of wildfire in the WUI is compounded by a lack of adequate road infrastructure to accompany the rapid growth of housing (Church and Cova 2000). Communities are being developed with a high ratio of houses to community road-network exits which creates a risk of difficult evacuation and may have contributed to some of the most devastating WUI fires (Cova 2005). Together, the risk of wildfire and the lack of infrastructure in the WUI create a potentially disastrous situation.

To address this concern, my research asks: within the fire-prone Hays County Wildland-Urban Interface, which communities face the highest potential of disaster due to the compound risk of wildfire and constrained evacuation? To answer this question, I employ the GIS techniques of spatial analysis, proximity analysis, and spatial overlay to compute the community household-to-exit ratios and to quantify the wildfire risk level at the neighborhood scale. I make use of a road network and address point dataset from the Capital Area Council of Governments and wildfire analysis layers from the Texas A&M Forest Service Texas Wildfire Risk Assessment (TWRA).

4.1 Data Collection

- Analysis Objective 1: Calculate the household-to-exit ratio for neighborhoods within the Hays County Wildland-Urban Interface
    - Hays County *Road Centerlines February 2022* dataset available through the Capital Area Council of Governments Open Data Download website.

    - Hays County *Address Points February 2022* dataset available through the Capital Area Council of Governments Open Data Download website.
    - Texas Wildfire Risk Assessment (TWRA) *Wildland-Urban Interface* GIS Layer available through the Texas A&M Forest Service Texas Wildfire Risk Explorer advanced viewer website.
- Analysis Objective 2: Calculate the risk of wildfire at the neighborhood scale
    - Texas Wildfire Risk Assessment (TWRA) *Wildfire Threat* GIS Layer available through the Texas A&M Forest Service Texas Wildfire Risk Explorer advanced viewer website.
    - Texas Wildfire Risk Assessment (TWRA) *WUI Response Index* GIS Layer available through the Texas A&M Forest Service Texas Wildfire Risk Explorer advanced viewer website.

4.2 Data Analysis

Assessing the combined risk of wildfire and constrained evacuation at the community level necessitates evaluating the risk in two separate parts: the risk of constrained evacuation and the risk of wildfire.

To assess the risk of constrained evacuation, I employ GIS spatial analysis techniques to compute the community household-to-exit ratio and compare this to the risk threshold of 200 households per exit adopted from Cova et al. (Cova et al. 2013). I employ a methodological approach derived from the methods of Cova et al., however I deviate and adapt from this technique in two key ways (Cova et al. 2013).

First, rather than adhere to the methods which require a robust road network with lane capacity and impedance values as a dataset, and a computationally complex spatial optimization technique to define neighborhoods and exits as the methodology (which is done outside of a GIS using optimization software), I make use of a public dataset of roads set to the NENA Next Generation 9-1-1 GIS Data Model (NG9-1-1) standard. The NG9-1-1 data model was widely adopted in 2014 and serves to support the exchange of address and road information required for emergency 9-1-1 calls across government agencies (URISA 2021). The 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" (NENA Data Structures Committee 2020). As public street data is created at the municipal or county level, technicians assign this *Neighborhood Community* attribute to streets within designated communities (URISA 2021). Using a roads layer set to the NG9-1-1 standard eliminates the need for the complex network analysis used by Cova et al. to extract neighborhoods from a network and brings this analysis well within the capabilities of a desktop GIS (Cova et al. 2013). 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.

The second way in which I adapt and deviate from the methods used by Cova et al. to calculate neighborhood household-to-exit ratios is in the way that households are counted (Cova et al. 2013). Li, Cova, and others argue that a national address point dataset is needed to improve wildfire research and that population estimates using address points can improve upon estimates made using Census block level population or housing density data (Li et al. 2019). The methodology of the 2013 research by Cova and others uses this former approach of estimating population and households based on Census block level and other data (Cova et al. 2013). I employ this updated approach suggested by Li et al. and make us of an address points layer from the same NG9-1-1 dataset as the roads layer, to estimate the number of households in each neighborhood (Li et al. 2019).

