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Corresponding author:
Anita Lee Mitchell;
Email: leemitchell@boisestate.edu

Identifying Health Care Access Gaps in Areas of Oregon at High Risk of Respiratory Hospitalization During Wildfires

Anita Lee Mitchell PhD[1,2], Su Jin Lee PhD[1,3], Pooya Naderi PhD[1], Ashley Hansen MPH[1], Kerry Farris MS[1,4] and Kyle Chapman PhD[1,5]

[1]Oregon Institute of Technology AIRE Center, Klamath Falls, OR, USA; [2]Boise State University, eCampus Research and Innovation, Boise, ID, USA; [3]Oregon Institute of Technology, Geomatics Department, AIRE Center, Klamath Falls, OR, USA; [4]Oregon Institute of Technology, Natural Sciences Department, AIRE Center, Klamath Falls, OR, USA and [5]Oregon Institute of Technology, Humanities and Social Sciences Department, AIRE Center, Klamath Falls, OR, USA

Abstract

Objectives: Wildfire smoke causes respiratory health concerns. The study estimates respiratory hospitalization risk from wildfires, determines distance to a hospital, and identifies concentrations of smoke-sensitive groups far from a hospital to facilitate public health and emergency preparedness in Oregon using spatial analysis.
Methods: Statistically significant environmental factors were identified with regression and used with wildfire and pollution concentrations to predict respiratory hospitalizations. A weighted overlay of the significant factors formed a statewide risk layer. Proximity to the hospital nearest to each Census block was determined by driving distance. Clusters of smoke-sensitive groups, determined by relevant Census demographics, were identified through a Hot Spot Analysis.
Results: This process allowed for highlighting locations of smoke-sensitive groups in areas at high risk for respiratory hospitalization from wildfire smoke who were far from a hospital. The results allow local officials to identify the type and magnitude of needs they can expect in the event of a wildfire.
Conclusions: The results demonstrate a process to facilitate wildfire preparedness in Oregon. This process could be adapted to inform wildfire resilience strategies in other regions facing similar challenges, such as California. Understanding local needs allows officials to target communications more effectively, stage resources more efficiently, and identify gaps that can be addressed before a disaster strikes.

Wildfire risk is growing globally, from continental Europe, to Africa, Australia, and South America and the diverse landscapes of India, Canada, and the US, including the Pacific Northwest region.[1–6] The urgency of this issue is highlighted by the devastating January 2025 wildfires in Los Angeles County - an unprecedented winter fire event that demonstrates how climate change is extending fire seasons and expanding fire risk into unexpected times and places.

Fine particulate matter, $PM_{2.5}$, is a main pollutant of concern from wildfire smoke. $PM_{2.5}$ creates respiratory health risks.[7,8] A previous study shows an increase of 10 micrograms per cubic meter of $PM_{2.5}$ pollution from wildfire smoke is associated with an 8% increase in emergency department visits for asthma across the state of Oregon.[9] Some people are more susceptible than others to impacts.[4] Health impacts are strongest in people with existing chronic diseases, in children, and in older adults.[10] Having a low income and working outdoors present further unique wildfire smoke exposure concerns. Hazard communications need to be tailored differently in areas with residents who have Limited English Proficiency.[11]

The wildfire smoke hazard is increasing along with wildfires in the Pacific Northwest. Identifying both the degree of exposure expected across the landscape and the vulnerability of the population can help target risk-reduction efforts most effectively.[12] Quantifying these risks can inform health and emergency service providers so they will be prepared to accommodate needs and provide adequate care to affected populations. Communities most at risk can be targeted for development of smoke management plans to improve community resilience to the effects of wildfire smoke.[13] Community vulnerability to wildfire smoke has previously been explored at the county level across the continental US.[13] Taking a more granular approach, our study examines vulnerability at a finer spatial resolution by analyzing block-level data within the state of Oregon.

The current study identifies the locations of Oregonians most susceptible to wildfire smoke impacts who live further than 40 km from a hospital. The risk of respiratory hospitalization from wildfire smoke was modeled across the state using a geographic information system (GIS). A proximity analysis was used to determine hospital access. A cluster analysis relied on demographic data to highlight vulnerable members of the population in the high-risk zone far from a hospital. Identifying the locations of these vulnerable populations will facilitate public health and disaster preparedness by focusing attention on areas of greatest concern.

Methods

Environmental characteristics and human exposure and vulnerability influence the risks from wildfire smoke.[12,14] Considering this range of factors through a socio-ecological perspective can highlight areas ill-equipped for wildfire response.[15] This study explores factors related to the natural environment, the built environment, and socio-demographic characteristics to quantify risks from smoke exposure through a socio-ecological perspective.

The analytic hierarchy process leverages multiple factors to analyze complex problems and facilitate decision-making.[16] Applying this process allows researchers to identify the most general and easily controlled factors, then rank and assign weights to the factors based on importance. GIS is a suitable tool for applying the analytic hierarchy process to facilitate multiple-criteria decision-making. Geoprocessing tools can integrate diverse environmental hazard variables as well as measures of social vulnerability.[14,17] This study relied on ArcGIS Pro 3.1.0 for geoprocessing.[18] The data and analysis techniques described in this section are shown in Figure 1.

