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The wildland – urban interface in Europe: Spatial patterns and associations with socioeconomic and demographic variables

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HIGHLIGHTS

- We present the first high-resolution map of the Wildland-Urban Interface in Europe.
- The WUI covers about 7.4 % of the European area.
- WUI cover varies considerably within and among countries.
- The WUI is significantly related to various socio-economic and demographic factors.

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ABSTRACT

The wildland – urban interface (WUI) is the zone where human settlements are in or near areas of fire-prone wildland vegetation. The WUI is widespread and expanding, with detrimental consequences to human lives, property, and neighboring ecosystems. While the WUI has been mapped in many regions, Europe does not have a high resolution WUI map to date. Moreover, while most WUI research has been focused on quantifying spatial and temporal patterns, little is known about the relationship between the WUI and the socioeconomic conditions that drive its formation. Here, we present the first high-resolution map of the European WUI and provide the first macro-scale analysis of the relationship between the WUI and some of its potential drivers. We found that the WUI covers about 7.4 % of Europe, but its extent varies considerably both across and within countries, with sub-national WUI cover varying from nearly zero to almost 90 %. WUI cover is significantly related to socioeconomic variables such as GDP per capita, the proportion of the population above 65 years old, population density, road density, and the proportion of protected areas, but these effects are complex and interactive. This suggests that WUI drivers are likely to differ across and within countries, and hints about the importance of both top-down and local socioeconomic processes in driving the WUI. Our new WUI map can facilitate local as well as regional-scale wildfire risk and ecological assessments that inform policy and management decisions aimed at reducing the detrimental outcomes of the WUI in Europe.

1. Introduction

The frequency and extent of wildfires increased in many parts of the world in recent decades (Kasischke & Turetsky, 2006; Shvidenko & Schepaschenko, 2013; Weber & Yadav, 2020), as has wildfire hazard in general (Jolly et al., 2015). Such wildfires have profound effects on ecosystem structure and function (Silva et al., 2018; Wardle et al., 2003), and they are among the most significant natural disasters in terms of losses of human lives and property (McWethy et al., 2019). In coming decades, this trend of increasing wildfire hazard may even worsen in some regions, due to both the increasing frequency of extreme weather events such as droughts (Ruffault et al., 2020; Silvestrini et al., 2011), and rapid land use changes which make landscapes more prone to fire initiation and spread (Pausas & Keeley, 2021). These processes have been especially evident in the European Union, where 72,500 fires burned about 450,000 ha annually from 1990 to 2019. The Mediterranean countries (i.e., Portugal, Spain, France, Italy, and Greece) accounted for 86 % of the burned area (European Commission. Joint

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Research Centre, 2021).

The effects of wildfires on people are concentrated in the wildland-urban interface (WUI), where human development is adjacent to or interspersed with flammable vegetation that can support fire spread (Radeloff et al., 2005). The WUI is widespread in many countries (Bar-Massada et al., 2014) and growing (Godoy et al., 2022; Radeloff et al., 2018), resulting in a substantial and increasing exposure of human lives, property, and infrastructure to wildfires. Quantifying and mapping the extent and geographic patterns of the WUI is therefore crucial to understanding wildfire problems in fire-prone regions with human settlements. Previously, broad-scale WUI maps have been developed for the US (Radeloff et al., 2005, 2018; Theobald & Romme, 2007; Carlson et al., 2022), and across Europe at continental (Modugno et al., 2016), and regional (Alcasena et al., 2018; Del Giudice et al., 2021; Lampin-Maillet et al., 2010; Mitsopoulos et al., 2020) scales, as well as for other areas such as central and western Argentina (Argañaraz et al., 2017; Godoy et al., 2022). However, the scale and resolution of WUI maps are often limited by the specifications of the input data, and lower-resolution data can challenge their interpretation. For example, a prior WUI map of Europe (Modugno et al., 2016) is based on CORINE land cover data (Buttner & Kosztra, 2007), which has a minimum mapping unit of 25 ha. Consequently, that WUI map does not capture small settlements or individual buildings, and instead only identifies WUI patches which may comprise multiple land cover types, some of which might not allow for fire spread. Similarly, the commonly-used US WUI map (Radeloff et al., 2005) was based on US decennial census block data, which are polygons that vary in shape and size and can contain a large number of buildings. Such maps provide insights about coarse WUI patterns in a given region or state, but miss fine-scale variations, limiting their value for landscape and urban planning (Bar-Massada et al., 2013). Fine-grain WUI maps, on the other hand, provide very valuable information for decision making, but are often constrained by a lack of sufficiently detailed input data (especially on building locations) for large areas. Consequently, a continental-scale fine-grained map of the WUI across Europe is still lacking, and this is unfortunate given that wildfire problems in the WUI are a major challenge there (Alcasena et al., 2019; Galiana-Martín, 2017; Vacca et al., 2020).

While the conceptual definition of WUI is fairly consistent among the many studies that have mapped the WUI, the exact definition and the parameter settings for the mapping differ considerably (Bento-Gonçalves & Vieira, 2020). Common among all existing approaches is the combination of two types of land cover data: built-up areas and flammable vegetation. However, approaches differ in how these are defined (i.e., what comprises built-up areas and which fuel types are considered as flammable), how to quantify their amount (e.g., how many buildings per unit area? What is the proportion of flammable vegetation nearby?), and how spatial juxtaposition is defined (i.e., at what distance a built-up area should be from flammable vegetation to be considered as WUI). Furthermore, WUI maps vary considerably in their thematic resolution, from two-class representations (i.e., WUI versus non-WUI) to multiclass representation with multiple WUI types. In the simplest case, the WUI is divided into interface (built-up areas with little vegetated cover, that are within a certain distance to continuous swaths of flammable vegetation, and are consequently mostly exposed to showering embers and home-to-home ignitions) and intermix areas (built-up areas that are interspersed within flammable vegetation) (Radeloff et al., 2005; Theobald & Romme, 2007). Multi-class WUI typologies divide the WUI into additional sub-classes according to different combinations of building configurations and vegetation types (Del Giudice et al., 2021; Lampin-Maillet et al., 2010) or different types of wildfire exposure potential (Beverly et al., 2010), which may subsequently be assigned levels of fire risk (Caballero et al., 2007).

The most widely used WUI mapping approach was developed based on the US Federal Register definition (USDA and USDI 2001) and distinguishes WUI intermix and interface classes (Radeloff et al., 2005). For an area to be WUI requires that: [1] there are enough buildings exposed to wildfire risk, i.e., >6.17 houses per km^2 or one house per 40 acres (the rationale is that isolated buildings are not part of the WUI); [2] there is sufficient coverage of flammable vegetation (>50 %) around those buildings to facilitate direct fire spread. Those areas that meet both criteria [1] and [2] are classified as the intermix WUI. [3] areas that conform with [1] but not with [2] but are within a certain distance of a large and contiguous patch of flammable vegetation that can produce firebrands, are categorized as interface WUI. The US approach assumes a 2.4 km distance and a minimal patch size of 5 km^2. While these parameter choices were made according to wildfire issues in the US WUI, other parameterizations might be more suited in regions where land cover patterns and fire regimes differ, such as Europe. Hence, it is important to custom-tailor the parameter settings of WUI maps to the specifics of a given landscape, as WUI maps should vary depending on utilization, geographic setting, and aim (Stewart et al., 2009).

