A Practical Approach to Assess the Wildfire Ignition and Spreading Capacities of Vegetated Areas at Landscape-scale

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Abstract

We bring a practical and comprehensive GIS-based framework to utilize freely available remote sensed datasets to assess wildfire ignition probability and spreading capacities of vegetated landscapes. The study area consists of the country-level scale of the Romanian territory, characterized by a diversity of vegetated landscapes threatened by the consequences of climate change. We utilize the Wildfire Ignition Probability/ Wildfire Spreading Capacity Index (WIPI/ WSCI). WIPI/ WSCI models rely on a multi-criteria data mining procedure assessing the social, environmental, geophysical, and fuel properties of the study area based on open access remote sensed data. We utilized the Receiver Operating Characteristic (ROC) analysis to weigh each indexing criterion's impact factor and assess the model's overall sensitivity. Introducing ROC analysis at an earlier stage of the workflow elevated the final Area Under the Curve (AUC) of WIPI from 0.705 to 0.778 and WSCI from 0.586 to 0.802. The modeling results enable discussion on the vulnerability of protected areas and the exposure of man-made structures to wildfire risk. Our study shows that within the wildland-urban interface of Bucharest's metropolitan area, there is a remarkable building stock like healthcare, residential and educational that are significantly exposed to wildfire spreading the risk.

Keywords: climate change; disaster risk reduction; fuel; QGIS; remote sensing.

1. Introduction

Climate change and global warming are expected to affect natural hazards like flooding and wildfires worldwide. These may have multiplied domino effect consequences on other natural and urban systems leading to severe disasters at local scales [1-3]. While the emergence of flooding events relies mostly on the weather conditions and the natural/ artificial properties of the catchment area, wildfires implicate human behavioral activities. The multifaceted character of the wildfire phenomena is acknowledged in the literature. Chapin et al. [4] define wildfire as a wicked problem. According to Levin et al. [5], wildfires are multi-layered phenomena that implicate diverse interacting cycles between causes and effects acting in certain territories. Identifying the relevant factors that significantly correlate with the wildfire regimes remains a critical challenge to scientists [6-8].

In the classical wildfire assessment approach, the interaction of favorable weather conditions with the study area's geophysical and fuel properties is considered the core prerequisite of the fire environment triangle [9]. Lightning strikes are the primary igniters [10]. However, most wildfires are reported to have been caused by human activity, either intentionally or accidentally [11]. Human activity patterns have become a determinant during the wildfire ignition phase [12,13].

Mansuy et al. [14] contrast the anthropogenic factors to the macro-environmental ones and report that the human footprint affects almost equal wildfire risk both inside and outside the North-American protected landscapes. The consequences of human activities on fire regimes are reported to leave under shadow the effects of climate change [15]. The effect of societal habits like the Daylight-Saving Time (DST) alterations have been acknowledged to upsurge the number of wildfire ignitions. For example, Kountouris [16] reports that DST transition during the Spring season has increased the number of non-prescribed wildfire ignitions by about 30% in the US, relying on around 2 million wildfire ignition of 23 years records.

A more recent study presents the impact of COVID-19 lockdown on the wildfire regimes in a wildfire-prone region like the Mediterranean [3,17]. The authors report a significant decrease in the total burned area during this period compared to the estimations that counted for similar drought-related circumstances to previous years. The decrease in social activities has resulted in a significant reduction of wildfire events. Thus,

57 the integration of anthropogenic factors within the wildfire risk assessment tools has become indispensable to
58 increase the models' sensitivity [18].

59 Although the anthropogenic factors that impact wildfire events have gained considerable attention in the
60 literature, their combined usage alongside hydro-meteorological and biophysical factors in wildfire spreading
61 capacities models is not spread enough. In this study, we shortlisted sixteen criteria about the anthropogenic
62 (S-social), hydro-meteorological (E-environmental), geophysical (P-physical), and fuel (F) properties of the
63 study area (Romania) following our earlier GIS-based method [19]. Through literature review and evaluating the
64 available open access geospatial data, we considered the following criteria; population density (S1), distance
65 to settlements (S2), distance to transportation network (S3), distance to main roads (S4), agriculture distance
66 (S5), solar radiation (E1), precipitation (E2), maximum temperature (E3), wind speed (E4), slope (P1), aspect
67 (P2), altitude (P3), distance to water sources (P4), fuel type (F1), tree cover density (TCD) (F2), and
68 normalized difference vegetation index (NDVI) (F3), Unlike our previous studies [19,20], we introduced
69 population density as a new criterion within the wildfire ignition probability/ wildfire spreading capacity index
70 (WIPI/WSCI) model, considering that the current literature tightly correlates the population density and the
71 wildfire ignition risk [21,22].

72 This study aims to develop a comprehensive and practical GIS-based model for assessing the wildfire
73 ignition and spreading capacities based on freely available geospatial data. The proposed model is aimed to
74 be reproducible to other vegetated surfaces where the remotely sensed data are available. Another goal is to
75 test the utility of the ROC/AUC method in weighting each criterion's impact factor by comparing it with the
76 analytic hierarchy process (AHP) that has been widely used in previous studies. Here we aim to deliver
77 tangible graphical (maps) and statistical results about the wildfire ignition and spreading capacities in
78 Romania, supporting disaster risk reduction agendas nationwide.

79 **2. Materials and Methods**

80 *2.1. Study Area*

81 The study area is represented by Romania's territory, a country located in the central-eastern part of
82 Europe with an area of 238391 km^2 (Fig. 1). Romania has a vast diversity of landforms, each with

representative forestry variation, which includes: the Transylvanian Depression located in the center of the Carpathian Mountains arc, a territory that offers the right conditions for the development of deciduous forests, i.e., with species such as *Carpinus betulus, Fagus sylvatica, Tillia tomentosa, Ulmus minor, Quercus petraea* extended over large areas). The Romanian Carpathian Mountains (RCM) occupy 57% of the country's territory, where extensive forests are spread over large areas.

According to Romanian legislation, a forest is considered an area of at least 0.25 hectares of land occupied by forest vegetation. The mature specimens reach 5m in height under normal vegetation conditions and have a coverage index (consistency) of more than 10% (0.1). To these territories are added the areas covered with junipers (*Juniperus*) in the high mountain area of over 1800-2000m in altitude and forest protection curtains with more than 0.5 hectares and a width of more than 20 meters. Forest protection curtains are accepted crucial interventions in forest protection policy. They are projected to have a significant protective effect on Romanian forest cover on the brink of climate change [23].

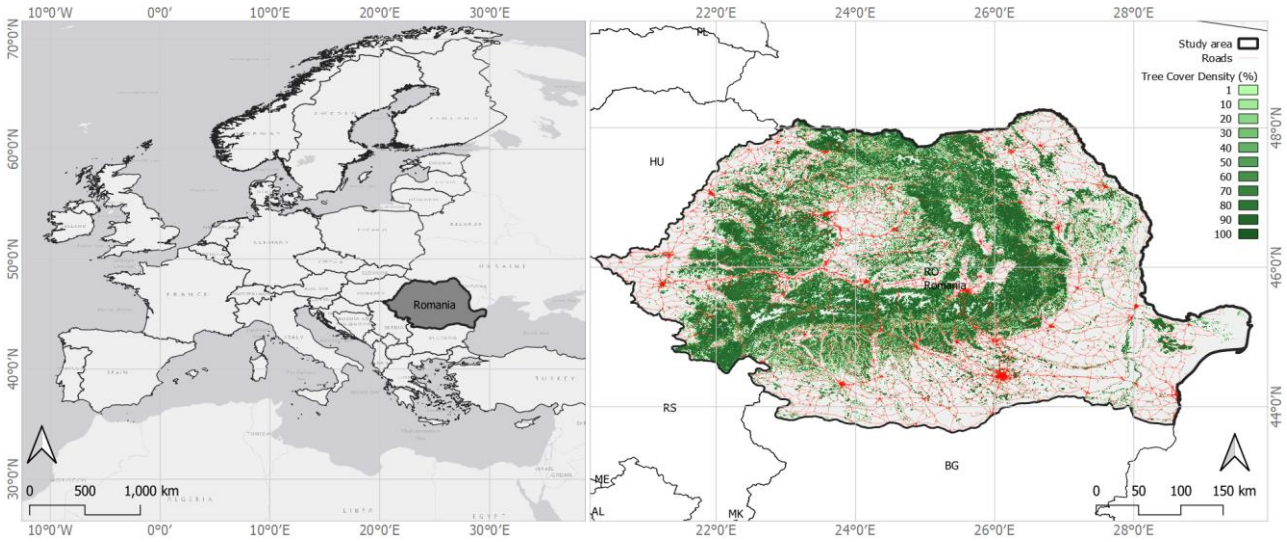

Figure 1. Romania within Europe (a), and Romanian territory including tree cover density (TCD)and transportation network distribution (b).

At the territorial level of Romania, 29.9% of the surface is covered by different forests, covering 7.13 million hectares [24]. Romania is one of the countries with the highest percentage of occupied forest areas, with the latest estimates having a significant growth rate (19.3 million m^3/year for conifers, 19 million m^3/year for beech, 8.1 m^3/year for quercinea, 8.6 million m^3/year for hardwoods and 3.4 million m^3/year for softwoods), to which are added old forests and virgin forests in different stages of conservation. Large forest areas are

predominantly in the mountainous and hilly areas and areas with lower altitudes. There is a higher density of human settlements, a crucial aspect considering the present study's objectives. We have included further details about Romania's forest structure in Table S1 (see Supplementary files online).

Changes over time in the areas covered by forest are under the direct influence of natural factors such as the influence of climate change on the consistency and composition of forests, the migration of forest species beyond known ecological limits, the negative influence of floods with short return periods, the decrease of physical and chemical properties of soils due to soil erosion and vegetation fires with natural causes. Anthropic changes are also present due to deforestation caused by logging, legal and illegal, whose rate increased after 2000 [25,26]. However, some territories showed a forest gain due to the afforestation of large areas of abandoned pastures [26]. Furthermore, the Spatio-temporal evolution of forest cover in Romania is tightly correlated with the forest management regimes affected by socio-political fluctuations starting from the early 19th century [27].

2.2. WIPI/ WSCI model and the current updates

This study methodologically relies on the Wildfire Ignition Probability/ Wildfire Spreading Capacity Index (WIPI/ WSCI). Initially, the method defines criteria that have proven relation with either the wildfire occurrence or behavior. The number of criteria varies according to the available data and the specifics of the study area. Each reference point location within the vegetated surface is loaded with unique absolute values through a multi-criteria inventory procedure [19]. Each criterion's relative weighted factor was initially assigned via Analytical Hierarchy Process (AHP) pairwise comparison method. The sensitivity of the model has been assessed via ROC/AUC method in another study focusing on the case of Montenegro [28].

Fig. 2 presents the methodical workflow of this study. It includes the updates that we push forward as improvements of WIPI/ WSCI, applied in Romania's case. At this stage, the workflow consists of seven sequential stages. Besides the inventory procedure, the first stage includes defining the vegetated surfaces within the study area and the reference points that spatially represent the vegetation surfaces. The reference points serve a data collecting pivots loaded with all 16 criteria' unique values, as shown in Fig. 2. The unequal range of inventory values necessitates a normalizing procedure before indexing calculations. This stage equalizes the range of inventory values of each criterion into a gradient between 0 and 1. The max/min

normalizing procedure is selected as it is accepted as the most right and straightforward method for well-known sets of records [29].

The third stage consists of subgrouping the criteria into two sets according to their relationship with either wildfire ignition or spreading (see Fig.2, third stage). This division is based on a literature review shown in our earlier work [19]. Moreover, a relevancy indicator is given to each criterion according to their direct or indirect relationship with wildfire regimes. This is explained in detail in Table 1. The first three methodical stages are borrowed from our previous studies.