Data

A 2-county sample area including Josephine and Jackson Counties in southwestern Oregon was used to derive model parameters for the risk of respiratory hospitalizations. The sample covered fire season during the years 2016-2019. Fire season for this study is defined as June-September.[19] The sample area was limited by available hospitalization data.

Health impacts from increased $PM_{2.5}$ during wildfire smoke events were measured through hospital and emergency room admissions for respiratory conditions at 3 hospitals in the study area. The data was subset to admissions during fire season and to patients with home addresses in the sample area, focusing on times when wildfire smoke would be a main driver of air quality concerns and on people who were exposed to the local air quality conditions. Patient home data was reported at the zip code level. A previous analysis with the data demonstrated a positive relationship between the $PM_{2.5}$ monitor values and hospital admissions during the 2018 fire season.[20]

Air quality monitor data was used to assign estimates of the respiratory patients' exposure to $PM_{2.5}$ from wildfire smoke.[21] Six air quality monitors, locations shown in the Supplemental Materials, provided daily average $PM_{2.5}$ concentration measurements in the sample area during the study period. Exposure estimates were assigned to patients based on the monitor nearest to each patient's home zip code. Missing air quality data was estimated using the average values from the nearest monitor with recorded data. Daily averages were used to generate average annual exposure.

Acreage burned and proximity to wildfires have been useful metrics for identifying risk in previous research.[12,22,23] Perimeters of reported wildfires were downloaded from the National Interagency Fire Center and subset to the study area.[24] The area covered by these perimeters each year was apportioned to each intersecting zip code to generate the annual area burned by wildfire. The Near geoprocessing tool was then used to calculate the distance to the nearest fire for each zip code for each year. Two years, 2017 and 2018, had relatively high fire activity in the sample area, while 2016 and 2019 had relatively low fire activity, shown in the Distance to Fire maps in the Supplemental Materials.

Topographical, meteorological, and fuels data can be used to identify areas at risk for wildfires and smoke exposure.[17,25] Factors

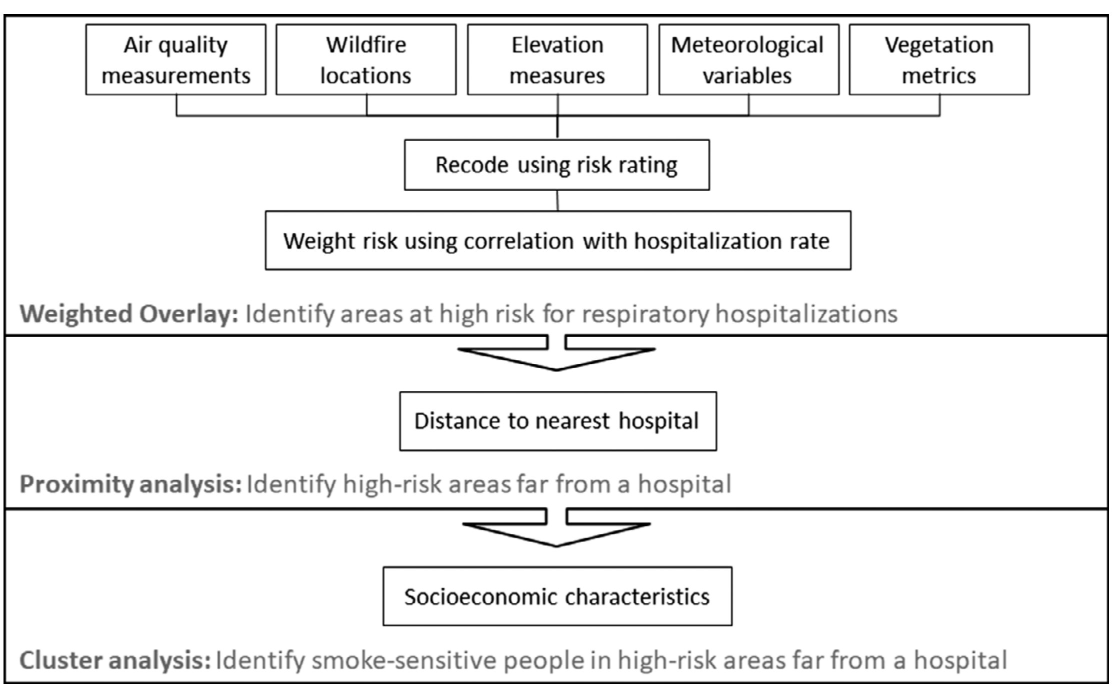

Figure 1. Factors and analysis techniques used to identify smoke-sensitive people in areas far from a hospital that are at high-risk for respiratory hospitalizations from wildfire smoke.

identified by previous researchers and explored in this study include terrain variables like elevation; weather factors like relative humidity and temperature; and fuel biomass metrics, such as those derived from indices like the Leaf Area Index (LAI) and Normalized Difference Vegetation Index (NDVI).

