Evidence-based mapping of the wildland-urban interface to better identify human communities threatened by wildfires

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Abstract

The wildland-urban interface (WUI) is the spatial manifestation of human communities coupled with vegetated ecosystems. Spatial delineation of the WUI is important for wildfire policy and management, but is typically defined according to spatial relationships between housing development and wildland vegetation without explicit consideration of fire risk. A fire risk-based definition of WUI can enable a better distribution of management investment so as to maximize social return. We present a novel methodological approach to delineate the WUI based on a fire risk assessment. The approach establishes a geographical framework to model fire risk via machine learning and generate multi-scale, variable-specific spatial thresholds for translating fire probabilities into mapped output. To determine whether fire-based WUI mapping better captures the spatial congruence of houses and wildfires than conventional methods, we compared national and subnational fire-based WUI maps for Chile to WUI maps generated only with housing and vegetation thresholds. The two mapping approaches exhibited broadly similar spatial patterns, the WUI definitions covering almost the same area and containing similar proportions of the housing units in the area under study (17.1\% vs. 17.9\%), but the fire-based WUI accounted for 13.8\% more spatial congruence of fires and people (47.1\% vs. 33.2\% of ignitions). Substantial regional variability was found in fire risk drivers and the corresponding spatial mapping thresholds, suggesting there are benefits to developing different WUI maps for different scales of application. We conclude that a dynamic, multi-scale, fire-based WUI mapping approach should provide more targeted and effective support for decision making than conventional approaches.

1. Introduction

The Wildland-Urban Interface (WUI) is the spatial manifestation of the coupling of human communities and vegetated ecosystems, where interactions can take many forms (Bar-Massada et al 2014). In many parts of the world, the most important issue facing the WUI is wildfire (Radeloff et al 2005, 2018) because it is where wildfire-related fatalities and structures losses are concentrated. Indeed, the WUI accounts for large percentages of fire prevention and suppression expenditures (Chen and Mcaneney 2004, Moritz et al 2014, Kramer et al 2018). Wildfires in the WUI thus constitute a serious and growing socio-environmental
and security problem as well as an economic one. Knowing which parts of the WUI are most fire-prone could help protect both people and the surrounding ecosystems via targeted fire risk mitigation efforts (Spyratos et al 2007) or focused fire prevention programs (Balch et al 2017). Therefore, a fire-risk evidence based definition of the WUI is critical to an effective prioritizing of areas for preventive action and management investments in rural and urban areas near wildlands (Calkin et al 2014, Tonini et al 2018).

Delineating the WUI is an increasingly important and complex global issue given the potential for climate, demographic, and land-use change to intensify growing interaction between human communities and fire-prone ecosystems, whose effects vary from region to region (Syphard et al 2009, Argañaraz et al 2017, Radellof et al 2018, Tonini et al 2018). Fire-prone ecosystems may expand due to natural regeneration on abandoned land or changes in land use to more flammable vegetation based on production activity (Mcwethy et al 2018, Badia et al 2019, Blackhall and Raffaele 2019). Population growth can lead to changing development patterns either via urban sprawl, the intensification of the road network, or rural-urban migration (Tonini et al 2018, Blackhall and Raffaele 2019). These changes in turn can alter the human-wildlands interaction zones and the distribution of human-caused ignitions (Ganteaume and Syphard 2018). Collectively, these types of dynamics are already generating rapid changes in the spatial extent and distribution of the WUI (Kaim et al 2018, Radellof et al 2018), and future global change has the potential to dramatically increase human and natural communities’ vulnerability to wildfire.

Given this context and the potential for WUI expansion, successful human coexistence with wildfires will necessitate informed maps that can assist with community and landscape planning to identify where mitigation practices should be adopted to minimize fire risk (Calkin et al 2014, Moritz et al 2014, Keeley and Syphard 2019). Although many WUI mapping efforts have been undertaken in response to this need, they have focused mainly on delineating the values at stake (human lives and integrity, communities, infrastructure) without explicitly including fire risk (Thomas and Butry 2014, Jhonston 2016, Argañaraz et al 2017, Johnston and Flannigan 2018). Of the more than 30 different definitions (Jhonston 2016), the most common ones incorporate three types of criteria (Radellof et al 2005, Lampin-Mailet et al 2010, Platt 2010, Jhonston 2016): (i) residential or population density and its development, (ii) vegetation cover and type, and (iii) the minimum distance between them (Johnston and Flannigan 2018). In general, the WUI has been delineated using a fixed threshold, informed by expert opinion that quantifies the degree of spatial overlap between these criteria. However, WUI spatial delimitation and area are sensitive to the thresholds used for each variable (Radellof et al 2005, Stewart et al 2007, Platt 2010). Fixed thresholds provide a clear and quick method for mapping purposes, but identifying the appropriate ones for different socio-ecological contexts at multiple local or national scales remains a significant challenge (Stewart et al 2007, Amato et al 2018).

