Natural Hazards (2021) 107:911–935
https://doi.org/10.1007/s11069-021-04615-x

ORIGINAL PAPER

Evaluating rural Pacific Northwest towns for wildfire evacuation vulnerability

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Received: 11 September 2019 / Accepted: 28 January 2021 / Published online: 11 February 2021

Abstract

Wildfire is an annual threat for many rural communities in the Pacific Northwest region of the United States. In some severe events, evacuation is one potential course of action to gain safety from an advancing wildfire. Since most evacuations occur in a personal vehicle along the surrounding road network, the quality of this network is a critical component of a community's vulnerability to wildfire. In this paper, we leverage a high-resolution spatial dataset of wildfire burn probability and mean fireline intensity to conduct a regional-scale screening of wildfire evacuation vulnerability for 696 Oregon and Washington rural towns. We characterize each town's surrounding road network to construct four simple road metrics related to the potential to quickly and safely evacuate: (1) the number of paved lanes leaving town that intersect a fixed-distance circular buffer; (2) the variety of lane directions available for egress; (3) the travel area that can be reached within a minimum distance while constrained only to movement along the paved road network; and (4) the sum of connected lanes at each intersection for the road network within a fixed-distance circular buffer. We then combine the road metrics with two metrics characterizing fire hazard of the surrounding landscape through which evacuation will occur: (1) burn probability and (2) mean fireline intensity. By combining the road and fire metrics, we create a composite score for ranking all towns by their overall evacuation vulnerability. The most vulnerable towns are those where poor road networks overlap with high fire hazard. Often, these towns are located in remote, forested, mountainous terrain, where topographic relief constrains the available road network and high fuel loads increase wildfire hazard. An interactive map of all road quality and fire hazard metrics is available at https://www.fs.fed.us/wwetac/brief/evacuation.php.

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Keywords Wildfire · Evacuation · Oregon · Washington · Rural · Road networks

1 Introduction

Wildfire is a natural part of many ecological systems, but population growth in the western U.S. has heightened human interactions with burnable landscapes, resulting in hazards including property loss and death (Moritz et al. 2014; Keeley 2017). Researchers are more frequently suggesting a people-centric approach to wildfire planning, with a focus on limiting loss of life and property (Keeley and Syphard 2019, Kolden and Henson 2019, Schoennagel et al. 2017). The human aspect of wildfire hazard has moved into the spotlight in recent years, with large fires spurring evacuation, personal injury, and loss of life and property: see, for example, the 2018 Camp Fire in Butte County, California, which killed 88 people (CalFire 2018a), the cluster of large fires that encroached the wildland-urban interface of southern and central California in 2017 (Nauslar et al. 2018), the mass evacuations forced by the 2016 Fort McMurray fire in Alberta (McGee 2019), and the September 2020 wildfire season in the Oregon Cascades (The Oregonian, 2020a; The Oregonian, 2020b). Understandably, significant resources are being invested to map potential impacts of wildfire on communities at the state and federal level (e.g., Colorado State Forest Service 2018; CalFire 2018b; Gilbertson-Day et al. 2018; Scott et al. 2020), in academic research (e.g., Haas et al. 2013; Cova et al. 2013; Ager et al. 2015), and in investigative journalism (e.g., Larson and Wagner 2019).

For remote rural communities embedded in forest, shrublands, and grasslands of western North America, wildfire remains a perennial threat to personal safety. Wildfire impacts on rural communities can be assessed in terms of vulnerability, considering the combined hazard and resilience (Vaillant et al. 2016). By relying primarily on physical forces driving wildfire—e.g., weather, topography, and fuels—wildfire hazard is more straightforward to quantify than resilience. Recently, high-resolution raster (120 m x 120 m) spatial wildfire hazard datasets have become available for many parts of the United States, including the Pacific Northwest (Gilbertson-Day et al. 2018; Scott et al. 2020). These datasets capture burn probability and fireline intensity calculated from high-resolution stochastic simulations of wildfire ignition and spread. While these data quantify hazard, they do not capture resilience, nor the ability of people affected to react to fire. Resilience to wildfire hazard has contributing variables, including socio-economic status, infrastructure, mobility, and housing density of the community (Davies et al. 2018; Gilbertson-Day et al. 2018; Nielsen-Pincus et al. 2019). When a wildfire forces a community to evacuate, the quality of the road evacuation network becomes a major component of resilience.

Because a wildfire evacuation has so many prior unknowns, including if, when, and where to evacuate, definitively linking drivers of fire spread with the uncertainties of evacuation is difficult. Evacuation scenarios depend on a combination of official policy, individual priorities, perception of the hazard, sufficient infrastructure, and the degree of wildfire hazard (Cova et al. 2009, Paveglio et al. 2012; Drews et al. 2014; McCaffrey et al. 2018). For most self-sufficient evacuations, the spatial constraints of egress options are determined by the availability of roads conducive to travel in a personal vehicle (Murray-Tuite and Wolshon 2013). Despite the uncertainties of predicting wildfire evacuation vulnerability, communities would benefit from awareness of potential evacuation options before wildfire becomes an imminent threat. Residents can then make informed, premeditated decisions about whether evacuation is the best course of action during a wildfire and identify what evacuation options are available.

One of the most effective ways to convey evacuation potential is through map-based analyses (Steelman et al. 2015; Cao et al. 2016). Effective map-based analyses invoke a variety of methods, scales, and approaches. One approach is transportation network modeling, which simulates the outflow of vehicles along a road network during a specific evacuation scenario. Variations of network modeling approaches have been successfully applied to individual communities, including Julian, CA (Dennison et al. 2007; Li et al. 2019), Colorado Springs, CO (de Araujo et al. 2014), Santa Barbara, CA (Cova and Church 1997), Summit Park, UT (Wolshon and Marchive 2007), and Emigration Canyon, UT (Cova and Johnson 2002). However, transportation simulations are costly to perform in terms of input data required and computing resources; for this reason, they often require other necessary concessions, such as limiting the analysis to a single community. One exception to this is a west-wide study published by Cova et al. (2013), where intensive evacuation network simulations were performed across a large spatial domain; however, because the spatial domain is so large, most of the results and conclusions are understandably dominated by southern California communities, with less consideration given to less densely populated rural towns where wildfire hazard is still high.

While individual household- and car-based traffic simulations are ideal for evaluating egress routes for individual communities under specific scenarios, regional-scale analyses can screen for communities where high fire probability, high fireline intensity, and poor evacuation potential coincide, allowing prioritization of communities for further investigation. To this end, we designed and applied a regional-scale geographic analysis method to assess the road network quality of 696 rural communities across Oregon and Washington, U.S.A. In this approach, we calculated four basic metrics based on the quality of the surrounding road network, substituting the computational expense of individual household- and car-based traffic simulations for the advantages of an efficient, regional-scale screening tool. Then, we combined these four road metrics with each town's wildfire hazard to construct rankings of overall vulnerability.

To our knowledge, a simple, regional-scale, geographic assessment of wildfire evacuation vulnerability does not exist formally in the scientific literature for the Pacific Northwest. Likely, this omission is due to the difficulty of defining a single measure of evacuation vulnerability that applies across all communities; we mitigate this problem by calculating multiple metrics that each describe unique aspects of a town's evacuation vulnerability. On its own, a single metric is unlikely to fully capture the evacuation vulnerability of a town; but, by combining an ensemble of metrics with a geographic examination of a town's road network, we can evaluate alternative aspects of each town's egress network at a heretofore unpublished regional scale. Assessing wildfire vulnerability is complicated, and our work is certainly not the final, definitive doctrine; nor do we advise for or against evacuation during wildfire. Rather, we hope that our analyses will be a starting point that stimulates further refinements and innovations of evaluating community wildfire evacuation at the regional scale.

2 Methods

To perform our regional analysis, we obtained the most current spatial maps of rural communities, road networks, and wildfire hazard. Then, we calculated four road quality metrics to capture the basic features of the surrounding road network that could potentially be used for evacuation, and two wildfire hazard metrics to characterize the surrounding wildfire hazard. Each of the data layers and the metrics are described below.

2.1 Data layers

2.1.1 Towns and roads

We used the U.S. Census Bureau cartographic boundary shapefiles to derive spatial locations of Oregon and Washington census-designated places (US Department of Commerce, 2017a and b). Census-designated places are communities for which the U.S. Census Bureau maintains boundaries; many unincorporated rural towns do not have official boundaries and are thus not included in this version of our analysis. In the original shapefile, each town is drawn as a polygon representing its boundary; we converted each town into a single point by calculating each polygon's centroid. For all analyses, we consider this center point as the starting point for wildfire evacuations. Clearly, representing each town as a single point does not fully indicate individual home locations, but for smaller rural towns without significant urban spread, we consider it to be a simple and useful designation suitable to our purposes.

