A comprehensive spatial-temporal analysis of driving factors of human-caused wildfires in Spain using Geographically Weighted Logistic Regression

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Abstract

Over the last decades, authorities responsible on forest fire have encouraged research on fire triggering factors, recognizing this as a critical point to achieve a greater understanding of fire occurrence patterns and improve preventive measures. The key objectives of this study are to investigate and analyze spatial-temporal changes in the contribution of wildfire drivers in Spain, and provide deeper insights into the influence of fire features: cause, season and size. We explored several subsets of fire occurrence combining cause (negligence/accident and arson), season (summer-spring and winter-fall) and size (<1Ha, 1-100 Ha and >100Ha). The analysis is carried out fitting Geographically Weighted Logistic Regression models in two separate time periods (1988-1992, soon after Spain joined the European Union; and 2006-2010, after several decades of forest management). Our results suggest that human factors are losing performance with climate factors taking over, which may be ultimately related to the success in recent prevention policies. In addition, we found strong differences in the performance of occurrence models across subsets, thus models based on long-term historical fire records might led to misleading conclusions. Overall, fire management should move towards differential prevention measurements and recommendations due to the observed variability in drivers' behavior over time and space, paying special attention to winter fires.

Keywords: wildfire; driving factors; season; fire size; cause; GWLR

1. Introduction

Nowadays it is widely agreed that forest fires are a global threat to ecosystems and landscapes (Pausas and Keeley, 2009) affecting 30–46 million km^2 per year (Randerson et al., 2012). Wildfire has been traditionally known as a natural process responsible for the evolution of forest communities (Pyne, 2009; Wagtendonk, 2009) controlled by multiple factors such as climate, fuel and physiography. Nonetheless, fire remains significantly tied to human activity (Leone et al., 2009) often finding humans acting as both initiators and suppressors, thus altering the natural fire regime (Chuvieco et al., 2008; San-Miguel-Ayanz et al., 2013). This may lead to undesired effects on vegetation structure and composition, the modification of soil properties, increased carbon emissions or hindering ecosystem's services (Doerr and Santín, 2016; Román et al., 2013; Vallejo et al., 2009; van der Werf et al., 2010). In this context, Mediterranean Europe outstands as one of the most fire-affected regions globally while being a highly populated territory with ongoing socio-economic changes influencing wildfire activity (Ganteaume et al., 2013; Vilar et al., 2016). In Mediterranean-type fire-prone ecosystems, such as Spain, several works have reported changes in fire regime (Jiménez-Ruano et al., 2017a) as a result of fire management policies (Moreno et al., 2014), climate (McBean and Ajibade, 2009; Pausas and Fernández-Muñoz, 2012) or human activities (Bal et al., 2011; Vilar et al., 2016).

In recent decades, prevention measures in Spain have gained increased attention after achieving and adequate efficacy in fire suppression (MAPAMA, 2012). In this sense, several initiatives and legislative procedures relating wildfire management have been promoted. We find examples of those policy implementations in the "*Plan of Priority Action Against Forest Fires*" (MAPA, 1988a) or the "*Royal Decree for the regulation of compensation for the cost of fire suppression*" both targeting improvements to suppression infrastructures and also supporting fire monitoring and prevention. Furthermore, fire prevention has been progressively encouraged over the last two decades via National and European regulations (CEE, 1992, 1986; MAPA, 1988b) promoting awareness campaigns, energy production from forest biomass or funding forest fire prevention teams. All these policies and initiatives have most likely induced changes in the drivers of wildfires (Moreno et al., 2014).

Up to date, models of human-caused ignition and/or occurrence probability have usually been developed on a long-term basis; regardless of the time cycles that drive human behavior and environmental conditions. Structural models and assessments based on long-term historical fire records have fulfilled a key role discovering and unraveling the function of the main drivers of wildfires. Fire science is now a mature discipline, after having acquired a considerable base of knowledge on either what tools and techniques should we employ (Costafreda-Aumedes et al., 2017); and what factors, variables or drivers must be accounted for (Leone et al., 2003, 2009; Rodrigues and de la Riva, 2014a).

