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Mapping wildfire evacuation vulnerability in the western US: the limits of infrastructure

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Abstract Residential development in fire-prone areas of the western United States is a growing concern. The steady addition of homes to this region places more people and property at risk each year. In many areas housing is increasing without commensurate improvements in the road network, particularly in regards to the number, capacity and arrangement of community exit roads. This results in steadily increasing minimum evacuation times, as each additional household contributes to potential evacuation travel-demand in a wildfire. The goal of this research is to perform a comprehensive geographic search of the western U.S. for communities in wildfire-prone areas that may represent difficult evacuations due to constrained egress. The problem is formulated as a spatial search for fire-prone communities with a high ratio of households-to-exits and solved using methods in spatial optimization and geographic information systems (GIS). The results reveal an initial inventory and ranking of the most difficult wildfire evacuations in the West. These communities share a unique vulnerability in that all residents may not be able to evacuate in scenarios with short warning time. For this reason they represent prime candidates for emergency planning, and monitoring their development is a growing need.

Keywords Evacuation · Wildfire · Transportation

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Introduction

Residential development in fire-prone areas of the western U.S. (hereafter referred to as the West) is a growing concern. The ongoing addition of homes to areas in or near wildlands (commonly referred to as the wildland-urban interface or WUI) places more people and property at risk each year (Cohen 2000; Haight et al. 2004; Radeloff et al. 2005; Spyratos et al. 2007). Theobald and Romme (2007) estimate that residential development in fire-prone areas in the West expanded by 52% from 1970 to 2000, and the WUI now constitutes more than 12.5 million homes on 465,000 km^2. At the same time, climate change is altering the drought cycle through precipitation and temperature regimes leading to an increase in fire frequency and associated forest consumption (Westerling et al. 2006). Stephens et al. (2009) credit exurban development in fire prone areas combined with extreme, drought-induced wildfire events for a geometric increase in structure loss in recent decades.

In most cases housing units are added to fire-prone canyons and hillsides without improving the road infrastructure. This means that although new roads may be added to a community to support the development of additional homes, an improvement in the number, direction, and capacity of the primary exits is much less common. This has implications for future evacuations, as exiting roads can place a significant constraint on clearing a community of its residents in an urgent scenario, or one with little warning time (Lindell and Perry 2004; Gill and Stephens 2009). In short, the minimum evacuation time of a community increases incrementally with each new household, as its occupants may contribute to potential evacuation travel demand in a wildfire (Cohn et al. 2006; Dash and Gladwin 2007; Mozumder et al. 2008). At the same time, there is growing concern that the fuel to support an intense wildfire in many communities is accumulating from the addition of wood structures, as well as the suppression of wildfires near populated areas. For this reason, Schoennagel et al. (2009) concluded that strengthening evacuation planning is needed in the WUI, as well as assisting public agencies in coordinating fuel-reduction treatments.

The primary result of the tandem increase in fuel and minimum evacuation times is a steady spiral upward in fire hazard and human vulnerability (Cutter et al. 2000) in many communities. This has been laid bare by enormous losses in recent wildfire events throughout the West, many of which also demonstrate that urgent evacuations can be impeded by limited road infrastructure. Two recent examples include the 2008 Tea Fire and 2009 Jesusita Fire in Santa Barbara County. The Tea Fire, which started just north of the town of Montecito, allowed proximal households less than an hour to evacuate, leading to the extreme case where Westmont College chose to recommend shelter-in-place in a gymnasium for an estimated 800 students, as there was not enough time to ensure that all students could safely leave on the campus roads before the fire arrived. In the 2009 Jesusita Fire, which started just north of the city of Santa Barbara, traffic congestion occurred during an evacuation of Mission Canyon when residents that had been monitoring the fire for days were caught off guard by a sudden increase in the fire's spread-rate and intensity toward their community. This resulted in highly concentrated evacuation travel demand on narrow roads in low visibility due to smoke.

Given this tandem increase in threat (fuel) and exposure (housing and residents) in fire-prone communities throughout the West, emergency planning and mitigation is a growing need (Perry 1985; Tierney et al. 2001; Platt 2006). The level of preparedness among the residents of these areas varies substantially, as evacuation planning is not required in fire-prone communities in the U.S. However, there are many efforts underway, local to national, to address the broader problem of ongoing development in fire-prone areas from many perspectives (Moritz and Stephens 2008). One step toward improving the allocation of planning and response resources in the WUI is a comprehensive geographic assessment of the potential for road infrastructure to impede an evacuation. For example, what fire-prone communities in the West have relatively few exits and a high density of housing units? How are these communities distributed across the eleven states that make up the West? What canyons and hillside communities represent the worst (most constrained) potential evacuations in the West? Answers to these questions would help initially focus emergency planning efforts and resources on communities with the greatest need (Cova and Johnson 2002; Church and Sexton 2002; Wolshon and Marchive 2007; Chen and Zhan 2008).

The goal of this research is to systematically search the western U.S. for fire-prone communities that have the greatest potential to experience evacuation problems due to road infrastructure constraints. Although this geographic variation has been studied at the scale of an individual city (Cova and Church 1997; Church and Cova, 2000), a broad-scale search and comparison of communities across the 11 Western U.S. states represents uncharted territory. The next section provides background on the problem including a discussion of concepts and prior work. The "Methods" Section reviews the data sources, pre-processing and spatial optimization modeling. The "Results" Section presents the findings, and the paper concludes with a discussion of the strengths, weaknesses, implications and potential for further research.

Background

The problem of performing a search for neighborhoods that may be difficult to evacuate due to constraints imposed by road infrastructure was presented by Cova and Church (1997). The concept of *egress*, or a means of exiting an area, is central to this work. The process of developing measures of egress is similar to developing spatial accessibility measures in general, but with a particular focus on the ease (or lack of ease) with which a threatened population can leave an area in an emergency. The initial measure applied in this work was the ratio of population in an area (demand) to the number of lanes in the set of exit roads (supply). This was extended to the concept of "bulk lane demand" where the numerator was changed to an estimate of the number of vehicles that might be used in a worst-case evacuation (i.e. the case where most of the community is at home) (Church and Cova 2000). While egress is rarely the binding constraint in evacuations as most events allow sufficient lead time to clear an area safely, it can represent a bottleneck in urgent scenarios when travel demand exceeds the capacity of the roads (Cova and Johnson 2002).