We used a road layer obtained internally through the U.S. Forest Service that incorporates detailed network information from HERE Technologies and the U.S. Department of Homeland Security. This layer was considered most complete upon evaluation against other widely available road datasets. We retained only paved roads from this layer, assuming this as the absolute minimum requirement for a road to be considered a potential evacuation option.

2.1.2 Rural town designations

To identify rural towns only, we used the University of Washington Rural Health Research Center's zip code approximation of rural–urban commuting areas (RUCA), version 2.0 (ZIP Code RUCA Approximation Methodology 2005). RUCA 2.0 zip code level data are linked to the original census tract level data produced by the U.S. Department of Agriculture (USDA 2005). A zip code's degree of rurality is categorized on a 10-point scale that incorporates travel patterns based on 2000 US Census Bureau commuting data and 2004 zip codes. Since our spatial scale of analysis is the town, this made the designations simpler to assign. In QGIS v3.4.9 (QGIS Development Team), we performed a spatial intersection with the town point shapefile and the U.S. Census Bureau 5-Digit Zip Code Tabulation Areas shapefile (US Department of Commerce, 2017c) to assign each town a zip code, and then joined the corresponding zip code with its numeric RUCA designation. In cases where a town had multiple zip codes, we used the one that overlapped the town's centerpoint. To define rural towns only, we excluded towns that were designated in RUCA as a "Metropolitan area core: primary flow within an urbanized area" (e.g., large metropolitan areas like Portland, Seattle, and Bend), producing a final dataset of 696 towns.

2.2 Road network quality screening metrics

We analyzed the quality of the road network within the immediate area surrounding a town. For example, all roads within a certain distance from the center of a town might be considered as potential evacuation corridors. We calculated all metrics using a distance rule of 15 km from each town's center point. Whereas others have adjusted their vulnerability metrics by population (e.g., Scott et al. 2018), this will amplify the vulnerability of more populated over less populated areas; we decided not to adjust by population to avoid reducing the vulnerability of sparsely populated areas that may otherwise get overlooked. Although 15 km distance rules are used for final presentation of results and discussion, we also performed a simple sensitivity analysis of metrics calculated using 10 km and 25 km distance rules.

2.2.1 Exit capacity vulnerability metric

The exit capacity metric summarizes the number of lanes that are available at a fixed distance from a town's center point. With the QGIS "Buffer" tool, we constructed a circular fixed-distance buffer line surrounding each town (QGIS Development Team). Then, using the "Line Intersect" tool, we created a point layer of paved road lanes intersecting the buffer, which we refer to as "exits." Because the buffer is straight-line distance, not road travel distance, the intersection may include roads that are not actually reachable from the town's center point (e.g., towns on the Oregon side of the Columbia River appear to have exits on the Washington side of the river, even when a bridge is not available). To minimize this problem, we first constructed a 50 km travel area (details for travel area constructed are described in Sect. 2.2.3) for each town and intersected these roads with the buffer so that only exits that can physically be reached from the town's center point are recorded.

2.2.2 Road directionality vulnerability metric

The road directionality metric is based on the idea of flexible evacuation planning (Montz et al. 2012). Towns with a larger variety of potential exit directions have better flexibility during a wildfire evacuation. Evacuating toward the advancing wildfire front is generally not an option; more available exit directions means that a town could have a variety of other, safer choices.

With the QGIS "Hub Lines" tool, we constructed a set of straight lines connecting each town's center point with each of its exit lanes. The final directionality metric was calculated as the circular variance of all azimuths of a town's hub lines, using the circular variance function in the R package "circular," which coerces data to a circular classification (Agostinelli and Lund 2017). Higher variances indicate more diverse directionality, and thus better exit flexibility. We note that variance does not always perform well on bimodal circular data, for example a town with two exits at 0° and 180°, but for our initial screening purposes we have accepted this drawback. A brief example of how variance can alter the directionality metric is provided in Appendix 1.

2.2.3 Travel area vulnerability metric

The travel area metric quantifies travel distance along a network rather than straight-line distance (Guttierez et al. 2008; Kermanshah and Derrible 2017; O'Neill et al. 1992).

This is an important distinction when evaluating the road evacuation network, since egress conducted in a personal vehicle will be constrained along these roads. Essentially, the travel area contains the maximum set of places that can be reached within a specified distance from a starting point while traveling exclusively along the path of a network. Although more computationally demanding than counting exits intersecting a fixed-distance buffer, the travel area could present a more complete representation of the egress road network, since it better represents the curviness of roads exiting a town. For example, in a town where exit roads are straight, the travel area will be larger than a town where exit roads are windy; alternatively, the fixed-distance buffer will not make this distinction as both towns will have the same number of exits.

Using the “Service Area” tool in the QGIS “Network Analysis” plug-in, we calculated travel areas along the paved road network starting from each town’s center point, where each point was initially snapped to the nearest road segment. We then created a convex hull bounding polygon surrounding the outer edge of each travel area network; the area, in square kilometers, of each town’s bounding polygon is the travel area metric. The area of the bounding polygon is simply a way to summarize the travel area. Towns with a larger travel area are considered less vulnerable—the larger the travel area, the more potential road space is available to drive farther away from the town. The maximum 15 km travel area would approximate the area of the 15 km fixed-distance buffer circle, with straight roads emanating out in all directions in an "asterisk" shape.

2.2.4 Connectivity vulnerability metric

The connectivity vulnerability metric is established based on the concept of connectivity in network analysis. Well-connected streets provide efficient accessibilities to possible destinations and directions (Handy et al. 2003). In addition, better connectivity also helps to improve the quality of emergency responses, especially wildfires. This metric quantifies the road connectivity, which summarizes the total number of connected lanes at each road intersection. A higher value indicates better flexibility, greater emergency access, and higher possibility of improved service efficiency during a wildfire evacuation.

We use the Line and Junction Connectivity tool in ArcGIS Pro (available at https://www.arcgis.com/home/item.html?id=3fa41b1f8b764879be8f21b4e7ffbabd) to calculate the connectivity vulnerability metric. The tool returns road intersections as points, with an attribute showing the total number of connected lanes at each intersection. To evaluate the connectivity vulnerability for each town, we use 15 km fixed-distance buffer circles to spatially join the intersection point layer separately. For the intersections overlapped with a fixed-distance buffer circle, we sum up the number of connected lanes for all these intersections as connectivity per town. This returned value of connectivity indicates the total number of connected lanes within a fixed distance around a town’s center point.

2.3 Wildfire hazard screening metrics

We used a raster layer for Oregon and Washington that maps the annual burn probability (BP) and mean fireline intensity (MFI) of large fires for each 120 m × 120 m pixel

(Gilbertson-Day et al. 2018). This layer was produced by running 10,000—60,000iterations of FSim, a stochastic, spatially aware wildfire simulation model (Finney et al. 2011). FSim applies historical wildfire occurrence and weather data to simulate ignition and spread and has been used across the western U.S. to evaluate wildfire hazard to people and resources (e.g., Scott et al. 2012; Haas et al. 2013; Thompson et al. 2013). The BP and MFI layers were generated using landscape and fuels from the 2014 version of Landfire, meaning that any post-2014 wildfires are not included in the simulations.

2.3.1 Burn probability vulnerability metric

Using BP from FSim has one singular advantage over other ways to represent landscape fire probability, in that FSim stochastically simulates spread of thousands of fires under a range of plausible weather conditions and ignition locations based on historical wildfire and weather of a particular region. Wildfire probability in evacuation modeling studies is typically not represented in this way. For example, Li et al. (2019) used spatially explicit simulations of wildfire spread toward the town of Julian, CA with the model FlamMap (Finney 2006), an approach similar to FSim, but which only allows simulations under a single scenario of fixed weather parameters. And, Cova et al. (2013) designated wildfire hazard according to Landfire land cover categories (Rollins 2009), which reflects potential burnability based on the expected historical wildfire regime without a stochastic spread component. Now that an FSim BP grid is available for Oregon and Washington, it provides another angle for incorporating wildfire into evacuation analyses. In these rasters, annual BP of each 120 m x120m pixel is defined as the number of times that a pixel burns divided by the number of iterations, or “fire years,” simulated by FSim. Using the "Zonal Statistics" tool in QGIS, we calculated the mean BP of all raster cells within each town’s fixed-distance circular buffer.