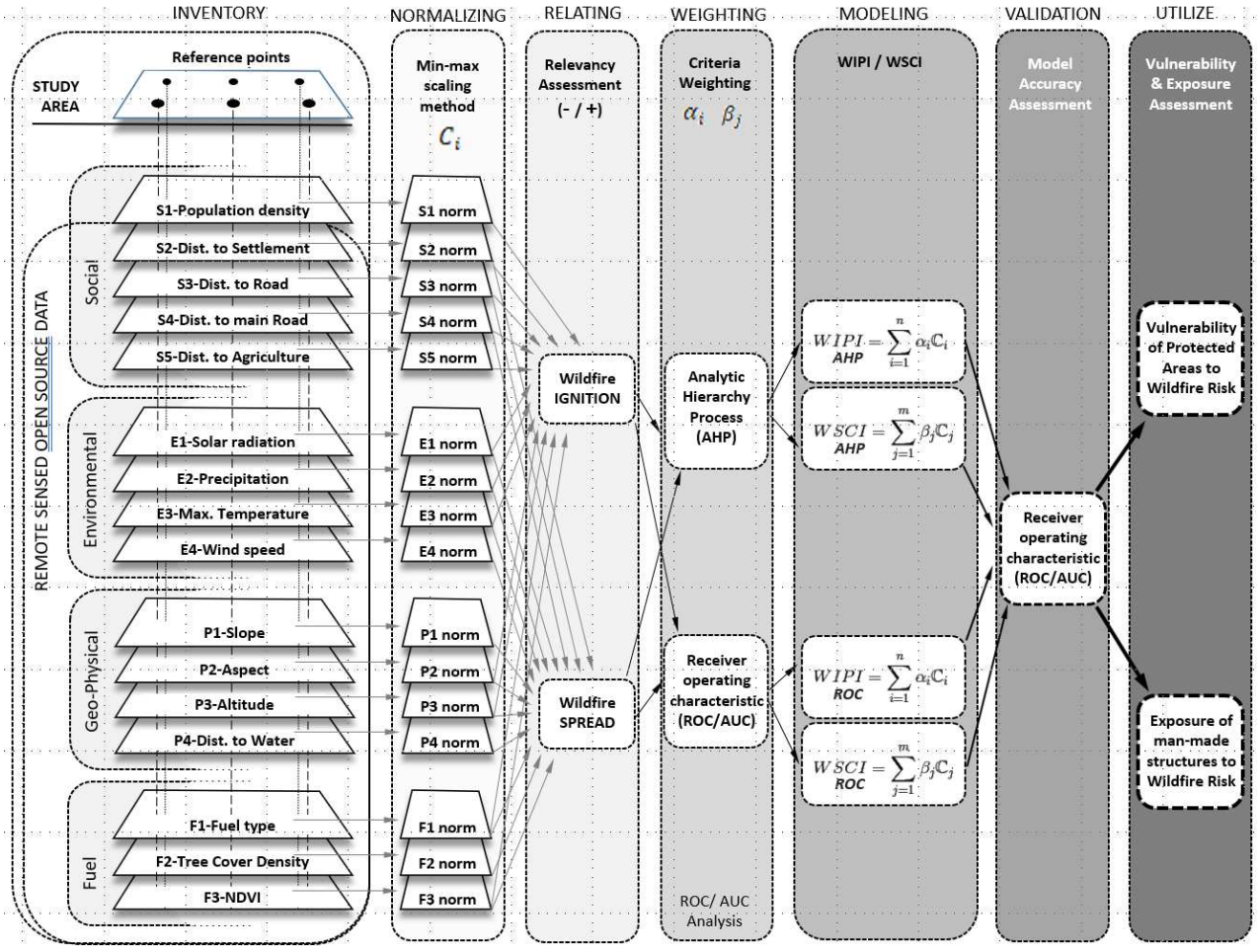

Figure 2. Workflow seven stages of the method.

In the fourth stage, we propose ROC/AUC analysis (via SPSS software) as a weighting method among criteria, besides the analytic hierarchy processing (AHP) pairwise comparison method. This relies on the

specific characteristics of the study area and historical data on fire regimes. Indexing values are calculated as the sum of the products between inventory value and each criterion's impact factor, as shown in Eq.1 and 2.

$$WIPI=\sum_{i=1}^{n} \alpha_i C_i \quad (1)$$

Where; WIPI is the normalized wildfire ignition probability index, $C_i$is the inventory value of criterion i, α_i *the* weighted impact coefficient of criterion i.

$$WSCI=\sum_{j=1}^{m} \beta_j C_j \quad (2)$$

Where; WSCI is the normalized wildfire spreading capacity index, C_j is the inventory value of criterion j, β_j weighted impact coefficient of criterion j.

We compare the earlier model results (WIPI/ WSCI) and the updated one (WIPI_ROC / WSCI_ROC) as applied in Romania's case. During the sixth stage, the ROC/AUC method is used to assess both models' accuracy, leading to a comparative discussion. At the final stage, the WSCI_ROC model results are used in vulnerability assessment of protected areas and exposure analysis of urbanized zones.

2.3. Data acquisition

This study depends on a variety of free access to remotely sensed geospatial data. These data are acquired from various sources. We have included detailed information in Table S2 (Supplementary files online), which presents the full list of the data name, data type, Minimum Mapping Unit (MMU), the source, and utility within the method's workflow. CORINE Land Cover (CLC) is a pan European vector data provided by the European Environment Agency (EEA), which delivers a hierarchical classification of 44 land cover types [30]. The classification method simultaneously utilizes the Sentinel-2 satellite imagery (i.e., the 1st dedicated European satellite for land monitoring) Landsat-8 images for gap-filling. In this study, we rely on the data of 2018 to gather geospatial information about vegetation surfaces, settlements (S2), fuel type (F1), and agricultural areas (S5). EEA supplies other data such as Digital Elevation Model (DEM) and Tree Cover Density (TCD). DEM is delivering information about slope (P1), aspect (P2), and altitude (P3) in raster format of 25m in resolution.

Normalized Difference Vegetation Index (NDVI) data is extracted from the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (MOD13Q1) Version 6. These data are produced in a resolution of 250m by choosing the most reliable pixel value among daily values within 16 days. The low percentage of cloud coverage, low view angle, and the highest NDVI value are among the applied selection criteria [31,32]. In this study, we used the period between 28 July and 12 August within the fire season of 2018.

Raster data about solar radiation (E1), precipitation (E2), maximum temperature (E3), and wind speed (E4) are derived from Worldclim 2.0 database (http://www.worldclim.com/version2). It consists of raster images of 30s resolution that provide monthly average values recorded between 1970 and 2000[33]. In this study, we use August's average records as the weather conditions for wildfire spread are highest. The remaining criteria, like distance to water (P4) and transportation network (S2 & S3), stand on Open Street map (OSM) data enabled for free via the Geofabrik portal.

The population density information is produced based on population records at the smallest local administrative unit level, as shown in Fig. S1 (Supplementary files online) based on the data provided by the National Institute of Statistics of Romania. Another crucial piece of data used in this study is the Burned Area (BA) products acquired from Copernicus Climate Change Service (2019). They provide information about the total BA at the pixel level (250 m). The results are prepared via reflectance change analysis of medium resolution sensors like Terra MODIS, Sentinel-3 OLCI combined with the thermal data by MODIS. These products are vital raw data for research that focuses on themes like climate change, land use and land cover dynamics, wildfire risk assessment, among others [34]. MODIS products are the most widely used global dataset by the scientific community[35-37]. According to Fig. S2, 70410 reference points overlap with the vegetated surfaces. Further details about the data curating are included in the supplementary files online.

3. Results

3.1. Multi-criteria Inventory of wildfire-related factors in Romania

First, the method delivers inventory results on an individual level per each criterion. Fig. 3 presents the relative wildfire proneness map of vegetated surfaces (Fig. 3q) in Romania based on each criterion. The color palette is set as the gradient of red-yellow-green, where red shows the highest risk areas while green the least

risk. The gradient is assigned according to the relative indicator, as explained in Table 1. For example, criteria like solar radiation (E1) and precipitation (E2) are shown under reversed color gradient. In other words, the highest solar radiation values indicate the highest risk. In contrast, the highest precipitation records correlate with the lowest risk.

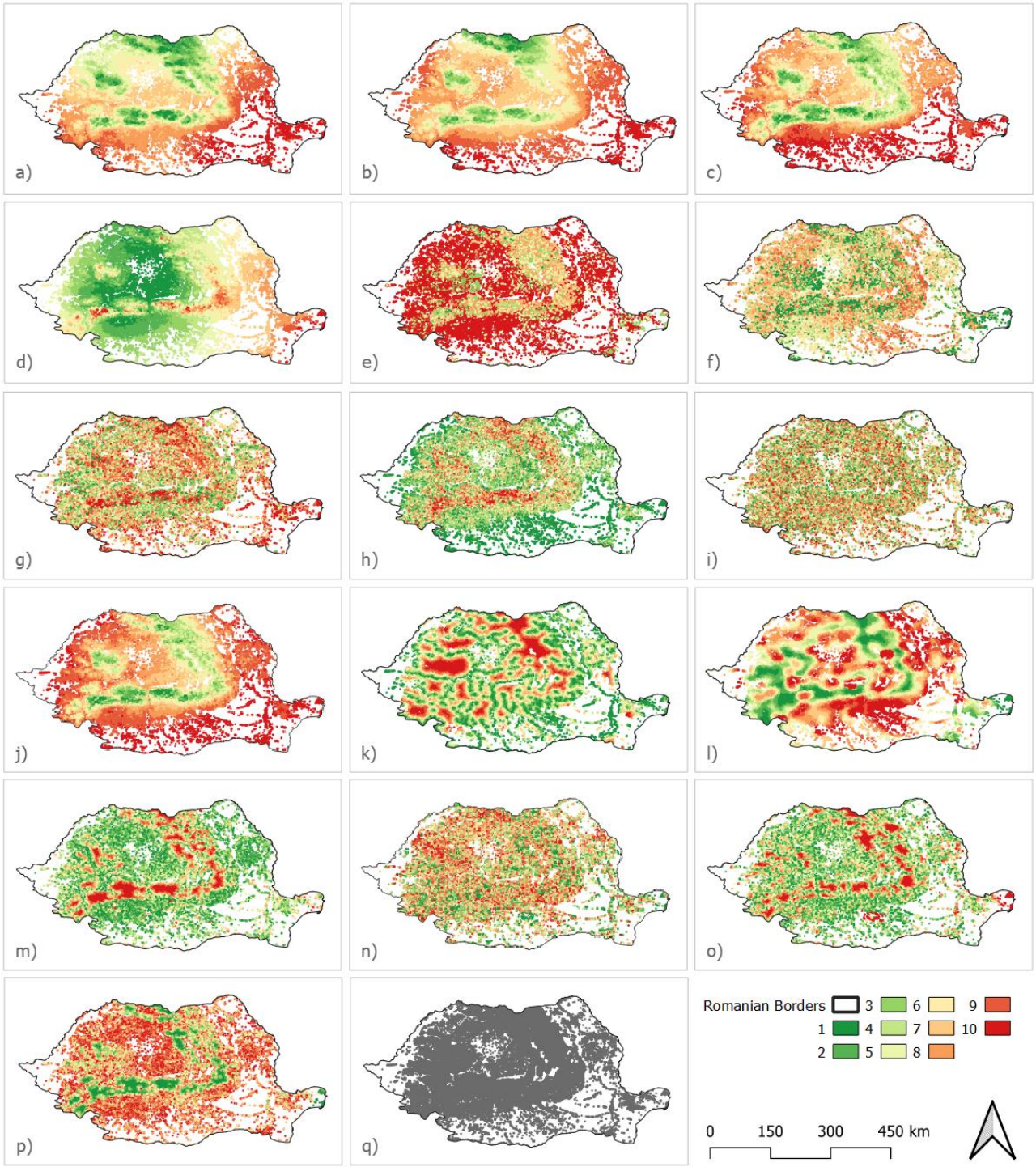

Figure 3. The relative risk of vegetated surfaces (q) in Romania for each criterion; (a) solar radiation, (b) precipitation, (c) maximum temperature, (d) wind speed, (e) fuel type, (f) tree cover density, (g) NDVI, (h) slope, (i) aspect, (j) altitude, (k) distance to water, (l) distance to urban centers, (m) distance to settlements, (n) distance to any road, (o) distance to main roads, (p) distance to agriculture.