Beyond the question of where the WUI is, identifying what factors determine where the WUI is most common is a knowledge gap that hinders our understanding of WUI growth. A major driver of WUI development is exurban growth, which is related to the socioeconomic processes that cause people to settle in or near natural ecosystems (Gude et al., 2006; Pejchar et al., 2007; Taylor, 2009). Exurban growth can result from bottom-up, “pull” factors, such as the desire to live near scenic amenities such as forests or recreational opportunities (Sullivan, 1994; Taylor, 2009), or from “push” factors, for example, when government policies or macro-economic processes make it cheaper to live afar from urban centers (Boarnet et al., 2011; Millward, 2002). Exurban growth can directly lead to WUI formation in areas dominated by wildland vegetation outside urban boundaries (Robinson et al., 2005). Yet the WUI might be formed even when exurban growth occurs in agricultural areas, as it may reduce the distance between wildland vegetation and built-up areas (Badia et al., 2019; Martinuzzi et al., 2007). At the same time, the WUI can likewise emerge by an opposite process, where agricultural abandonment near settlements allows vegetation to regrow, thereby increasing the contact zone between built areas and natural or semi-natural vegetation (Radeloff et al., 2018). An example is the rapid increase of commercial eucalypt and conifer plantations in marginal agricultural lands and pastures, which engulfed many small rural communities in the wetter Mediterranean areas (Badia et al., 2019; Moreira et al., 2023). Still, the extent and the specific factors tied to WUI development across broad spatial scales are not well known but are important to understand in order to devise land use policies aimed at reducing the WUI fire problem (Moritz et al., 2022).

Our objective here was to generate the first wall-to-wall map of the European WUI at a high resolution and then to assess the role of different socioeconomic variables in explaining the extent of the WUI within different European countries. To that end, we present a detailed quantification of WUI variation at finer spatial scales to understand better the relationships between the WUI and fundamental socioeconomic drivers. In addition, our work provides valuable insight into identifying the regions where rapidly evolving socioeconomic trends may substantially increase the number of vulnerable households in fire-prone European areas.

2. Methods

2.1. Built-up and vegetation data

We aimed to map the WUI across Europe, which we defined as the Schengen Zone plus the British Isles and those Balkan countries for which sufficient socioeconomic data were available, to facilitate subsequent analyses of WUI drivers (Fig. 1). We first obtained built-up data for Europe from the 2019 World Settlement Footprint dataset (Marconcini et al., 2020). This global dataset was generated by automated interpretation of 10-m resolution Sentinel-1 and Sentinel-2 satellite imagery, and each pixel is either built-up or not. Next, we gathered vegetation data from the 2020 European Space Agency (ESA) global

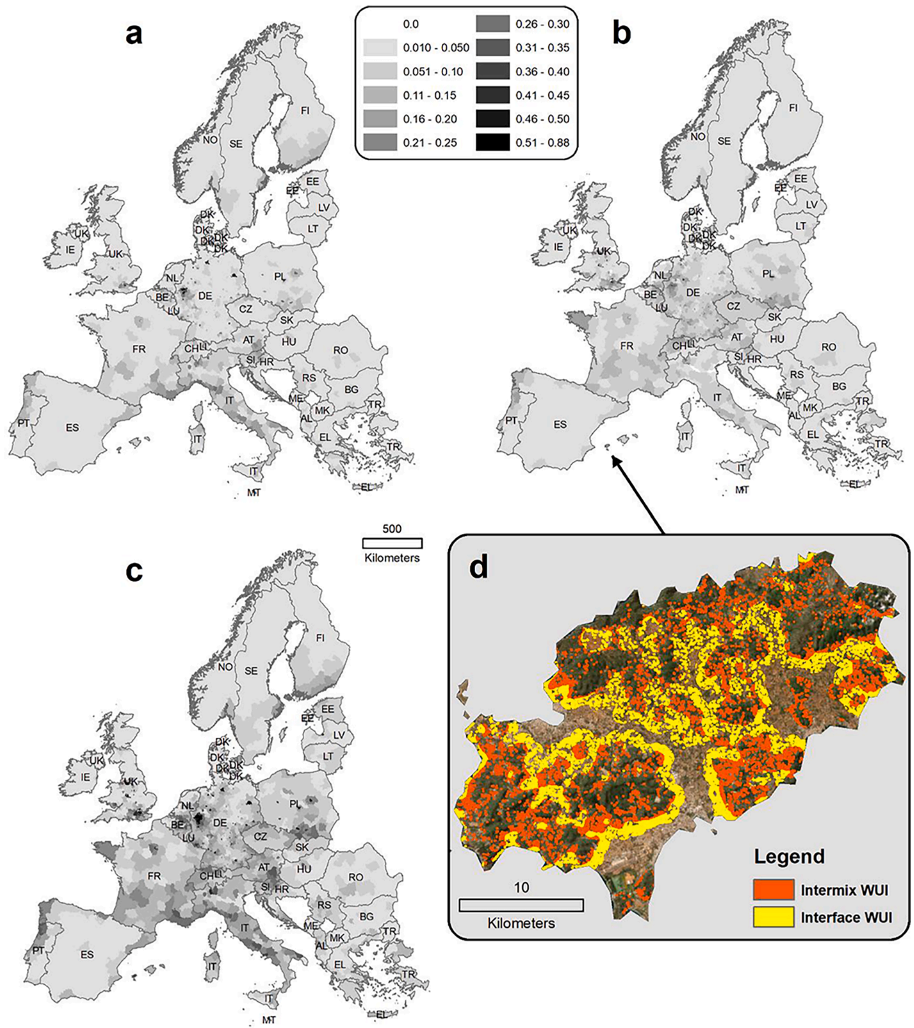

Fig. 1. Proportion of WUI in NUTS-3 zones across Europe, 2020, for intermix WUI (a), interface WUI (b), and total WUI (c). Missing countries are those without NUTS-3 data. (d): high-resolution WUI map of the Island of Ibiza, overlaid on top of a true-color satellite image (where dark colors depict wildland vegetation patches). See country abbreviations in Table 1.

land cover product (Zanaga et al., 2021). This dataset classifies the same 10-m Sentinel-1 and Sentinel-2 satellite imagery, in conjunction with auxiliary data, into 11 land cover classes. Finally, we reclassified the dataset into two classes: woody vegetation classes ('forests' and 'shrublands', "1") and others ("0"). Hence, we focused on fire hazard in built-up areas only from woody vegetation, regardless of species identity and fuel characteristics. We implicitly assume that given sufficiently dry conditions, any woody vegetation can potentially support fire spread, even if there are considerable differences in flammability. This assumption was necessary because ESA's landcover map does not contain detailed information about fuel types. We opted to include only woody fuels for two reasons: [1] on average, woody fuels generate more extreme fire behavior than grassland fuels; [2] they require considerably more resources to manage pre-fire than grasslands.

2.2. Wildland-Urban interface mapping

To map the WUI, we modified the parameters of the existing point-based WUI mapping approach (Bar-Massada et al., 2013), which is based on the original US WUI mapping approach (Radeloff et al., 2005). Our new approach adapts the 10 m-cell grid of the underlying datasets and includes the following steps: [1] we included all cells within 100 m of a built-up cell as candidate WUI locations, regardless of the housing density within (and around) them in order to identify all built-up areas that are potentially at risk, as well as their immediate surroundings, which could be targeted for fuel reduction treatments to reduce fire exposure in the home ignition zone (Cohen, 2000). We omitted the housing density threshold of 6.17 buildings/km^2 because it precludes the inclusion of lower-density housing developments in the WUI, and our objective here was to account for all buildings exposed to wildfire risk in Europe. [2] we calculated the percent cover of woody vegetation within a 500 m radius (Bar-Massada et al., 2013; Carlson et al., 2022) around candidate WUI location cells; if the woody cover was $>$50 %, these cells were mapped as 'intermix WUI'. We chose the 500 m radius because it excludes most urban parks from the WUI (Carlson et al., 2022). [3] we identified patches of woody vegetation that were $>$5 km^2 [in line with Radeloff et al., (2005)]. [4] we identified all candidate WUI locations within a 600 m buffer to large vegetation patches (found in [3]); these cells were mapped as 'interface WUI'.

The choice of 600 m reflects findings about the approximate *median* value of maximum travel distances of showering embers (Storey et al., 2020), which is corroborated by empirical findings that 100 % of buildings burnt by wildfires in the US were within 850 m of a 5 km^2 (or larger) patch of wildland fuels, and nearly 100 % were within 600 m of those patches (Caggiano et al., 2020). This threshold differs from the previously used distance of 2,400 m (Argañaraz et al., 2017; Carlson et al., 2022; Radeloff et al., 2018), which reflects *maximum* travel distances. To assess the sensitivity of our map to this threshold, we generated an additional WUI map using the original parameter of 2400 m and compared the resulting WUI maps across Europe. Finally, based on our WUI maps, we quantified the overall extent and the spatial distribution of interface, intermix, and total WUI at the country level for each country in our study area.