To assess the wildfire hazard of each neighborhood, I use a data from the Texas Wildfire Risk Assessment (TWRA) for Hays County created by the Texas A&M Forest service. The TWRA contains a set of GIS layers that can be used, among other things, to identify areas prone to wildfire based on estimated fuel load, likelihood of ignition, potential impact to life and property, as well as identify the wildland-urban interface and areas with the highest need for wildfire mitigation (Texas A&M Forest Service 2022a). From this dataset I will use the WUI Response Index layer and the Wildfire Threat layer to assess the wildfire hazard across the neighborhoods within the WUI. Together these layers provide an indication of the likelihood of a fire occurring at a particular location, and the impact that fire is likely to have based on existing structures.

The Wildfire Threat layer describes the "likelihood of a wildfire occurring or burning into an area" and is derived by from a combination of physical landscape characteristics such as surface and canopy fuel loads, historical fire occurrence, historical weather observations, and terrain characteristics (Texas A&M Forest Service 2022a). The Wildfire Threat index ranges from 1 being low threat to 7 being a very high threat of wildfire, with a separate category for areas considered Non-Burnable (Texas A&M Forest Service 2022a). The WUI Response Index layer is a rating of, "the potential impact of a wildfire on people and their homes" which can be used to "determine where the greatest potential of impact to homes and people is likely to occur"

(Texas A&M Forest Service 2022a). The index is derived from measures of housing density, and susceptibility to fire such based on potential flame length; the index scale ranges from -1 being low potential impact to -9 as being the most negative impact (Texas A&M Forest Service 2022a).

These neighborhood characteristics-the household to exit ratio, the Wildfire Threat level and the WUI Response Index level-will be used to assess the combined risk of constrained evacuation and wildfire hazard on neighborhoods within the Hays County WUI.

4.2.1 Annotated Pseudocode

To evaluate the risk of constrained evacuation at scale of individual neighborhoods, modifications will be made to existing methods described by Cova et al., such that calculating a household-to-exit ratio for each neighborhood can be done within a traditional GIS. This will be done using the standard spatial analysis techniques of extract, intersect, dissolve, join and spatial join, and proximity analysis. The details for this process can be found in steps 1-8 of the annotated pseudocode below. Assessing the wildfire threat and potential impact from the Texas A&M Forest Service Texas Wildfire Risk Assessment (TWRA) layers at the neighborhood scale requires only the standard GIS techniques of spatial overlay and minimum bounding geometry, the details of which can be found in steps 9-10 of the annotated pseudocode. Finally, the combined risk of constrained evacuation and wildfire threat will be assessed by ranking the selected neighborhoods in terms of their primary wildfire threat level given by the TWRA layer of Wildfire Threat, then by their potential impact given by the TWRA WUI Response Index and lastly by selecting neighborhoods that reach the 200 households-per-exit established by Cova et al. and ranking them by this metric in descending order within the previous groupings (Cova et al. 2013). The details of this process can be found in step 11 below.

Analysis Objective 1: Calculate the household-to-exit ratio for neighborhoods within the Hays County Wildland-Urban Interface from the TWRA WUI layer, and the CAPCOG February 2022 Road Centerlines and Address Points Datasets.

1. Dissolve input road network on *Neighborhood* attribute (See Figures 3a & 3b).

Making use of the CAPCOG Roads layer which is created to the NENA NG9-1-1 standard allows for the identification of neighborhood roads by the *Neighborhoods* attribute. This attribute eliminates the need for complex network analysis techniques, instead neighborhoods can be designated by dissolving the roads layer on the *Neighborhoods* attribute. Dissolving in this manner combines individual road segments that are part of the same neighborhood road network (Figure 3b).