One of the initial problems in searching for neighborhoods with a high demand-to-capacity ratio is the definition of an "exit" when the evacuation zone boundary is not pre-defined (Cova 2005). One way to approach this problem is to search for the most constraining bottleneck-set (exit links) for a set of contiguous intersections (nodes). This set of network arcs that connects the nodes to the rest of the network is referred to as the minimum "cut set" in graph theory, as it represents the fewest arcs that, when removed, separate a node set (community) from the rest of the road network. For example, if a community has only one exit, the cut-set is easily identified as this link, but if there are two or more exits, the search for the minimum cut-set in a complex road network is a combinatorial optimization problem. If the minimum cut-set is large (e.g. 5 or more arcs), then the community that depends on these arcs would not generally be considered constrained by road infrastructure in an evacuation, but this depends to a large degree on the housing density, the configuration of the road network, and the urgency of an evacuation scenario (i.e. travel demand in space and time).

To address the combinatorial search for neighborhoods that might be difficult to evacuate from the set of all possible evacuations, Cova and Church (1997) presented an integer programming (IP) model called the Critical Cluster Model (CCM). The focus of this model is maximizing the ratio of population-to-exits for a fixed "root node" and associated scale limit (in nodes) in a larger network. While the CCM defined the problem, it can only be solved optimally on very small networks, and the search in real (larger) road networks is performed with a heuristic region-growing algorithm. This algorithm treats each node in a road network as a separate local problem by posing the question, "What is the worst-case evacuation (greatest ratio of population-to-exits) that this node might experience within a limited scale?" Scale in this context is defined as a node limit that represents a form of network-based search window. Thus, an example search might entail finding the set of contiguous intersections (nodes) that represents the worst-case evacuation (greatest demand to exiting lanes) within which a household assigned to that intersection (or node) might experience.

The CCM and associated region-growing heuristic were originally applied to a city network on the order of 5,000 nodes. Given that each node represents a separate sub-problem in a road network, the procedure can be applied to a network of any size. In other words, the computational effort to solve the CCM for each node is not an exponential function of the total number of nodes in the network. Rather, it is a linear function of the number of nodes, as a network of n nodes requires the heuristic to be solved n times, once at each node. However, the heuristic process is an exponential function of the search window (in nodes). For example, as the search window around a given node is expanded, the solution time to find the node-set that maximizes the ratio of demand (e.g. population, vehicles, housing) to supply (e.g. exiting roads) increases exponentially. Thus, the search can be performed on a network of any size, but the time to solve a given instance of the problem increases rapidly with the scale limit (or search window). Nonetheless, with a reasonably sized search window and modern desktop computing power, a much larger network can be analyzed than addressed in prior studies.

Methods

Study area and data

The primary challenge in this project is the extent of the study area. In moving from the city-scale to the eleven western U.S. states, the initial hurdle was acquiring and pre-processing the required data sets.

Two layers were needed—one representing the fire hazard at a level of detail sufficient enough to assign a hazard level to each node in a road network, and one representing the road network itself with each housing unit (single or multi-family structure) assigned to its closest intersection (or node). The general approach was to use the fire-hazard layer to screen the road network data, so as to only include roads in fire-prone areas—or a WUI roads layer. This greatly reduced the size of the road network by screening urban areas that have little to no wildfire risk. For example, the downtown centers of major cities (e.g. Denver, Phoenix, and San Francisco) were not included in the WUI road data set because they are not prone to wildfires. Other more remote areas with little to no fire hazard (e.g. agricultural land, deserts) were also removed, but these areas typically have sparse roads, so this reduction had less impact on the size of the resulting WUI roads layer (nodes and arcs) than the removal of urban areas. We used a national roads database (ESRI StreetMap 2006), which was pre-processed and separated into 12 files (10 states and Southern and Northern California).

The fire-hazard map used in this study is the LANDFIRE dataset (Rollins 2009), which is a 30-m resolution map with fire-hazard categories assigned to each cell. We based the fire hazard on the fire regime categories III and IV—or vegetation types that are characterized by low to stand-replacing severity with a 35–200-year fire frequency. The fire-hazard level of each intersection (node) in the road network was calculated as the proportion of fire-prone raster cells within a 2-mile radius of each node. This yields a 0–1 scale from no fire-hazard (0) to extreme fuel loads in a node's surroundings (1).

We estimated the number of housing units that would evacuate from each intersection (node) in the road network using the method presented in Cova and Church (1997). Thiessen polygons were computed for the network node layer and the number of housing units in each polygon was interpolated using equal-area weighting. To represent housing units, we used estimates based on U.S. Census 2000 block-level data and refined by land ownership, land cover, groundwater well density, and travel time to urban areas (Theobald 2005; Theobald and Romme 2007; Bierwagen et al. 2010). The resulting 1-hectare resolution raster of housing units was re-sampled to 30-m to ensure that a Thiessen polygon formed around each node would not fall below the resolution of the fire hazard map.

Critical cluster model and region growing heuristic algorithm

The heuristic algorithm used in this research begins at a root node and incrementally adds nodes on the (contiguous) fringe of the existing cluster (node set). The fringe is comprised of all nodes that are adjacent to the current cluster at any iteration by one arc (or link). The objective function that the heuristic attempts to maximize is the ratio of housing units in a node cluster (potential demand) to the road capacity that connects it to the rest of the network (supply):

$$\max \frac{P_k}{C_k} \tag{1}$$

where P_k is the total number of housing units in cluster k and C_k is the total link capacity connecting the cluster to the rest of the network. Additional constraints in the CCM include: (1) the root node must be included in the cluster, (2) the cluster must be contiguous, and (3) the cluster must be limited in size (nodes). These constraints can be handled with a region-growing algorithm that begins at a given (root) node and terminates at a pre-defined cluster size (in nodes). In general, a network-based region-growing algorithm begins at a node (constraint 1), grows by adding nodes on the fringe of the current cluster (constraint 2), and terminates when a given cluster size is reached (constraint 3).