2.3. Socioeconomic and demographic data

We obtained data at sub-national levels for most European countries from Eurostat, the statistical office of the European Union (https://ec.europa.eu/eurostat/web/regions/data/database; last accessed on August 17th, 2022). Eurostat collects data at four hierarchical levels: countries, NUTS-1 (major socioeconomic regions, 92 in total), NUTS-2 (basic regions for the application of regional policies, 242), and NUTS-3 (small regions for specific diagnoses, 1187 of which had sufficient data). Therefore, to maximize the level of geographic detail for our analyses of WUI drivers we analyzed NUTS-3 data, even though fewer socioeconomic variables are collected at that level. These variables included: [1] population density (persons/km^2): this variable serves as the precursor to settlement development both in and outside the WUI and is directly related to fire risk (Hanberry, 2020; Syphard et al., 2009); [2] proportion of the population over 65 years old: this variable was included as we assumed that older populations manifest rural exodus in low-income regions in rural WUI areas (Badia et al., 2019); alternatively, in richer countries, secondary homes for retirees might be prevalent in WUI areas given their scenic amenities (Davis, 1990); and [3] gross-domestic production per capita in 2019 (GDP, in 1000s of EURO): we included it to test if WUI occurrence depends on the economic development of a region. Ideally, we would have had additional variables (such as housing prices), but our choice of variables was limited by what was available from Eurostat, which aggregates source data from 27 different countries, and is the best data source for consistent socioeconomic data for our entire study area.

In addition, we calculated from other sources the following environmental variables: road density using the primary, secondary and tertiary road network (km/km^2; OpenStreetMap, https://download.geofabrik.de/europe.html, last accessed on August 29, 2022); this variable is an indirect measure of the accessibility of wildland areas to human development (Hawbaker et al., 2006), and proportion of protected areas (UNEP-WCMC, 2019); to reflect the 'pull' factor of natural areas to human settlements (Radeloff et al., 2010).

2.4. Statistical analysis

We modelled the effects of various demographic variables on the relative proportion of the WUI (intermix and interface combined) at a finer spatial scale. To that end, we quantified the amount of WUI at NUTS-3 level, corresponding with available socioeconomic and demographic data. In addition, we used the same datasets that were used in the WUI mapping stage, built-up areas, and wildland vegetation, to calculate the proportions of these two variables per NUTS-3 region to remove their confounding effect on the proportion of WUI per region.

We used a two-step process to model the effects of the above predictor variables on the proportion of WUI area (pWUI). First, we applied a generalized linear mixed effects model with a Beta error distribution to estimate the variation in pWUI that was directly related to the proportion of wildland vegetation and the proportion of built-up areas. To fit the model, we added 0.0001 to the proportion of WUI in three NUTS-3 zones with no WUI, as the beta distribution requires positive numbers. The model included the above two predictors, standardized to zero mean and unit variance, as interactive fixed effects, and country code as a random intercept effect to test for baseline differences in WUI among countries.

Second, we aimed to quantify the effects of our suite of socioeconomic variables on the proportion of WUI after accounting for the confounding effects of the proportion of wildland vegetation and the proportion of built-up areas. To that end, we modelled the residuals of the first model in a linear mixed effects model with the following fixed effects: proportion of population above 65 years old, population density, population density squared, road density, GDP per capita, and proportion of protected areas. All predictors were standardized to zero mean and unit variance. The model also included interaction terms to account for potential interactions among the effects of these predictors:

- GDP per capita and proportion of population above 65 years old (to test if WUI is more prevalent in regions with lower socioeconomic levels where land abandonment is common and rural population is older. Or, alternatively, to denote the high prevalence of second homes in rural areas in wealthier countries).
- Road density and population density (as high road density can point to building dispersion in highly populated areas, which may lead to increased interfaces between settlements and wildlands where the latter are also prevalent).
- Population density and proportion of protected areas (to test if scenic amenities are a 'pull' factor for settlement development).

Finally, country code was included as a random intercept effect to account for potential inherent differences in WUI drivers across countries. We fitted both models using maximum likelihood and assessed the significance of model predictors using a type-II Wald's chi-square test. We calculated each model's marginal and conditional R^2 (Nakagawa & Schielzeth, 2013). Given the spatial structure of the data, and to evaluate the assumption of data independence, we assessed if model residuals were spatially autocorrelated by semi-variogram analysis. We found no evidence for spatial autocorrelation in the residuals of either model. We conducted all analyses using R (R Core Team, 2013), with the packages 'glmmTMB' (Brooks et al., 2017), 'lme4' (Bates et al., 2013) and 'performance' (Lüdecke et al., 2021).

3. Results

3.1. WUI patterns

The total area of the WUI in Europe in 2020 was about 363,000 km^2, or 7.4 % of the land area. Of that, 169,312 km^2 was intermix WUI (46.6 %), and 193,974 km^2 was interface WUI (53.4 %). There were considerable differences among countries in the WUI's relative cover and the composition of intermix vs interface WUI (Fig. 1, Table 1). With 23 % of its area in WUI, Lichtenstein had the highest relative WUI cover in Europe, followed by Slovenia (16.13 %) and Switzerland (15.67 %). France, the largest country we analyzed, had the highest absolute WUI area (38,288 km^2 of intermix, 26,291 km^2 of interface). Malta (0.02 %) had the smallest proportion of WUI area in Europe, followed by Ireland (0.95 %) and Norway (2.08 %). Twenty-five countries had more interface than intermix WUI, and 11 countries had more intermix than interface WUI (Table 1). Kosovo (2.86 times more interface than intermix), Ireland (2.38), the United Kingdom (2.1), and Denmark (2.03) had more than twice the area of interface WUI. In contrast, Malta had no interface WUI at all, Finland had almost 2.7 times more intermix WUI, and Sweden 1.66 (Table 1). There was considerable variation in the proportion of WUI across NUTS-3 zones within countries (Fig. 2). For example, proportions of WUI across 401 German NUTS-3 zones ranged from zero (Straubing) to 87.8 % (Herne). In Bulgaria, on the other end, proportions of WUI tended to be low across its 28 NUTS-3 zones, as the range was between 0.01 % (Yambol) and 10.9 % (Kardzhali).

Our WUI map was sensitive to the choice of mapping parameters. Increasing the distance threshold to the nearest >5 km^2 vegetated patch from 600 m to 2400 m led to a considerable increase in WUI area across most of Europe (Fig. S1), from 363,000 km^2 to 493,356 km^2, (35.8 % increase), totaling ca. 10 % of the study area. Virtually all the increase in WUI was in interface WUI, which is the component directly affected by the value of this parameter.

Table 1
Country-level statistics of interface and intermix WUI. Countries marked with asterisks do not have NUTS-3 data. Country abbreviations correspond to the maps in Fig. 1.