Risk in general terms is typically defined as the coincidence of hazard potential and the probability of exposure to and harm from this hazard if it does occur (Scheer et al 2014). Fire risk, therefore, can be viewed as the chance that a fire might start and then behave in response to multi-scale spatial and temporal interactions among climate, vegetation (or fuel type), topography, and the human footprint (Ganteaume and Syphard 2018) in areas where it can do the most damage. Spatial patterns of fire occurrence thereby reflect the local, complex sociological processes that promote fire ignition, extent, and behavior. Defining the WUI thresholds based on fire occurrence drivers and their interactions therefore expands upon previous mapping approaches and helps to maximize social return by diminishing fire risk in areas with the potential for the most severe damage. This approach also allows for a more mechanistic way to account for future scenarios that result from human and biophysical interactions, by integrating fire risk and values at risk (Argañaraz et al 2017, Johnston and Flannigan 2018). Another challenge is to determine an appropriate scale for mapping the WUI. Tonini et al (2018) note that most studies defining and mapping the WUI are performed locally at the spatial scale of houses or in small regions, although some approaches are much larger in extent (Montiel Molina and Galiana-Martín 2016, Radellof et al 2018).

Accounting for the full range of effects and interactions among environmental and anthropogenic drivers of fire risk is difficult using traditional statistical modeling approaches (Elith et al 2008). Artificial intelligence (AI) algorithms provide a compelling alternative for evaluating risk based on multiple drivers because they can capture complex relationships among predictors and response variables (Elith et al 2008). AI methods, particularly those of machine learning (ML), are useful for finding complex interactions between the study variables directly from the data (Olden et al 2008). They are particularly beneficial in practical applications where there are difficulties in finding parametric models that explain the phenomena in question in terms of both linear and non-linear relationships and their interactions (Elith et al 2008).

The overall goal of this study was to evaluate the effect of defining WUI spatial limits based on fire-risk evidence and its variation. Specifically, we aimed to: (i) fit AI models at national and subnational scales to understand spatially explicit drivers of fire risk

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The overall goal of this study was to evaluate the effect of defining WUI spatial limits based on fire-risk evidence and its variation. Specifically, we aimed to: (i) fit AI models at national and subnational scales to understand spatially explicit drivers of fire risk
based on historical ignition patterns, (ii) identify fire risk-based spatial thresholds for the WUI at different scales, and (iii) evaluate the effect of defining the WUI based on fire risk compared to the most widely used definition operationalized by Radenoff et al (2005) for the United States in terms of area, fire occurrence and people within the defined WUI. We therefore used AI tools first to model fire risk across the landscape and then define thresholds for mapping the WUI at national and subnational scales.

2. Material and methods

2.1. Study area

We tested our approach using south-central Chile as a case study. Wildfires activity and its human impacts in the WUI have occurred with increasing frequency over the last several decades. In 2017, Chile experienced the most active wildfire season in its history with ~530,000 ha burned, 10 times the national average (55,000 ha yr⁻¹). As a result, substantial losses both environmental (e.g. air pollution, endemic forest loss) and economic were reported, including 11 fatalities and 3000 houses destroyed (Bowman et al 2019), all associated with the WUI. This increase in human-related wildfire losses in the WUI is highly representative of those in other Mediterranean-type ecosystems and fire-prone regions across the world (Keeley et al 2011, Gill et al 2013, Price and Bradstock 2014).