At each step the algorithm evaluates all nodes on the fringe of the current cluster using the following growth function (or rule):

$$g_i = \frac{C_k(P_k - a_i)}{P_k(C_k + (o_i - c_i))} \tag{2}$$

where:

i = index of nodes
k = index of iteration
g_i = gain in the objective if node i is selected
P_k = total population of cluster at iteration k
C_k = total exit capacity of cluster at iteration k
a_i = population at node i
o_i = new exit capacity node i would open, if selected

c_i = existing exit capacity node i would close, if selected

This function assigns a value g_i to each node on the fringe of the current cluster (at each iteration) to specify the gain in the objective value if that node is selected. The algorithm can be run in a straight greedy fashion, in which case the node that most increases the objective function (Eq. 1) is selected, but Cova and Church (1997) demonstrated that a semi-greedy approach (Hart and Shogan 1987) consistently yielded the best results. In this approach, a parameter α is added to the algorithm to allow the selection of the best node to be within α percent of the node with the greatest gain value, which is also known as a GRASP approach (Feo and Resende 1989). The algorithm is then re-started n times from each root node, and the best overall run is saved (i.e. the one with the greatest objective value). One other improvement can be made in that any optimal cluster found from a given root-node can be automatically assigned to all the constituent nodes of that cluster. For this reason, an optimal cluster (i.e. constrained evacuation) will be found in a network if any of its constituent (root) nodes discovers it.

Results

The search for potentially difficult wildfire evacuations across the West due to limited road infrastructure yielded a wide variety of densely populated communities with high fire-hazard and relatively low egress. The search was accomplished by separating the 11 states that comprise the West (AZ, CA, CO, ID, MT, NM, NV, OR, UT, WA, WY) into 12 files, one for each state but two for CA because of its size in terms of nodes and arcs (NoCal and SoCal). The scale limit was set to 100 nodes (or intersections) for the search which means the process was capable of finding relatively complex communities up to 100 contiguous intersections. However, this means that if a low-egress community has over 100 intersections, it would be missed in the search. The implications of this threshold are that changing the scale-limit would yield a different ranking of low-egress communities because larger ones could be included that were not seen at a smaller scale limit. However, this limitation would exist at any selected threshold, and for the purposes of this project, 100 nodes was deemed a sufficient scale limit to locate the low-egress communities that had been discovered visually in prior manual searches.

Table 1 summarizes the input data, which represented a significant geo-computational challenge (Cutter 2003). The data for each state consists of an ESRI Shapefile™ of the road network with node attributes that include the fire-hazard for each node and the respective number of housing units assigned to that node (i.e. closest assignment from Thiessen polygons). This GIS-based data was used to generate a network text-file for input into the heuristic algorithm described in Section "Methods". The heuristic algorithm was set to run in a semi-greedy fashion with 25 re-starts at each node and an alpha parameter of 0.90, and the run times ranged from 15 to 60 min depending on the number of nodes in a given file (i.e. file sizes ranged from Wyoming at 97,980 nodes to SoCal at 481,899). The results of the algorithm runs were then rejoined to the appropriate Shapefile™ for each state to visualize and map the results.

Another challenge in performing this search was defining the minimum fire hazard that must be present in a community for it to qualify as "wildfire prone" and the minimum level of egress for it to be considered a "constrained" evacuation. Initial searches without regard to the fire-hazard level in a community yielded thousands of low-egress communities, many that would not be considered fire-prone. The higher the threshold

Table 1 A summary of the network input data for the 11 western states

State	Nodes	Arcs	Housing units	Mean fire hazard
AZ	206,381	261,776	418,346	0.64
SoCal	481,899	638,032	6,438,861	0.63
NoCal	171,406	209,408	968,636	0.50
CO	196,720	234,151	413,066	0.73
ID	192,480	238,915	398,382	0.74
MT	162,594	189,335	218,789	0.72
NM	202,263	249,134	334,235	0.64
NV	97,980	123,664	186,303	0.69
OR	310,886	360,412	927,770	0.70
UT	162,206	196,011	493,514	0.70
WA	299,781	368,642	1,522,378	0.67
WY	123,186	161,842	97,401	0.81
Total	2,607,782	3,231,322	12,417,680	

that defines the minimum required fire-hazard for a given node cluster (or community) to be considered wildfire-prone, the fewer communities that will found. Similarly, the higher the threshold that defines the minimum ratio of households-to-exits for a community to be considered a “constrained” evacuation, the fewer communities that will be returned. To develop an initial list of communities, we set the median fire hazard in a community (node set) to a minimum of 0.7 on a scale of 0–1 and the minimum ratio of households-to-exits to 200 (e.g. a community with 200 homes and 1 exit). The median fire-hazard threshold was more effective than the mean fire hazard because many nodes had a fire hazard level of 0, and the mean is very sensitive to outliers. This yielded a host of communities with relatively high fire-hazard and low egress in regards to an urgent evacuation scenario (Fig. 1).

While the dots in Fig. 1 depict the spatial clustering and arrangement of some of the communities that were found, Figs. 2, 3, 4 show a representative selection of communities. Figure 2 depicts the Glen Oaks Canyon subdivision in Glendale, California. This community has an estimated 776 homes and 1 exit (776/1 = 776 households-per-exit). Figure 3 depicts the Dillon Lake Area of Silverthorne, Colorado which has an estimated 743 homes and 2 exits (743/2 = 371.5 homes per exit). Figure 4 shows Bryant Ranch in Yorba Linda, California which has an estimated 1,222 homes and 3 exits (1,222/3 = 407.3 homes per exit). All three of these communities met the minimum wildfire-hazard level to qualify as fire-prone, but the actual fuel loads in and around each community returned by the search varied significantly. However, these three cases provide sufficient evidence that, despite the large extent of the search (11 states) relative to the level of detail (individual intersections and street segments), the approach presented locates communities that would represent challenging wildfire evacuations.