Country	Interface WUI (km^2)	Intermix WUI (km^2)	Interface WUI (%)	Intermix WUI (%)	Total WUI (%)	Interface/Intermix
Albania (AL)	979.92	1340.01	3.40	4.65	8.06	0.73
Austria (AT)	6008.86	5408.89	7.16	6.44	13.60	1.11
Belgium (BE)	2520.08	2030.62	8.22	6.62	14.84	1.24
Bosnia and Herzegovina*	2248.67	2823.26	4.39	5.51	9.90	0.80
Bulgaria (BG)	2242.53	2043.75	2.02	1.84	3.86	1.10
Croatia (HR)	2042.15	3253.81	3.61	5.76	9.37	0.63
Czech Republic (CZ)	6056.36	3171.05	7.68	4.02	11.70	1.91
Denmark (DK)	1293.97	634.60	3.00	1.47	4.47	2.04
Estonia (EE)	1750.16	1343.90	3.86	2.96	6.82	1.30
Finland (FI)	4420.46	11963.06	1.31	3.54	4.85	0.37
France (FR)	38288.36	26291.31	6.98	4.79	11.76	1.46
Germany (DE)	26739.93	15602.13	7.48	4.36	11.84	1.71
Greece (EL)	3686.76	5378.42	2.80	4.08	6.88	0.69
Hungary (HU)	2999.58	1792.57	3.23	1.93	5.15	1.67
Ireland (IE)	464.51	194.40	0.67	0.28	0.95	2.39
Italy (IT)	16652.09	26744.35	5.54	8.90	14.44	0.62
Kosovo*	403.25	140.70	3.70	1.29	4.99	2.87
Latvia (LV)	1927.33	1149.38	2.98	1.78	4.76	1.68
Liechtenstein (LI)	22.11	14.71	13.81	9.19	23.01	1.50
Lithuania (LT)	2455.83	1230.52	3.78	1.90	5.68	2.00
Luxembourg (LU)	267.23	116.67	10.29	4.49	14.79	2.29
Macedonia (MK)	504.27	354.58	1.98	1.39	3.38	1.42
Malta (MT)	0.00	0.07	0.00	0.02	0.02	
Montenegro (ME)	197.93	261.39	1.43	1.88	3.31	0.76
Netherlands (NL)	2116.34	1166.55	5.66	3.12	8.78	1.81
Norway (NO)	2707.07	4025.90	0.84	1.25	2.09	0.67
Poland (PL)	19164.02	10682.26	6.14	3.42	9.57	1.79
Portugal (PT)	4253.39	3827.78	4.79	4.31	9.10	1.11
Romania (RO)	5799.70	3932.32	2.43	1.65	4.08	1.47
Serbia (RS)	2691.09	2647.14	3.47	3.42	6.89	1.02
Slovakia (SK)	2158.91	1306.22	4.40	2.66	7.07	1.65
Slovenia (SI)	1262.66	2006.63	6.23	9.90	16.13	0.63
Spain (ES)	11444.37	10888.95	2.31	2.19	4.50	1.05
Sweden (SE)	5348.11	8874.27	1.19	1.97	3.16	0.60
Switzerland (CH)	4006.25	2463.28	9.70	5.97	15.67	1.63
United Kingdom (UK)	8850.20	4206.53	3.62	1.72	5.34	2.10

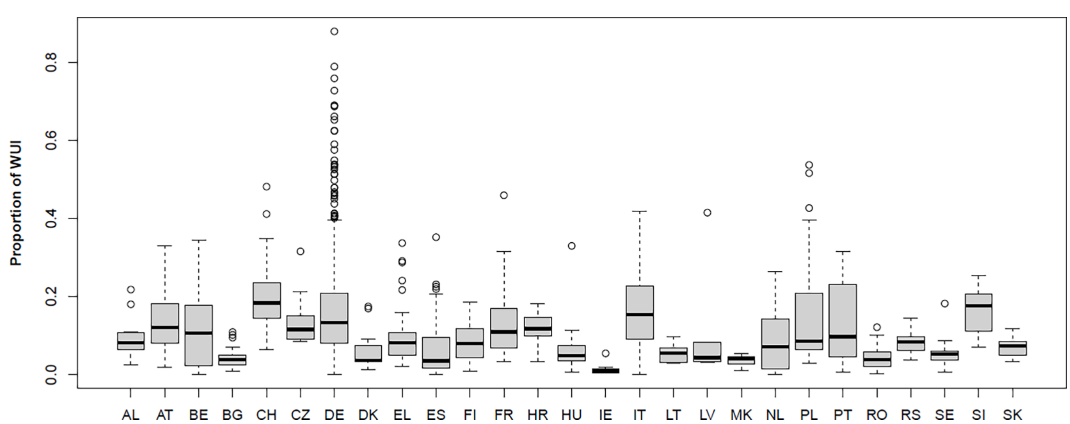

Fig. 2. The distribution of WUI proportions at national scales, for countries with at least five NUTS-3 zones. The thick horizontal line depicts the median, and box outlines depict the 25 %–75 % range. Whiskers reflect 95 % confidence intervals and circles are extreme values. For country abbreviations, see Table 1.

3.2. The Wildland-Urban interface and socioeconomic variables at NUTS-3 level

The proportion of WUI areas in the 1187 NUTS-3 zones varied greatly from nearly zero to 87.8 %. The initial model that was based solely on the proportion of wildland vegetation, built-up areas, and their interaction explained 55.5 % (fixed effects) and 73 % (fixed and random effects) of the variation in the proportion of total WUI (according to Nakagawa's marginal r-square). In the secondary model, multiple socioeconomic variables explained the residuals of the first model (i.e., variations in pWUI unrelated to differences in the proportion of wildland vegetation and built-up areas) in complex and interactive ways (Table 2). This model's fixed effects explained 14.1 % of the variation in the residuals of the initial model, and the combination of fixed effects and random effects (which reflect random variation across countries) explained marginally more (14.8 %). On average, pWUI was significantly positively related to road density and population density squared; and significantly negatively related to population density, GDP per capita, and proportion of the population over 65 years old. All three model interaction terms were statistically significant (proportion of protected areas and population density, proportion of population over 65 years old and GDP per capita, and population density and road

Table 2
Fixed effects and interactions based on the GLMER model of the proportion of WUI at NUTS-3 zones across Europe. Note: predictors were standardized prior to model fit. Colons represent interaction terms.

Fixed effect	Estimate	Standard error	p-value
Baseline model			
Intercept	−2.2	0.07	<0.001
Proportion of forested areas	0.58	0.02	<0.001
Proportion of built-up areas	0.5	0.01	<0.001
Proportion of forested areas: Proportion of built-up areas	0.35	0.02	<0.001
Model of residuals			
Population density	−0.01	0.006	<0.001
Population density (quadratic)	0.006	0.0007	<0.001
GDP per capita	−0.003	0.002	0.002
Proportion of population >65 years	−0.002	0.002	0.04
Proportion of protected areas	0.001	0.002	0.2 (NS)
Proportion of population >65 years: GDP per capita	0.006	0.002	<0.001
Population density: Road density	−0.01	0.001	<0.001
Proportion of protected areas: Population density	0.01	0.002	<0.001

density), indicating complex patterns. The proportion of the population above 65 years old positively affected pWUI when GDP was high, but had no effect when GDP was low, suggesting that the prevalence of the older population in the WUI occurs mainly in wealthier countries (Fig. 3A). Population density had a positive nonlinear effect on pWUI when road density was low. Nevertheless, when road density was high, the effect of population density on the amount of WUI had a U-shape pattern, reflecting a negative relationship between population density and WUI amounts up to ca. 10,000 people/km^2 (for context, the population density in Barcelona is 16,149 people/km^2), and a positive relationship at higher population densities (Fig. 3B). This suggests that in urbanized regions, the WUI is associated with lower road densities, or less concentrated urban patterns, whereas in less populated regions the WUI is associated with higher road densities. Finally, the positive nonlinear effect of population density on the amount of WUI increased in magnitude as the percentage of protected areas increased (Fig. 3C). That is, having more protected areas in densely populated regions led to increased WUI amounts.

4. Discussion

We present the first wall-to-wall high-resolution map of the WUI in Europe and reveal the relationships between the amount of WUI in different regions and various socioeconomic variables. Furthermore, our approach expands the geographic coverage of previous high-resolution maps in Europe, which were limited to specific countries or sub-regions (Alcasena et al., 2018; Del Giudice et al., 2021; Lampin-Maillet et al., 2010), and the spatial resolution compared to a previous wall-to-wall map (Modugno et al., 2016). We found that the WUI is a prevalent land cover type in Europe, as it covers 7.4 % of the surface area (compared to 16.2 % for the US, but using a different algorithm; (Carlson et al., 2022)). However, the amount of WUI varies considerably among countries, from almost no WUI in Malta to almost one-quarter of the country's area is a WUI in Lichtenstein. There was also a significant variation in WUI proportion within countries, especially in larger countries with diverse landscapes, such as Germany, where forest cover varies greatly among sub-regions.