However, human drivers are known to be non-stationary, thus a temporal approach is highly recommended (Carmona et al., 2012; Zumbrunnen et al., 2011). Most attempts to produce fire risk or danger models that actually deal with the human component of ignition are based on long-term historical fire records and stationary predictors (Arndt et al., 2013; Chuvieco et al., 2012; Guo et al., 2016; Martínez et al., 2009; Miranda et al., 2012; Narayanaraj and Wimberly, 2011; Rodrigues et al., 2014; Rodrigues and de la Riva, 2014b). According to Rodrigues et al. (2016), human drivers of wildfire evolved over time, reporting significant shifts in the contribution of anthropogenic factors triggering fires which could, ultimately, be related to recent efforts to improve prevention measures (MAPAMA, 2012) or increased environmental sensitivity to the harmful effects of fire. Knowledge on the causes and drivers of fires is indispensable to achieve effective fire prevention and modeling (Ganteaume et al., 2013). In that regard, the analysis of intra-annual –seasonal– variability of causes, or the influence of fire size on the contribution of human factors is particularly interesting (Jiménez-Ruano et al., 2017b; Pereira et al., 2011; Rodrigues et al., 2014). In this sense, Geographically Weighted Regression is a powerful modeling tool able to capture non-stationary relationships amongst response and predictors. It has been extensively used in several topics (Cardozo et al., 2012; Chalkias et al., 2013; Wang et al., 2013; Xiao et al., 2013) and specifically in wildfire science. Without being exhaustive we found some recent examples of application around the globe (Avila-Flores et al., 2010; Nunes, 2012; Oliveira et al., 2014; Song et al., 2017; William et al., 2017) and in the particular case of Spain (Koutsias et al., 2010; Martínez et al., 2013; Rodrigues et al., 2016; Rodrigues et al., 2014).

In this work we investigate the effect of seasonality, fire size and cause in the explanatory performance of human factors in Spain by means of Geographically Weighted Logistic Regression models (GWLR). To our knowledge this is the first attempt to provide spatial and temporal insights on fire drivers exploring at the same time inter and intra-annual variability coupled to ignition source and resultant fire size and exploring the Standardized Precipitation-Evapotranspiration index as an ignition driver. Our main goals are to (i) identify spatial-temporal differences in human drivers of wildfires in Spain; (ii) explore dissimilarities in the triggering factors among cause (unintended *vs* arson) and fire size; and (iii) determine whether climate factors are taking over human drivers.

2. Materials and methods

2.1. Study area

The study area is mainland Spain; covering an overall surface around 498,000 km^2. Mainland Spain is a very diverse territory, presenting contrasting topographic, climatic, and environmental (Figure 1). The relief is characterized by mountain ranges. There are different climatic situations from Oceanic humid conditions (*Cf*) in the north-west areas to Mediterranean and steppe in central, south and east regions (*Cs* and *Bs*). These variety of climates translates into contrasting biogeographical conditions ranging from evergreen coniferous forest (*Pinus radiata* and *Eucalyptus globulus*) in mountain ranges to oak (*Quercus ilex*, *Quercus suber, Quercus robur, Fraxinus excelsior* and *Fagus sylvatica*) and pine forest (*Pinus halepensis*, *Pinus sylvestris*, *Pinus nigra*, *Pinus pinea* or *pinaster*) or scrublands on the Mediterranean. This diversity influences socioeconomic conditions as well. Overall, we find huge differences in the spatial pattern of settlements and population density which peaks mainly along the Mediterranean coast and the central region of Madrid. In turn, complex mosaics of land use and land cover are present all over the regions, ultimately leading to contact areas (the so-called interfaces) between human and forest covers. Therefore, the complexity of socioeconomic conditions plays a decisive role in forest fire assessments (Rodrigues et al., 2014).

2.2. Fire data and response variables

Fire information was retrieved from the Spanish EGIF database (MAPAMA, n.d.). EGIF is the official database on wildfires in Spain, compiled by the "*Departamento de Defensa contra los Fuegos Forestales"* in the Ministry of Agriculture, Food, and Environment from forest fire reports starting in 1968. The EGIF database is one of the oldest and most complete databases in Europe (Vélez, 2001) being built from individual fire reports provided by firefighting services.