Tables 2, 3 and 4 show the top communities that were found across the West sorted by the objective value of the ratio of households-to-exits. The tables are separated into communities with 1-exit, 2-exits and 3-exits because the infrastructure vulnerability of these three sets of communities is qualitatively different. While a community with 2 or 3 exits might have a higher ratio of households-to-exits than one with 1 exit, the additional exits provide the community with a backup plan if one (or more) exits is lost to a wildfire or traffic accident. Communities with one exit would be in a shelter-in-place only (e.g. active home-defense) scenario if the sole exit was removed (Handmer and Tibbits 2005; Paveglio et al. 2008; McCaffrey and Rhodes 2009; Cova et al. 2009; Stephens et al. 2009).

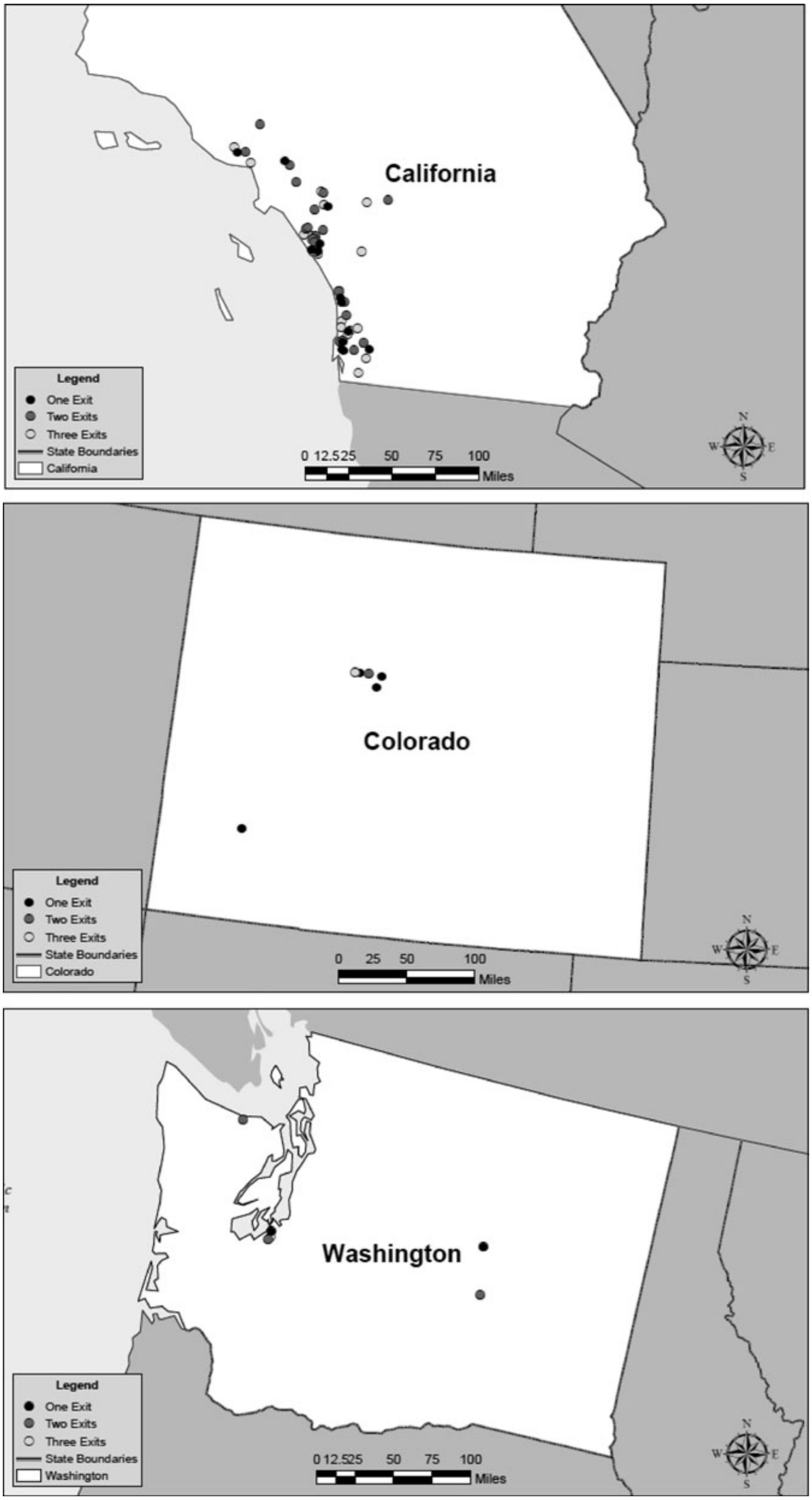
A dominant theme in these tables is the prevalence of Southern Californian (SoCal) communities in the ranking. SoCal has a very unique combination of high fire-hazard, dense population, and topographic constraints that has resulted in scores (if not hundreds) of fire-prone, low-egress developments. Although other western states (including Northern California) may have a similar combination of wildfire hazard and low egress in isolated locales, no region in the West comes close to the widespread coincidence of fire and egress factors present in Southern California.

Discussion

This work provides the first analysis of fire-prone, low-egress communities for a broad geographic extent. The results provide a rigorous comparison of communities in the arid West that may be useful for prioritizing efforts to mitigate or monitor the risk of wildfire events to canyon and hillside communities. Although the findings using this approach were promising, the results of the search can only be considered an initial step toward enumerating and ranking fire-prone, low-egress communities in the U.S. We caution that there are many hurdles in terms of data quality, methods, and validation that stand in the way of strong statements regarding the completeness or quality of the resulting list. This limitation arises primarily from the extent of the study area (11 western states) relative to the level of detail of the analysis (intersections).