A 10 m resolution Digital Elevation Model (DEM) was downloaded from the USGS National Map and clipped to the State of Oregon.[26] The Summarize Elevation geoprocessing tool captured the minimum, average, and maximum elevation value per zip code. The elevation range was calculated by subtracting the minimum from the maximum.

Annual temperature and dew point data for 2016-2019 were downloaded from Oregon State University's PRISM Climate Group.[27] The data were provided as continuous surfaces with 4 km resolution. The mean and maximum temperature and dew point data were clipped to the Oregon boundary. These were used to calculate mean and maximum relative humidity (RH) using the Magnus-Tetens formula.[28] The Zonal Statistics geoprocessing tool was used to capture the average of each of these weather metrics per zip code per year in the sample area.

Vegetation metrics derived from MODIS data were downloaded from the USGS EarthExplorer site.[29] One metric explored productivity and vegetation coverage: the 500 m resolution MCD15A2H Version 6.1 Combined Fraction of Photosynthetically Active Radiation (FPAR) and LAI product. The eMODIS NDVI v6 dataset with 250 m resolution captured vegetation density and health. Data with minimal cloud cover over the study area near the 1st of June was downloaded for each year for both metrics. The Zonal Statistics geoprocessing tool was used to capture the average and majority values within each zip code for each metric each year. Land cover was considered, but the temporal resolution of available data was insufficient for the 4-year study period.

Socioeconomic status, occupation, and individual health status can place some people at a higher risk for adverse health effects from wildfire smoke. This includes people under 18 or over 65 years old, people with preexisting respiratory or cardiovascular conditions, people with low incomes, and outdoor workers.[10] Language barriers can also increase risks through ineffective emergency communications.[11] Census data have been shown effective for identifying social vulnerability to wildfire smoke.[15,22,30] The Enrich geoprocessing tool was used to capture Census counts of people in these sensitive groups at the block level. The tool provided 2022 data for individual characteristics and 2021 data for household characteristics. Children and elderly people were reported as counts of the population under 18 years old and 65 years and older, respectively. A metric for people with chronic health conditions was not available but counts of households with 1 or more persons with a reported disability were used as a substitute population with notable health concerns. The federal poverty level was adopted as the metric for low socioeconomic status. Primary language was not available so counts of Hispanic people were used to identify areas where Spanish may be more commonly spoken in the home. To identify outdoor workers, counts of people working in farming, fishing, forestry, construction, and extraction were captured. This does not capture the full range of outdoor professions but can highlight workplace concerns from wildfire smoke for these industries.

Access to health care is another vulnerability people face, particularly the rural areas. Health care access was defined based on proximity to a hospital. The locations of acute care facilities were downloaded from the Oregon Spatial Data Library.[31] The Generate Drive Time geoprocessing tool generated 8, 16, 40, and 80 km (5, 10, 25, and 50 mi) driving distance zones for each hospital.

These health outcome, air quality, wildfire, topographical, meteorological, fuels, sociodemographic, and health care access datasets were used to identify populations within Oregon most vulnerable to respiratory hospitalization from wildfire smoke and with limitations on health care access. The factors most influential for predicting respiratory patient counts were derived from wildfire, $PM_{2.5}$, and environmental data.

Variable Selection

The ArcGIS Forest-based Regression geoprocessing tool identified key factors for predicting patient counts. Candidate Factors included $PM_{2.5}$ annual average and cumulative measurements from the nearest air quality monitor, the acreage burned per zip code, and distance to nearest fire; mean elevation, maximum elevation, and elevation range per zip code; mean and maximum temperature, mean and maximum dew point, mean and maximum relative humidity; mean and majority NDVI and FPAR/LAI values per zip code. The tool generates a summary of the variables most important for predicting the outcome. Variables identified as not important in this summary, including maximum elevation, maximum relative humidity, and majority FPAR/LAI, were excluded from further study, and are shown in Table 1.

The Generalized Linear Regression geoprocessing tool was used to explore the impact of varying combinations of the remaining variables. The log of patient counts generates a distribution close to normal, appropriate for a linear regression, based on a skewness value of 0.47, less than the absolute value of 2, and a kurtosis value of 2.72, less than the absolute value of 7.[32] Some variables, like humidity and dew point, were strongly correlated with each other,

Table 1. List of variables considered for the risk analysis, with variables excluded based on Forest-based Regression stricken through and final variables chosen through Generalized Linear Regression in bold italics

Variable list
Average air quality measurements
Cumulative air quality measurements
Acreage burned by wildfire
Distance to nearest wildfire
Mean elevation
~~Maximum elevation~~
Elevation range
Mean temperature
Maximum temperature
Mean dew point
Maximum dew point
Mean relative humidity
~~Maximum relative humidity~~
Mean NDVI
Majority NDVI
Mean FPAR/LAI
~~Majority FPAR/LAI~~

so this process allowed us to find a balance between parsimony and model significance. The final model was chosen based on minimizing the sum of the standardized residuals. The final zip code level variables, shown in Table 1, include mean elevation, mean temperature, mean NDVI, average annual $PM_{2.5}$ concentrations, and distance to the nearest fire.