For each fire event within the periods 1988-1992 and 2006-2010 we retrieved information about the starting location (recorded on a 10x10 km reference grid), ignition source (negligence/accident or arson), fire size, and ignition date. Fires are then split according to their combination of time period ignition source, season (spring-summer, May to September; and fall-winter, October to April) and fire size interval (less than 1 Ha, 1-100 Ha and more than 100 Ha), leading to a total of 24 occurrence subsets. Table 1 summarizes fire count data and Figure 2 displays the spatial distribution of fire occurrence. Negligence and accidental fires will be further referred to as 'unintended'. Then, we build a set of binary (1-presence and 0-absence) dependent variables for each subset. Each cell where at least one fire has occur was classified as presence and remaining cells as potential absence (Rodrigues et al., 2016).

2.3. Wildfire driving factors

2.3.1. Human driving factors

We selected and constructed human-related covariates according to previous works (Chuvieco et al., 2012; Marcos Rodrigues et al., 2016; Rodrigues et al., 2014; Rodrigues and De la Riva, 2014), other studies at regional or national scales (Nunes, 2012; Nunes et al., 2016; Padilla and Vega-García, 2011) and a recent review on fire occurrence modeling by (Costafreda-Aumedes et al., 2017). Selected covariates are well-known indicators of fire occurrence and relate to the typology of factors and drivers proposed and described in Leone et al. (2009, 2003):

- *Wildland-Agricultural Interface (WAI)*. Distance of the boundary between agricultural plots (either rainfed or irrigated) and wildlands per grid cell, obtained from Corine Land Cover (CLC) 1990 and 2006.
- *Wildland-Urban Interface (WUI)*. Length of the contact line between urban (populated) and wildland areas within each 10x10 km grid, obtained from CLC 1990 and 2006.
- *Demographic potential (DPT)*. The demographic potential is an index reflecting current demographic power as well as the ability to provide population growth in the future. Data on DPT was retrieved from Calvo and Pueyo (2008). It was originally calculated at 5x5km resolution and resampled to 10x10km according to the average value.
- *Power lines (PWL)*. Length of electric transport power lines crossing wildland areas within each cell. Network location was obtained from *Base Cartográfica Nacional 1:200,000* (BCN200). Same as WUI and WAI, wildland areas were defined according to CLC 1990/2006.
- *Railroads (RR)*. Length of the conventional railroad network crossing wildland areas within each 10x10 km grid, obtained from BCN200. Wildland areas were defined according to CLC.
- *Forest tracks (TRK)*. Distance of tracks, paths or trails inside forest areas per grid cell (BCN200).
- *Natural protected areas (NPA)*. Total area under protected management and belonging to the Natura 2000 network or National Parks.

2.3.2. Climate-related driving factors – Standardized Precipitation-Evapotranspiration index (SPEI)

To explore the potential influence of climate on fire occurrence we computed the Standardized Precipitation-Evapotranspiration index (SPEI); a meteorological drought index that standardize drought across regions endorsed as a key drought indicator (WWO, 2012). Standardized Precipitation-Evapotranspiration was initially proposed by Vicente-Serrano et al. (2009) and later updated in Beguería et al. (2014) and has been employed in recent wildfire analyses such as Turco et al. (2017). The concurrency of high temperatures and extended drought periods boost wildfire activity by promoting larger fires. Several studies report this behavior in southern Europe (Camiá and Amatulli, 2009; Urbieta et al., 2015), the Iberian Peninsula (Trigo et al., 2016) or the Mediterranean sector in Portugal (Ferreira-Leite et al., 2017) or Spain (Piñol et al., 1998; Turco et al., 2013). In our particular case, Rodrigues et al. (2016) suggest an increased role of climate variables (temperature and precipitation) in fire occurrence models. In the present work, SPEI was employed to determine the extent to which this is true, far beyond the already known contribution to burnt area (Turco et al., 2017). Note that SPEI reflects not only climate patterns but also topographic gradients as physiography has a direct influence in the spatial distribution of weather and climate (Martín-Vide and Olcina, 2001).