From a data quality perspective, there are many issues to be addressed. GIS-based street network data can have missing links and nodes which can lead to results that differ significantly from reality. For example, a missing exit in the network data might lead a 2-exit community to appear as a 1-exit community in the computed ranking, effectively doubling its ratio of households-to-exits. The housing data is also dated and should be updated to the 2010 U.S. Census. From a methodological point of view, there are a number of sources of error and uncertainty that can lead to limitations in the results. This spans many step of the

Fig. 1 Fire-prone, low-egress communities (1–3 exits) in California, Colorado and Washington



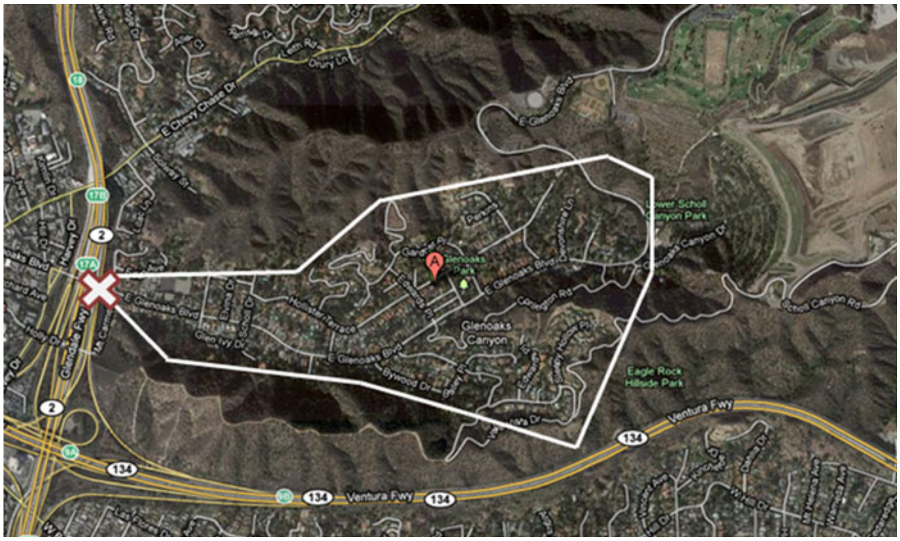


Fig. 2 The Glen Oaks Canyon subdivision in Glendale, CA has an estimated 776 homes and 1 exit (*Image source*: Google Maps)

Fig. 3 The Dillon Lake Area in Silverthorne, CO has a community with an estimated 743 homes and 2 exits (*Image source*: Google Maps)

process from: (1) the creation and assignment of fire-hazard levels to the network nodes (Finney 2005), (2) the assignment of housing units to nodes, and (3) the heuristic nature of the search algorithm.

Another source of uncertainty arises from using housing units as a proxy for travel demand in an emergency without including the time-dependency of the presence of residents. Many of the communities that were found in this search are ski resorts and country clubs, as these facilities can have a very high density of housing units and few exits. This is generally due to either their topographic context or a desire for social exclusivity. For the ski-resort case, occupancy levels during the peak fire season in the northern hemisphere (May–Oct) may be much lower (e.g. less than 50%) than the winter months, but summer use in these areas is increasing (Riebsame et al. 1996). This makes housing units an imperfect measure of potential wildfire-evacuation travel-demand. In terms of the country-club example, the fire hazard may not be as high as the method in this paper implies because the landscaped vegetation in many of these areas is not very fire prone. These issues among others represent fertile areas for improving the overall search process and comparison of fire-prone, low-egress communities.

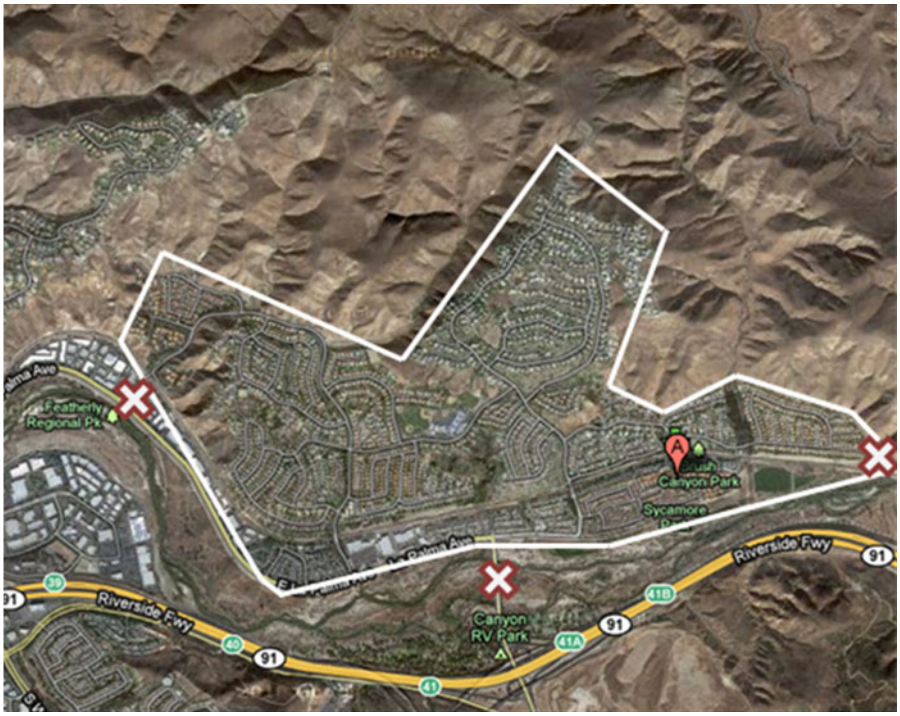


Fig. 4 Bryant Ranch in Yorba Linda, CA has an estimated 1,222 homes and 3 exits (*Image source*: Google Maps)

Conclusion

The WUI now comprises a large and growing number of homes, and many of these communities have relatively few exits and a growing housing density. The goal of this research was to perform a comprehensive geographic search for fire-prone, low-egress communities in the West. The results yielded a wide variety of communities across 11 states with an egress ratio of greater than 200 households-to-exits (and in select cases much higher). These communities represent challenging evacuations in cases when warning time is short. Although we presented an initial ranking of communities that represent the most