Weighted Overlay Analysis

The weighted overlay analysis requires data to be formatted as a continuous surface.[33] Each of the datasets downloaded as discrete locations were converted to continuous surfaces. Inverse distance weighting was applied to the yearly $PM_{2.5}$ averages for the 6 monitors to generate the continuous exposure surfaces shown in the Supplemental Materials. The surfaces were reclassified from 1-5 using an equal distribution of values at 20% intervals. The $PM_{2.5}$ concentrations had a positive relationship with patient counts, so higher pollution values were associated with a higher hospitalization risk; $PM_{2.5}$ coded as a 1 is associated with the smallest concentrations and a code of 5 is associated with the largest concentrations.

The Distance Accumulation geoprocessing tool was used to generate a continuous surface for distance to the nearest fire across the 2-county sample area (Supplemental Materials). The distance to a fire was then reclassified from 1-5, using equal 20% intervals. Distance to a fire was reverse coded, as lower values were associated with a higher risk, so 1 shows the lowest risk furthest from a fire and a 5 shows the highest risk when close to a fire.

The environmental layers were all continuous surfaces natively, so to prepare for them for the weighted overlay analysis, they were reclassified from 1-5 using equal 20% intervals. Higher temperatures were associated with higher risk, so the layer was coded with 1 for the smallest values and 5 for the largest values. Elevation and NDVI were reverse coded as lower values were associated with a higher risk. Examples of the recoded layers are provided in the Supplemental Materials.

Layer weights were generated from the correlation values between each variable and the patient counts. The correlations were normalized by summing, dividing by the number of layers, and multiplying by 10. This generated a list of weights that sum to 100, as shown in Table 2.

These weights were used in the Weighted Overlay geoprocessing tool to generate a final layer representing the risk, 1-5, of respiratory hospitalization during a wildfire. To validate the final layer, it was compared to the patient counts during fire season for each of the study years. The Tabulate geoprocessing tool was used to determine the number of patients in each risk category. Most patients are associated with the highest risk categories as shown in the Supplemental Materials. These weights were then applied to each of the input layers to create a single layer representing the risk of respiratory hospitalization from wildfire smoke statewide.

To explore the risk of respiratory hospitalizations in the event people experience a wildfire nearby, the fire distance and daily average $PM_{2.5}$ exposure were set to the greatest risk level. That is, both layers were set to a risk level of 5 to explore the impacts of wildfires creating concerning levels of particulate matter pollution if smoke occurs nearby. The risk statewide was then estimated using these layers along with the mean elevation, NDVI, and temperature layers. Because fire distance and PM concentrations were set at the highest risk, no area of the state has a respiratory hospitalization risk category under 2 in the results, as shown in Figure 2. The largest proportion of the state, approximately 56 750 km^2, was in risk category 4.

Table 2. Final weight values in percent for the layers used to generate the risk of respiratory hospitalizations during a wildfire

Layer	Weight (%)
Distance to fire	3
Daily average $PM_{2.5}$	18
Mean elevation	23
Mean NDVI	23
Mean temperature	33

Hospital Proximity Analysis

Access to care was determined by how far people need to drive to reach the nearest hospital. The Generate Drive Time geoprocessing tool, with generalized polygon outputs, created approximately 8, 16, 40, and 80 km buffers for each hospital across the state (Supplemental Materials). A 40 km minimum distance from the nearest hospital defined the measure for access concerns.

The distance to the nearest hospital and the risk category for respiratory hospitalization from smoke if a wildfire occurs nearby were joined to Census blocks that have at least 1 person living there. The join captured the majority distance values that occurred per block. This data (Figure 3) highlights locations of populations that may have difficulty accessing health care in a timely manner. Hospitals are symbolized proportionally by number of available beds; bigger circles are bigger hospitals. In the southeastern part of the state, people are a long way from a hospital and the hospitals nearest to them are small and less equipped to meet patient surges.

Cluster Analysis

Concentrations of smoke-sensitive groups were identified using the fixed distance band with Euclidian distances in the geoprocessing Hot Spot Analysis tool based on the Getis-Ord Gi* statistic.[34] The z-score output from this tool identifies statistically significant local clusters with high values, such as a Census block with a high proportion of a sensitive group surrounded by blocks with high proportions. Identification of statistically significant clusters is useful for social and emergency services planning.[35,36]

While counts of sensitive populations are important for preparing for the magnitude of potential health concerns during a wildfire, proportions can highlight areas where a high proportion of residents have extra needs. The sensitive conditions in each block were summed to generate total counts. Some people are counted within multiple sensitive groups, such as a senior person with a disability, so the count of sensitive conditions can be greater than the total number of people in the block. Clusters of sensitive conditions were calculated with the Hot Spot geoprocessing tool, allowing us to explore the relative intensity of each high-risk population across the state. Counts and clusters together can highlight differential intensities of need across geographies with different population magnitudes.