In the last 50 years, central and southern Chile have experienced highly dynamic land cover change (Miranda et al 2015). Clearing native forests for cropland, pasture, forest plantation, and shrublands is extensive throughout south-central Chile (figure 1) (Miranda et al 2017). In central (33°–34° S) and southern (40°–42° S) Chile, the main change has been the conversion of native forest to shrublands as a result of wildfires and degradation from selective logging. In addition, there has been a ten-fold increase in dense exotic forest plantations, expanding in area from 300,000 ha in 1974 to three million ha in 2018. Consisting of Pinus radiata, Eucalyptus globulus and E. nitens for use in pulp and paper production, these plantations have created highly homogeneous (Miranda et al 2017) and flammable landscapes (Mcewethy et al 2018). Generally speaking, central and southern Chile are the locations of the most extensive anthropogenic land uses, representing 79% of the country’s urban and industrial zones, 94% of its agriculture, and 98.7% of the exotic tree plantations (Miranda et al 2017). These areas have also experienced a dramatic change in population distribution, going from an urban-rural ratio of 1:1 in 1960 to approximately 9:1 by 2017 (INE-Chile, www.ine.cl/estadisticas/sociales/censos-de-poblacion-y-vivienda).

2.2. Wildfire data

We used a subset of the public database of wildfires provided by the Chilean Forest Service (CONAF, www.conaf.cl/conaf/seccion-estadisticas-historicas.html) that gives the spatial coordinates of ignition points for every fire within 0.01 ha mapping units. We created a subset for the period January 2013 to December 2015. This time window was chosen because the most accurate land cover map for the country was developed in 2014 (Zhao et al 2016). The definitive dataset included 19,413 fires covering a total area burned of 245,815 ha spanning all land cover classes.

2.3. Wildfire risk drivers

The list of potential variables selected for our model was based on factors found to be important in driving fire occurrence in Chile as well as other regions (Bar Massada et al 2013, Collins et al 2015, Syphard et al 2019). We considered three different groups of drivers: (i) human activity, (ii) geographical and topographical factors, and (iii) land cover (Mcwethy et al 2018, Gómez-González et al 2019). For each group, we prepared a set of spatially explicit variables, which were assigned to each ignition point (figure 1). We calculated the drivers for each ignition point by extracting the pixel value(s) either (1) at the precise ignition point coordinates, or (2) based on zonal statistics for a 500 m diameter buffer zone around the ignition point (table S3 (available online at (stacks.iop.org/ERL/15/094069/mmedia))).

2.4. Modeling approach

Our main objective in conceptual and computational terms was to determine which drivers were related to fire ignitions. In addition to the database of ignition point locations, we also randomly generated a background dataset of 20,000 non-ignition points. We eliminated those that were less than 2 km from any ignition point to avoid overlap or bias. We then built a full database of 33,773 points, each one marked by a binary code with a value of ‘1’ if there was a fire and ‘0’ otherwise. We implemented a bagged decision tree (BDT) method (Breiman 1996) to relate fire occurrence to spatially explicit drivers. BDT is used in classification and regression models (Opitz and Maclin 1999). It is a type of ensemble method, meaning that different classification models (called ‘weak learners’) are combined to obtain a more robust prediction. In BDT, each ‘weak learner’ is built by drawing random training sets from the given sample. This resampling is usually done using a bootstrapping technique, where numerous versions of the training set are created by sampling with replacement and each one is then employed to build a different learning model. Full details of the mathematical models are in Supplemental Methods. Our modeling approach allowed us to retain all the selected variables that
could interact with fire ignition. To reduce computational cost and obtain a model that is less likely to be overfit, variables were retained in the models only if they had a relative importance value higher than 2%. We fit a national model with the complete dataset and local models with a geographical subset for each individual subnational zone (SNZ; figure 1).

2.5. WUI fire risk thresholds
For national and subnational threshold definitions, we used partial dependence plots (PDPs) to analyze the relationships between features and predicted responses (Friedman 2001, Elith et al 2008). They consist of line plots of occurrence probability estimated by the BRT model against a single predictor variable. A PDP can show whether the relationship between the fire risk and a specific variable is positive, negative, monotonic, or more complex. We assumed that an inflection point or abrupt change in the slope of the curve revealed thresholds for specific variables where a management action could potentially attain the best social return for decreasing fire risk. In general, these functions can be very irregular since they depend directly on the observations, making it difficult to determine these threshold points accurately. We therefore fit different algebraic curves using nonlinear least squares thereby obtaining more robust and reliable thresholds. The spatially explicit thresholds referenced in table 1 delineate the WUI and define high-risk areas near or within human communities.