Table 2 The top communities in the West with median fire hazard above 0.7 (0–1) and 1 exit

Rank	Nodes	Fire haz	Homes	Exits	Homes-to-exits	Lat	Long	State
1	57	0.75	806.4	1	806.4	33.167	−117.134	SoCal
2	59	0.70	803.6	1	803.6	33.192	−117.319	SoCal
3	64	0.90	776.7	1	776.7	34.152	−118.211	SoCal
4	79	0.95	755.9	1	755.9	39.627	−106.417	CO
5	51	0.84	748.3	1	748.3	39.619	−106.100	CO
6	75	0.88	630.7	1	630.7	39.593	−106.010	CO
7	47	0.81	597.1	1	597.1	39.474	−106.058	CO
8	66	0.86	571.7	1	571.7	32.941	−117.158	SoCal
9	13	0.74	560.2	1	560.2	34.169	−118.530	SoCal
10	44	0.83	552.7	1	552.7	33.150	−117.291	SoCal
11	9	0.77	535.4	1	535.4	39.501	−106.158	CO
12	23	0.88	527.6	1	527.6	47.201	−122.514	WA

Table 2 continued

Rank	Nodes	Fire haz	Homes	Exits	Homes-to-exits	Lat	Long	State
13	31	0.82	514.9	1	514.9	33.881	−117.661	SoCal
14	85	0.84	501.2	1	501.2	33.000	−117.184	SoCal
15	93	0.84	500.4	1	500.4	37.932	−107.855	CO
16	41	0.89	467.8	1	467.8	34.130	−118.723	SoCal
17	41	0.75	467.0	1	467.0	47.49	−122.693	WA
18	35	0.77	458.4	1	458.4	32.833	−116.898	SoCal
19	8	0.79	457.0	1	457.0	32.778	−117.181	SoCal
20	43	0.85	441.3	1	441.3	33.229	−117.141	SoCal
21	19	0.75	436.5	1	436.5	35.144	−106.546	NM
22	19	0.75	435.3	1	435.3	33.572	−117.653	SoCal
23	20	0.76	434.2	1	434.2	34.115	−117.765	SoCal
24	3	0.71	428.5	1	428.5	34.726	−120.511	SoCal
25	5	0.77	425.2	1	425.2	47.11	−122.582	WA
26	22	0.86	423.7	1	423.7	33.746	−117.924	SoCal
27	9	0.77	423.2	1	423.2	33.508	−117.721	SoCal
28	24	0.80	416.7	1	416.7	32.945	−117.206	SoCal
29	49	0.84	399.2	1	399.2	33.559	−117.695	SoCal
30	5	0.90	394.9	1	394.9	33.819	−118.013	SoCal
31	11	0.76	394.7	1	394.7	32.772	−117.170	SoCal
32	19	0.70	394.0	1	394.0	33.660	−117.644	SoCal
33	11	0.88	389.4	1	389.4	32.922	−117.114	SoCal
34	22	0.82	383.0	1	383.0	32.789	−117.181	SoCal
35	100	0.77	378.9	1	378.9	40.624	−111.488	UT
36	38	0.88	375.4	1	375.4	47.551	−119.452	WA
37	25	0.75	373.3	1	373.3	32.784	−117.159	SoCal
38	38	0.74	372.8	1	372.8	33.517	−117.657	SoCal
39	20	0.89	370.6	1	370.6	32.850	−117.187	SoCal
40	9	0.77	368.2	1	368.2	32.837	−116.903	SoCal

Table 3 The top communities in the West with median fire hazard above 0.7 (0–1) and 2 exits

Rank	Nodes	Fire haz	Homes	Exits	Homes-to-exits	Lat	Long	State
1	64	0.77	1,865.1	2	932.6	34.410	−118.452	SoCal
2	60	0.74	1,862.1	2	931.1	33.617	−117.716	SoCal
3	90	0.73	1,729.5	2	864.8	33.686	−117.652	SoCal
4	5	0.84	1,717.8	2	858.9	47.121	−122.526	WA
5	88	0.83	1,558.7	2	779.4	33.161	−117.265	SoCal
6	64	0.81	1,353.7	2	676.8	32.807	−117.056	SoCal
7	37	0.74	1,322.8	2	661.4	33.598	−117.705	SoCal
8	100	0.97	1,287.2	2	643.6	39.640	−106.405	CO
9	72	0.74	1,145.7	2	572.9	32.872	−116.973	SoCal
10	58	0.70	1,125.1	2	562.5	33.492	−117.671	SoCal
11	32	0.71	1,098.5	2	549.3	33.739	−117.847	SoCal

Table 3 continued

Rank	Nodes	Fire haz	Homes	Exits	Homes-to-exits	Lat	Long	State
12	60	0.81	1,002.4	2	501.2	33.595	−117.735	SoCal
13	78	0.84	939.8	2	469.9	33.230	−117.350	SoCal
14	89	0.82	907.7	2	453.9	32.847	−117.224	SoCal
15	43	0.78	889.5	2	444.7	33.661	−117.831	SoCal
16	100	0.75	866.2	2	433.1	33.824	−117.786	SoCal
17	16	0.83	865.2	2	432.6	32.918	−117.139	SoCal
18	45	0.88	852.4	2	426.2	32.858	−117.192	SoCal
19	68	0.81	835.5	2	417.8	33.535	−117.670	SoCal
20	43	0.87	830.5	2	415.2	34.147	−118.827	SoCal
21	100	0.94	790.9	2	395.5	48.075	−123.375	WA
22	82	0.90	773.1	2	386.5	34.147	−118.638	SoCal
23	69	0.70	772.1	2	386.1	34.198	−118.917	SoCal
24	77	0.93	766.7	2	383.4	32.908	−117.066	SoCal
25	33	0.78	764.9	2	382.5	33.673	−117.815	SoCal
26	54	0.81	756.4	2	378.2	33.571	−117.710	SoCal
27	50	0.72	751.0	2	375.5	34.390	−118.560	SoCal
28	57	0.74	745.8	2	372.9	33.970	−117.739	SoCal
29	68	0.86	734.6	2	367.3	39.630	−106.288	CO
30	60	0.80	733.3	2	366.7	32.961	−117.231	SoCal
31	64	0.76	733.0	2	366.5	33.662	−117.976	SoCal
32	100	0.74	716.7	2	358.4	33.505	−117.636	SoCal
33	44	0.76	710.9	2	355.4	33.496	−117.697	SoCal
34	99	0.71	687.9	2	344.0	47.135	−119.323	WA
35	95	0.91	686.3	2	343.1	33.063	−117.215	SoCal
36	8	0.98	678.6	2	339.3	34.124	−118.148	SoCal
37	61	0.85	676.5	2	338.2	33.550	−117.729	SoCal
38	16	0.87	676.0	2	338.0	32.937	−117.116	SoCal
39	6	0.80	674.4	2	337.2	34.030	−117.056	SoCal
40	40	0.73	661.8	2	330.9	34.007	−118.042	SoCal