Human Subjects Review

This is a secondary analysis that relies on de-identified data. The Southern Oregon Institutional Review Board determined this

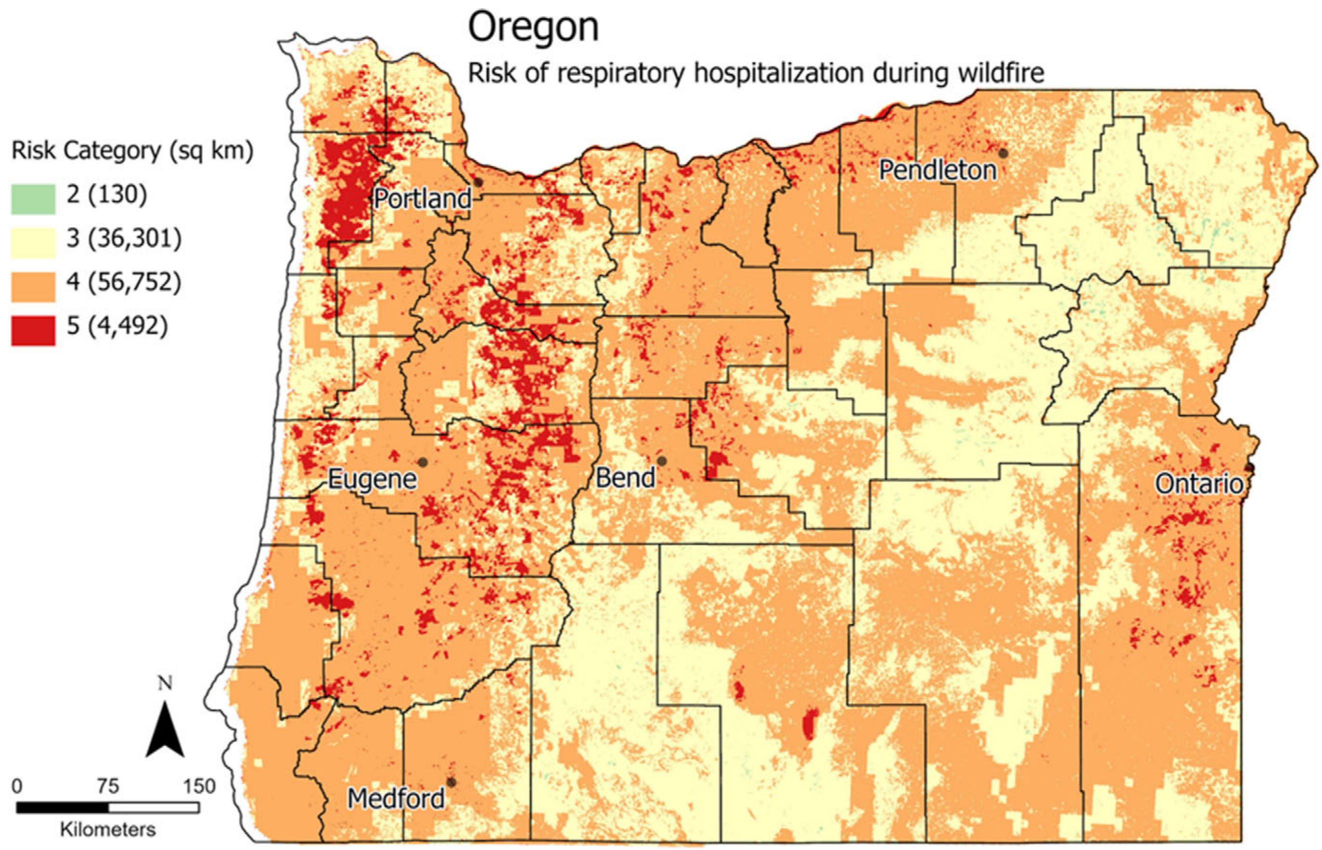

Figure 2. The risk of respiratory hospitalization during wildfire in Oregon.

research, described through the "Air Quality and Respiratory Admissions" questionnaire, was exempt from IRB oversight on May 1, 2019.

Results

The analysis generated maps of locations of people with smoke-sensitive conditions in areas far from emergency medical care who are at high risk for respiratory hospitalizations from wildfire smoke exposure. This allows us to identify areas within Oregon at the greatest risk environmentally and socially, a socio-ecological perspective that can be useful for prioritizing hazard response and mitigation efforts in an environmentally just way.[15]

The final dataset provides block level data on the risk of respiratory hospitalization during a wildfire, the distance to the nearest hospital, and counts of smoke-sensitive groups. The map on the left of Figure 4 shows the count of sensitive conditions, indicating the magnitude of the problem. The western part of the state shows the highest concentrations but also has the highest total population. As shown in the map on the right side of Figure 4, clusters with high concentrations of sensitive conditions are more prominent in the southwest and northeastern parts of the state. Clusters identified at a 99% confidence level are shown in red while clusters identified at a 90% confidence level are shown in yellow. This perspective indicates the intensity of potential concerns. Taken together, planners can explore both the magnitude of resources that may be required and the intensity of need across the landscape. For example, southwestern areas of the state have both high counts and clusters of sensitive needs, highlighting a priority area for disaster planning.