2.3.2 Mean fireline intensity vulnerability metric

Fireline intensity measures the rate of energy released by the burning fuels along the fire’s front (Rothermel 1972). It is calculated in FSim following Rothermel (1972) for surface fires and Scott and Reinhardt (2001) for crown fires. Fireline intensity will vary for a given pixel based on fuel moisture, fuel type, wind speed, and the direction the fire approaches the pixel (backing, flanking, or heading) (Finney et al 2011). In this work, we used the mean fireline intensity (MFI) output from FSim, which gives the mean intensity of each pixel. While many forested pixels will burn sometimes as a surface fire and other times as a crown fire, the MFI, combined with burn probability, can be used as a rough measure by which to compare hazard across different sites (i.e., Scott et al., 2012). MFI does not indicate anything about fire effects (severity), but has been shown to be a useful metric in wildfire response settings (Keeley 2009). A site with a low MFI will generally experience fires that are easier to contain and pose less risk to highly valued resources (such as homes) than a site with a high MFI. However, any individual fire may be an exception to this rule, since a site with relatively low MFI may have the potential to experience a high-intensity fire while a site with a high MFI may also experience low-intensity fires under some weather conditions. As a rule, though, the MFI can be used to indicate sites with higher versus lower hazard. High MFI is often indicative of forested areas that experience crown fire, a phenomenon likely to launch embers, a frequent cause of house loss (Cohen 2000). We used a 120 m x 120 m resolution raster layer of mean fireline intensity provided in the same report described in Sect. 2.3.1 (Gilbertson-Day et al 2018). To construct the metric, we calculated the mean MFI of all raster pixels within each town's fixed-distance circular buffer.

2.4 Overall vulnerability metric

To enable construction of an overall metric, we first normalized each of the individual metrics to a scale of 0 to 1. Whereas lower values for road metrics indicate higher vulnerability (i.e., poorer road quality), high values for fire metrics indicate higher vulnerability (i.e., higher hazard); for this reason, we inverted the fire metrics before performing the normalization so that all metrics could be interpreted on the same scale. These normalized scores are primarily useful for comparing rankings of towns across metrics and should not be interpreted as raw values (i.e., a town with a normalized score of 0.4 does not necessarily indicate twice the vulnerability of a town with a score of 0.8). For each town, we calculated an overall vulnerability metric as follows: $\mathrm{OV} = \mathrm{mean}\left[\mathrm{Road\ Quality, Fire\ Hazard}\right]$, where OV is overall vulnerability, road quality is the mean of exit capacity, directionality, travel area, and connectivity, and fire hazard is the mean of burn probability and mean fireline intensity. In this way, the road and fire metrics each contribute 50% to the overall vulnerability rankings.

We then order all towns by their normalized metrics to create rankings 1 – 696, where 1 is highest overall vulnerability/poorest road quality/highest fire hazard. We subsequently divide the town ranking into quartiles: Highest overall vulnerability/poorest road quality/highest fire hazard (Towns ranked 1 – 174); High overall vulnerability/poor road quality/high fire hazard (ranks 175 – 348); Low overall vulnerability/good road quality/low fire hazard (ranks 349 – 522); and lowest overall vulnerability/best road quality/lowest fire hazard (ranks 523 – 696). For clarity, towns are also discussed in terms of these rankings, rather than solely in terms of their normalized metrics.

2.5 Cluster analysis of towns

To identify natural clusters for summarizing the six-vulnerability metrics, we applied the k-means, an unsupervised clustering algorithm (MacQueen 1967, DATAtab Statistics Calculator https://datatab.net), to the normalized metric values. The analysis identified four clusters. Although the initial centroids of the clusters are randomly chosen, repeating the analysis did not yield significantly different results.

3 Results

3.1 Road quality

Road quality contributes 50% of the overall vulnerability equation and consists of equal parts exit capacity, directionality, travel area, and connectivity (Fig. 1a). Towns that have the highest road vulnerability have the poorest combined road quality in the four contributing road metrics. The five towns with the worst road quality are as follows: 1) Lonerock, OR (1st in exit capacity, 1st in directionality, 6th in travel area, 2nd in connectivity); 2) Conconully, WA (3rd in exit capacity, 2nd in directionality, 10th in travel area, 13th in

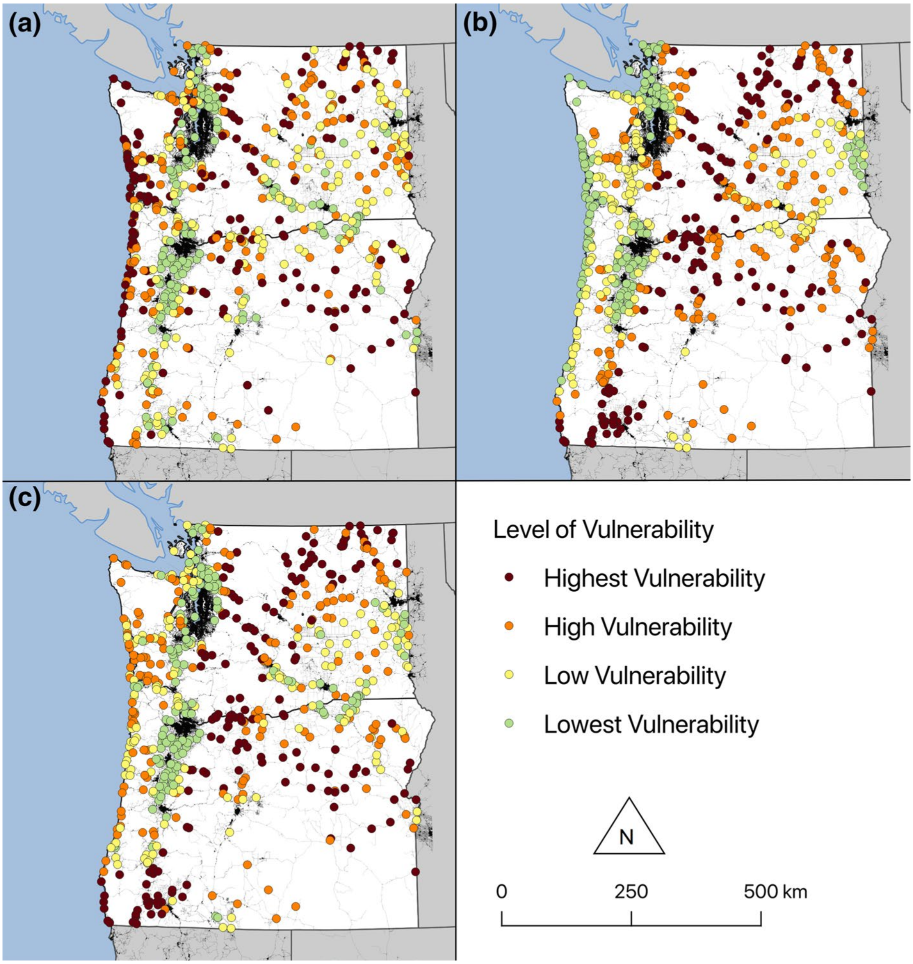

Fig. 1 Geographic distribution of ranked quartiles for **a** road quality, **b** wildfire hazard, and **c** overall vulnerability for 696 rural Pacific Northwest towns. Towns are colored by quartile (174 towns per quartile). Road quality is the average of the exits, directionality, travel area, and connectivity metrics, where "highest vulnerability" indicates the poorest road metrics, and "lowest vulnerability" indicates the best road metrics. Wildfire hazard is the average of the burn probability and mean fireline intensity metrics, where "highest vulnerability'' indicates highest hazard, and "lowest vulnerability" indicates lowest hazard. Overall vulnerability is the average of road quality and wildfire hazard

connectivity); 3) Laurier, WA (6th in exit capacity, 11th in directionality, 1st in travel area, 1st in connectivity); 4) Disautel, WA (3rd in exit capacity, 4th in directionality, 36th in travel area, 3rd in connectivity); and 5) Skykomish, WA (2nd in exit capacity, 3rd in directionality, 60th in travel area, 31st in connectivity). Note that exit capacity is constrained to whole numbers (e.g., a town can have 1 or 2 exits, but not 1.2 or 1.3 exits). For this reason, towns such as Conconully and Disautel both rank 3rd in exit capacity, since they both have 3 exits.