Figure 3a Input Roads Layer

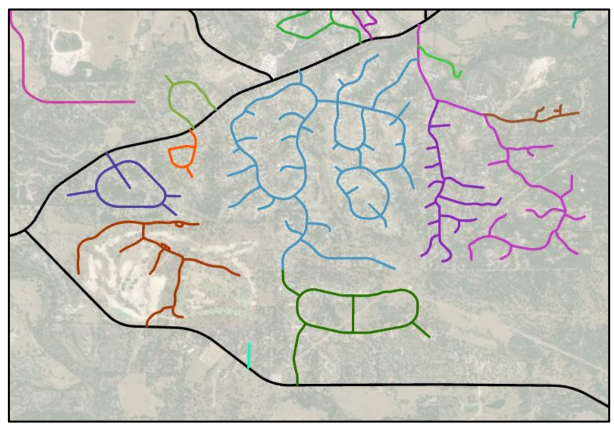

Figure 3b Roads Layer dissolved on *Neighborhoods* attribute, with differences in color indicating different neighborhood names

2. Separate Roads network into Neighborhoods and Non-Neighborhood roads (see figure 3b).

Given that all roads in the road network either do or do not have an assigned neighborhood (i.e., either the *Neighborhoods* attribute for each road segment contains information or does not), the network can be separated into roads that are part of a neighborhood road network, or roads outside of neighborhoods, thereby providing the basis for identifying neighborhood exits and calculating the household-exit-ratio.

3. Dissolve adjacent, intersecting neighborhoods into single features (see figures 3b & 4).

Neighborhood names are generally created by developers and approved by municipal or county Planning departments. This can lead to subsections of neighborhoods with different names (often designating a more secluded subsection with higher priced houses) even though they would colloquially be considered the same neighborhood (see figure 3b). Because these subsections also share the same neighborhood road infrastructure and have no access to neighborhood exits on their own, it is necessary to further dissolve (combine) adjacent neighborhoods where they intersect the overarching communities of which they are a part. Doing so assures that each neighborhood road network intersects the non-neighborhood road network and these intersections can be defined as neighborhood exits.

Figure 4 Roads Layer dissolved on *Neighborhoods attribute* and adjacent intersect

4. Intersect Neighborhoods with TWRA WUI layer and extract WUI Neighborhoods.

Only neighborhoods within the WUI need be considered for analysis. As stated by Cova et al., this is done to reduce the extent of the search to cut down processing time and was justified by remarking that the threat of wildfire is largely limited to neighborhoods within the WUI (Cova et al. 2013). By the same justification, this research will limit the search to neighborhoods at least partially within the WUI. However, given that an estimated 79.6% of the Hays County population lives within the WUI and just under half of the land area is considered WUI, this step may not be effective at reduce processing times (Texas A&M Forest Service 2022a).

5. Count intersections between WUI Neighborhood roads and non-neighborhood roads > store as *Exit Count* attribute (see figure 5).

Having separated the road network into neighborhood roads and non-neighborhood roads, neighborhood exits can be defined as the intersections between these two road networks. These exits represent a change from low-capacity local roads to high-capacity roads that can be used to evacuate the area. This is similar to reaching the doors leading outside of a building in the case of a building evacuation. After creating the intersection points, a spatial join can be used to count the number of exits for each neighborhood. This count will be assigned to the neighborhoods as a new *Exit Count* attribute.

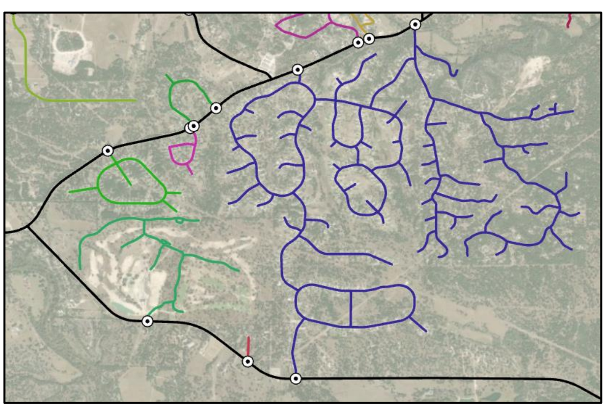

Figure 5 Neighborhood exits defined as the intersection between neighborhood and non-neighborhood roads