Standardized Precipitation-Evapotranspiration was computed from climatic data from MOTEDAS (Monthly Temperature Dataset of Spain, Gonzalez-Hidalgo et al. 2015; Peña-Angulo et al. 2016) and MOPREDAS (Monthly Precipitation Dataset of Spain. González-Hidalgo et al. 2011) datasets (1950-2010). Two separate SPEI were calculated, one in 1998-1992 and another for 2006-2010. Both indexes were calculated using a 60 month time window and the Hargreaves equation (Hargreaves, 1994; see equation 1) to calculate potential evapotranspiration.

$$PET_m = 0.0023\, Ra_m \left(T_m + 17.8\right) \left(T_{max,m} - T_{min,m}\right)^{0.5} \qquad (1)$$

where PET_m is the potential evapotranspiration (mm) in a given month m; Ra is the extraterrestrial radiation, which depends on latitude and latitude; T_m is the monthly mean temperature; $T_{min,m}$ is the monthly average minimum temperature; and $T_{max,m}$ is the monthly average maximum temperature.

2.4. Generalized Linear Models (GLM)

Generalized Linear Models are an extension of linear models able to deal with non-normal distributions of the response variable such as Poisson, binomial, negative binomial, and gamma (Nelder and Wedderburn, 1972). Generalized Linear Models are a widespread approach in many research fields and also in fire science being logistic regression one of the most popular approaches in occurrence modeling (Bar Massada et al., 2012; Chuvieco et al., 2010; Costafreda-Aumedes et al., 2017; Ferreira-Leite et al., 2016; Martínez et al., 2009; Padilla and Vega-García, 2011; Vega-Garcia et al., 1995).

We explored 1000 GLM-logistic models for each combination of period-season-cause-size. These models were created resampling the absence values sample (0) in the construction of the dependent variable. We randomly selected as many absence grids as presence grids (1) do exist on a given occurrence subset, to then construct the corresponding dependent variable. The resulting models allowed (i) to determine which variables were significant ($p < 0.05$) and (ii) examining whether the spatial location of absence values was influencing variable performance. Overall, if a variable was significant in at least 25% of the models (250 times) it is selected as candidate for the final GWR models.

2.5. Geographically Weighted Logistic Regression (GWLR)

Geographically Weighted Regression is a spatial-explicit statistical technique considered as a spatial disaggregation of global regression models. Geographically Weighted Regression extend global regression models allowing to calibrate sets of spatially limited models, thus yielding local regression outputs (Fotheringham et al., 2002). Such modelling often outperforms global regression models as well as enables further interpretation of the analyzed phenomena. Same as their global counterpart, GWR models produce several statistical outputs such β regression coefficients and significance tests but, rather than a single set of statistical parameters, we obtain a collection of parameters for each location apiece; thus allowing to account for the spatial variability in the predictors. A conventional GWR model is described as follows (Fotheringham et al., 2002):

$$y_i = \sum_k \beta_k \left(u_i, v_i\right) x_{k.i} + \varepsilon_i \qquad (2)$$

where y_i , $x_{k,i}$ and ε_i are, respectively, dependent variable, k_{th} independent variable, and the Gaussian error at location i; (u_i,v_i) is the X/Y coordinate of the i_{th} location; and coefficients $\beta\ (u_i,v_i)$ are varying depending on the location.

Logit GWR (Geographically Weighted Logistic Regression or GWLR) was applied to each occurrence subset of period, season, cause, and fire size. Model fitting was conducted using optimized *Adaptive Bisquare Kernel* bandwidth (according to the Corrected Akaike Information Criterion) considering all predictors as local covariates (see Nakaya et al. (2009) for additional specifics on the method). For each subset we adjusted 20 different models using the same resampling procedure described in the GLM section. The calibration of the GWLR models include a *Leave-one-out* cross-validation procedure (LOOCV). Outputs from the LOOCV were used to compute the area under the Receiver Operating Characteristic (ROC) curve (AUC), a threshold-independent approach to determine and compare the performance of binary models (Hanley and McNeil, 1982).