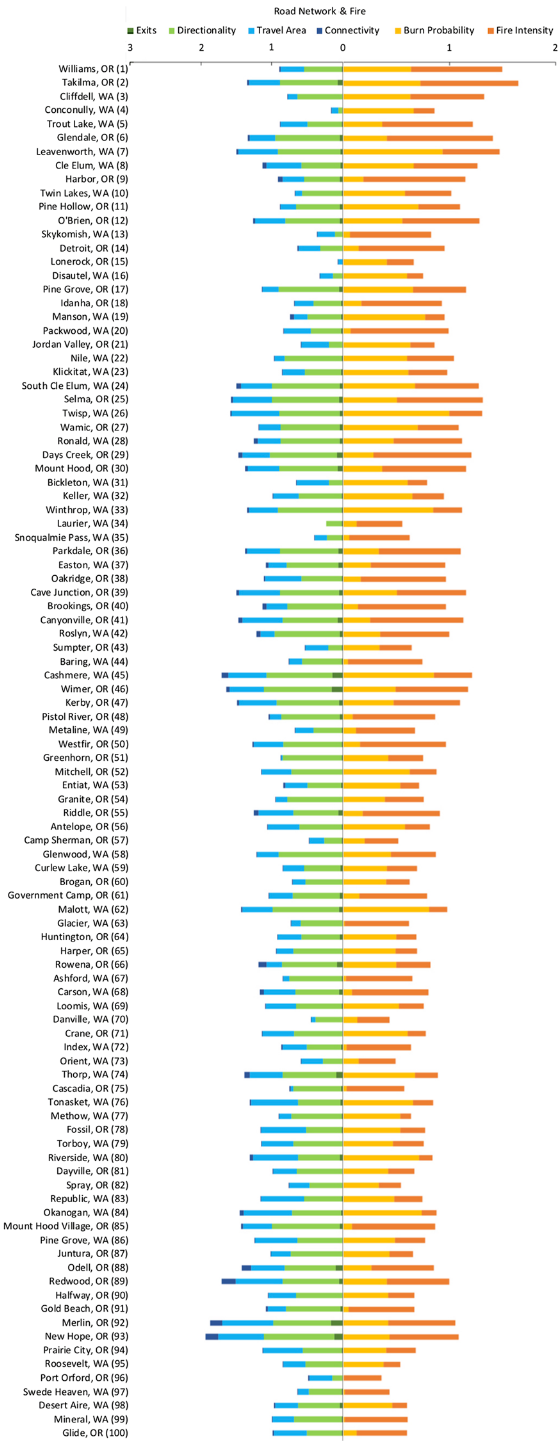

Fig. 2 Hundred most vulnerable towns, ranked from highest overall vulnerability (top) to the lowest overall vulnerability (bottom). Normalized road quality metrics are displayed on the left, and normalized wildfire hazard metrics are on the right. Note that with road quality metrics, shorter bars represent poorer quality, while with the fire hazard metrics, shorter bars represent lower hazard

3.2 Wildfire hazard

Wildfire hazard contributes 50% of the overall vulnerability equation, and consists of equal parts BP and MFI (Fig. 1b). Towns with the highest wildfire hazard have relatively high BP and MFI. The five towns with the highest wildfire hazard are: 1) Takilma, OR (8th in BP, 3rd in MFI); 2) Williams, OR (22nd in BP, 7th in MFI); 3) Leavenworth, WA (2nd in BP, 54th in MFI); 4) Glendale, OR (85th in BP, 1st in MFI); and 5) Cliffdell, WA (24th in BP, 25th in MFI).

3.3 Overall vulnerability

Towns ranking highly in overall vulnerability are those with both poor road quality and high wildfire hazard (Figs. 1c, 2). The five towns with the highest overall vulnerability are as follows: 1) Williams, OR (56th in road quality, 2nd in wildfire hazard); 2) Takilma, OR (240th in road quality, 1st in wildfire hazard); 3) Cliffdell, OR (34th in road quality, 5th in wildfire hazard); 4) Conconully, WA (2nd in road quality, 56th in wildfire hazard); and 5) Trout Lake, WA (55th in road quality, 11th in wildfire hazard).

An interactive map of road quality, wildfire hazard, and overall vulnerability of all 696 towns included in this analysis is available at https://www.fs.fed.us/wwetac/brief/evacuation.php, and a text dataset of all metrics is provided in Appendix 2.

3.4 Clustering of towns

The *k*-means cluster analysis identified four clusters (Fig. 3). These clusters can be used as a way to visualize and interpret natural groupings of towns according to their combined metrics. Cluster 1 comprises towns with some of the most limited road networks that are located in generally high fire hazard areas. Its member towns have few exits and the poorest connectivity. The directionality and travel area of towns in Cluster 1 range widely, although the median values are the poorest for directionality and the second poorest for travel area, among the four clusters. The two fire hazard metrics for Cluster 1 also range widely, but the

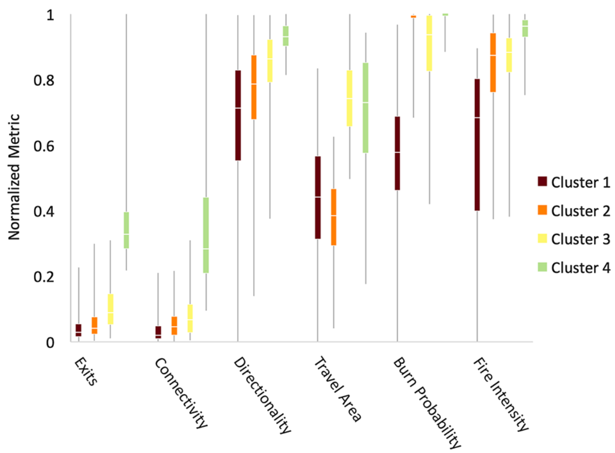

Fig. 3 K-means cluster analysis of the six individual metrics. Four clusters were identified from normalized vulnerability metrics. The distributions of metric values within each cluster are plotted as box plots. Colored boxes represent the two middle quartiles, where the break between the two boxes represent the median. The lines extending above and below the colored boxes represent the highest and the lowest quartiles, respectively. Clusters are numbered arbitrarily. Lower metric values represent higher vulnerability

two metrics have the lowest median among the four clusters, representing high vulnerability in both fire metrics. A few towns in this cluster have high hazard in both BP and MFI. For example, Takilma, OR, ranks 8th and 3rd, respectively in the two metrics. However, for the majority of towns in this cluster, a high value in one metric is balanced by a lower value in the other. For example, Idanha, OR has high MFI hazard (ranked 19th) but low BP hazard (ranked 201st).

In contrast to Cluster 1, Cluster 4 comprises towns with some of the best road quality metrics and lowest fire hazard. In particular, the towns in this cluster have a relatively high number of exits and good connectivity, and their BP and MFI hazards are the lowest among the four clusters. No town in this cluster is ranked higher than 251st in BP or 156th in MFI. Typically, towns in this cluster are situated on flat terrain, surrounded by agriculture (e.g., Green Bluff, WA), or on a coastal plain (Oyehut, WA).

Clusters 2 and 3 occupy the middle range between Cluster 1 and 4. The towns in these clusters are similar to towns in Cluster 4, in that they have low BP and MFI hazard. However, the towns in these clusters have fewer exits and poor connectivity, increasing their vulnerability in case evacuation is needed. Additionally, Cluster 2 has poor travel area quality. In fact, Cluster 2′s median travel area value (normalized travel area metric of 0.39) is marginally lower than that of Cluster 1 (normalized travel area metric of 0.44). Granger, WA, exemplifies towns in this cluster, served primarily by one freeway running through the town.

3.5 Sensitivity analysis of distance used for vulnerability evaluation

Because the distance that a town will need to evacuate will probably vary with the specific circumstances of the wildfire, we also evaluated 10 km and 25 km evacuation travel distances in addition to the 15 km distances presented in the results and discussion. A simple sensitivity analysis reveals little difference in the spreads of the four metrics according to the distance used (Fig. 4). The obvious exception is the travel area metric, where a larger travel distance designation will always result in a larger service area. Overall, rankings are also minimally different (full 10 km results in Appendix 3; full 25 km results in Appendix 4).

4 Discussion

4.1 Geography of evacuation vulnerability

Overall, evacuation vulnerability is highest in towns where the poorest road networks coincide with the highest wildfire hazard. The Pacific Northwest has a fairly distinctive geography of vulnerability and discussed in the following four sections for each of the four overall vulnerability quartiles.