Our WUI map showed similar spatial patterns compared to those previous works conducted in Europe (European Commission. Joint Research Centre, 2020; Modugno et al., 2016). The most striking WUI hotspots in Europe (WUI cover >25 %) were in northwestern regions of the Iberian Peninsula, the western-central countries (Netherlands,

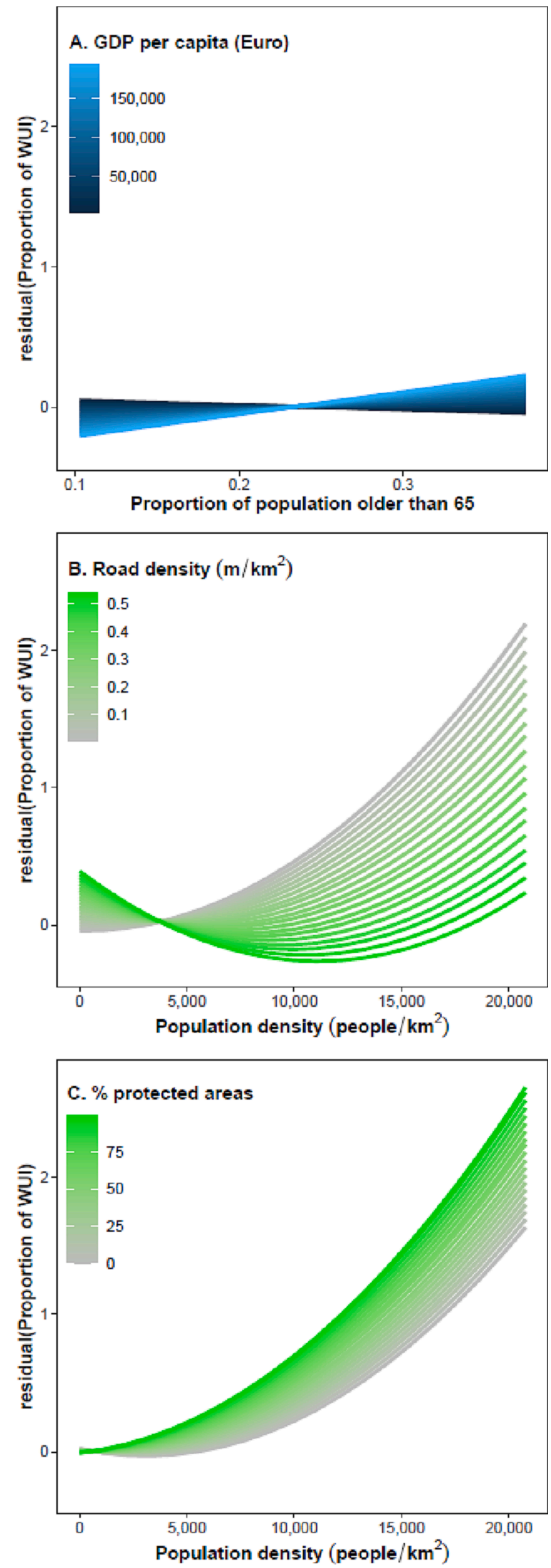

Fig. 3. Interaction plots of the joint effects of different pairs of predictors on the residuals of the relationship of proportion of WUI as a function of the proportion of wildland vegetation and proportion of built-up areas in NUTS-3 administrative units. Main predictor names appear as the x-axis labels, and curves with different colors depict the interacting predictor.

Belgium, Luxemburg, and the north Rhine in Germany), the open valley bottoms in mountainous central areas of central Europe, regions containing the most populated cities and metropolitan areas (e.g., London), and a thin belt along the Mediterranean coastline (Fig. 2c). The lowest values (WUI area <10 %) were located in the most remote septentrional regions (northern portions of Norway, Sweden, and Finland), the southeastern European countries, and the interior areas of the Iberian Peninsula except for the province of Madrid in Spain. Interestingly, the highest disagreement between our map and previous maps occurred in Ireland and the northern United Kingdom, likely due to the consideration of herbaceous fuels in WUI mapping by other authors (European Commission. Joint Research Centre, 2020). Thus, it is clear that results are heavily affected by mapping thresholds and parameters when comparing values from different works, which ranged from 2.5 % (Modugno et al., 2016) to 12 % total WUI area cover in Europe (Schug et al., in review). The first pan-European map (Modugno et al., 2016) defined WUI cover as the overlap area between a 200 m buffer to urban development and a 400 m buffer to hazardous fuels. These buffer distances are smaller than ours, which might explain the lower overall amount of WUI they found across Europe (see comparison across nations in Fig. S2). In contrast, a new global WUI map (Schug et al., in review) implemented a conceptually similar approach to ours but includes grasslands as wildland vegetation and uses a 2.4 km distance to delineate interface WUI extent (whereas we used 600 m), which can explain why they found a considerably larger WUI area (~12 % compared to 7.4 % here). An additional reason for our diverging results is that we adopted a categorization of wildland vegetation that focused on woody vegetation and did not include grassland vegetation. This choice has been made by others before (Kaim et al., 2018) and reflects a more restrictive view of the WUI as being related solely to forest and shrubland ecosystems. In our case, there was also a practical consideration for this choice: there were considerable classification errors in that grasslands and croplands were confused in the landcover dataset we used (Tsendbazar et al., 2021), and another high-resolution landcover dataset we initially tested (ESRI's global landcover map) suffered from the same problem. Including grasslands as wildland vegetation would have created large WUI areas in agricultural regions with little natural vegetation. As a result, the exclusion of grassland vegetation in some agropastoral lands may lead to an underestimate of the WUI area, where flashy fuels cover large portions and play a prominent role in risk transmission (Salis et al., 2022). In contrast, we included all types of woody vegetation classes as wildland vegetation, regardless of their ability to support wildfire spread. In terms of fire risk assessment, this may lead to an overestimate of potential settlement exposure to wildfires, in areas where the flammability of the dominant woody vegetation is low.

Still, we argue that under changing climatic conditions, the flammability of many species is likely to change (Knorr et al., 2016), making regions with a low fire hazard more prone to wildfires in the future. Finally, the specific distance thresholds that we used followed precedent in some cases (e.g., the 500 m buffer distance and the wildland vegetation thresholds are in line with (Carlson et al., 2022)), but not in others (reducing the 'distance to large wildland patch' from 2400 m to 600 m as a more realistic estimate of the distance embers spread). We did modify the latter threshold because initial sensitivity tests suggested an overestimate of the WUI in urban areas adjacent to wildlands based on the original threshold. Indeed, the higher threshold would have increased the proportion of WUI by ca. 35.8 % (S1). However, we stress that there is no 'correct' set of thresholds and methodological choices for mapping the WUI, because these maps are context-specific, and always reflect the subjective choices made during their creation (Stewart et al., 2009).

In general, two main processes can cause WUI growth. The first is exurban development in and near natural ecosystems, either due to 'pull' factors, such as the desire to live near natural amenities (Sullivan, 1994; Taylor, 2009), or by 'push' factors, such as increasing housing prices in cities pushing housing development deeper into rural areas where property prices are lower (Millward, 2002). We found that the amount of WUI in a given region was correlated with the proportion of protected areas in it, possibly indicating a 'pull' factor. The WUI area growth in the Mediterranean coastline is a good example, where vacation housing areas used for recreational purposes continue to expand in the vicinities of protected sites (Chappaz and Ganteaume, 2022; Sirca et al., 2017). In a related US example (Radeloff et al., 2010), housing growth near the boundaries of national parks exceeds nationwide housing growth, highlighting the attractiveness of these areas for exurban development.