Table 4 The top communities in the West with median fire hazard above 0.7 (0–1) and 3 exits

Rank	Nodes	Fire haz	Homes	Exits	Homes-to-exits	Lat	Long	State
1	91	0.79	4,700.3	3	1,566.8	33.767	−118.086	SoCal
2	76	0.75	2,070.9	3	690.3	33.607	−117.715	SoCal
3	39	0.86	1,557.4	3	519.1	47.142	−122.504	WA
4	51	0.80	1,517.2	3	505.7	33.603	−117.737	SoCal
5	80	0.76	1,264.7	3	421.6	33.582	−117.207	SoCal
6	90	0.83	1,241.9	3	414.0	32.947	−117.141	SoCal
7	94	0.87	1,228.5	3	409.5	33.981	−117.765	SoCal
8	77	0.76	1,221.9	3	407.3	33.877	−117.702	SoCal
9	90	0.83	1,152.2	3	384.1	33.612	−117.750	SoCal
10	47	0.79	1,147.9	3	382.6	33.777	−118.387	SoCal

Table 4 continued

Rank	Nodes	Fire haz	Homes	Exits	Homes-to-exits	Lat	Long	State
11	91	0.81	1,131.1	3	377.0	33.233	−117.337	SoCal
12	71	0.74	1,119.7	3	373.2	33.220	−117.310	SoCal
13	100	0.92	1,108.4	3	369.5	34.137	−118.660	SoCal
14	98	0.79	1,103.8	3	367.9	33.633	−117.569	SoCal
15	86	0.86	1,102.8	3	367.6	39.62	−106.488	CO
16	64	0.83	1,098.0	3	366.0	33.614	−117.836	SoCal
17	74	0.70	1,083.6	3	361.2	32.634	−116.958	SoCal
18	48	0.82	1,080.4	3	360.1	33.515	−117.689	SoCal
19	88	0.83	1,077.1	3	359.0	32.755	−116.915	SoCal
20	89	0.79	1,075.5	3	358.5	33.497	−117.703	SoCal
21	34	0.85	1,073.3	3	357.8	33.756	−117.910	SoCal
22	99	0.74	1,070.3	3	356.8	34.435	−118.484	SoCal
23	99	0.88	1,059.4	3	353.1	34.009	−117.791	SoCal
24	100	0.78	1,059.3	3	353.1	33.975	−117.265	SoCal
25	87	0.88	1,053.5	3	351.2	33.004	−117.248	SoCal
26	81	0.77	1,052.6	3	350.9	32.916	−117.159	SoCal
27	47	0.74	1,045.1	3	348.4	33.783	−118.128	SoCal
28	100	0.77	1,040.9	3	347.0	39.716	−105.171	CO
29	97	0.70	1,040.0	3	346.7	33.490	−117.647	SoCal
30	59	0.83	1,007.0	3	335.7	33.585	−117.742	SoCal
31	31	0.74	1,003.1	3	334.4	33.508	−117.668	SoCal
32	45	0.74	1,000.1	3	333.4	32.980	−117.070	SoCal
33	59	0.73	994.4	3	331.5	32.957	−117.239	SoCal
34	76	0.74	972.7	3	324.2	34.043	−117.859	SoCal
35	34	0.80	962.7	3	320.9	47.262	−122.521	WA
36	59	0.84	958.8	3	319.6	33.875	−117.630	SoCal
37	85	0.87	951.3	3	317.1	34.074	−118.560	SoCal
38	89	0.79	944.5	3	314.8	34.163	−118.768	SoCal
39	66	0.80	918.3	3	306.1	32.643	−117.045	SoCal
40	90	0.79	909.7	3	303.2	33.681	−117.636	SoCal

constrained cases in terms of road infrastructure, a significant amount of work remains in improving the overall search process and associated results. In the longer term, there is a need to identify and rank these communities to target them for emergency planning, as well as to encourage local governments to consider the public safety implications of unchecked development in fire-prone areas.

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References

Bierwagen, B.G., Theobald, D.M., Pyke, C.R., Choate, A., Groth, P., Thomas, J.V. Morefield, P (2010) National housing and impervious surface scenarios for integrated climate impact assessments. *PNAS* doi/10.1073/pnas.1002096107.

Chen, X., & Zhan, F. B. (2008). Agent based modeling and simulation of urban evacuation: Relative effectiveness of simultaneous versus staged evacuation strategies. *Journal of the Operational Research Society, 59*(1), 25–33.

Church, R. L., & Cova, T. J. (2000). Mapping evacuation risk on transportation networks using a spatial optimization model. *Transportation Research Part C: Emerging Technologies, 8*(1–6), 321–336.

Church, R.L., and Sexton, R.M. (2002) Modeling small area evacuation: Can existing transportation infrastructure impede public safety? Online: <http://www.ncgia.ucsb.edu/vital/research/pubs/200204-Evacuation.pdf>.

Cohen, J. D. (2000). Preventing disaster: Home ignitability in the wildland-urban interface. *Journal of Forestry, 98*(3), 15–21.