4.1.1 Highest vulnerability

Towns with the highest overall vulnerability are located primarily along the west and east sides of the Cascade crest, northeastern Washington, southwestern Oregon, and Oregon's Blue Mountains (Fig. 1c, dark red dots; geographic features mentioned in text are referenced on Fig. 5). The remote mountainous locations contribute to poor road networks;

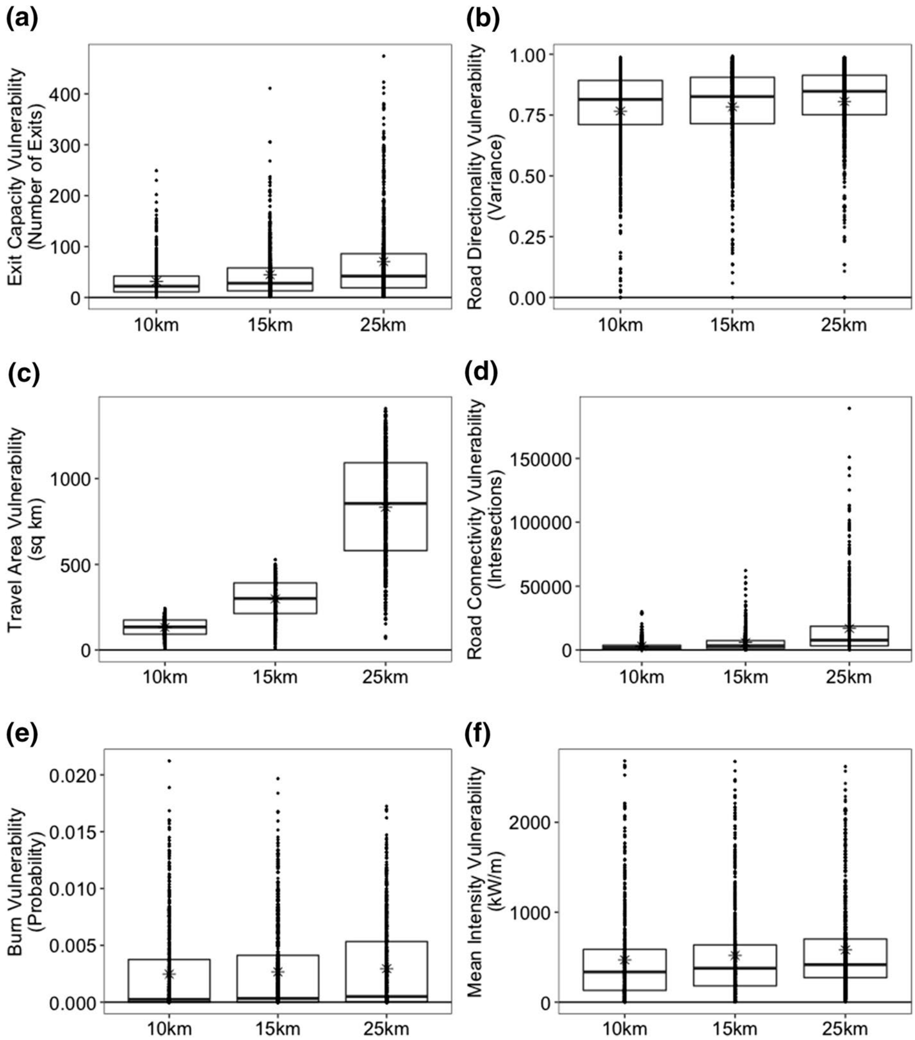

Fig. 4 Boxplot distributions of each vulnerability metric for 696 rural towns using 10 km, 15 km, and 25 km distance designations: **a** Exit capacity; **b** Directionality; **c** Travel area; **d** Connectivity; **e** Burn probability; and **f** Mean fireline intensity. Note that these plots show "raw" metric values, not the normalized values constrained between 0 and 1. Each town's value is plotted as an individual point. Boxes bound the 25th and 75th percentiles. Solid black horizontal lines indicate medians, and black asterisk indicates the mean

combining poor roads with high BP and/or MFI give towns in these regions the highest vulnerability rankings in the Pacific Northwest. It is critical to note here that many areas where BP is very high do not necessarily coincide with areas where MFI is also high; in fact, high BP tends to more often coincide with low MFI (Fig. 5). For example, BP is high in the flatter, open shrubland landscapes of the Columbia Plateau in southeastern Washington and the Oregon Plateau in southeastern Oregon; however, because shrublands do not hold nearly as much burnable biomass as forested landscapes, MFI is relatively low. Alternatively, MFI is highest in high-fuel landscapes, such as the dense forests of the western

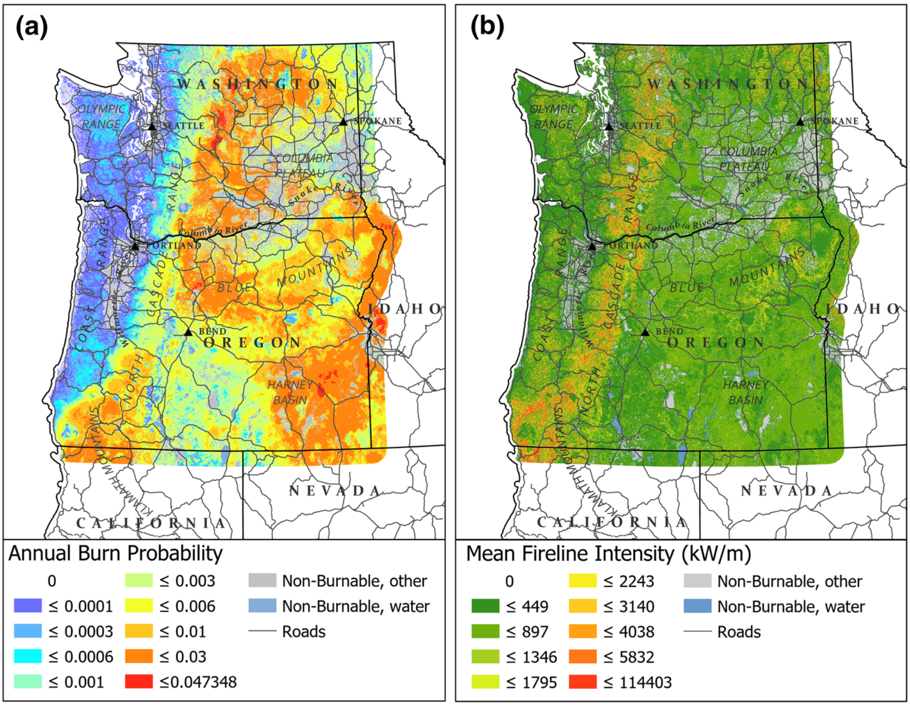

Fig. 5 Map of 120 m × 120 m average annual burn probability **a** and mean fireline intensity **b**. Raster data taken from the Pacific Northwest Quantitative Wildfire Risk Assessment (Gilbertson-Day et al. 2018). Geographic features and major cities mentioned in the text are shown. Roads include class 1–3 highways (US Census Bureau 2000). Non-burnable pixels include agriculture, development, barren ground, ice, and water as classified in LANDFIRE (2014)

Cascade crest or the southwestern Oregon mountains. For this reason, a combination of high MFI, moderate-to-high BP, and poor road networks emerges as the perfect storm identifying “Highest Vulnerability” towns. Notable examples in this quartile include:

Williams, OR (#1) – Located in the mountains of southwestern Oregon, Williams ranks as the town with the highest evacuation vulnerability. It is in the quartiles of poorest road metrics, highest BP, and highest MFI.

Leavenworth, WA (#6)—A popular tourist destination in central Washington, Leavenworth has very high fire hazard and its mountainous location in the Wenatchee River Canyon constricts the road network. It ranks in the poor road metrics, highest BP, and highest MFI quartiles.

Detroit (#14) and *Idanha (#18)*, OR—These two towns are located near each other in the Santiam Canyon on the western slopes of the Cascade crest. Both are in the poorest road metrics, highest MFI, and high BP quartiles, accounting for their overall highest vulnerability ranking. During the September 2020 Beachie Creek Fire in the vicinity of Detroit and Idanha, 683 homes were destroyed (The Oregonian, 2020a), five people were killed (The Oregonian, 2020b), and both towns were under emergency evacuation orders and experienced severe property damage.