2.6. WUI mapping
We used the above-defined thresholds to map the WUI for Chile at both national and subnational scales. The WUI were mapped with the commonly used USDI—US (2001) definitions operationalized by Radeloff et al (2005) for the United States (hereafter ‘US-based WUI definitions’). Radeloff et al (2005) differentiate between Intermix (where houses intermix with wildland fuels) and Interface (where homes meet the wildland fuels) as the two main WUI components. Both must contain at least 6.17 housing units km$^{-2}$, but in the case of Intermix more than 50% of the area must be covered by wildland vegetation whereas for Interface, vegetation cover must be less than 50% with dense forest fragments (>75%
Table 1. Threshold definitions for national and subnational models. The upper threshold is indicated by $\uparrow$, the lower threshold by $\downarrow$, and (*) denotes a non-relevant threshold with a fire risk for the variable of less than 0.5.

| Subnational zone | Percentage of ignitions (%) | Accuracy assessment (%) | City distance (km) | Housing density (housing units km$^{-2}$) | Forest plantation (%) | Native forest (%) | Croplands (%) |
|------------------|----------------------------|------------------------|-------------------|-------------------------------------------|----------------------|-----------------|--------------|
| SNZ1             | 22.2                       | 90                     | 1.3 $\downarrow$  | 4.9 $\uparrow$                            | 5 $\uparrow$         | 11–13           | 20–60        |
| SNZ2             | 9.5                        | 83                     | 1.1 $\downarrow$  | 3.3 $\uparrow$                            | 2.2 $\uparrow$       | 19–29           | 40–60        |
| SNZ3             | 52.6                       | 88                     | 1.7 $\downarrow$  | 5.7 $\uparrow$                            | 9.8 $\uparrow$       | 13–28           | 9.4 $\downarrow$ |
| SNZ4             | 11.8                       | 83                     | 1.1 $\downarrow$  | (*)                                       | 5.4 $\uparrow$       | 17.3 $\downarrow$| 40 $\uparrow$ |
| SNZ5             | 3.2                        | 86                     | 0.8 $\downarrow$  | (*)                                       | (*)                  | (*)             | (*)          |
| National         | 89                         |                        | 1.2 $\downarrow$  | 5.6 $\uparrow$                            | 4.5 $\uparrow$       | 18–50           | 20–60        |
Table 2. Effect of change in WUI spatial threshold definition in area, housing units and ignitions within the WUI at national and subnational level and with US-based WUI definitions.

| Zone   | US-based WUI |          |          | National model |          |          |          | Subnational model |          |          |
|--------|--------------|----------|----------|----------------|----------|----------|----------|------------------|----------|----------|
|        | WUI Area (%) | Ignitions (%) | Housing units (%) | WUI Area (%) | Ignitions (%) | Housing units (%) | WUI Area (%) | Ignitions (%) | Housing units (%) |
| SNZ1   | 1.0          | 12.3     | 8.3      | 1.2            | 16.3     | 9.3      | 1.3      | 16.8            | 9.3      |
| SNZ2   | 0.5          | 4.7      | 2.7      | 0.6            | 5.7      | 2.9      | 0.9      | 6.8             | 2.9      |
| SNZ3   | 0.8          | 12.0     | 3.2      | 0.9            | 20.1     | 3.7      | 1.0      | 21.2            | 3.7      |
| SNZ4   | 0.6          | 3.0      | 2.4      | 1.0            | 5.6      | 3.2      | 0.1      | 1.7             | 0.8      |
| SNZ5   | 0.3          | 1.3      | 1.4      | 0.4            | 1.8      | 1.6      | 0.0      | 0.6             | 0.5      |
| National | 3.2       | 33.2     | 17.9     | 4.1            | 49.5     | 20.6     | 3.2      | 47.1            | 17.1     |
wildland vegetation) extending over an area of at least 5 km² and located at a distance of less than 2.4 km.

We join Intermix and Interface in an integrated WUI and compare the resulting WUI maps using the different approaches. For national and subnational delineation we used the proposed thresholds detailed in table 1. The final WUI considers the value of distance only outside the perimeter of the city. The WUI mapping results include public and private lands but exclude the urban part of the WUI, thus retaining only the rural area (table 2).