6. Buffer WUI Neighborhoods by 100 feet to create Neighborhood polygons and contain Address Points (see Figure 6).

Li et al. argue for the need of a national address point dataset which would improve wildfire evacuation warning and modelling and would facilitate wildfire damage assessments (Li et al. 2019). The CAPCOG February 2022 Address Points dataset serves this purpose for Hays County and will be used to estimate the number of households within each neighborhood. To estimate the number of address points (representing the location of households) within each neighborhood, proximity analysis will be used. Proximity analysis in GIS is a method for selecting geographic features based on their distance from other geographic features (Wade and Sommer 2006). For selecting and counting address points within each neighborhood, the neighborhood road network centerlines will be buffered by 100 ft. and the resulting buffer polygon will be used to count the address points within each neighborhood (see Figure 6). 100 ft. represents the conservative estimate of the distance between the road centerlines and the adjacent address points. Neighborhood street widths are generally 50ft or 60ft, setbacks are generally 15ft, 25ft, or 40ft, and address points are generally centered on structures. The sum of the street width (between the centerline and the edge of the street) and the maximum setback

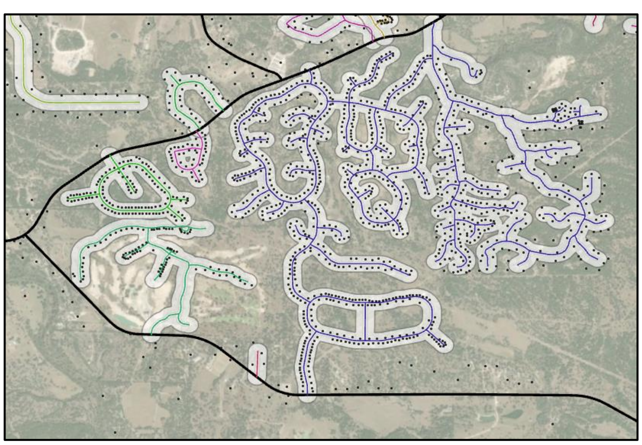

Figure 6 100 ft Neighborhood-Road Buffer to begin Neighborhood polygons and to collect Address points.

distance is 70ft, which leaves 30ft to account for variation in the placement of the address point on the households.

7. Use Buffer from step 6 to count address points per neighborhood > store as *households* attribute on neighborhoods layer.

The buffer created from the proximity analysis in step 6 will be used to sum the number of address points within each neighborhood. This count will be joined to the neighborhoods road network layer and stored as the *households* attribute.

8. Calculate household-to-exit ratio for each neighborhood from *Exit Count* and *households* attributes.

Using the *households* count attribute from step 7 and the *Exit Count* attribute from step 5, the crucial households-to-exit ratio can be calculated for each neighborhood

Analysis Objective 2: Calculate the risk of wildfire at the neighborhood scale from the TWRA Wildfire Threat and WUI Response Index layers.

9. Create convex hull minimum bounding geometry polygons from step 6 buffers to complete neighborhood polygons (see Figure 7).

For the purpose of performing an overlay analysis between the neighborhoods and the TWRA WUI Response Index and Wildfire Threat layers, a polygon representing each neighborhood is needed. This requires considering how to estimate the spatial extent of a neighborhood. The most accurate estimation of each neighborhood would likely be to make use of a countywide dataset of parcels and to select all the parcels intersecting the neighborhoods road layer. This would be an accurate representation, but it requires an additional dataset.

Adding another dataset would increase the processing time and perhaps more importantly, it reduces the greater applicability of the methods created here. This methodology hinges on the use of public road network and address point datasets set to the NENA NG9-1-1 data standard. This standard was created and has steadily grown in application since 2014 (URISA 2021). Because of the widespread use of the NG9-1-1 data model, the methodology created here has the potential to be applied broadly among municipal, county, or state governments, and while a countywide dataset of parcels exists for Hays County, this may not be true across other areas of potential study. Considering the broader applicability of these methods, I argue that a spatial estimation of the extent of each neighborhood, a convex hull minimum bounding geometry, will suffice. A convex hull polygon is defined as the smallest convex polygon that encloses a set of