Each smoke sensitive group has unique needs. To understand differential public health and disaster preparedness needs across the state, the magnitude and intensity of each group across the landscape should be considered. Maps in the Supplemental Materials show clusters for each sensitive group in areas at highest risk for respiratory hospitalization during wildfires over 40 km from hospital.

Seniors comprise the largest group of individual people sensitive to wildfire smoke in this risk zone, even though children are the largest group overall in the state. Over 28 000 seniors live greater than 40 km from a hospital in an area at high risk for respiratory hospitalization from wildfire smoke, as shown in Table 3. Approximately 4% of Oregon's seniors live in this risk zone, spread throughout the state. The highest counts of seniors are in the west and north, though clusters of high proportions spread from the southwest to the northeast.

Children are the second largest group, with over 16 000 in the highest risk areas far from a hospital. Approximately 2% of Oregon's children can be found distributed across the state in this risk zone, though the highest counts are in the western half of the state. Clusters of high concentrations of children appear in the central part of the state.

Almost 15 000 households in this risk zone have at least 1 disabled person. Approximately 3% of all households with at least 1 disabled person live within the risk zone. The southwest and northeastern parts of the state have the highest concentrations of clusters of disabled people.

Over 5500 households living in poverty, approximately 3% of the total, are in this risk zone. Clusters of these households appear in

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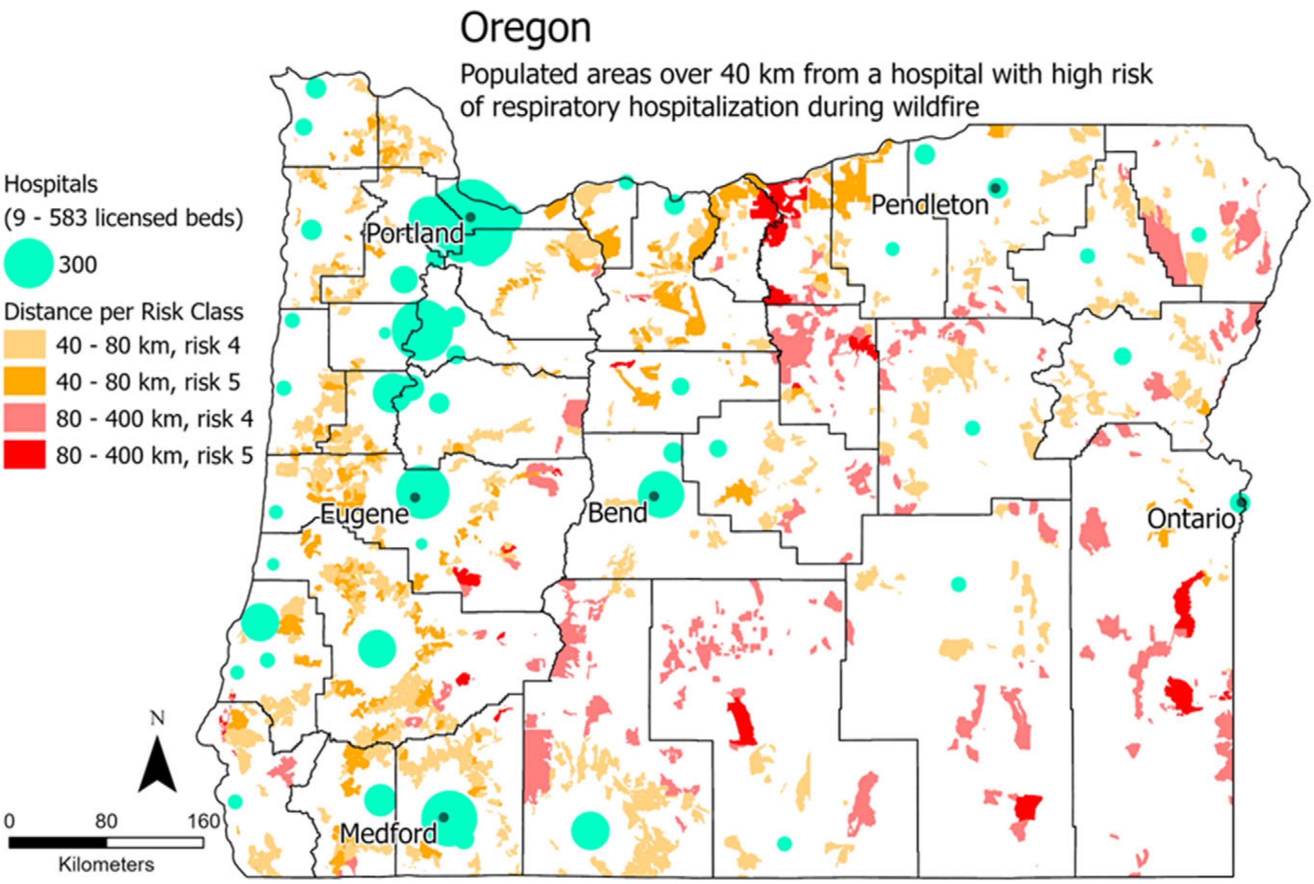

Figure 3. Populated Census blocks in areas at greatest risk from respiratory hospitalizations from wildfire smoke greater than 40 km from a hospital with the proportional size of hospitals.