3. Results

3.1. National and subnational fire risk model accuracy and variable importance

At the national scale, the best model was 89.3% accurate in predicting fire occurrence in test locations. The most important variables explaining fire risk included road density and distance to roads (human activity), elevation and latitude (geographic variables), and forest plantation and native forest (land cover variables) (figure 2). While overall the human activity variable was dominant, accounting for 40% of relative importance, latitude was the most important single variable related to fire occurrence, with fires being highly concentrated between 35°S and 38.5°S (table S1, figure 2).

At the subnational scale, the fire risk models also achieved a high level of accuracy (range: 83%–90%, table 1), and revealed substantial variation in the relative importance of variables between zones (table S2). Land cover variables displayed the greatest differences in this factor between subnational zones (CV = 55.5%), followed by geographical (CV = 48.1%) and human activity variables (CV = 34.4%). The importance of the land cover group variables varied between zones from almost no difference for adjacent subnational zones (e.g. SNZ1 and SNZ2) to double the importance in other cases (SNZ3 and SNZ4). In SNZ4, the importance of land cover variables was 50.5%, the highest values accounted for by the proportions of shrublands, native forest, and forest plantation (table S2). That forest plantation had the lowest value of the three was related to its lower percentage of landscape cover in SNZ5 (table S1). In the subnational zones, however, landscape cover percentage was not always correlated with prediction importance (tables S1 and S2). Human activity variables had the highest mean importance value in SNZ1, SNZ2, and SNZ3, where the main cities and human population in the country are most concentrated. Among these variables, two of the most important were road density and distance, with SNZ3 showing the maximum fire-risk value in areas associated with roads. In areas with low human and road density landscapes such as SNZ4 and SNZ5, the main variable was city distance (table S2).

3.2. Wildland-urban interface mapping thresholds

The relationships between the individual variables and fire risk were found to have three different functional forms: (i) monotonically decreasing effect curve (MD) (figures 3(A) and (B)), (ii) monotonically increasing effect curve (MI) (figures 3(C) and (E)) and (iii) plateau effect curve (Pl) (figures 3(D) and (F)). These patterns of interaction dictated how we subsequently defined the types of thresholds proposed for mapping (SI Methods).

At the national scale, the human activity group of variables were found to have an effect on fire risk for the most important WUI definition variables, as did other variables related to human activities. Proximity to cities and roads had a local effect of maintaining high fire risk, especially for the first 1200 m and 1500 m respectively (figures 3(A) and (B)). However, the trends in these relationships differed. Fire risk was continuously decreasing in distance to roads (figure 3(B)), while for distance to cities it maintained a high constant probability up to 1200 m before falling to 0.6 at 8 km (figure 3(A)). For housing density we found a nonlinear effect, with an exponential trend of increasing ignition probability of more than 10% from zero to 5.6 housing units km⁻², which increased thereafter only by an additional 3.5% to 35 housing units km⁻² (figure 3(C)).

The individual land cover variables displayed differing relationships with fire risk (figure 3). Forest plantation had the strongest individual effect, the risk increasing sharply with more cover. When forest plantation cover increased from 0% to 20%, the fire risk probability rose to 0.65. However, the highest rate of growth in fire risk was found when cover increased from 0% to 4.5%, which was therefore defined as the threshold beyond which fire risk probability stabilized (figure 3(E)). By contrast, the native forest cover proportion had a rapidly increasing effect up to a maximum fire risk from 18% to 50% cover, after which there was a steep decreasing trend (figure 3(D)). Croplands also showed an increasing effect but with a stabilization threshold at 20% which fell after 60% (figure 3(F)).

The same functional forms for the relationships between variables and fire risk in the national scale model were found with the subnational models (MD, MI, and Pl) except that in some SNZs the effect of individual variables was negligible, not exceeding 0.5 of fire risk (table 1). Human activity variables generally showed higher individual effects on fire risk for all SNZs except SNZ1 and SNZ4, where the highest values were exhibited by croplands and forest plantations, respectively. For every SNZ, distance to cities had a strong and consistently decreasing effect on fire occurrence probability, ranging from 0.8 km to a maximum of 1.71 km in SNZ3. The stabilization of fire risk in terms of housing density varied from 3.3 to 5.7 housing units km⁻², and the variable did not show a significant effect in southern SNZs (table 1).
Figure 2. Left panel: predicted national fire risk, Low: 0–0.5 prob., medium: 0.5–0.75 prob., medium-high: 0.75–0.9 prob. and high: 0.9–1 prob. Right panel: variables relative importance for national model.