The second process behind WUI development is wildland vegetation growth, often due to land abandonment, stemming from the rural exodus. In Europe (primarily southern and eastern), land abandonment has been rampant in recent decades (Lasanta et al., 2017), and this has been associated with more wildfires (Mantero et al., 2020), and may increase wildfire occurrence even further (Salis et al., 2022; Ursino and Romano, 2014). Another aspect of land abandonment is that the median age rises in areas with rural exodus, and GDP per capita often drops. However, we did not find a significant relationship between the proportion of residents older than 65 years and the amount of WUI in regions with lower GDP. One potential reason for this is that we accounted for the effect of wildland vegetation cover in the first step of our modeling. Thus, our wildland vegetation variable may have also captured the indirect effects of land abandonment, which may be concentrated in areas with older populations and low GDP, on the amount of WUI. In contrast, we did find a positive association between WUI and the proportion of aging population in regions with high GDP. This may reflect an increasing preference of wealthier people to retire in rural areas (Norris & Winston, 2009).

The suite of socioeconomic variables we used to explain the residual amount of WUI (after accounting for the confounding effects of vegetation and built areas) explained only a modest amount of variation in WUI patterns (14.1 %). This is probably due to several reasons. Ideally, we would also have data on property prices in rural vs urban areas, and about long-term changes in age distribution in rural areas at the European scale, but these data do not exist. Another reason why these macroscale variables explain WUI patterns only moderately well was that NUTS-3 units are spatially coarse, and much coarser than our WUI map. The fact that these variables could explain some variation in WUI patterns despite the scale-mismatch hints at the importance of socioeconomic processes as WUI drivers and calls for future studies at smaller spatial scales, where it is possible to collect high-resolution data on socioeconomic conditions.

The scale of the analysis is a condition for interpreting the results and correctly using WUI maps, as there is a fundamental difference between broad-scale and local-scale WUI maps in terms of purpose and feasibility. Ours and previous broad-scale maps depict large areas, require less-detailed information, and assume constant parameterization values across vast areas where distant landscapes differ in climate conditions, forest fuels, and fire regimes (Modugno et al., 2016; Radeloff et al., 2018; Theobald & Romme, 2007). Consequently, as was our goal here, these maps are often used to identify high-hazard hotspots in populated areas, inform policy, and facilitate comparisons among different administrative regions to initiate wildfire risk management programs. To complement them at local scales, fine-scale WUI mapping approaches may be used to aid the planning of fuel-management actions in and around WUI settlements (Beverly et al., 2010; Caballero & Beltran, 2003). Fine-scale WUI mapping captures the local details but requires precise information about building materials and the fine-scale distribution of highly flammable vegetation near buildings. Recent developments of high-resolution remote-sensing products that focus on built-up areas in general (Corbane et al., 2021; Pesaresi et al., 2016) and individual building locations in particular (Microsoft Open Source, 2022) provide an opportunity to create such fine-grain WUI maps (Alcasena et al., 2022; Bar-Massada, 2021; Carlson et al., 2022).

5. Conclusions

Our study provides the first detailed map of WUI areas across Europe, and we found that about 7.4 % of Europe's land area is comprised of settlements that may have a considerable wildfire risk (at present, or more so under future climatic conditions). Moreover, we show the WUI's association with several socioeconomic variables, highlighting the role of different land use and demographic processes that determined our observed WUI patterns. The WUI problem in Europe is expected to increase due to ongoing land abandonment in Mediterranean and East European countries (which increases vegetative cover around settlements), more secondary home development in rural areas (which pushes settlements into wildlands), and changes in fire regimes including the introduction of wildland fires into previously non-fire prone areas. These processes, among others, are increasing the exposure of people and property to wildfires, and there is an urgent need to inform policy decisions that may reduce this risk through better land use planning. Our new WUI map may offer helpful information to achieve this aim.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2023.104759.

References

Alcasena, F. J., Ager, A. A., Bailey, J. D., Pineda, N., & Vega-García, C. (2019). Towards a comprehensive wildfire management strategy for Mediterranean areas: Framework development and implementation in Catalonia, Spain. *Journal of Environmental Management, 231*, 303–320. https://doi.org/10.1016/j.jenvman.2018.10.027

Alcasena, F., Ager, A. A., Belavenutti, P., Krawchuk, M., & Day, M. A. (2022). Contrasting the efficiency of landscape versus community protection fuel treatment strategies to reduce wildfire exposure and risk. *Journal of Environmental Management, 309*, Article 114650. https://doi.org/10.1016/j.jenvman.2022.114650

Alcasena, F. J., Evers, C. R., & Vega-Garcia, C. (2018). The wildland-urban interface raster dataset of Catalonia. *Data in Brief, 17*, 124–128. https://doi.org/10.1016/j.dib.2017.12.066

Argañaraz, J. P., Radeloff, V. C., Bar-Massada, A., Gavier-Pizarro, G. I., Scavuzzo, C. M., & Bellis, L. M. (2017). Assessing wildfire exposure in the Wildland-Urban Interface area of the mountains of central Argentina. *Journal of Environmental Management, 196*, 499–510. https://doi.org/10.1016/j.jenvman.2017.03.058

Badia, A., Pallares-Barbera, M., Valldeperas, N., & Gisbert, M. (2019). Wildfires in the wildland-urban interface in Catalonia: Vulnerability analysis based on land use and land cover change. *Science of The Total Environment, 673*, 184–196. https://doi.org/10.1016/j.scitotenv.2019.04.012

Bar-Massada, A. (2021). A comparative analysis of two major approaches for mapping the wildland-urban interface: A case study in California. *Land, 10*, 679. https://doi.org/10.3390/land10070679

Bar-Massada, A., Radeloff, V. C., & Stewart, S. I. (2014). Biotic and abiotic effects of human settlements in the Wildland-Urban Interface. *BioScience, 64*, 429–437. https://doi.org/10.1093/biosci/biu039

Bar-Massada, A., Stewart, S. I., Hammer, R. B., Mockrin, M. H., & Radeloff, V. C. (2013). Using structure locations as a basis for mapping the wildland urban interface. *Journal of Environmental Management, 128*, 540–547. https://doi.org/10.1016/j.jenvman.2013.06.021

Bates D, Maechler M, Bolker B, Walker S (2013) lme4: Linear mixed-effects models using Eigen and S4. http://CRAN.R-project.org/package=lme4.

Bento-Gonçalves, A., & Vieira, A. (2020). Wildfires in the wildland-urban interface: Key concepts and evaluation methodologies. *Science of The Total Environment, 707*, Article 135592. https://doi.org/10.1016/j.scitotenv.2019.135592

Beverly, J. L., Bothwell, P., Conner, J. C. R., & Herd, E. P. K. (2010). Assessing the exposure of the built environment to potential ignition sources generated from vegetative fuel. *International Journal of Wildland Fire, 19*, 299. https://doi.org/10.1071/WF09071

Boarnet, M. G., McLaughlin, R. B., & Carruthers, J. I. (2011). Does state growth management change the pattern of urban growth? Evidence from Florida. *Regional Science and Urban Economics, 41*, 236–252. https://doi.org/10.1016/j.regsciurbeco.2010.12.004

Brooks M E, Kristensen K, Benthem K J ,van, Magnusson A, Berg C W, Nielsen A, Skaug H J, Mächler M, Bolker B M (2017) glmmTMB Balances Speed and Flexibility Among Packages for Zero-inflated Generalized Linear Mixed Modeling. *The R Journal* 9, 378. 10.32614/RJ-2017-066.

Buttner, G., & Kosztra, B. (2007). *CLC2006 technical guidelines*. Publications Office: Luxembourg.

Caballero D, Beltran I (2003) Concepts and ideas of assessing settlement fire vulnerability in the W-UI zone. In 'Proceedings (Eds Xanthopoulos, G.) of the international workshop WARM, Forest fires in the wildland-urban interface and rural areas in Europe: an integral planning and management challenge. Athens, Greece', 47–54.

Caballero, D., Beltrán, I., & Velasco, A. (2007) Forest fires and wildland-urban interface in Spain: types and risk distribution.