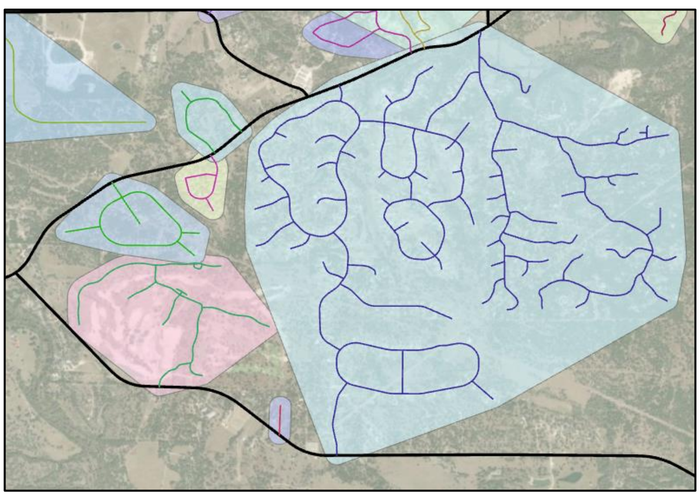

Figure 7 Neighborhood Convex Hull Minimum Bounding Geometry Polygons

points or objects (Wade and Sommer 2006). This technique will be used on each neighborhood buffer polygon from step 6 to create neighborhood polygons representing the extent of each neighborhood.

10. Overlay Texas A&M Forest Service WUI Response Index, and Wildfire Threat layers onto neighborhood polygons and calculate for each neighborhood the percent of neighborhood

polygon area covered by each index level of the WUI Response Index and Wildfire Threat layers (see figures 8A and 8B). For example: *27% of the Rim Rock neighborhood is in the index level 7 high wildfire threat area and 73% is in the index level 6 medium threat level.*

Overlying the Wildfire Threat and WUI Response index layers onto the neighborhood polygons and then assigning to each neighborhood the portion of each threat level that overlies the neighborhoods will provide the necessary characteristics to assess the combined risk of wildfire and constrained evacuation.

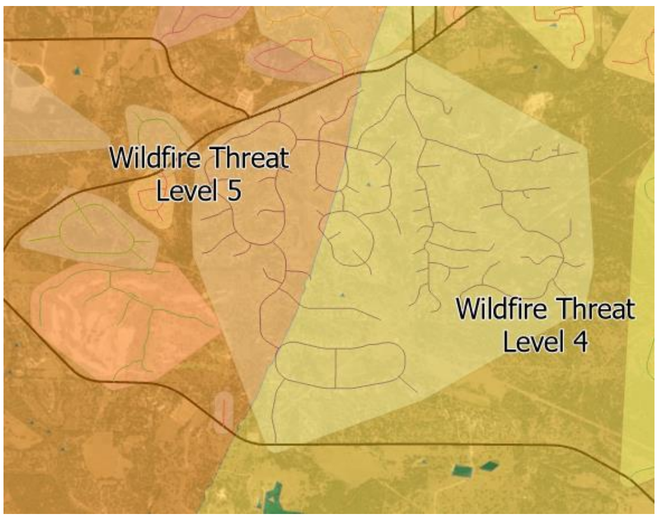

Figure 8A Wildfire Threat Layer Overlay

Figure 8B Wildfire Threat Layer apportioned to neighborhoods

Analysis Objective 3: Rank neighborhoods based on their combined risk of wildfire and constrained evacuation.

11. Rank neighborhoods by combined threat of constrained evacuation and wildfire potential.

Having quantified the household-to-exit ratio and assessed the risk of wildfire, the final ranking of Hays County neighborhoods at-risk of the combined threat of constrained evacuation and wildfire can be made. This will be done in three steps. First, the neighborhoods will be ranked based on their wildfire potential by arranging the neighborhoods in descending order by their primary level of wildfire threat set by the overlay of the TWRA Wildfire Threat layer- descending from class 7 "Very High" threat to class 1 "Low" threat (Texas A&M Forest Service 2022a). In this way, the neighborhoods that face the highest potential of, "a wildfire occurring or burning into" the area will be ranked highest (Texas A&M Forest Service 2022a). Next, a second rank within each the 7 groupings of wildfire threat will be made based on the overlay of the WUI Response Index layer. The WUI Response Index represents "potential impact of a wildfire on people and their homes" (Texas A&M Forest Service 2022a). Within each of the 7 wildfire threat classes, the neighborhoods that face the highest potential impact from wildfire will be ranked highest. Finally, all neighborhoods that meet the 200 households-to-exit threshold set by Cova et al. will be extracted and ranked in descending order of households-to-exits (Cova et al. 2013).