According to Fig.3, the RCM that cross the Romanian territory in the central region from north to south-west direction stand as a determinant of the spatial distribution of the relative risk for the majority of the criteria. First, the hydro-meteorological criteria visually correlate with the topography of the study area. Fig. 3a shows that solar radiation (E1) is higher at lower altitudes, especially in the south-east of RCM, and lower at high altitudes. Similarly, the recorded maximum temperatures (E3) are on the same line with the altitude (P3) values presented in Fig. 3j.

Wind speed (E4) is the only environmental criterion that is not tightly correlated with altitude (Fig. 3d). The slopes of RCM face south and south-east and remain an exposed area to winds flowing from the Black Sea and the Mediterranean. Similarly, the remaining plain territories in Romania's south-eastern region facing the Black sea are exposed to considerable average wind speeds compared to the north-western plains (Fig. 3d). Among geophysical criteria, slope (P1) is the only criterion that correlates with the altitude values (Fig. 3h). Most of the sloped surfaces are found along with the RCM layout. Whereas the aspect (P2) values are more uniformly dispersed in the territory (Fig. 3i) and distance to water surfaces (P4) follows the spatial distribution of water elements in the landscape (Fig. 3k), independently to the altitude values.

3.2. Calibrated weighting of Criteria

For the previous version, we adopted the weighted factors as assigned via an AHP pairwise comparison method [28], as listed in Table 1. Besides, the revised weighted impact factors are assigned according to each criterion's sensitivity analysis concerning the historical fire regimes. Fig. 4 presents the ROC analysis values per each criterion under four groups; hydro meteorological- environmental (E), fuel (F), geophysical (P), and anthropogenic- social (S).

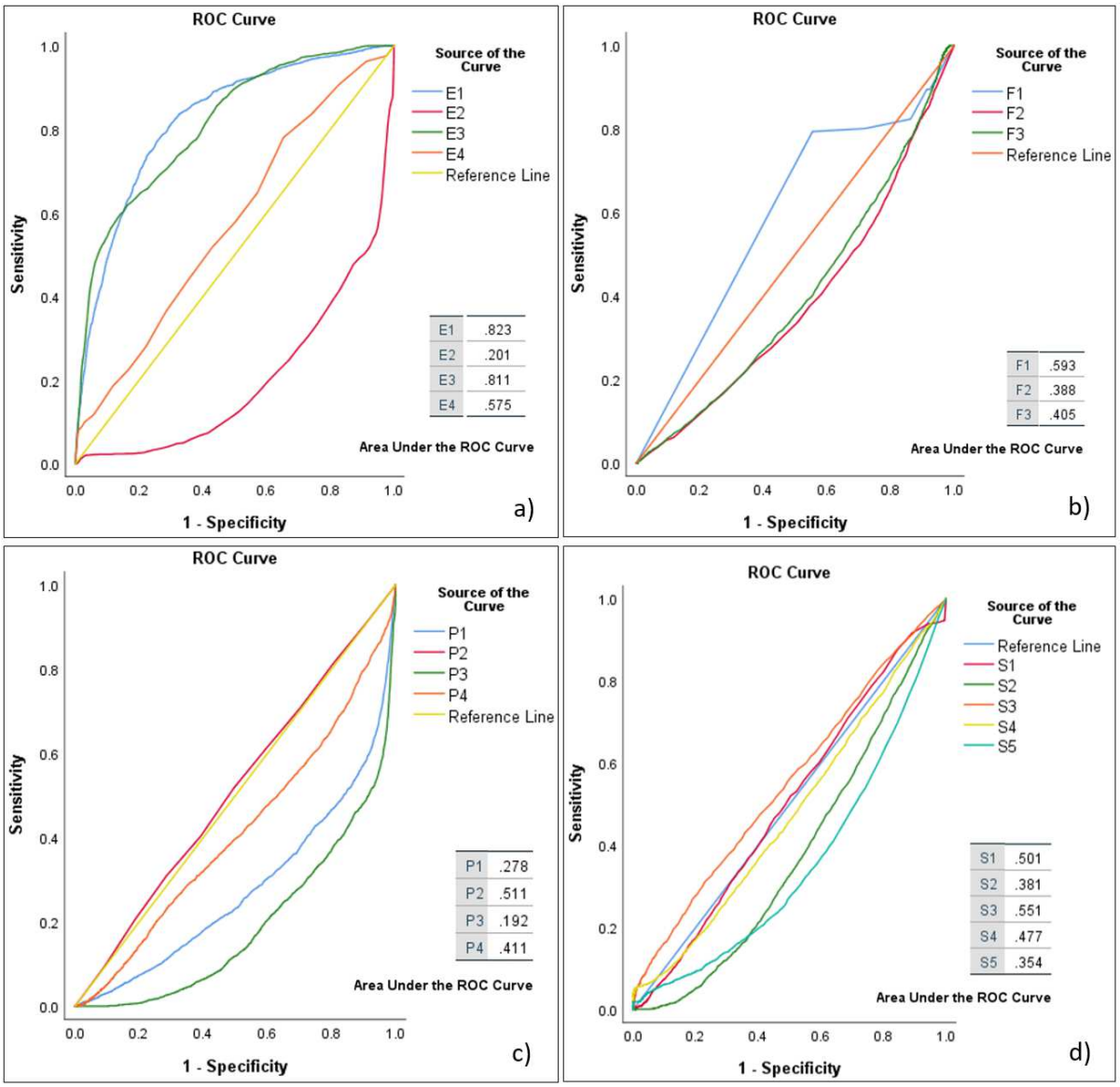

Figure 4. ROC curve analyses for (a) hydro-meteorological (E1-solar radiation, E2-precipitation, E3-maximum temperature, E4-wind speed), (b) fuel (F1-fuel type, F2-tree cover density, F3-ndvi), (c) geophysical (P1-slope, P2-aspect, P3-altitude, P4-distance to water), and (d) anthropogenic/ social (S1-population density, S2-distance to settlements, S3-distance to any road, S4-distance to main roads) factors about burned regime values.

The sensitivity analysis is performed in SPSS software via the ROC analysis tool. According to the inventory phase results, there are 70410 reference point locations within Romania's vegetated surfaces. The distance between points is 1km, and each point represents a vegetated surface of 1km^2. One thousand nine hundred fifty-six points have a five-year cumulative burned area fraction (2015-2019) value above 100%. These points are considered positive samples in the ROC analysis procedure in finding each criterion's sensitivity.

The results presented in Fig. 4 reveal the hypothetical models' sensitivity that has a single determinant, being each criterion. It is a way to find the correlation between inventory measurements of each criterion with the burned area fraction in Romania (see Fig. S2 in Supplementary files online). According to Fig.4, the highest AUC value belongs to E1 (solar radiation) and E3 (maximum temperature), respectively 0.823 and 0.811. In other words, it means that a model that was based just on the criterion of solar radiation would have a predictability of 82%. While, the lowest AUC values are recorded for E2 (precipitation), P1 (slope), and P3 (altitude), respectively, 0.201, 0.278, and 0.192. In principle, the lowest the AUC value, the lowest the correlation between the criterion and the wildfire recorded burned area fraction. The criteria that score an AUC value less than 0.5 have an indirect correlation with the wildfire records. The first two columns of Table 1 present the absolute and normalized AUC values of all criteria.

Table 1. The weighted impact factors (WIPI and WSCI) of each criterion via AHP and ROC/AUC methods.

					WIPI				**WSCI**		
		ROC/ AUC	AUC/ norm	+ -	AHP	ROC	AUC/ norm	+ -	AHP	ROC	AUC/ norm
E1	Solar radiation	.823	.110	+	.032	.823	.110	+	.011	.823	.103
E2	Precipitation	.201	.027	-	.097	.799	.107	-	.048	.799	.100
E3	Max. Temp.	.811	.109	+	.032	.811	.108	+	.022	.811	.101
E4	Wind speed	.575	.077					+	.155	.575	.072
F1	Fuel type	.593	.080	+	.056	.593	.079	+	.033	.593	.074
F2	TCD	.388	.052					+	.299	.388	.048
F3	NDVI	.405	.054	-	.125	.405	.054	-	.170	.595	.074
P1	Slope	.278	.037					+	.033	.278	.035
P2	Aspect	.511	.069	+	.049	.511	.068	+	.013	.511	.064
P3	Altitude	.192	.026	-	.016	.808	.108	-	.006	.808	.101
P4	Dist. To water	.411	.055					+	.070	.411	.051
S1	Pop. density	.501	.067	+	.026	.499	.067				
S2	Dist. Settlements	.381	.051	-	.076	.619	.083	+	.017	.381	.048
S3	Dist. roads	.551	.074	-	.140	.449	.060	+	.006	.551	.069
S4	Dist. main roads	.477	.064	-	.045	.523	.070	+	.047	.477	.060
S5	Dist. agriculture	.354	.048	-	.305	.646	.086				

The following columns deliver each criterion's relative impact factors as calculated via AHP pairwise comparison and ROC/AUC analysis. Besides, each criterion is assigned an indicator for either direct (+) or inverse (-) relation with the wildfire risk. This indicator is assigned based on assumptions inferred from the literature review on the relationship between wildfire regimes and driving factors [19]. For example, the highest the solar radiation, maximum temperature, fuel type, and aspect values, the wildfire ignition and spread the

risk. On the other side, the lower the precipitation, NDVI, and altitude values, the higher the wildfire risk. Simultaneously, anthropogenic criteria like distance to settlements and transportation networks are unevenly related to wildfire ignition and spreading phases.

3.3. Comparing between WIPI/ WSCI and WIPI_ROC/ WSCI_ROC Results

We calculated the WIPI and WSCI index values of each reference point according to Eq. 1 and Eq. 2 using the weighted values via the AHP method. The results of the ROC/AUC analysis show the relatively low sensitivity of the model. According to Fig. 5, the AUC of WIPI is 0.705 and an overall model quality of 0.69. It is significantly higher than the WSCI model sensitivity marking an AUC value of 0.587 and an overall model quality of 0.57. It can be inferred that the model, which relies on the weighted values calculated via AHP, is more accurate for predicting wildfire occurrence events rather than the wildfire spreading process.

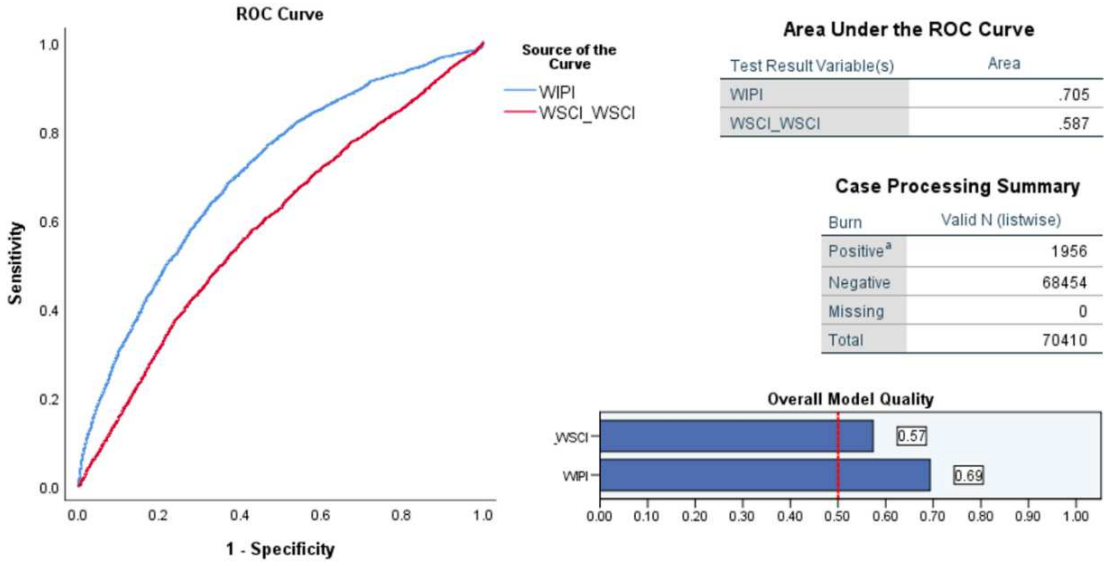

Figure 5. Sensitivity analysis of the WIPI and WSCI models based on burned surfaces (2015-2019) as positive cases (1956 out of 70410-point locations).