Skykomish, WA (#13) and *Oakridge, OR (#38)*—Although not directly impacted by the September 2020 wildfires that caused damage to Detroit and Idanha, Skykomish and

Oakridge are both located in similar settings on the western slope of the Cascades, and both experience a similar combination of vulnerability (poorest road metrics, high BP, and highest MFI quartiles).

Mill City (#140) and Gates (#141), OR—These towns are located near each other, to the west of Detroit, OR at lower elevations in the Santiam Canyon. Each town experienced emergency evacuations and significant property damage during the September 2020 Beachie Creek Fires.

4.1.2 High vulnerability

Many towns along the Pacific coastline and in the Coast Range and Olympic Mountains fall into the high vulnerability quartile (Fig. 1c, orange dots). Poor road networks are typical of many coastal towns (Fig. 1a, dark red dots along the Pacific Ocean), where roads are constrained by rugged mountains immediately to the east and the Pacific Ocean to the West. Despite the relatively lower wildfire hazard of coastal towns, wildfires can and do occur; the exceptionally limited road networks increase their overall evacuation vulnerability in the event of a wildfire. Coastal and Coast Range mountain towns in the high vulnerability category differ from their highest vulnerability counterparts by means of lower BP and lower MFI. While the road networks of these towns are amongst the most limited in the Pacific Northwest, they have objectively lower wildfire hazard leading to their slightly lower vulnerability rating. Notable examples in this quartile include the following:

Centerville, WA (#188)—Located in the predominantly shrub and agricultural Columbia Plateau region of south-central Washington, Centerville is characteristic of towns that may experience frequent wildfire, but due to the low fuel loads of surrounding shrubland vegetation, the fires that do occur will have relatively low MFI. Centerville ranks in the poor road metrics, highest BP, and low MFI quartiles.

Clallam Bay, WA (#194)—A coastal Washington town constrained by the Strait of Juan de Fuca to its north and the Olympic Mountains to its south, Clallam Bay ranks in the poorest road metrics, lowest BP, and lowest MFI quartiles. Clallam Bay is characteristic of many coastal towns in the high vulnerability quartile, where exceptionally poor road networks constrained by the adjacent ocean and mountains counteract their relatively low fire hazard to produce overall high vulnerability scores.

Alsea, OR (#212)—Alsea is typical of towns nestled in the rugged Coast Range of Oregon, ranking in the poorest road metrics, low BP, and highest MFI quartiles. Many towns in the Coast Range possess similarly poor road networks, constrained by the high topographic relief, as well as the low BP and high MFI characteristic of the wetter, densely forested regions of western Oregon and Washington.

Madras, OR (#295)—Madras is located east of the Cascades and has high fire hazard, ranking in the highest BP and high MFI quartiles; however, it also has an exceptionally good road network, making it slightly less vulnerable than other towns with similar wildfire hazard in the Highest Vulnerability quartile.

4.1.3 Low vulnerability

Towns in this quartile (Fig. 1c, yellow dots) tend to be located in coastal areas with slightly better road networks, on the periphery of flat agricultural valleys where the landscape is transitioning to the more mountainous and forested foothills of mountain ranges, and in many of the central Oregon and Washington communities where fire hazard is still high, but that have advantageous road networks. Notable examples in this quartile include:

Bellfountain, OR (#353)—Located in the southwestern edge of the agricultural Willamette Valley near the adjacent foothills of the Coast Range, Bellfountain ranks in the poor road metrics, low BP, and low MFI quartiles. Bellfountain is representative of several towns in the Low Vulnerability category that are situated in a location of transition from a generally low vulnerability agricultural valley to a higher vulnerability mountainous or forested area.

Prineville, OR (#377)—The central Oregon town of Prineville has high fire hazard (highest BP and high MFI quartiles). However, it is in the best road metrics quartile, thereby decreasing its overall vulnerability. Although we did not include population in our analysis, Prineville is more populous than many towns on our list, potentially creating riskier evacuation scenarios.

Malden, WA (#432)—This eastern Washington town ranks in the poor road metrics, low BP, and lowest MFI quartiles. However, a September 2020 wildfire fanned by 45 mile per hour winds prompted emergency evacuations. All evacuations were successful (no loss of life), albeit the fire inflicted extreme property damage to the town.

Grandview, WA (#480)—Located in the agricultural Yakima River valley of southern central Washington, Grandview possesses many similar characteristics to Centerville (4.1.2c), but has a much better road network. It ranks in the good road metrics, high BP, and lowest MFI quartiles.

Yacolt, WA (#489)—Although it ranks in the high MFI quartile, a good road network coupled with low BP ultimately rank Yacolt in the Low Vulnerability category. However, extreme wildfires can and have occurred in the area—Yacolt sits near the western burn perimeter of the infamous Yacolt Fire, which burned 500,000 acres in 1902.

4.1.4 Lowest vulnerability

The least vulnerable towns tend to be situated in the sparsely forested Willamette Valley of Oregon, the Snake and Columbia River Valleys of eastern Washington, and the exurban communities outside of Portland, Seattle, and Olympia. These are areas with minimal wildfire hazard and exceptional road networks; however, their inclusion in the Lowest Vulnerability quartile does not argue that wildfires do not occur in these towns, but simply that their vulnerability is lower than most other Pacific Northwest towns. Notable examples in this quartile include:

Sandy, OR (#575)—An exurban community to Portland, OR, Sandy is in the best road metrics, low BP, and high MFI quartiles, giving it an overall Lowest Vulnerability ranking. However, the Riverside Fire in Clackamas county in 2020 prompted state officials to keep Sandy under Level II evacuation orders for several days, indicating that residents should leave preemptively or be ready to flee at a moment's notice.

Yelm, WA (#560)—On the outskirts of the metropolitan areas of Olympia and Tacoma, Yelm exemplifies the exurban communities situated between the Cascade foothills and Washington's Seattle-Tacoma-Olympia urban corridor. Yelm ranks in the best road metrics, low BP, and high MFI quartiles. Yelm's high MFI, overall rankings, and exurban setting lend similarity to Sandy, OR, which was under Level II evacuation orders during September 2020.

Stayton, OR (#640)—Stayton is situated where the eastern edge of the Willamette Valley meets the Cascade foothills, near the Santiam Canyon. Stayton is in the best road metrics, lowest BP, and lowest MFI quartiles. During the Beachie Creek fire in Marion County in 2020, adjacent towns just miles to the east of Stayton were destroyed—i.e., Detroit, Idanha, Mill City. While no damage was reported in Stayton, the town was under Level II evacuation orders for three days and experienced hazardous smoke conditions for more than a week.

St. Paul, OR (#624)—St. Paul is typical of low-risk towns in the agricultural Willamette Valley region and is surrounded primarily by flat agricultural land. It ranks in the best road metrics, lowest BP, and lowest MFI quartiles.

4.2 Different faces of fire hazard: Burn probability versus mean intensity and "westside" versus "eastside"

Our results demonstrate that wildfire hazard (burn probability and fire intensity) is an important characteristic of evacuation vulnerability and helps identify communities that would otherwise not be identified as vulnerable had we used only BP or MFI singly, including many western Oregon and Washington towns (hereafter called "westside," referring to the Pacific Northwest west of the Cascade crest, as opposed to "eastside," or east of the Cascade crest). If wildfire hazard was defined only by probability of occurrence, for example, then there would be few or no westside communities in the highest vulnerability quartile. Instead, our results show communities along the west Cascades and even the Coast Range, where long fire return intervals regularly exceed 200 years (Spies et al. 2020; Agee 1996), as among the most vulnerable in the Pacific Northwest. No matter how infrequent, westside wildfires do happen and our results illustrate that when they do, particular communities may face very difficult evacuation challenges, in part because of limited road networks, but also because of extremely intense fires (Fig. 5; approximately BP $\leq$ 0.006, MFI > 1346). Extremely intense wildfires spread quickly, and often both ground and aerial suppression efforts are ineffective or impossible (Hirsch and Martell, 1996). In those instances, efficient evacuation is especially important because there is little that can be done to protect homes, making shelter-in-place protocols inappropriate (Cova et al. 2011).