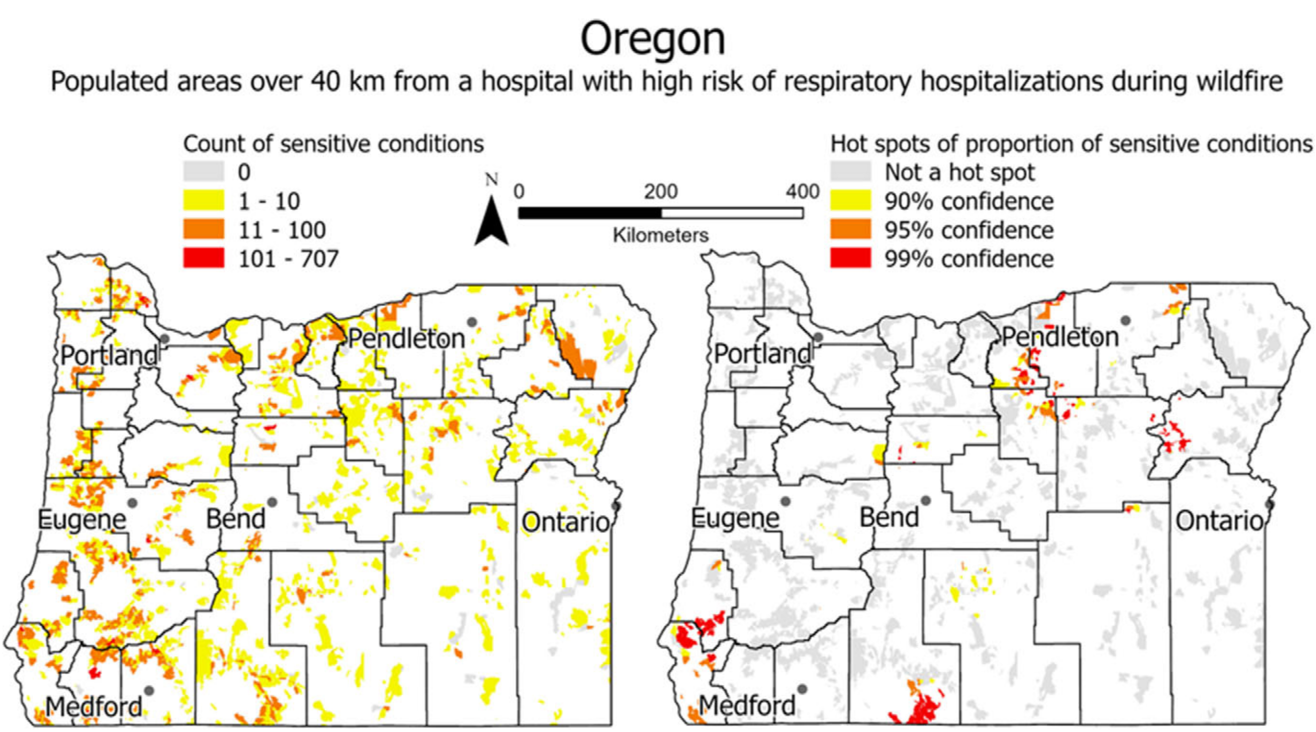

Figure 4. Counts and clusters of sensitive conditions per Census block in areas at greatest risk from respiratory hospitalizations from wildfire smoke greater than 40 km from a hospital.

Table 3. Count of sensitive groups in areas at highest risk for respiratory hospitalizations greater than 40 km from a hospital

	Risk 4		Risk 5			
	40 - 80 km	80 - 400 km	40 - 80 km	80 - 400 km	High risk total	Statewide total
Seniors	22 600	1770	4058	238	**28 666**	**823 731**
Children	13 000	893	2325	132	**16 350**	**866 604**
Disabled	11 773	925	2158	103	**14 959**	**462 253**
Low income	4457	424	734	37	**5 652**	**193 680**
Hispanic	5071	283	958	68	**6 380**	**588 757**
Outdoor Workers	2443	155	517	28	**3 143**	**122 562**
Total	**59 344**	**4450**	**10 750**	**606**	***75 150***	**3 057 587**

the southwest and, to a lesser extent, in the north central parts of the state.

While the third most populous group statewide, lower only than seniors and children, only 6000 Hispanic persons, about 1% of the state's Hispanic population, live in this high-risk zone. Clusters with high concentrations of Hispanic persons appear most prominently in the north-central and south-central parts of the state.

The smallest smoke sensitive group overall, outdoor workers in the Farm/Fish/Forestry and Construction/Extraction industries, have over 3000 people living in this high-risk zone. This corresponds with about 2% of outdoor workers in these industries. Clusters of high concentrations of these workers are spread throughout the state.

Limitations

The study has several limitations that could be addressed in future research. Pre-defined Census categories do not always align well with definitions of groups sensitive to wildfire smoke. The effectiveness of using specific demographic variables to represent smoke-sensitive populations should be explored.