Later, we recalculated each reference point's index values as the sum of the products between normalized inventory value and the weighted factor via the ROC/AUC method (Fig. 2). The revised weights, as presented in Table 1, led to improved model sensitivity. Fig. 6 presents a comparative ROC/AUC analysis between the former WIPI/WSCI and the revised WIPI_ROC/ WSCI_ROC models.

The updated models' curves are shown in green color, while the previous versions are shown in red. According to Fig.6a, the AUC value of WIPI_ROC has jumped to 0.778, marking a sensitivity increase of 0.073. The overall model quality of the WIPI model has been improved by 12% (from 0.69 to 0.77). The improvement is more visible in the case of the WSCI model (Fig. 6b). The revised model (WSCI_ROC) records an AUC value of 0.802, 37% higher than the earlier version. A similar escalation is recognized in the overall model quality. We rely on the WSCI_ROC results during the final stage of vulnerability and exposure analysis.

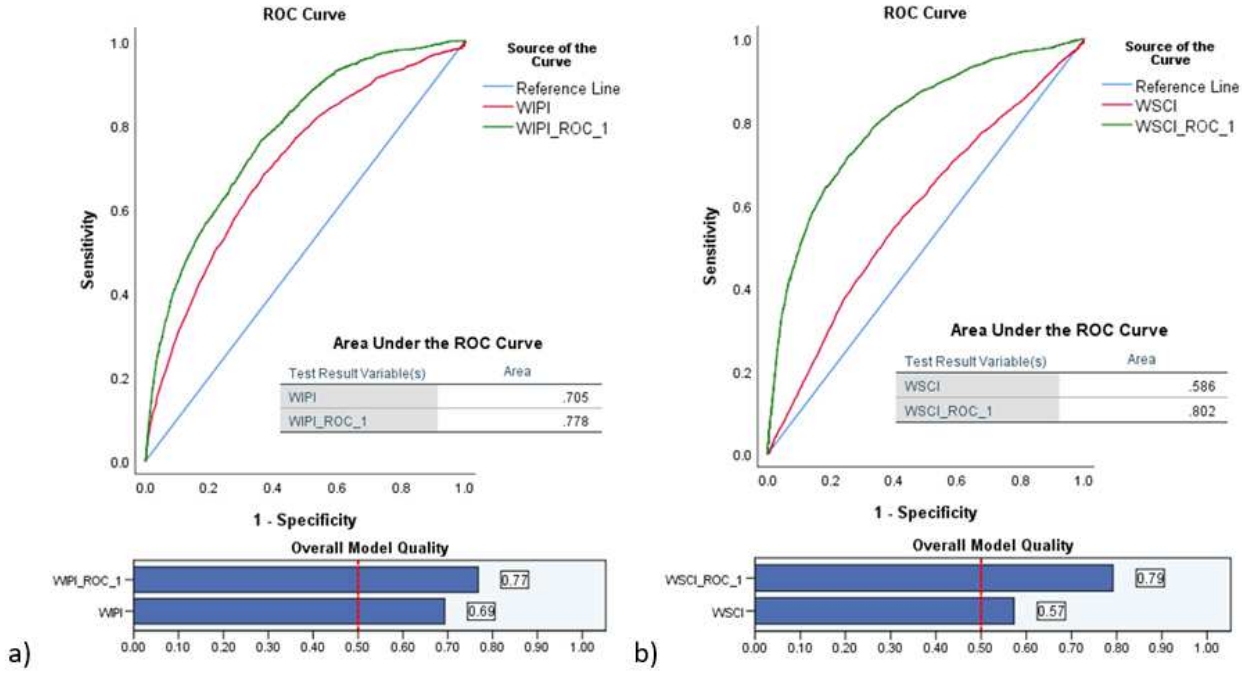

Figure 6. Comparative Sensitivity analysis; (a) between WIPI and WIPI_ROC models, and (b) between WSCI and WSCI_ROC models.

Beyond statistical analysis about the model accuracy, the results of the WSCI_ROC model delivers essential findings of the spatial distribution of the wildfire spreading the capacity risk of vegetated surfaces in Romania. According to Fig. 7, the highest wildfire spreading risk is concentrated in its eastern and southern regions. A secondary area under wildfire spreading capacity risk is along the western borders. Simultaneously, the central and the northern regions appear to be safer from wildfire, spreading the risk. These regions coincide with the surfaces which are high in elevation and located away from human activities. Among them, the sub-regions that record the lowest WSCI_ROC values are surfaces that are oriented towards the northern direction and gaining a minimum of solar radiation. The gradient of green color indicates these surfaces.

Furthermore, Fig.7 incudes the administrative boundaries of the third level (NUTS-L3) of Romania. Referring to the Eurostat data, Romania has 42 local administrative units at the third level. According to the results presented in Fig. 7 and Fig. S3 (see Supplementary file online), 41 units consist of at least 1km^2 of vegetated surface that has been indexed here. The only unit that has no wildland vegetated surface is the capital city of Romania. As highlighted in Fig. 7, Bucharest is the smallest in surface area compared to the other units. However, it does not mean that it is safer. On the contrary, when jointly considered with the metropolitan area of Ilfov, which envelopes the urban area of Bucharest, the wildfire ignition and spreading risk in the wildland-urban interface (WUI). We further discuss this issue in the following sections while assessing human-made structures' exposure to wildfire spreading risk.

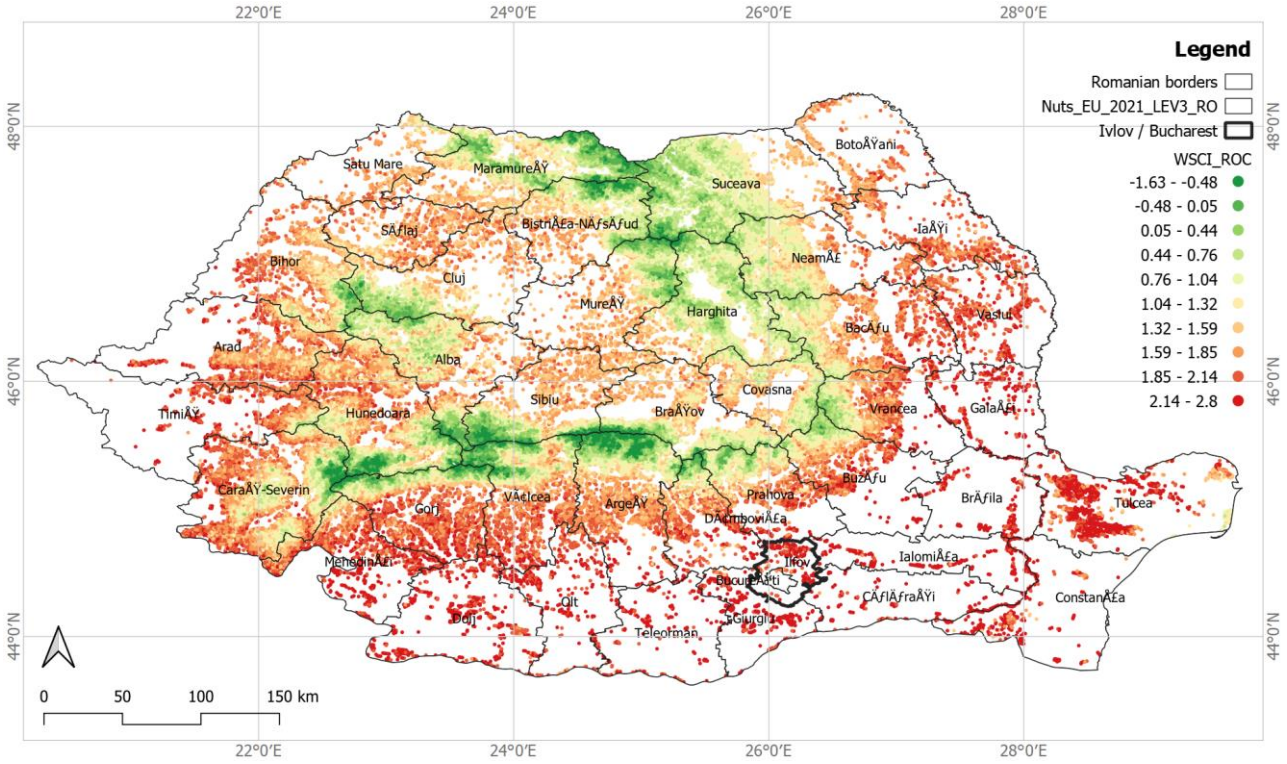

Figure 7. Wildfire spreading capacity map of vegetated surfaces on Romania (WSCI_ROC) with the highlighted metropolitan area of Ilfov.

The overlapping of wildfire spreading capacity risk and the local administrative units highlights the municipalities that need to enhance their wildfire prevention measures. Fig. S3 (Supplementary files online) presents the box plots that show the WIPI_ROC and WSCI_ROC values distribution by local administrative units. According to the results plotted in Fig. S3a, the administrative units with the highest WIPI_ROC index values are located in the country's south-eastern and southern regions.

4. Discussions on Vulnerability and Exposure analysis

Wildfires are native events on earth estimated to have been happening during the last 350 million years [38]. They are accepted to significantly contribute to vegetation recovery at their natural schedule, the biogeochemical cycles of carbon and nitrogen, and the atmosphere's chemical properties [39-41]. However, they are also reported to have considerable consequences on the territory's ecological and social systems. Protected areas are among the land surfaces where the ecological and socio-cultural interests converge with each other. Uncontrolled fires in the vegetated protected areas may cause unrecoverable consequences on the native vegetation structure. On the other side, the WUI zone is boldly highlighted in scientific reports. Wildfire events threaten human activities. We expand our findings by discussing further concerning protected areas' vulnerability and exposure to human-made structures.

4.1. The vulnerability of the Romanian Protected areas to Wildfires

Globally speaking, the protected areas are under consistent threat caused by the processes of climate change, land-use alterations, provisioning of raw materials, socio-cultural activities, and flourishing of invasive species [42,43]. Jones et al. [44] conclude that only two-thirds of the protected areas are safe from globally intensive human activities. While Schulze et al. [45] list fire and fire suppression activities as the third out of 36 threats that protected areas usually face according to the list of level two threats included in the IUCN-CMP Threats Classification Scheme. Forest fires can lead to an invasive plant expansion in disturbed sites [46]. The native species in Romania's protected areas have been at risk of several natural and human-induced hazards [47]. Thus, assessing the vulnerability of the protected areas to wildfires is of great concern in Romania.

This assessment relies on the European inventory of nationally designated protected areas, as acquired from the EEA open-source datasets. According to these data, Romania has 946 protected sites, covering a total area of 13985 km^2. Fig. 8 presents the protected areas overlapping the WIPI_ROC results. Most of these areas are found in the alpine lands along with the RCM. About 13% of the 70410 reference points within the vegetated surfaces we analyzed are located within the protected areas. Consequently, we may infer that 65% of Romania's protected surfaces are vegetated and potentially vulnerable to wildfire risk.