Caggiano, M. D., Hawbaker, T. J., Gannon, B. M., & Hoffman, C. M. (2020). Building Loss in WUI Disasters: Evaluating the Core Components of the Wildland-Urban Interface Definition. *Fire, 3*, 73. https://doi.org/10.3390/fire3040073

Carlson, A. R., Helmers, D. P., Hawbaker, T. J., Mockrin, M. H., & Radeloff, V. C. (2022). The wildland–urban interface in the United States based on 125 million building locations. *Ecological Applications, 32*. https://doi.org/10.1002/eap.2597

Chappaz F, Ganteaume A (2022) Role of land-cover and WUI types on spatio-temporal dynamics of fires in the French Mediterranean area. *Risk Analysis* risa.13979. 10.1111/risa.13979.

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

Corbane, C., Syrris, V., Sabo, F., Politis, P., Melchiorri, M., Pesaresi, M., … Kemper, T. (2021). Convolutional neural networks for global human settlements mapping from Sentinel-2 satellite imagery. *Neural Computing and Applications, 33*, 6697–6720. https://doi.org/10.1007/s00521-020-05449-7

Davis, J. B. (1990). The Wildland-Urban interface: Paradise or battleground? *Journal of Forestry, 88*, 26–31. https://doi.org/10.1093/jof/88.1.26

Del Giudice, L., Arca, B., Scarpa, C., Pellizzaro, G., Duce, P., & Salis, M. (2021). The wildland-anthropic interface raster data of the Italy-France maritime cooperation area (Sardinia, Corsica, Tuscany, Liguria, and Provence-Alpes-Côte d'Azur). *Data in Brief, 38*, Article 107355. https://doi.org/10.1016/j.dib.2021.107355

European Commission. Joint Research Centre. (2020). *European wildfire danger and vulnerability in a changing climate: Towards integrating risk dimensions: JRC PESETA IV project: Task 9 forest fires*. Publications Office: LU. https://data.europa.eu/doi/10.2760/46951.

European Commission. Joint Research Centre. (2021). *Forest Fires in Europe, Middle East and North Africa 2020*. Publications Office: LU. https://data.europa.eu/doi/10.2760/216446.

Galiana-Martín, L. (2017). Spatial planning experiences for vulnerability reduction in the wildland-urban interface in Mediterranean European Countries. *European Countryside, 9*, 577–593. https://doi.org/10.1515/euco-2017-0034

Godoy, M. M., Martinuzzi, S., Masera, P., & Defossé, G. E. (2022). Forty years of wildland urban interface growth and its relation with wildfires in Central-Western Chubut, Argentina. *Frontiers in Forests and Global Change, 5*, Article 850543. https://doi.org/10.3389/ffgc.2022.850543

Gude, P. H., Hansen, A. J., Rasker, R., & Maxwell, B. (2006). Rates and drivers of rural residential development in the Greater Yellowstone. *Landscape and Urban Planning, 77*, 131–151. https://doi.org/10.1016/j.landurbplan.2005.02.004

Hanberry, B. (2020). Reclassifying the wildland-urban interface using fire occurrences for the United States. *Land, 9*, 225. https://doi.org/10.3390/land9070225

Hawbaker, T. J., Radeloff, V. C., Clayton, M. K., Hammer, R. B., & Gonzalez-Abraham, C. E. (2006). Road development, housing growth, and landscape fragmentation in northern Wisconsin: 1937–1999. *Ecological Applications, 16*, 1222–1237. https://doi.org/10.1890/1051-0761(2006)016[1222:RDHGAL]2.0.CO;2

Jolly, W. M., Cochrane, M. A., Freeborn, P. H., Holden, Z. A., Brown, T. J., Williamson, G. J., & Bowman, D. M. J. S. (2015). Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature Communications, 6*, 7537. https://doi.org/10.1038/ncomms8537

Kaim, D., Radeloff, V., Szwagrzyk, M., Dobosz, M., & Ostafin, K. (2018). Long-term changes of the wildland-urban interface in the polish carpathians. *ISPRS International Journal of Geo-Information, 7*, 137. https://doi.org/10.3390/ijgi7040137

Kasischke, E. S., & Turetsky, M. R. (2006). Recent changes in the fire regime across the North American boreal region—Spatial and temporal patterns of burning across Canada and Alaska. *Geophysical Research Letters, 33*, L09703. https://doi.org/10.1029/2006GL025677

Knorr, W., Arneth, A., & Jiang, L. (2016). Demographic controls of future global fire risk. *Nature Climate Change, 6*, 781–785. https://doi.org/10.1038/nclimate2999

Lampin-Maillet, C., Jappiot, M., Long, M., Bouillon, C., Morge, D., & Ferrier, J.-P. (2010). Mapping wildland-urban interfaces at large scales integrating housing density and vegetation aggregation for fire prevention in the South of France. *Journal of Environmental Management, 91*, 732–741. https://doi.org/10.1016/j.jenvman.2009.10.001

Lasanta, T., Arnáez, J., Pascual, N., Ruiz-Flaño, P., Errea, M. P., & Lana-Renault, N. (2017). Space–time process and drivers of land abandonment in Europe. *CATENA, 149*, 810–823. https://doi.org/10.1016/j.catena.2016.02.024

Lüdecke D, Ben-Shachar M, Patil I, Waggoner P, Makowski D (2021) performance: An R Package for Assessment, Comparison and Testing of Statistical Models. *Journal of Open Source Software* 6, 3139. 10.21105/joss.03139.

Mantero, G., Morresi, D., Marzano, R., Motta, R., Mladenoff, D. J., & Garbarino, M. (2020). The influence of land abandonment on forest disturbance regimes: A global review. *Landscape Ecology, 35*, 2723–2744. https://doi.org/10.1007/s10980-020-01147-w

Marconcini, M., Metz-Marconcini, A., Üreyen, S., Palacios-Lopez, D., Hanke, W., Bachofer, F., … Strano, E. (2020). Outlining where humans live, the World Settlement Footprint 2015. *Scientific Data, 7*, 242. https://doi.org/10.1038/s41597-020-00580-5

Martinuzzi, S., Gould, W. A., & Ramos González, O. M. (2007). Land development, land use, and urban sprawl in Puerto Rico integrating remote sensing and population census data. *Landscape and Urban Planning, 79*, 288–297. https://doi.org/10.1016/j.landurbplan.2006.02.014

McWethy, D. B., Schoennagel, T., Higuera, P. E., Krawchuk, M., Harvey, B. J., Metcalf, E. C., … Kolden, C. (2019). Rethinking resilience to wildfire. *Nature Sustainability, 2*, 797–804. https://doi.org/10.1038/s41893-019-0353-8

Microsoft Open Source (2022) GlobalMLBuildingFootprints. https://github.com/microsoft/GlobalMLBuildingFootprints.

Millward, H. (2002). Peri-urban residential development in the Halifax region 1960–2000: Magnets, constraints, and planning policies. *Canadian Geographer-Geographe Canadien, 46*, 33–47. https://doi.org/10.1111/j.1541-0064.2002.tb00729.x

Mitsopoulos, I., Mallinis, G., Dimitrakopoulos, A., Xanthopoulos, G., Eftychidis, G., & Goldammer, J. G. (2020). Vulnerability of peri-urban and residential areas to landscape fires in Greece: Evidence by wildland-urban interface data. *Data in Brief, 31*, Article 106025. https://doi.org/10.1016/j.dib.2020.106025

Modugno, S., Balzter, H., Cole, B., & Borrelli, P. (2016). Mapping regional patterns of large forest fires in Wildland-Urban Interface areas in Europe. *Journal of Environmental Management, 172*, 112–126. https://doi.org/10.1016/j.jenvman.2016.02.013

Moreira, F., Leal, M., Bergonse, R., Canadas, M. J., Novais, A., Oliveira, S., … Santos, J. L. (2023). Recent trends in fire regimes and associated territorial features in a fire-prone Mediterranean region. *Fire, 6*, 60. https://doi.org/10.3390/fire6020060