By ranking the neighborhoods in this way, the most at-risk neighborhoods will be defined as those that: 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. Face the highest potential impact on people and their homes from said fire, and 3. Meet the threshold for, and have the highest value of being at-risk of constrained evacuation.

4.3 Limitations

The primary limitation of this method relates to the determination of the neighborhood household-to-exit ratio. The CCM developed by Church and Cova does not rely on a set of pre-defined neighborhoods, the model *defines* neighborhoods by searching a road network (Church and Cova 2000). 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 required by the NG9-1-1 standard can be populated. This means that only designed 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. However, for the officially named and designated neighborhoods, the calculation of households-to-exit is perhaps more accurate, and the method as a whole is more viable of being implemented broadly due both to its ability to be run inside a traditional GIS and its reliance on publicly available road datasets.

A second, lesser limitation is that the methods presented here do not consider road network impedance such as lane capacity or travel time as does the CCM and other evacuation models such as the Capacity Aware Shortest Path Evacuation Routing (CASPER) model (Church and Cova 2000, Manliguez et al. 2017). However, the CCM which this method is adapted from, only uses the impedance in defining neighborhoods and not in the final calculation of households-to-exits (Church and Cova 2000). And the purpose of models like CASPER are for evacuation *routing*, which neither the CCM nor the methods presented here are directly concerned with.

Finally, this method relies heavily on the accuracy of the *Neighborhood* attribute in publicly available datasets. Preliminary testing has shown that this will require thorough data cleaning to account for individual street segments missing or given an inaccurate neighborhood designation. While the rest of the workflow for this model can be automated, these corrections will have to be done manually (though the search for inaccuracies could be automated). This will add a considerable amount of time in the application of the method.

5 Conclusion

The rapidly expanding Wildland-Urban Interface land-use type is a growing problem for urban and emergency planners due to the risk of wildfire created by the adjacency of human development and flammable vegetation (Radeloff et al. 2005, Radeloff et al. 2018). The risk of wildfire in the WUI is compounded by the expected increase in drought severity caused by climate change and a lack of adequate road infrastructure to accompany the rapid housing growth (Church and Cova 2000, Cova 2005, Jolly et al. 2015, Schoennagel et al. 2017). With communities being built with upwards of 500 households per community road network exit, there exists the potential for a difficult and disastrous wildfire evacuation (Church and Cova 2000, Cova 2005, Cova et al. 2013). Together, the risk of wildfire and the lack of infrastructure in the WUI create a potentially disastrous situation and it is suspected that the rapid growth into the Hays County WUI has allowed for the development of such at-risk communities (Texas A&M Forest Service 2022a).

To address this concern, my research asks: within the fire-prone Hays County Wildland-Urban Interface, which communities face the highest potential of disaster due to the compound risk of wildfire and constrained evacuation? To answer this question, I employ the GIS techniques of spatial analysis, proximity analysis, and spatial overlay to compute the community household-to-exit ratios and to quantify the wildfire risk level at the neighborhood scale. It is expected that several Hays County neighborhoods will reach the 200 households-to-exit threshold set by Cova et al. as being at-risk of constrained evacuation, and that many of these neighborhoods will be in areas at a high risk of a potential wildfire, as determined by the Texas A&M Forest Service (Cova et al. 2013).

This research will contribute to the literatures of wildfire risk in the wildland-urban interface and community evacuation analysis. The GIS method adapted by this research broadly impacts the field of urban planning and emergency management in that the simplified methods for determining a household-to-community-exit ratio developed here can be computed in a traditional GIS and with datasets that are widely available. This research more directly impacts the Hays County communities identified as being at-risk of a potentially disastrous wildfire evacuation and Hays County planning and emergency response departments.

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