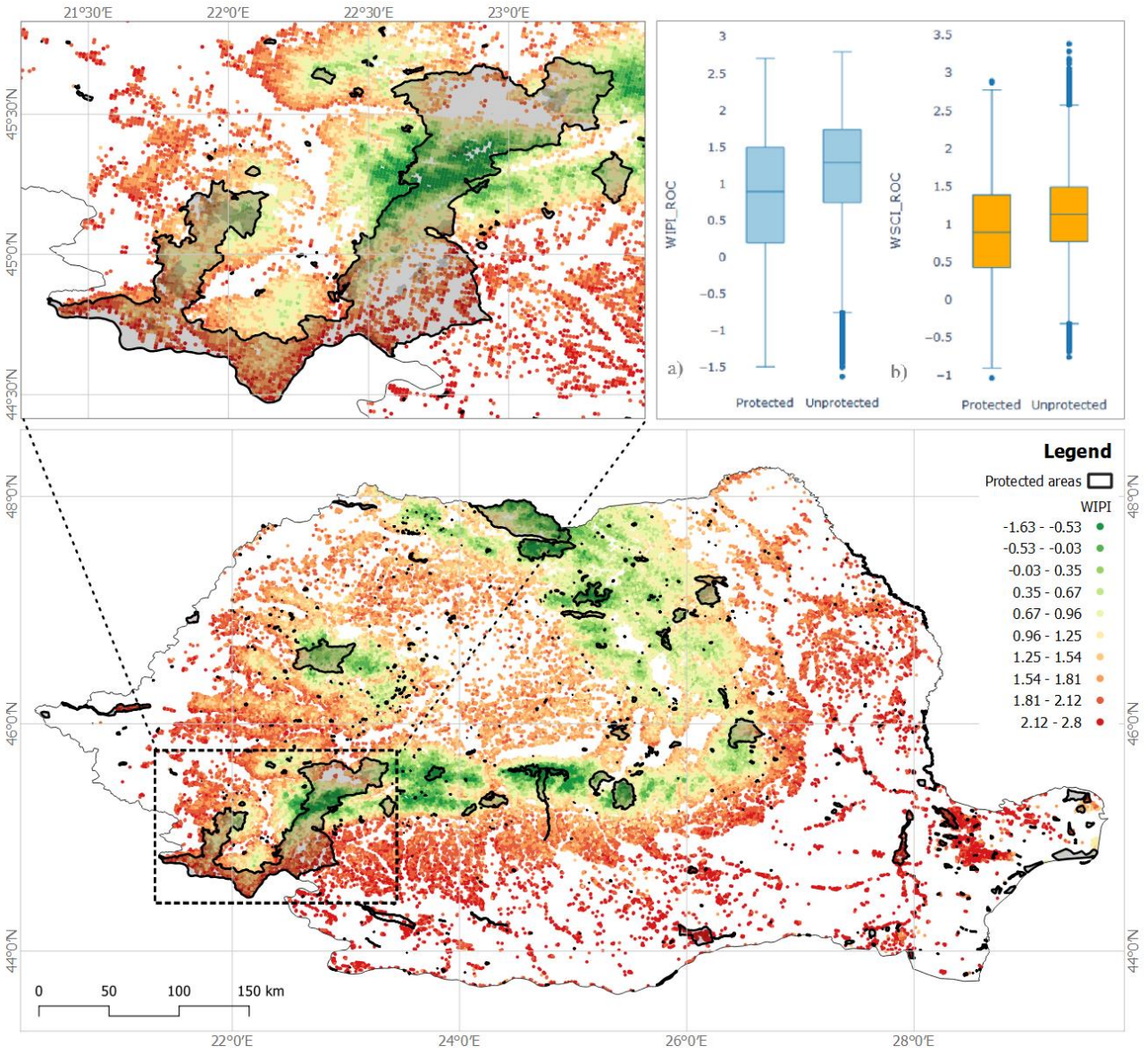

Figure 8. Wildfire spreading risk exposure map of protected areas in Romania, and comparative box plot of WIPI_ROC (a) and WSCI_ROC (b) value distribution between protected and unprotected vegetated surfaces in Romania.

According to the box plot in Fig. 8a-b, the protected areas have lower WIPI_ROC and WSCI_ROC values than unprotected surfaces. Furthermore, referring to Fig. 8, most vegetated surfaces within the protected patches are greenish, implying a relatively low wildfire spreading capacity (WSCI_ROC). These values' main reasons are the high elevation and remote location of protected surfaces to human activities (settlement and transportation network). However, some cases consist of a gradient of WSCI_ROC values within the same protected surface (see the enlarged protected patch in Fig. 8).

342 The relation between connectivity among vegetated landscape patches and wildfire spreading risk has
343 been a questionable literature topic [48]. O'Donnell et al. [49] report that the fragmentation among vegetated
344 landscapes in unmanaged Australian semi-arid shrublands and woodlands directly impacts the reduction of
345 wildfire intervals between 1940 and 2006. Thus, the connectivity among vegetated surfaces within the same
346 protected area may boost the wildfire, spreading greenish areas' risk. Future studies must focus on specifically
347 protected patches to assess the vulnerability to wildfire spreading risk at a finer spatial scale.

348 *4.2. Wildfire exposure of populated areas within the metropolitan area of Bucharest*

349 The urban fringes are critical hybrid areas where the human-made structures are exposed to different
350 environmental hazards [50]. Studies from developing countries report that uncontrolled urban expansion
351 increases inhabited surfaces' exposure to natural hazards like floods, landslides, fire, and sinkholes, among
352 others [51]. Sestras et al. [52] report landslide assessment at a local scale as an inherent threat in Romania's newly
353 developed suburban zones. The wildland-urban interface represents an area of contradiction where both the
354 settling interest and wildfire risk are significantly high [53,54].

355 We performed an exposure assessment of built structures to the wildfire spreading capacity of vegetated
356 surfaces within the Romanian capital city's metropolitan area (Fig. 9a). The wildfire exposure analysis relies
357 on the juxtaposition between the WSCI_ROC results and existing building stock, as shown in Fig. 9. We bring
358 a demonstrative example from Ilfov metropolitan area, which includes the capital city, Bucharest. The hazard
359 map of wildfire spreading capacity relies on the results reported in this article (see Fig. 7). The WSCI_ROC
360 point's layer is utilized for preparing the hazard heatmap (kernel density estimation) with a selection radius of
361 1km.

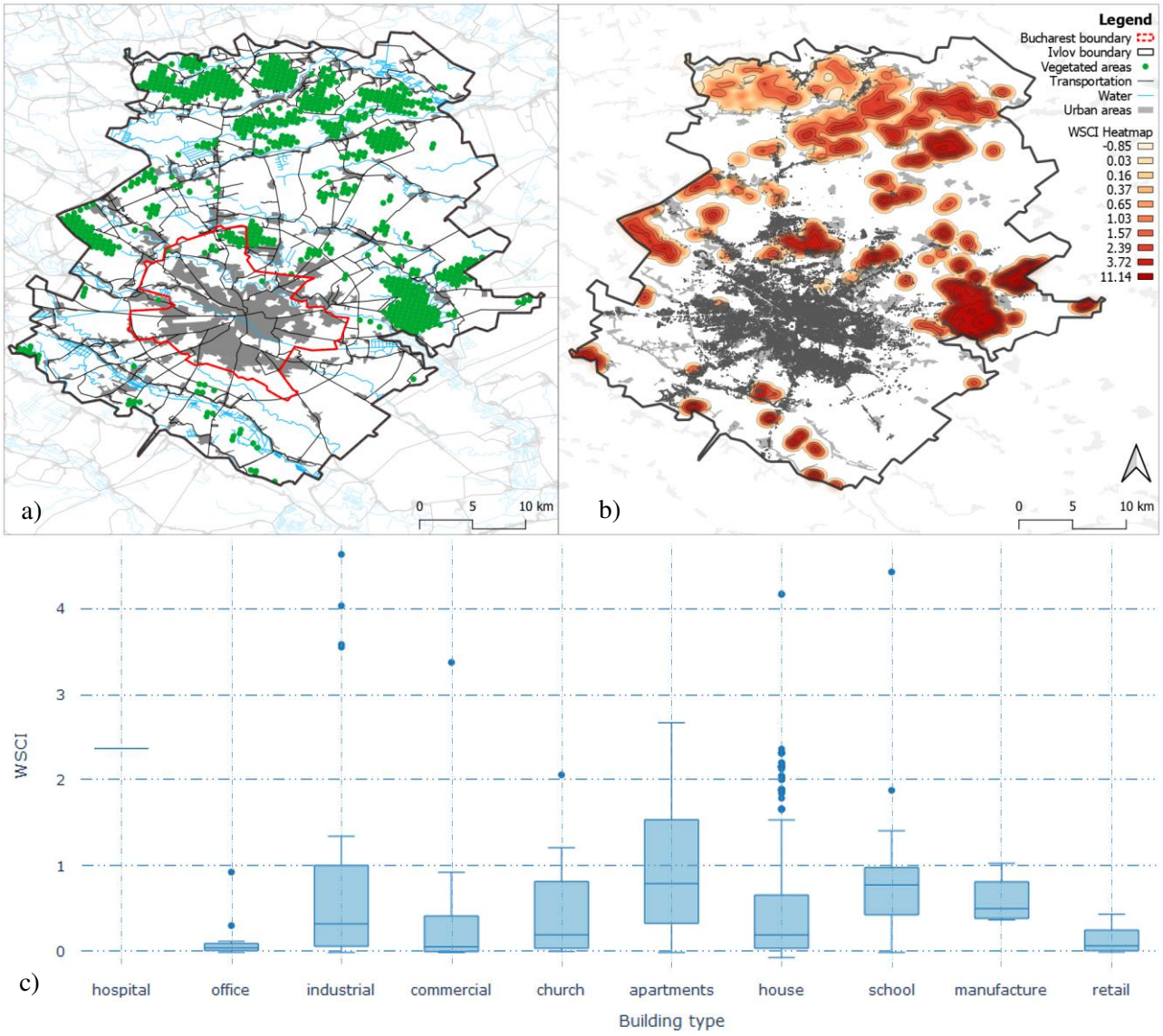

Figure 9. Wildfire exposure map of existing urban fabric (b) within Ilfov and Bucharest (a), and box plot of WSCI_cum distribution per building type of exposed structures (c).

OSM data provide the building stock within the focal study area. Nevertheless, OSM data accuracy is still debatable due to the lack of professional backgrounds [55]. A substantial number of building features that do not include building-use information. However, we bring this discussion as an exposure analysis method that can deliver critical information about the human-made structures under wildfire risk within WUI areas at a metropolitan scale if further improved by introducing validated building stock data.

According to Fig. 9b, 9596 structures overlap with the WSCI_ROC heatmap, exposing the minimum wildfire spreading capacity. Furthermore, 1734 out of the total exposed structures are building types of

significant socio-economic. This building stock's exposure to wildfire spreading risk may have critical consequences on socio-economical processes and their users' life security. Fig. 9c presents the box plot of WSCI_ROC heatmap values distribution per building type. We have included just the most critical building types like hospitals, industrial, residential, religious, leisure, and educational use. While other buildings like warehouses, greenhouses, and abandoned structures, have been ignored at this stage.

According to the box plot, just one hospital is located within the critical wildfire spreading capacity heatmap. Nevertheless, it has a WSCI_ROC heatmap value of 2.37, which indicates a significant exposure of its users to wildfire spreading risk. According to the outlier values (dots) shown in Fig. 9c, there are four industrial, one house, and one school building highly exposed to wildfire spreading the risk.

5. Conclusions

This study presented the indexing of vegetated surfaces in Romania by Wildfire Ignition Probability and Spreading Capacity Index (WIPI/ WSCI). The method offered here relies on open-source data, which supplies the analytical process with geospatial information about the anthropogenic, hydro-meteorological, geophysical, and fuel properties of the study area. We identified sixteen criteria that significantly impact either the wildfire ignition or spreading phase of the wildfire event in Romania. Nevertheless, the impact of each criterion on wildfire is weighted via ROC/ AUC analysis. During the analysis, the positive cases rely on the burned area fraction records between 2015 and 2019 (five years).