Figure 3. One-dimensional effect of human activities on fire risk at the national scale: (A) distance to cities (km), (B) distance to roads (km), (C) housing density (housing units km\(^{-2}\)), (D) native forest proportion (%), (E) forest plantation proportion and (F) croplands proportion (%).

For land cover variables, the effect of native forest in SNZ1 increased up to 11% of cover, beyond which the impact decreased. In SNZ2, fire risk continually increased up to complete native forest cover, but the highest increase in risk occurred between 19% and 29% (table 1). In all zones, we found positive and monotonically increasing fire risk for forest plantation cover, the greatest effect being in SNZ3 where the increase in fire occurrence probability was 16% for a tree plantation cover of 10% and continued to rise until 67% cover, the total gain in fire risk being 23%. Croplands for different SNZs showed all three types of relationships between individual variables and fire risk so different kinds of thresholds were proposed (table 1).

3.3. Comparison of WUI mapping approaches
In general, maps created using the US-based WUI definitions (figure 4(A)) showed similar broad spatial patterns for the WUI compared to our maps created with thresholds generated at the national (figure 4(B)) and subnational scales (figure 4(C)). However, differences between the maps become increasingly apparent toward the southern areas of the country, where the WUI on the maps using subnationally defined thresholds is substantially more concentrated and less extensive than on the other two.

An assessment of the spatial congruence between wildfire occurrence for the period 2016–2018, not used for threshold estimation, and mapped WUI showed that the maps created using fire risk-based
thresholds generally captured larger proportions of the fire ignitions than the maps created using the US-based WUI definitions, while accounting for the same numbers of housing units (table 2). These relative proportions varied somewhat across subnational zones, with most of the wildfires having occurred in SNZ1 and SNZ3. The spatial extent of the WUI was largest on the maps defined with the national thresholds, which overall covered 681 255 ha more than with the US-based definitions (figure 4, table 2). This translates into the subnational maps having the same WUI area mapped with the US-based definitions but 13.9% greater spatial congruence with wildfires (a relative difference of 44%), and 0.8% fewer housing units in the priority area (~155 000 fewer persons) (table 2). As regards spatial coincidence, 71% of the area of the subnational WUI overlapped the US-defined WUI. The spatial distribution difference represents the areas where our models found the population to be under greater threat than was indicated with US definitions.

4. Discussion and conclusions

This paper has presented a novel methodological approach that can be used to delineate the WUI based on an assessment of fire risk evidence. Our results suggest that this approach to WUI mapping is appropriate for fire policy and management, although other methods may still be more appropriate for non-fire applications (e.g. Bar-Massada et al 2014). Delineating the riskiest areas of the WUI is increasingly important for the efficient targeting of priority areas to focus management and prevention activities, particularly given the potential for increases in wildfires as a result of global changes in climate and land use. Delineating the WUI based on fire occurrence evidence reveals the spatial interaction that ultimately results in a wildfire but assumes the past spatial distribution of fires can describe future wildfire occurrence (Price and Bradstock 2014, Johnston and Flannigan 2018), a supposition that may not hold up in the face of global change (Balch et al 2017). By contrast, with an understanding of the explicit spatial interactions that explain fire risk, methodologies can be adapted to multiple realities and changing scenarios across scales and time.

In ecosystems where humans are the primary cause of wildfires, they are essentially the spatial and temporal manifestation of the human-fire relationship (Ganteaume and Syphard 2018). The interactions between humans and fire are locally defined by human factors such as culture, land use planning and fire prevention as well as biophysical factors like climate, land cover and topography (Bowman et al 2011, Moritz et al 2014, Syphard et al 2019). By modeling these interactions, we were able to generate a better spatial congruence between fire, people and the WUI than may be achieved by mapping the WUI using definitions based on housing and vegetation.