$PM_{2.5}$ measurements taken from fixed monitors do not capture the full range of exposures across the landscape. The community-based PurpleAir air monitoring program may provide more widespread coverage of pollution concentrations. Setting up targeted programs using low-cost monitors could also minimize measurement gaps.

Zip code resolution for patient data may not provide accurate exposure estimates. Opportunities for a finer resolution, such as block level, would improve exposure estimates; however, increasing spatial resolution requires careful consideration of data privacy and security. Future research should explore analytical methods that enhance geographic precision while also protecting private health information.

This analysis was also restricted by areas where we had access to patient data and records for determining the relationship between prediction factors and health outcomes, potentially biasing the results by not capturing the full range of Oregon's landscapes. While we used health outcome data from 3 of the 4 hospitals in the region to develop the risk model, missing data from the 1 hospital could have resulted in patient sampling bias.

This initial estimate of risk of hospitalization from wildfire smoke provides a foundation for a method to directly compare risks and needs. Iterative assessment and improvement cycles are needed for the method to become a reliable planning tool.

Discussion

The methods presented here demonstrate a process by which health risks among vulnerable populations can be better understood and supported at a local level, while also producing a statewide perspective for identifying and addressing service gaps. This can help ensure environmentally just interventions by foregrounding inequitable risks.[37]

Results from this study can be used in conjunction with other published research to enhance the decision-support potential and generate actionable guidance for local and regional public health and emergency preparedness activities. For example, older adults are more susceptible to negative health impacts from wildfire smoke and may face additional challenges when preparing for a disaster or evacuating compared to younger adults.[10,38] Public health and disaster preparedness personnel in areas with clusters of seniors may find television is the most effective channel for communications regarding smoke information and protective actions.[11]

Areas with clusters of children face an increased need for indoor spaces with clean air where children can be active.[10] Public health and disaster preparation officials in these areas should also be aware of the uncertainty of the long-term health impacts of wildfire smoke exposure on children, particularly in areas with repeated exposure events.[39]

Additional assistance with disaster preparation and evacuation may be required in the areas of the state with clusters of persons with a disability. Oregon officials in these areas may benefit from targeted training on how best to communicate and assist with different types of disabilities during a disaster.[40]

Areas with clusters of low-income households may find clean air shelters and financial assistance programs to adopt protective measures are effective strategies for mitigating harm from wildfire smoke.[11,41] This is particularly important due to findings that suggest lower-income Oregonians are less likely to report avoiding going outside or using masks or respirators to protect themselves (Coughlan et al 2022).

In areas with clusters of Hispanic persons, communications should be tailored to ensure health advisories are clearly conveyed.[42] Clean air shelters and programs providing access to personal protective equipment may be effective mitigation activities in these areas (Coughlan et al. 2022).

Outdoor workers face increased exposure to wildfire smoke.[37] OSHA-compliant respirator programs should be implemented in the areas of Oregon with clusters of outdoor workers.[10]

To address identified health care gaps, local officials could consider staging mobile health units in areas facing active wildfire threats, with community health workers available in areas with limited hospital access. Telehealth technologies could be useful tools for addressing access gaps. Regional collaborations could foster mutual aid agreements for sharing health care resources as well as coordinating emergency response data and efforts.

The next step will be to validate the risk model with a retrospective analysis comparing predicted risk areas with actual hospitalization rates from recent wildfires. After validation, the model can be piloted in select counties to assess the practical utility for informing public health and disaster preparedness officials in Oregon. Once validated, the methodology could inform wildfire resilience strategies in other places by targeting resource allocation and health communications for at-risk populations.

While this analysis focused on Oregon's predominantly rural landscape, the approach of combining wildfire risk and vulnerability assessments may be adapted for other regions and settings, including major metropolitan areas like Los Angeles. Though population density and health care access patterns differ between rural Oregon and urban California, the core challenge of protecting vulnerable populations from smoke exposure remains constant. Considering the recent wildfires in Los Angeles, service agencies could use the method presented here to make important decisions not only in the response to fire events, but in the planning of response efforts. The method and framework presented here are particularly relevant across the western US and British Columbia, where both rural and urban communities need enhanced smoke preparedness strategies.

Conclusions

Results from this study contribute to a better understanding of wildfire smoke risks in Oregon. This information is critical for public health and disaster planning. By focusing on the most vulnerable populations, officials can enhance preparedness, improve public health outcomes, and increase community resilience. Knowing areas with the most severe concerns can help target and maximize the impact from limited preparedness resources. The method presented here for identifying vulnerable populations at high risk can be replicated in other jurisdictions. The analysis has implications for research related to disaster communications and behavior analysis.

Supplementary material. The supplementary material for this article can be found at http://doi.org/10.1017/dmp.2025.131.

Author contribution. Su Jin Lee designed and supervised the analysis; Lee Mitchell performed the analysis; Kyle Chapman and Kerry Farris acquired the health data; Lee Mitchell, Pooya Naderi, and Ashley Hansen drafted the manuscript; All authors contributed to revising the manuscript, have approved the final version, and agree to be accountable for the accuracy and integrity of the work.

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Competing interests. The authors declare no competing interests.

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