Where eastside communities may already be engaged in emergency wildfire planning because wildfire is a relatively frequent hazard (i.e., high burn probability), wildfire-related emergency planning may not be a priority in westside communities where wildfire is a more distant concern, although this may be less likely to be true following the widespread fires of 2020 (Hall and Slothower 2009). Furthermore, there is evidence that even if emergency planning has occurred at regional and community levels, individual perceptions of low risk on the westside may inhibit timely or successful evacuation (McLennan et al. 2017). Our analysis of road networks and fire intensity alongside burn probability is intended to clarify the source of vulnerability and to demonstrate that wildfire preparedness is not simply a concern in high-frequency fire regimes. In fact, extreme wildfires that ignited on September 7, 2020 (Labor Day fires) in western Oregon sadly confirm the need to specifically consider low probability, high consequence events on the westside. The Labor Day fires resulted in evacuation orders for approximately 500,000 residents (Oregon Public Broadcasting 2020) and claimed at least 10 lives, the deadliest in state history; they destroyed towns like Detroit and Mill City, Oregon, which our analysis ranked among the most vulnerable in the Pacific Northwest. The Labor Day fires also resulted in major evacuations to westside towns like Molalla and Canby, Oregon, on the eastern edge of the Willamette Valley, which our analysis ranked among the least vulnerable. Beverly and Bothwell (2011) characterized populous regions with limited fire potential but which abut significantly more fire prone landscapes (i.e., towns in Oregon's Willamette Valley) as "areas of concern" in which descriptions of fire hazard should be careful to not undervalue extremely rare events given potentially extreme consequences. Communities in areas of concern exposed to low-probability, high-consequence events may well benefit from principles learned in catastrophic fires in Australia, namely: (1) residents should be preemptively evacuated during instances of extreme fire weather; (2) buildings are not defensible during extreme fire weather; and (3) residents should be encouraged to leave early (Whittaker et al., 2020).

In contrast to the westside, eastside fire hazard tends to be dominated by burn probability rather than intensity (Fig. 5; approximately BP > 0.006, MFI ≤ 1346). Residents of towns located in the Blue Mountains, Harney Basin, and Columbia Plateau live amongst much more frequent fire, with fire return intervals on the order of 10–20 years (Johnston et al. 2016). Drier conditions on the eastside contribute to consistently low fuel moisture in the shrub, grassland, and low-density forests representative of the eastern Pacific Northwest rain shadow. The proclivity for low fuel moistures and the rapid rates of spread in these flashy fuels produce high BP. However, these areas do not contain the dense concentrations of biomass that blanket the wetter, denser forests of the westside, so fires tend to be less intense. In this respect, fire hazard in eastside communities presents a somewhat opposite problem from westside fire hazard.

Because fires occur frequently on the eastside, fire preparedness tends to consistently occupy the local public consciousness (Hall and Slothower, 2009). While lower intensity on the eastside means that, on average, eastside fires are not as intense as on the westside, this by no means signifies that these fires are less dangerous, only that the fires present a different set of problems than westside fires. The short return intervals make fire a very real possibility somewhere on the landscape in any given season; additionally, the fast rates of spread characteristic of shrub and grassland fires mean that fires can spread from ignition site to a community in an extremely short time frame. As an example of the hazards these fires can present, a rapidly spreading fire moved through a low-intensity eastern Washington landscape during early September 2020, prompting urgent evacuation of the small agricultural community of Malden and eventually destroying 80% of the town's structures (National Public Broadcasting 2020). Relative to the coinciding Labor Day fires on the westside, the Malden fire would have spread with a lower intensity, but its rapid spread into the community made it a very dangerous evacuation scenario. The geographic remoteness of many eastside communities adds further weight to their vulnerability, besides having some of the poorest road networks (Fig. 1, especially northeastern Washington and east-central Oregon).

In cases of preemptive evacuation, the quality of the surrounding road network takes on increased importance. In fact, towns with the highest fire hazard often also have the poorest road networks (Fig. 6). This is likely a factor of geography. Areas of highest MFI occur primarily in the dense, fuel-rich forests of the westside Cascades (Fig. 5; approximately MFI > 1346). Towns in these areas are situated remotely amongst the mountainous topography, where the terrain precludes expansive road infrastructure. This phenomenon is visible in Fig. 7, where the westside towns ranking highest in MFI have the poorest road quality. Detroit and Idanha, OR, both affected by the 2020 fires, are among this subset. Towns with poor road quality also occur where MFI and BP are low (Fig. 7). These towns are primarily wedged into rugged coastlines, where the primary access roads run along the coast. A large number of them occur in the Olympic Peninsula, where population and road density are

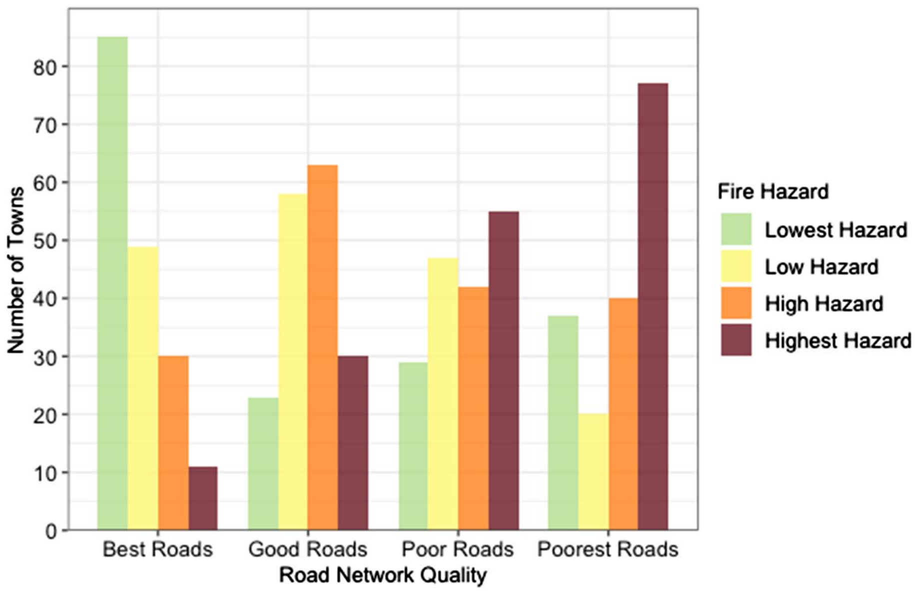

Fig. 6 Histogram of the fire hazard of all 696 towns, grouped by road quality quartiles. In each road quality quartile, the number of towns in each of the four fire hazard quartiles are plotted. Towns with the best roads tend to have the lowest fire hazard, and vice versa

low. Topography also constrains road quality on the eastside, where BP is greater than the westside (Fig. 7). On the eastside, however, towns with poor roads occur across a greater range of MFI and BP, reflecting a greater variety of fire histories and fuel conditions. Since there is no coastline on the eastside to constrain roads, eastside towns at lower elevations with relative flat terrain (lower right quadrant, Fig. 7) enjoy generally better road quality.

4.3 Assessing evacuation vulnerability is complicated and requires many approaches

In the wildfire evacuation literature, vulnerability of towns is rarely assessed using a regional-scale, map-based screening approach. The approach described herein enables regional exploration of vulnerable rural towns via their egress road network. A regional spatial assessment may assist resource allocation decisions and promote preparedness at the regional and local levels. Indecisiveness during an evacuation is dangerous, and it is imperative that residents have tools in hand to assess their options ahead of time should an evacuation be necessary (Steelman et al. 2015; McCaffrey et al. 2018). Preemptive exercises have proven valuable in understanding and improving exit networks for actual wildfires (de Araujo et al. 2014, Kolden and Henson 2019).

Whereas underlying environmental factors dictate wildfire hazard, human-related infrastructure is an important factor in the actual vulnerability of a place (Chakraborty et al. 2006). One example of human vulnerability is the complexity of the road network that can be used for egress (Dube et al. 2006). Evaluating the egress road network with just one measure of vulnerability is not sufficient, and relying on one such metric can easily lead to misrepresentation of the true vulnerability of a place (Chakraborty et al.