According to the results, the hydro-meteorological criteria have the highest correlation with the wildfire records. The vegetated surfaces in Romania's eastern and southern regions face the highest wildfire spreading capacity index values. Considering that these regions make home to urbanized lands of high population density, the high WSCI records indicate an elevated risk. We performed the wildfire spreading risk exposure analysis of the building stock within the capital city's metropolitan area, Bucharest. These results imply that critical structures like hospitals, residential and educational units are at significant risk.

On the other side, Romania's central areas scattered along the RCM have the lowest index values. This is generally driven by high altitude values, directly correlated with other climatic criteria such as solar radiation, precipitation, and maximum temperature. These regions include the majority of protected areas. According to

our results, some protected vegetated surfaces in Romania hold a gradient of wildfire spreading risk within the same protected area geometry. In such cases, the whole area within the protection borders must be considered under risk as the connectivity among vegetated surfaces in wildfire risk analysis is considered a weakness.

The method we presented in this study is reproducible in other wildfire-prone geographies. It is also flexible enough to integrate the most up-to-date and the most reliable remotely sensed geospatial data. The results presented in this study can help the institutions at the national and local levels responsible for wildfire risk reduction in Romania.

Data availability

The data generated during this study are included in this published article are shared via the PANGAEA database and can be accessed via the following link. https://issues.pangaea.de/browse/PDI-27019

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AUTHOR CONTRIBUTIONS STATEMENT

A.H. Defined the methodology, acquired the materials, performed the GIS modeling, produced the visual materials, wrote the draft manuscript. **V.S.** and **B.D.** Proposed the collaboration, supervised the study, acquired the funding. **S.R.** Contributed to the manuscript, curated data, provided raw data. **A.K.** Supervised the study, wrote and edited the final manuscript, curated the visual quality of figures. **Ș.B.** and **P.S.** Proposed the study, wrote the original manuscript, curated data, supervised the study, provided raw data. All authors reviewed and approved the manuscript.

COMPETING INTERESTS

The authors declare no competing interests

ADDITIONAL INFORMATION

Supplementary Information The online version contains supplementary material.

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Figures

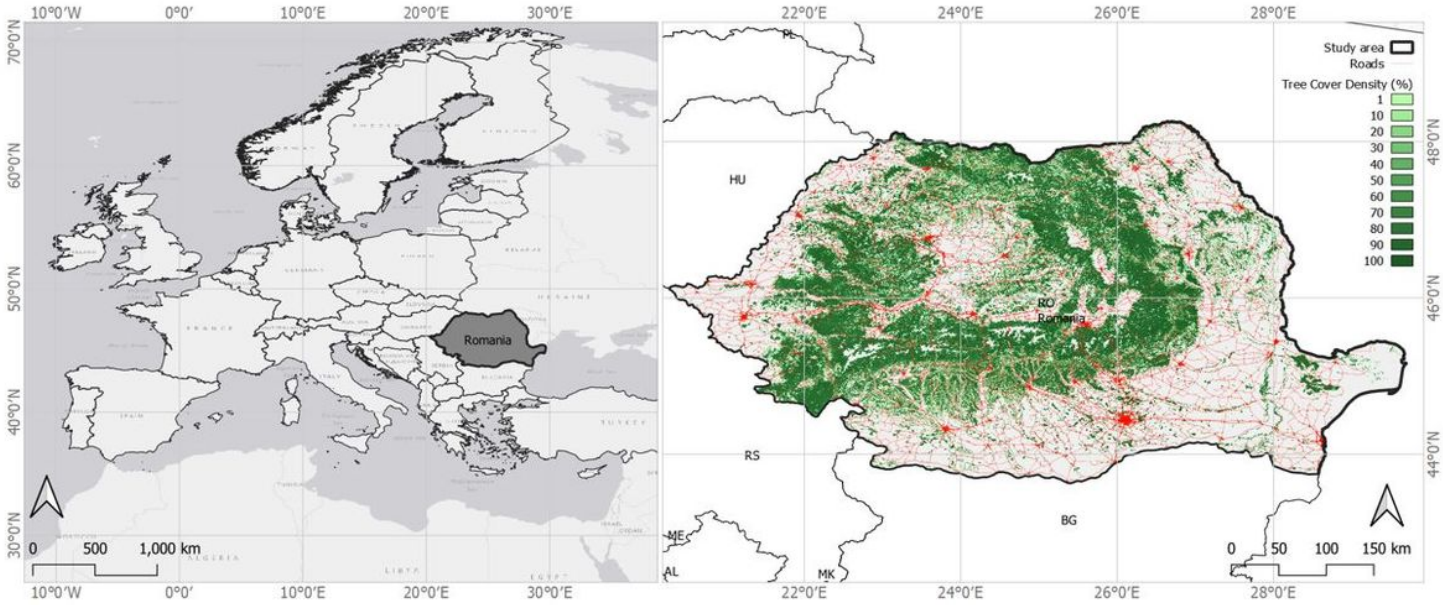

Figure 1

Romania within Europe (a), and Romanian territory including tree cover density (TCD)and transportation network distribution (b). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

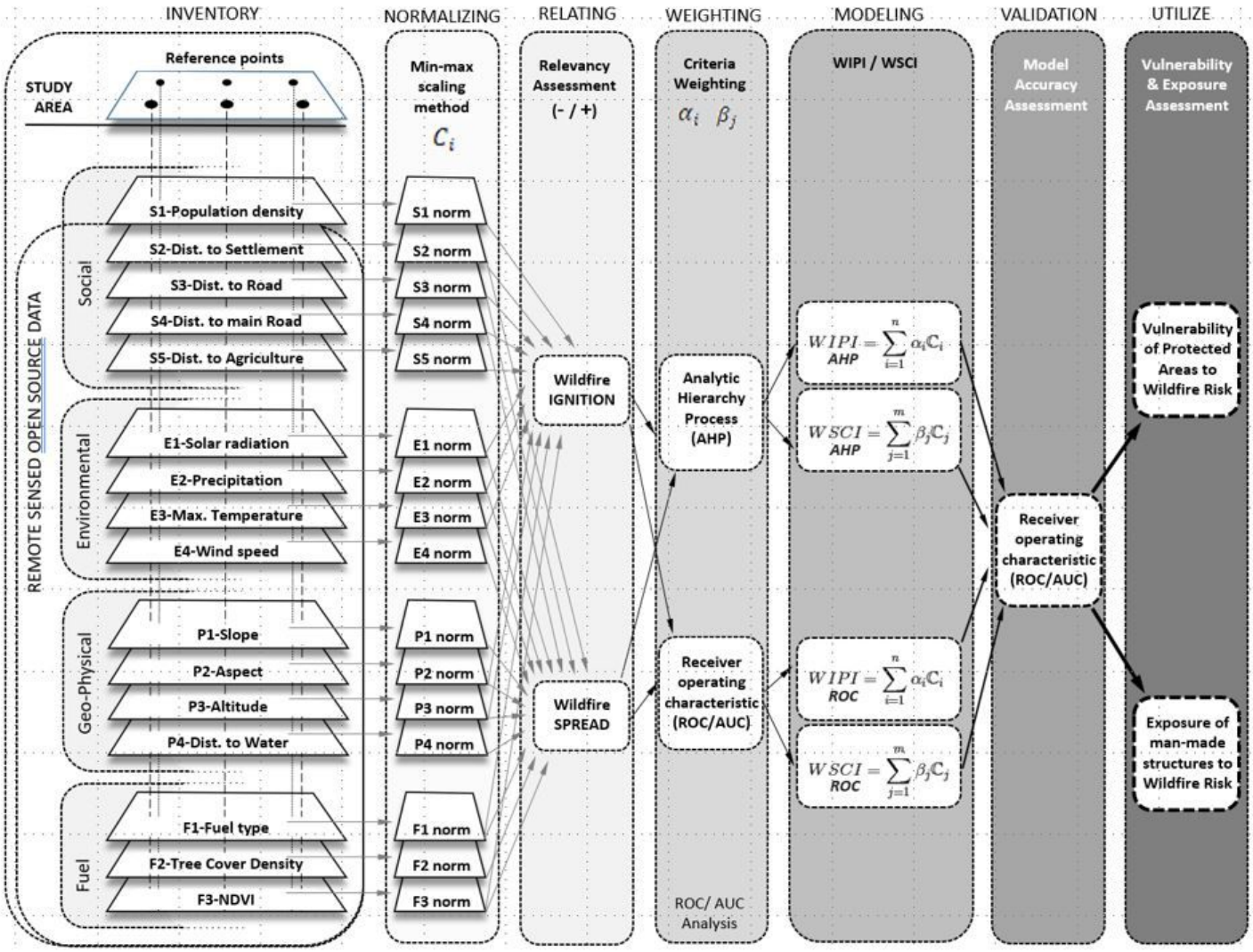

Figure 2

Workflow seven stages of the method.

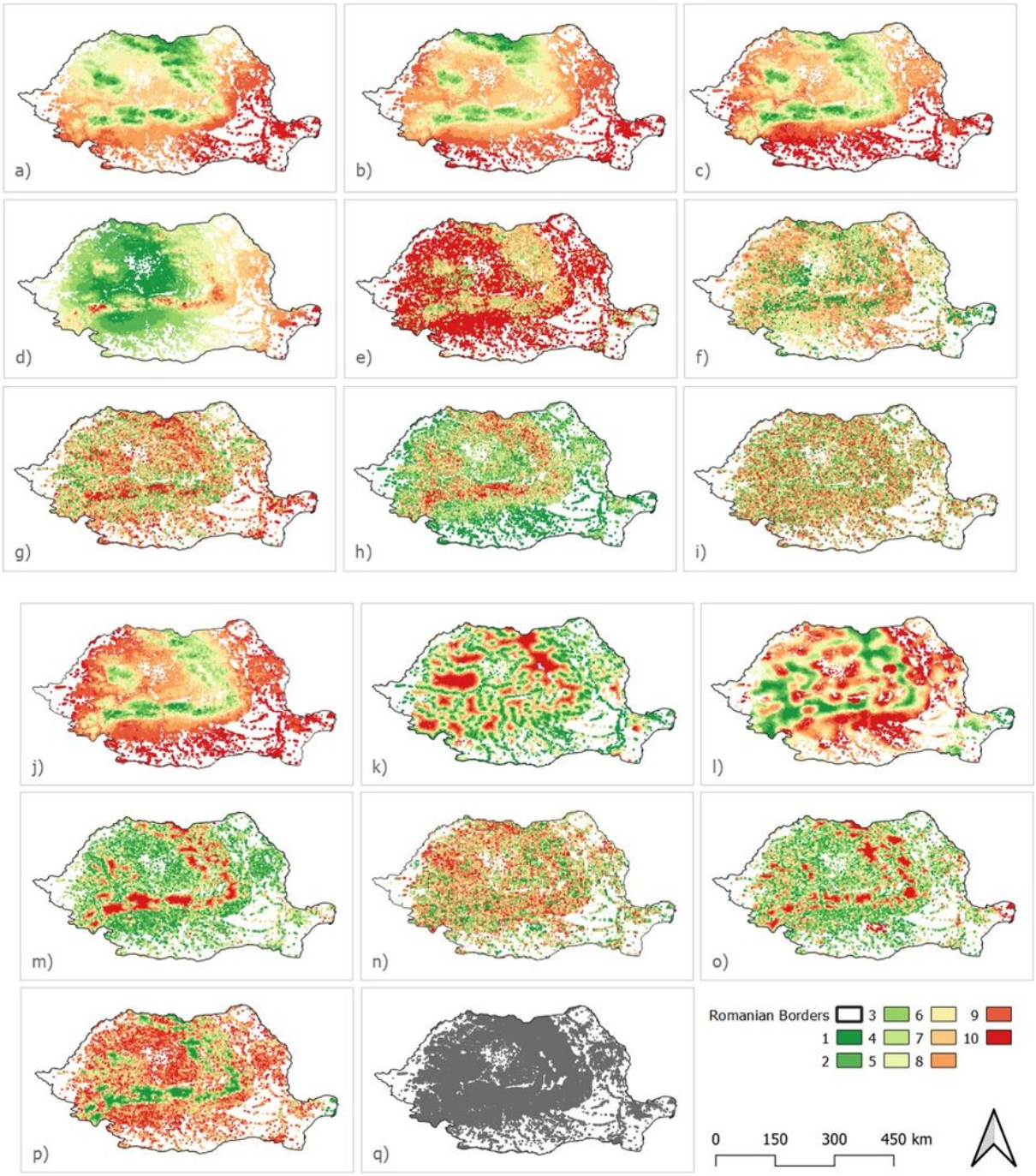

Figure 3

The relative risk of vegetated surfaces (q) in Romania for each criterion; (a) solar radiation, (b) precipitation, (c) maximum temperature, (d) wind speed, (e) fuel type, (f) tree cover density, (g) NDVI, (h) slope, (i) aspect, (j) altitude, (k) distance to water, (l) distance to urban centers, (m) distance to settlements, (n) distance to any road, (o) distance to main roads, (p) distance to agriculture. Note: The designations employed and the presentation of the material on this map do not imply the expression of