The reason that fire risk-based WUI mapping performed better at capturing the spatial relationship between people and fires is that not all combinations of people and vegetation are risky—rather, it depends upon the context. For example, our approach revealed a potentially dangerous combination of human infrastructure and forest plantation cover, but the risk was lower when the same proportion of land cover was native forest as opposed to forest plantations. The fire-based WUI maps reflected these differences, which resulted in more WUI mapped in areas where a substantial number of people were exposed to large...
patches of forest plantations in the southern part of the study area. The relationship between fire risk and forest plantations has been identified in other works (Mcwethy et al 2018, Gómez-González et al 2018), with risk being particularly high under extreme conditions (de la Barrera et al 2018, Bowman et al 2019). This suggests that these areas may be particularly vulnerable in the future, especially if population increases in areas with continuous forest plantation cover. Further exploration of this combined effect on fire risk is needed to obtain the n-dimensional optimal thresholds.

4.1. Multi-scale approaches that account for variable interactions are important for identifying appropriate thresholds for different applications

We found substantial local-scale variation in the effects of different combinations of, and interactions between, land cover and human activities across subnational zones. By modeling these regions separately, we were able to customize thresholds for mapping the WUI in subnational zones to reflect differences in local population density and its interaction with factors such as topography and land cover. The variable distribution of fire occurrence and differences in relationships between fire occurrence drivers across subnational zones therefore justify the use of a multi-scale modeling approach to WUI mapping. This approach can be employed to identify thresholds for large-scale applications as well as local thresholds more relevant to different regions’ management and planning targets such as a particular city. In local or regional applications, applying a strictly national-scale model could lead to an inaccurate estimate of variable importance. This is so because differences in geographic concentration of wildfires across the country influence the estimation of variable importance in model fitting.

In general terms, fire risk was higher near human infrastructure (cities, roads, houses) at both the national and subnational scales, which is consistent with the fact that more than 95% of fires in Chile are human-caused (González et al 2018). In addition, non-linear relationships were identified between population density and fire risk, a result that has also been shown globally (Syphard et al 2009, Aldersley et al 2011, Bistinas et al 2013). The dominance of human-caused fires is common in other regions with Mediterranean-type climates (Ganteaume and Syphard 2018), and human influence on fire occurrence is increasing globally with population growth and urban expansion into wildlands. We also found significant local variation in fire risk depending on land cover, demonstrating the existence of geographical variability across a human footprint gradient in alignment with previous studies (Urrutia-Jalabert et al 2018, Gómez-González et al 2019).

Another finding was that land cover is a strong indicator of human-fire relationships, which lends itself well to the use of an artificial intelligence-based analytical approach that takes into account such complex variable interactions. AI algorithms are particularly appropriate for fire risk modeling using a large number of variables with different types of interactions to define thresholds that allow for a realistic interpretation of these spatially complex processes.

The importance of land cover in our model suggests that in addition to influencing fire spread, it also affects ignition probability (Oliveira et al 2012), which could be a function of flammability together with the distribution of human presence. Even patterns of lightning ignitions are sensitive to fuels, climate, and topography (Ganteaume and Syphard 2018). This may be due to the fact that some land covers produce more flammable material like small branches and dry leaves, or are associated with different fuel conditions governing flammability (Cóbar-Carranza et al 2014, Blackhall and Raffaele 2019). Incorporating the unique effects of different spatial contexts on different fire patterns may help to better delineate the most vulnerable portions of the WUI.

The subnational models illustrated how drivers of fire risk could interact differently across bioclimatic zones (Ager et al 2014, Fusco et al 2016). In other words, different combinations of, and interactions between, climate, land cover and human activity produced unique local effects in different regions.

In SNZs 1, 2, and 3, where the majority of fires are concentrated (table 2), cities and roads are found mainly in the coastal mountain range and the central valley at low elevations. These are also the areas where most land covers reflect economic activities such as industrial forest plantation, agriculture, and productive pastures. There is a significantly higher proportion of native forest in less populated areas with lower fire frequency in the pre-Andean and Andean ranges. In the areas of the country where most fires occur, they are due to human-caused ignitions in combination with the replacement of native forest by homogenous forest plantations that now dominate the landscape (Miranda et al 2017).