Moritz, M. A., Hazard, R., Johnston, K., Mayes, M., Mowery, M., Oran, K., … Wesolowski, G. (2022). Beyond a focus on fuel reduction in the WUI: The Need for regional wildfire mitigation to address multiple risks. *Frontiers in Forests and Global Change, 5*, Article 848254. https://doi.org/10.3389/ffgc.2022.848254

Nakagawa, S., & Schielzeth, H. (2013). A general and simple method for obtaining R^2 from generalized linear mixed-effects models (RB O'Hara, Ed.). *Methods in Ecology and Evolution, 4*, 133–142. https://doi.org/10.1111/j.2041-210x.2012.00261.x

Norris, M., & Winston, N. (2009). Rising second home numbers in rural Ireland: Distribution, drivers and implications. *European Planning Studies, 17*, 1303–1322. https://doi.org/10.1080/09654310903053448

Pausas, J. G., & Keeley, J. E. (2021). Wildfires and global change. *Frontiers in Ecology and the Environment, 19*, 387–395. https://doi.org/10.1002/fee.2359

Pejchar, L., Morgan, P. M., Caldwell, M. R., Palmer, C., & Daily, G. C. (2007). Evaluating the potential for conservation development: Biophysical, economic, and institutional perspectives. *Conservation Biology, 21*, 69–78. https://doi.org/10.1111/j.1523-1739.2006.00572.x

Pesaresi, M., Corbane, C., Julea, A., Florczyk, A., Syrris, V., & Soille, P. (2016). Assessment of the added-value of sentinel-2 for detecting built-up areas. *Remote Sensing, 8*, 299. https://doi.org/10.3390/rs8040299

R Core Team (2013) R: A language and environment for statistical computing.

Radeloff, V. C., Hammer, R. B., Stewart, S. I., Fried, J. S., Holcomb, S. S., & McKeefry, J. F. (2005). The Wildland-Urban Interface in the United States. *Ecological Applications, 15*, 799–805. https://doi.org/10.1890/04-1413

Radeloff, V. C., Helmers, D. P., Kramer, H. A., Mockrin, M. H., Alexandre, P. M., Bar-Massada, A., … Stewart, S. I. (2018). Rapid growth of the US wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences, 115*, 3314–3319. https://doi.org/10.1073/pnas.1718850115

Radeloff, V. C., Stewart, S. I., Hawbaker, T. J., Gimmi, U., Pidgeon, A. M., Flather, C. H., … Helmers, D. P. (2010). Housing growth in and near United States protected areas limits their conservation value. *Proceedings of the National Academy of Sciences, 107*, 940–945. https://doi.org/10.1073/pnas.0911131107

Robinson, L., Newell, J. P., & Marzluff, J. M. (2005). Twenty-five years of sprawl in the Seattle region: Growth management responses and implications for conservation. *Landscape and Urban Planning, 71*, 51–72. https://doi.org/10.1016/j.landurbplan.2004.02.005

Ruffault, J., Curt, T., Moron, V., Trigo, R. M., Mouillot, F., Koutsias, N., … Belhadj-Khedher, C. (2020). Increased likelihood of heat-induced large wildfires in the Mediterranean Basin. *Scientific Reports, 10*, 13790. https://doi.org/10.1038/s41598-020-70069-z

Salis, M., Del Giudice, L., Jahdi, R., Alcasena-Urdiroz, F., Scarpa, C., Pellizzaro, G., … Arca, B. (2022). Spatial patterns and intensity of land abandonment drive wildfire hazard and likelihood in Mediterranean agropastoral areas. *Land, 11*, 1942. https://doi.org/10.3390/land11111942

Shvidenko, A. Z., & Schepaschenko, D. G. (2013). Climate change and wildfires in Russia. *Contemporary Problems of Ecology, 6*, 683–692. https://doi.org/10.1134/S199542551307010X

Silva, C. V. J., Aragão, L. E. O. C., Barlow, J., Espirito-Santo, F., Young, P. J., Anderson, L. O., … Xaud, H. A. M. (2018). Drought-induced Amazonian wildfires instigate a decadal-scale disruption of forest carbon dynamics. *Philosophical Transactions of the Royal Society B: Biological Sciences, 373*, 20180043. https://doi.org/10.1098/rstb.2018.0043

Silvestrini, R. A., Soares-Filho, B. S., Nepstad, D., Coe, M., Rodrigues, H., & Assunção, R. (2011). Simulating fire regimes in the Amazon in response to climate change and deforestation. *Ecological Applications, 21*, 1573–1590. https://doi.org/10.1890/10-0827.1

Sirca, C., Casula, F., Bouillon, C., García, B. F., Fernández Ramiro, M. M., Molina, B. V., & Spano, D. (2017). A wildfire risk oriented GIS tool for mapping rural-urban interfaces. *Environmental Modelling & Software, 94*, 36–47. https://doi.org/10.1016/j.envsoft.2017.03.024

Stewart, S. I., Wilmer, B., Hammer, R. B., Aplet, G. H., Hawbaker, T. J., Miller, C., & Radeloff, V. C. (2009). Wildland-urban interface maps vary with purpose and context. *Journal of Forestry, 107*, 78–83.

Storey, M. A., Price, O. F., Bradstock, R. A., & Sharples, J. J. (2020). Analysis of variation in distance, number, and distribution of spotting in southeast australian wildfires. *Fire, 3*, 10. https://doi.org/10.3390/fire3020010

Sullivan, W. C. (1994). Perceptions of the rural-urban fringe: Citizen preferences for natural and developed settings. *Landscape and Urban Planning, 29*, 85–101. https://doi.org/10.1016/0169-2046(94)90020-5

Syphard, A. D., Radeloff, V. C., Hawbaker, T. J., & Stewart, S. I. (2009). Conservation threats due to human-caused increases in fire frequency in Mediterranean-climate ecosystems. *Conservation Biology, 23*, 758–769. https://doi.org/10.1111/j.1523-1739.2009.01223.x

Taylor, L. (2009). No boundaries: Exurbia and the study of contemporary urban dispersion. *GeoJournal, 76*, 323–339. https://doi.org/10.1007/s10708-009-9300-y

Theobald, D. M., & Romme, W. H. (2007). Expansion of the US wildland–urban interface. *Landscape and Urban Planning, 83*, 340–354. https://doi.org/10.1016/j.landurbplan.2007.06.002

Tsendbazar, N.-E., Li, L., Koopman, M., Carter, S., Herold, M., Georgieva, I., Lesiv, M. (2021) WorldCover Product Validation Report. DV12-PVR.

UNEP-WCMC (2019) User Manual for the World Database on Protected Areas and world database on other effective area-based conservation measures: 1.6. (Cambridge, UK) http://wcmc.io/WDPA_Manual.

Ursino, N., & Romano, N. (2014). Wild forest fire regime following land abandonment in the Mediterranean region. *Geophysical Research Letters, 41*, 8359–8368. https://doi.org/10.1002/2014GL061560

Vacca, P., Caballero, D., Pastor, E., & Planas, E. (2020). WUI fire risk mitigation in Europe: A performance-based design approach at home-owner level. *Journal of Safety Science and Resilience, 1*, 97–105. https://doi.org/10.1016/j.jnlssr.2020.08.001

Wardle, D. A., Hörnberg, G., Zackrisson, O., Kalela-Brundin, M., & Coomes, D. A. (2003). Long-term effects of wildfire on ecosystem properties across an island area gradient. *Science, 300*, 972–975. https://doi.org/10.1126/science.1082709

Weber, K. T., & Yadav, R. (2020). Spatiotemporal Trends in Wildfires across the Western United States (1950–2019). *Remote Sensing, 12*, 2959. https://doi.org/10.3390/rs12182959

Zanaga, D., Van De Kerchove, R., De Keersmaecker, W., Souverijns, N., Brockmann, C., Quast, R., ⋯ Arino, O. (2021) ESA WorldCover 10 m 2020 v100. 10.5281/ZENODO.5571936.