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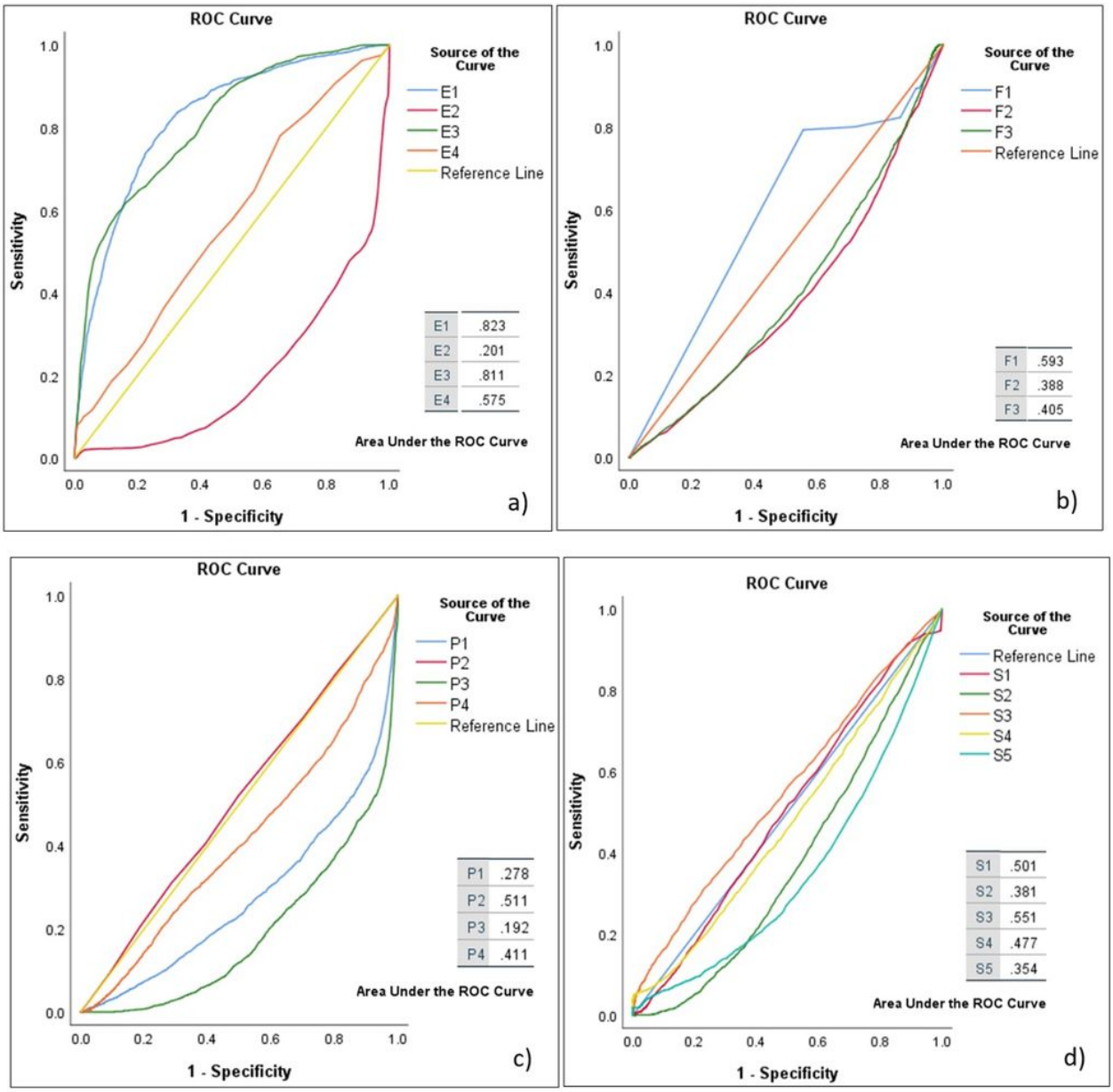

Figure 4

ROC curve analyses for (a) hydro-meteorological (E1-solar radiation, E2-precipitation, E3-maximum temperature, E4-wind speed), (b) fuel (F1-fuel type, F2-tree cover density, F3-ndvi), (c) geophysical (P1-slope, P2-aspect, P3-altitude, P4-distance to water), and (d) anthropogenic/ social (S1-population density,

S2-distance to settlements, S3-distance to any road, S4-distance to main roads) factors about burned regime values.

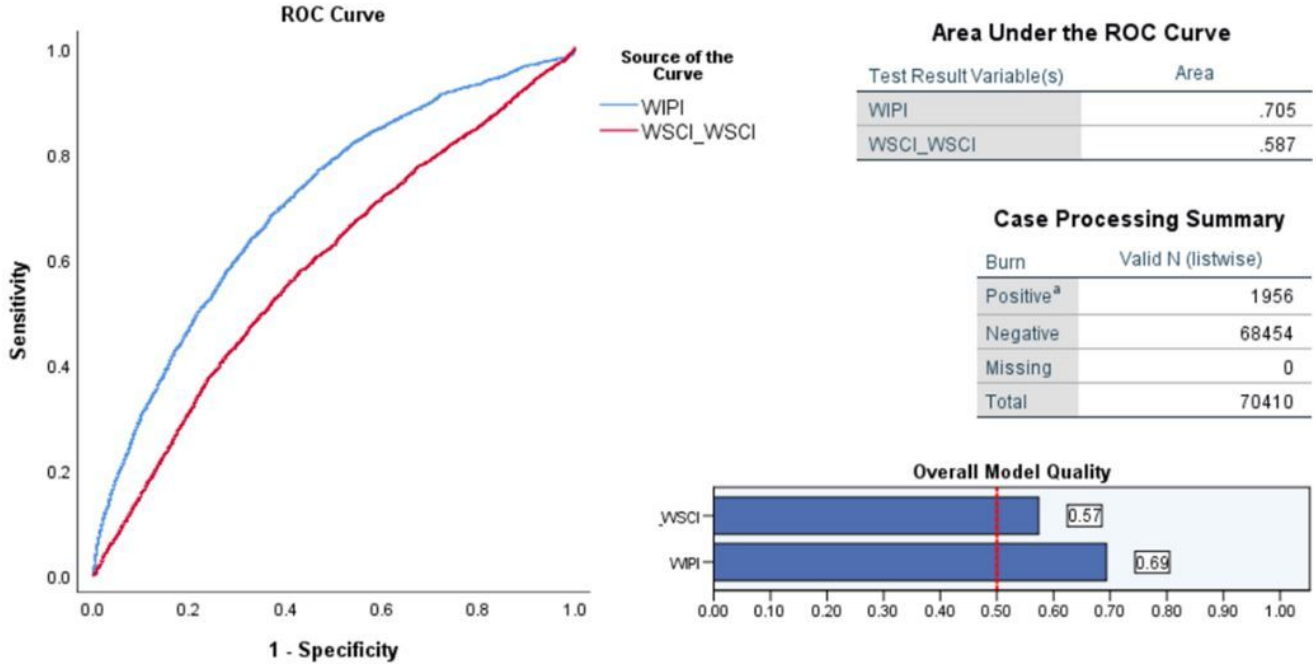

Figure 5

Sensitivity analysis of the WIPI and WSCI models based on burned surfaces (2015-2019) as positive cases (1956 out of 70410-point locations).

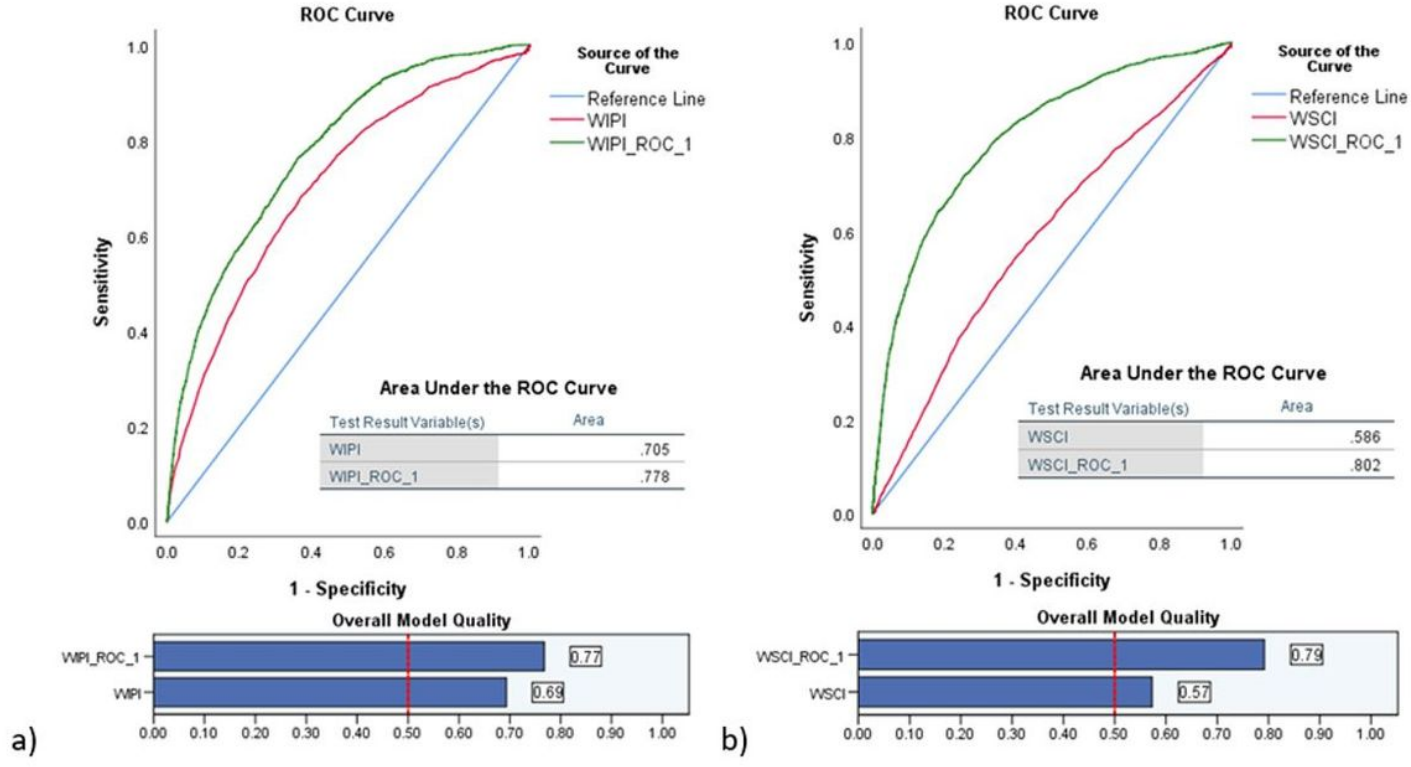

Figure 6

Comparative Sensitivity analysis; (a) between WIPI and WIPI_ROC models, and (b) between WSCI and WSCI_ROC models.