While central and southern Chile are currently the areas where these extensive anthropogenic land uses are concentrated (Miranda et al 2017), future land-use change may result in an expansion of wildfires, as has occurred in other countries (Balch et al 2017), in response to increases in population and exotic forest plantations. Note also that our study did not distinguish between intentional and accidental fire ignition; doing so could potentially change the results on the spatial pattern of fire risk (Syphard and Keeley 2015). Nevertheless, by lumping all ignition sources together we were able to capture the overall spatial pattern of human-caused ignitions.
4.2. WUI fire risk thresholds

A precise definition of WUI or the management of its components may have a substantial effect on hazard mitigation (Spyratos et al 2007). The WUI is commonly mapped by establishing certain thresholds of housing density, vegetation cover, and distance between fire-prone ecosystems and people, whose intersection generates value-at-risk areas of human development (Radloff et al 2005). This threshold is usually predefined as an adaptation of some standard definition, the result being that the thresholds used across the literature are inconsistent. Our approach to delineating thresholds based on fire risk is a step forward in achieving a WUI definition that incorporates the combination of fire ignition and spread, and vulnerability to fire damage (Chuvieco et al 2014).

Our machine learning modeling approach enabled us to identify thresholds for standard variables that influence fire risk in the WUI. In particular, these proposed thresholds indicated the values of each variable at which the fire probability or risk increased, stabilized, or decreased. Although these thresholds are generally independent of the value at risk to be protected, they could be applied to define the WUI in different scenarios of prevention, management, and landscape planning strategies. For example, the national model determined that the main increase in fire probability occurred between 0 and 5.6 housing units km$^{-2}$, after which it stabilized. If the objective is to reduce fire risk, a strategy could be adopted to prevent fire in low-density areas below this value or to increase management efforts in higher fire risk areas mapped as exceeding those thresholds. Syphard et al (2019) also found varying housing densities where structure loss was highest depending on the region.

One of the most common metrics used to define the WUI is the distance to large patches of vegetation (Johnston and Flannigan 2018). However, our results suggest that distance is not necessarily applicable for all kinds of vegetation given that we found different directions and magnitudes of effect depending on the type of land cover. This is consistent with the fact that different vegetation types tend to be associated with differences in fire regimes (Wells et al 2004, Mcwethy et al 2018) and that the patterns of fire vary across different resource gradients (Bradstock 2010, Krawchuk and Moritz 2011, Archibald et al 2013). Different land cover types may reflect those gradients differently. For instance, forest plantations are associated with hazardous fuel conditions closely related to wildfire activity (Mcwethy et al 2018, Bowman et al 2019, Gómez-González et al 2019). Up-to-date land cover maps are critical to determining which human communities are facing current or near-future wildfire threats.

Our results support the potential benefits of using a local definition of the WUI, which could strengthen the impact of prevention and landscape management strategies aimed at reducing fire risk. While the thresholds we identified are appropriate for the current landscape, it will also be essential to account for land use and land cover dynamics that are leading to a rapidly changing WUI in anthropogenic landscapes (Tonini et al 2018, Blackhall and Raffaele 2019). Therefore, it will also be important to update models and maps to define the WUI dynamically as the landscape changes (Mcwethy et al 2018, Badia et al 2019, Blackhall and Raffaele 2019). Knowing where people and fires are most likely to intersect would be beneficial for creating land use zoning or for prioritizing areas for homeowner mitigation or fuel break access for fire suppression.

Recommendations have been made in the literature for the thresholds used in planning to be flexible or probabilistic (Amato et al 2018), but until now there have been few attempts at establishing an empirical definition of the WUI based on different fire risk thresholds (Johnston 2016). And progress is needed in exploring local, multi-dimensional and multi-scale definitions of thresholds based on the spatially explicit interactions among drivers. Also beneficial would be the generation of datasets indicating real-time locations of houses and vegetation cover and automated analyses of their interactions. This could be done using Google Earth Engine (GEE), an open cloud-computing platform for geospatial analysis that contains a multi-petabyte public catalog of satellite images, topography, land covers, and other environmental datasets (Gorelick et al 2017). For example, the platform has an actualized dataset of annual vegetation cover change created by Hansen et al (2013). GEE is an opportunity for developing countries to generate their own low-cost database and local framework. This approach will help improve local spatial congruence between fire occurrence and people under threat. In addition, ongoing updates to geospatial datasets and analysis could focus prevention and management actions more precisely by taking into account short time-scale social and environmental dynamics. Multi-scale, evidence-based WUI and continuous mapping that incorporate fire risk may be better suited for optimal fire policy and management support.

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Data availability statement

The data that support the findings of this study are available upon request from the authors.

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