Cohn, P. J., Carroll, M. S., & Kumagai, Y. (2006). Evacuation behavior during wildfires: Results of three case studies. *Western Journal of Applied Forestry, 21*(1), 39–48.

Cova, T. J. (2005). Public safety in the urban-wildland interface: Should fire-prone communities have a maximum occupancy? *Natural Hazards Review, 6*(3), 99–108.

Cova, T. J., & Church, R. L. (1997). Modelling community evacuation vulnerability using GIS. *International Journal of Geographical Information Science, 11*(8), 763–784.

Cova, T. J., Drews, F. A., Siebeneck, L. K., & Musters, A. (2009). Protective actions in wildfires: Evacuate or shelter-in-place? *Natural Hazards Review, 10*(4), 151–162.

Cova, T. J., & Johnson, J. P. (2002). Microsimulation of neighborhood evacuations in the urban-wildland interface. *Environment and Planning A, 34*(12), 2211–2229.

Cutter, S. L. (2003). GIScience, disasters and emergency management. *Transactions in GIS, 7*(4), 439–446.

Cutter, S. L., Mitchell, J. T., & Scott, M. S. (2000). Revealing the vulnerability of people and places: A case-study of Georgetown, South Carolina. *Annals of the Association of American Geographers, 90*(4), 713–737.

Dash, N., & Gladwin, H. (2007). Evacuation decision making and behavioral responses: Individual and household. *Natural Hazards Review, 8*(3), 69–77.

Feo, T. A., & Resende, M. G. C. (1989). A probabilistic heuristic for a computationally difficult set covering problem. *Operations Research Letters, 8*(2), 67–71.

Finney, M. A. (2005). The challenge of quantitative risk analysis for wildland fire. *Forest Ecology and Management, 211*(1), 97–108.

Gill, A. M., & Stephens, S. L. (2009). Scientific and social challenges for the management of fire-prone wildland-urban interfaces. *Environmental Research Letters, 4*(3), 10 p.

Haight, R. G., Cleland, D. T., Hammer, R. B., et al. (2004). Assessing fire risk in the wildland-urban interface. *Journal of Forestry, 102*(7), 41–48.

Handmer, J., & Tibbits, A. (2005). Is staying at home the safest option in bushfires? Historical evidence for an Australian approach. *Environment Hazards, 6*(2), 81–91.

Hart, J. P., & Shogan, A. W. (1987). (1987) Semi-greedy heuristics: An empirical study. *Operations Research Letters, 6*(3), 107–114.

Lindell, M. K., & Perry, R. W. (2004). *Communicating environmental risk in multiethnic communities*. Sage Publications: Thousand Oaks.

McCaffrey, S. M., & Rhodes, A. (2009). Public response to wildfire: Is the Australian stay and defend or leave early approach an option for wildfire management in United States? *Journal of Forestry, 107*(1), 9–15.

Moritz, M. A., & Stephens, S. L. (2008). Fire and sustainability: Considerations for California's altered future climate. *Climatic Change, 87*(1), 265–271.

Mozumder, P., Raheem, N., Talberth, J., & Berrens, R. P. (2008). Investigating intended evacuation from wildfires in the urban-wildland interface: Application of bivariate probit model. *Forest Policy and Economics, 10*(6), 415–423.

Paveglio, T., Carroll, M. S., & Jakes, P. J. (2008). Alternatives to evacuation—protecting public safety during wildland fire. *Journal of Forestry, 106*(2), 65–70.

Perry, R. W. (1985). *Comprehensive emergency management: Evacuating threatened populations*. Greenwich, Conn: JAI Press.

Platt, R. V. (2006). A model of exurban land-use change and wildfire mitigation. *Environment and Planning B: Planning and Design, 33*(5), 749–765.

Radeloff, V. C., Hammer, R. B., Stewart, S. I., Fried, J. S., Holcomb, S. S., & McKeefry, J. F. (2005). The wildland-urban interface in the United States. *Ecological Applications, 15*(3), 799–805.

Riebsame, W. E., Gosnell, H., & Theobald, D. M. (1996). Land use and landscape change in the Colorado mountains I: Theory, scale, and pattern. *Mountain Research and Development, 16*(4), 395–405.

Rollins, M. (2009). LANDFIRE: A nationally consistent vegetation, wildland fire and fuel assessment. *International Journal of Wildland Fire, 18*(3), 235–249.

Schoennagel, T., Nelson, C. R., Theobald, D. M., Carnwath, G. C., & Chapman, T. B. (2009). Implementation of national fire plan treatments near the wildland-urban interface in the western U.S. *Proceedings of the National Academy of Sciences, 106*(26), 10706–10711.

Spyratos, V., Bourgeron, P. S., & Ghil, M. (2007). Development at the wildland-urban interface and the mitigation of forest-fire risk. *Proceedings of the National Academy of Sciences of the United States of America, 104*(36), 14272–14276.

Stephens, S. L., Adams, M., Handmer, J., Kearns, F., Leicester, B., Leonard, J., et al. (2009). Urban-wildland fires: How California and other regions of the US can learn from Australia. *Environmental Research Letters, 4*(1), 5 p.

Theobald, D. M. (2005). Landscape patterns of exurban growth in the USA from 1980 to 2020. *Ecology and Society, 10*(1), 32 p.

Theobald, D. M., & Romme, W. (2007). Expansion of the U.S. wildland urban interface. *Landscape and Urban Planning, 83*(4), 340–354.

Tierney, K. J., Lindell, M. K., & Perry, R. W. (2001). *Facing the unexpected: Disaster preparedness and response in the United States*. Washington, DC: Joseph Henry.

Westerling, A. L., Hidalgo, H. G., Cayan, D. R., & Swetnam, T. W. (2006). Warming and earlier spring increases Western U.S. forest wildfire activity. *Science, 313*(5789), 940–943.

Wolshon, B., & Marchive, E., I. I. I. (2007). Emergency planning in the urban-wildland interface: Subdivision-level analysis of wildfire evacuations. *Journal of Urban Planning and Development, 133*(1), 73–81.