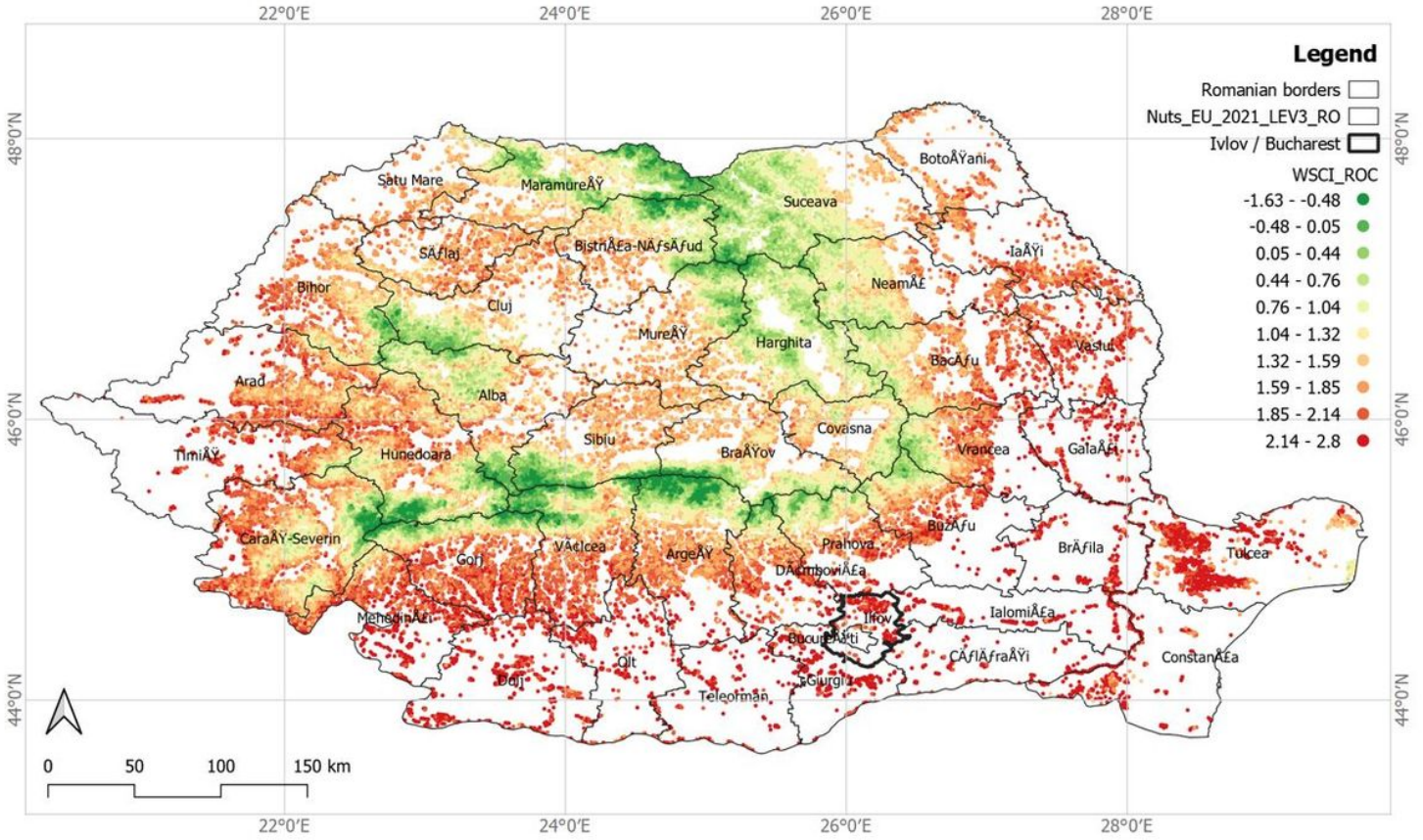

Figure 7

Wildfire spreading capacity map of vegetated surfaces on Romania (WSCI_ROC) with the highlighted metropolitan area of Ilfov. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

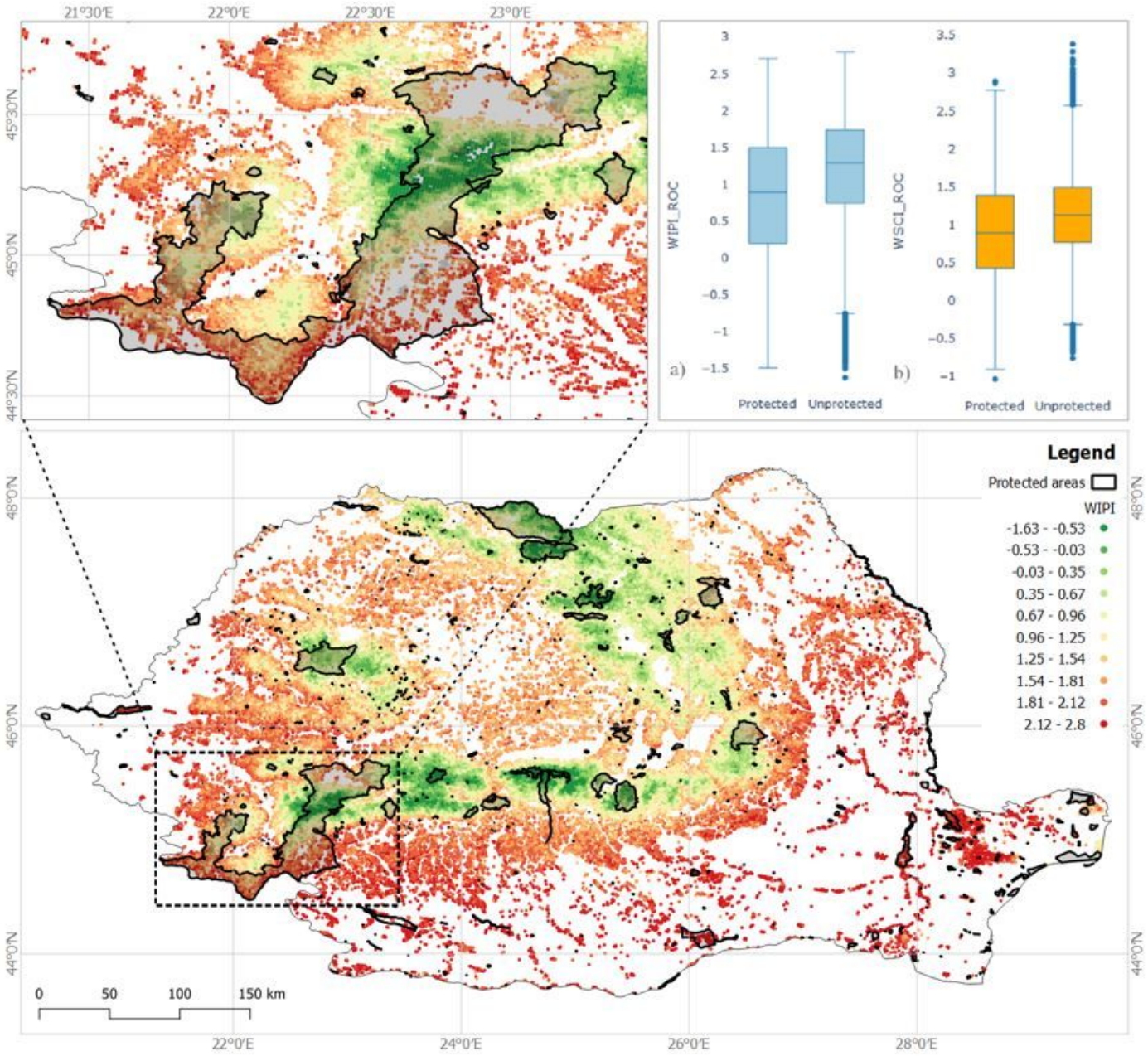

Figure 8

Wildfire spreading risk exposure map of protected areas in Romania, and comparative box plot of WIPI_ROC (a) and WSCI_ROC (b) value distribution between protected and unprotected vegetated surfaces in Romania. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

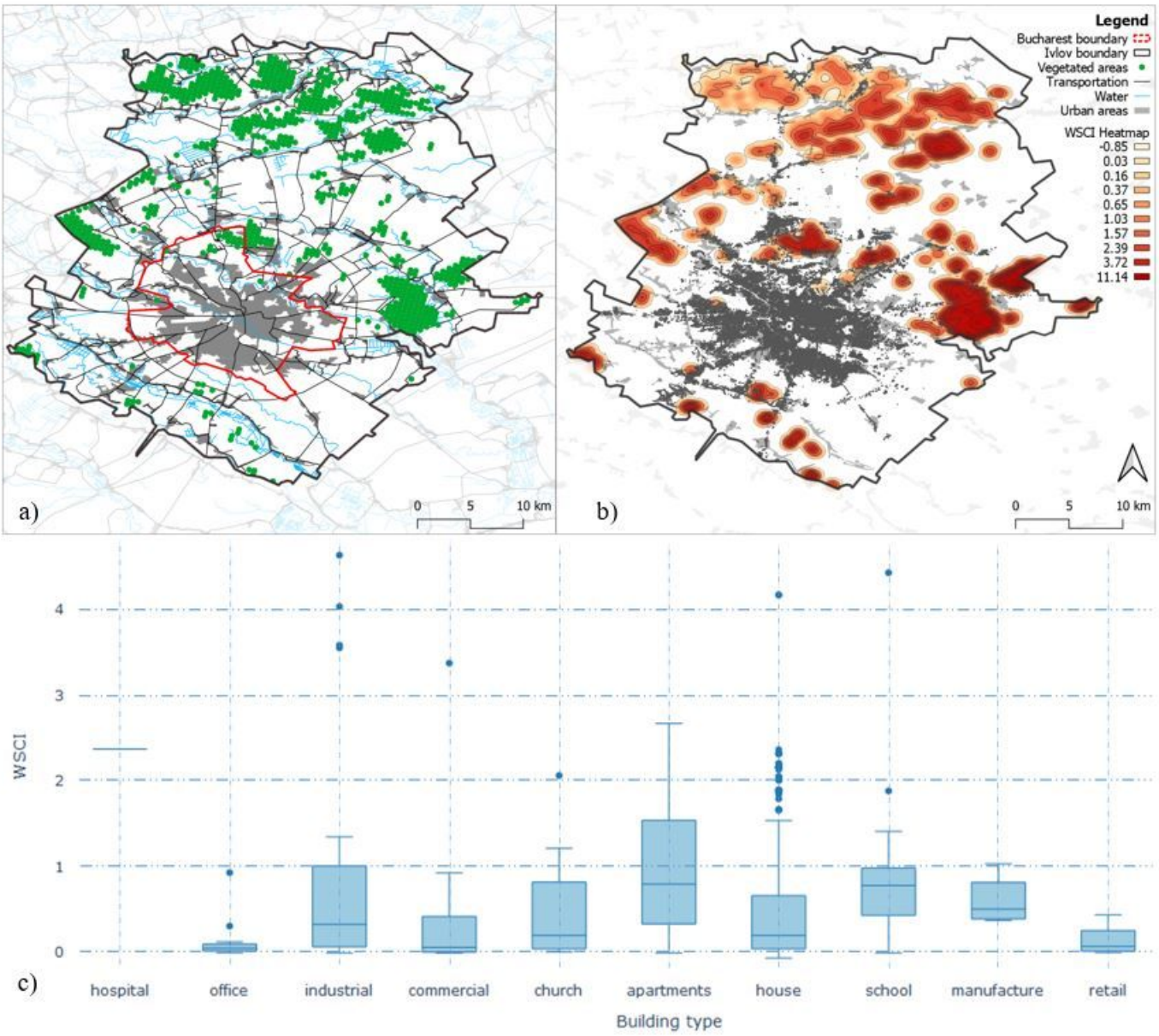

Figure 9

Wildfire exposure map of existing urban fabric (b) within Ilfov and Bucharest (a), and box plot of WSCI_cum distribution per building type of exposed structures (c). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Supplementary Files

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