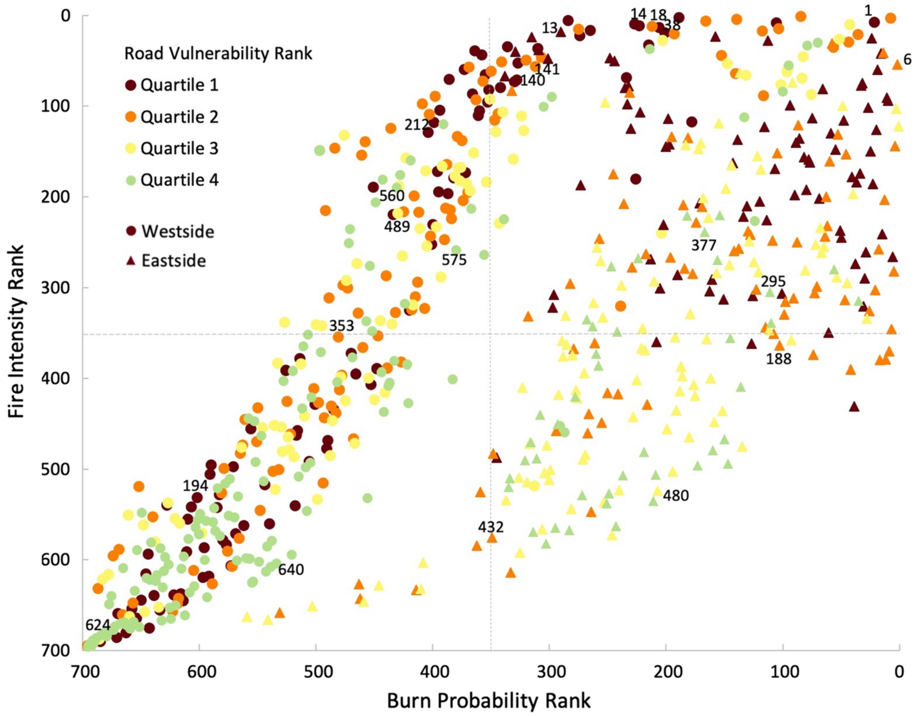

Fig. 7 Burn probability rank vs. mean fireline intensity rank of towns. Marker colors represent quartiles of road quality rank. Circles represent "westside" towns, located west of the crest of the Cascade Mountains, approximated as −121.5° longitude; and triangles represent "eastside" towns. Numbers annotate markers of towns listed in Sect. 4.1: Williams, OR (1), Leavenworth, WA (6), Detroit, OR (14), Idanha, OR (18), Skykomish, WA (13), Oakridge, OR (38), Mill City, OR (140), Gates, OR (141), Centerville, WA (188), Clallam Bay, WA (194), Alsea, OR (212), Madras, OR (295), Bellfountain, OR (353), Prineville, OR (377), Malden, WA (432), Grandview, WA (480), Yacolt, WA (489), Sandy, OR (575), Yelm, WA (560), Stayton, OR (640), and St. Paul, OR (624). Note that all numbers presented in the figure are ranks (i.e., 1 most vulnerable, 696 is least vulnerable), and not normalized vulnerability metrics

2006). Furthermore, in a wildfire, many factors contribute to decisions weighing the advantages of evacuation versus other options like remaining in place to defend a home or retrofitting a home for fire safety, and effectively evaluating these options require an overall spatial summary of evacuation options and an understanding of where fires are likely to occur (Montz et al. 2012; Beloglazov et al. 2016). Landscape fuel characteristics also can impact fire effects, with high-intensity crown fires more likely in dense forest types versus grass and shrub ecosystems, with an array of factors including agriculture, fuel type, housing density, and topography influencing the combined vulnerability of a community (Evers et al. 2019).

Our evacuation vulnerability evaluation is built on top of a road network. We established four road network vulnerability screening metrics to measure the complicated but required assessments of evacuation. First, the exit capacity vulnerability metric quantifies the evacuation possibilities and capacities in numbers at a regional scale. Road directionality vulnerability metric and travel area vulnerability metric describe the directions and areas of these evacuation exits, and explain the spatial flexibility: where and how far an evacuee can travel. The connectivity vulnerability metric summarizes the quality of connections internally for the road network at each intersection, where a moderate connectivity indicates the possible greater emergency access and more efficient response (Handy et al. 2003). These four-screening metrics examine the quality of the road network in various aspects: in the number, direction, size, coverage, and spatial capacity (Cova et al. 2013), which are the solid foundations of future spatiotemporal framework and traffic simulation models. The key contribution of our regional-scale road network vulnerability screening metrics is that they depict and aggregate large-scale effectiveness of evacuation spatially for rural Oregon and Washington towns, which can be accommodated with more complex spatial–temporal simulations to further examine the traffic dynamics at a smaller scale: e.g., travel time, lane types, and population (Cova and Johnson 2002; Wolshon and Marchive 2007; Li et al. 2019). We expect explorations of evacuation dynamics at different scales will positively build upon one another, enhancing the overall collective analyses.

4.4 Where do we go from here?

We chose this screening process as a necessary step in assessing, ranking, and comparing the evacuation vulnerability of towns, but it sacrifices local detail in order to do so. We hope our work will inspire further improvements and discussion. Importantly, we emphasize that a low vulnerability ranking by no means indicates that a town does not have fire hazard, nor that a town's road network will sufficiently facilitate evacuation of all residents. On the contrary, none of the towns we analyzed have zero fire hazard, and as the 2020 Labor Day fires demonstrate, towns with objectively low vulnerability (even towns in the Low and Lowest Vulnerability quartiles) can experience extreme, high-danger wildfire events. Further, our definitions of a good road network are purely geometric and do not consider factors like the physical quality of a road, number of evacuees, how many households have a working vehicle, whether residents are mentally prepared to evacuate, and how far evacuees will need to travel to be considered safe.

Considering the complicated nature of evacuation assessment, we have identified four key ways that our work could be refined and expanded in the future: 1) Our screening metrics could be supplemented by more advanced traffic network simulation modeling. Published work such as Cova et al. (2016), Li et al. (2019), or Wolshon and Marchive (2007) show how travel simulation can quantify the temporal and traffic capacity components of evacuation, a step that is needed to provide communities with specific evacuation route recommendations and quantify how many people can be moved in a set amount of time, including accounting for population of a town. For example, in practice a town with 8,000 residents will likely be more difficult to evacuate than a town with a similar road network, but only 2,000 residents; 2) Residents' perceptions of their evacuation vulnerability, including which routes they perceive as viable wildfire evacuation options, need to be assessed in more detail at the regional scale. In individual towns, interview methods have been successful to summarize the informational and tactical needs of residents in preparation for a wildfire evacuation (e.g., Cohn and Carroll 2006; Steelman et al. 2015; McCaffrey et al. 2018). A similar approach could be useful to gain a more complete summary of some of the towns we identified as most vulnerable and to develop more locally applicable insights; 3) Probabilistic modeling of the rate and direction of wildfire spread with regards to population centers and their evacuation network needs to be conducted, since the best evacuation route will always depend on the speed and direction of the advancing fire front. Studies such as Li et al. (2018) have simulated real-time advance of fire and how that creates time and directional constraints on evacuations, but these analyses need to be constructed beyond individual communities and applied at the regional scale; and 4) Analyzing the origin–destination capacity of towns, including identification of where people will evacuate to during a wildfire, will help identify which towns are constrained by their relative isolation. This aspect has been analyzed in the context of other natural disasters (e.g., Chang and Liao 2015), but not extensively in the fire evacuation literature.

The metrics presented here may help communities contemplate how their evacuation options may be limited by number of exits (Exit Capacity metric), variety of exit directions (Road Directionality metric), and drivable area (travel area metric) and will help prioritize communities for further study of vulnerability and evacuation options. In addition, this work may help in raising awareness of the vulnerability of rural communities in the Pacific Northwest to encroaching wildland fires. Where egress is limited, safety zones might be identified or constructed, homes might be retrofitted to reduce risk of burning, or landscaping might be adjusted to reduce the chance of home ignition. All in all, we hope that contemplating options for reducing vulnerability in rural Pacific Northwest towns with high wildfire hazard may help communities plan for future wildfires.

Supplementary information The online version contains supplementary material available at (https://doi.org/10.1007/s11069-021-04615-x)

Acknowledgements All opinions expressed in this paper are the author's and do not necessarily reflect the policies and views of USDA, DOE, or ORAU/ORISE. We thank Charlie Schrader-Patton for help with developing the web interface associated with this article.

Funding Funding was contributed by the USDA Forest Service Western Wildland Environmental Threat Assessment Center (WWETAC). Research was supported in part by an appointment to the United States Forest Service (USFS) Research Participation Program administered by the Oak Ridge Institute for Science and Education (ORISE) through an interagency agreement between the U.S. Department of Energy (DOE) and the U.S. Department of Agriculture (USDA). ORISE is managed by ORAU under DOE contract number 18IA11261952030.

Data availability The data and material used in this research are partly available in the body of the article and appendices; other data/material is publicly available to all users per a written request to the authors; all other data used are publicly available from its source.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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