Contrary to Gaussian GWR models, GWLR can only deliver predictions in measured locations, i.e., those points that make up for the dependent variable (Fotheringham et al., 2002; Nakaya et al., 2009). Following a similar approach to that by Rodrigues et al. (2014b) or Song et al. (2017), t-values from each model were spatialized using exact interpolation methods (Inverse Distance Weighting). This produces a set of 20 raster maps of t-values per covariate and occurrence subset. To analyze the results and thus provide insights into the spatial-temporal changes of variable contribution, t-values from each set of maps were aggregated according to the median. In addition, the absolute deviation to the median (MAD) was computed to provide a measure of the dispersion or uncertainty of the results (Leys et al., 2013). In this way, the spatial distribution of the central t-value and its dispersion-uncertainty were addressed.

In this work we explored 24 subsets of fire occurrence combining two time periods (1988-1992 and 2006-2010); two human-related ignition sources (negligence/accident and arson); two seasons (summer-spring and winter-fall); and three fire size intervals (<1 Ha, 1-100 Ha and >100 Ha). A set of 8 triggering factors (7 human-related and 1 climate-related) were selected and tested. For each occurrence subset 20 GWLR models were constructed and then averaged using the median. Every single covariate was then examined in terms of its spatial pattern of significance according to the Student's t values of the β coefficients. The temporal framework was selected on the basis of Rodrigues et al. (2016), considering data limitations. Fire records were only fully reliable since 1988 (Vélez, 2001) whereas climate data were only available until 2010 (Gonzalez-Hidalgo et al., 2015; González-Hidalgo et al., 2011).

All predictors (both human and climate; see section 2.3) were spatialized using a 10x10 km reference grid. Human-related variables were adapted to the study periods 1988-1992 and 2006-2010. Specifically, we used Corine Land Cover maps 1990 and 2006; and data on Demographic Potential corresponding to 1991 and 2006. In this way, we account for time-specific settings of the explanatory factors which may differ from one period to another due to socioeconomic changes. Additionally, predictors were submitted to collinearity analysis and were found to be independent (Variance Inflation Index < 4; Fox and Monette, 1992).

Data manipulation, model calibration, validation, plotting and mapping (except maps corresponding to the study area which were elaborated with ArcGIS 10.5) were developed using the R software for statistical computing (R Core Team and R Development Team Core, 2017) packages: *GWmodel* for GWLR modeling, *gstat* for data interpolation, *car* for multicollinearity assessment, *dismo* for bootstrapping and accuracy assessment, *spei* to calculate the Standardized Precipitation-Evapotranspiration index, *ggplot2* and *lattice* for mapping and plotting, *raster, rgdal* and *sp* for spatial data manipulation and *parallel* for parallel computing for model development.

3. Results and discussion

3.1. Contribution of driving factors across occurrence subsets

Table 2 summarizes the results from GLM variable selection. Overall, no variable was significant ($p < 0.05$) in all occurrence subsets apart from SPEI. Power lines and railroads, are the next predictors in terms of participation, appearing 18 times, followed by WAI and WUI (14 times each), forest tracks (13 times), natural protected areas (12 times) and, finally, demographic potential (10 times).

From the 'occurrence subset' point of view, there is great variability in the effective number of predictors. In general lines, subsets of small fires require more predictors than those considering large fires. Subsets covering medium-size fires are somewhat in-between, although closer to small fires'. There is no evident difference in the number of predictors amongst ignition source or period. However, some predictors do have some 'preference' towards a specific occurrence subset. The Wildland-Agricultural interface is more frequently selected in fall-winter (9 times). The Wildland-Urban interface appears more often in spring-summer (9 out of 14 times selected). Natural protected areas, despite being one of the predictors with less appearances, is most frequently select in present models (9 out of 12 times selected). Power lines, railroads and forest tracks do not show any preference, being present in most subsets. Again, SPEI is selected in all subsets.

3.2. Spatial and temporal patterns of wildfire driving factors

Figures 3-10 display the spatial pattern of the significance ($p < 0.05$, 0.01, 0.001) and explanatory relationship (either positive in brown; or negative in green) of the covariates. Point size is used to represent uncertainty –MAD– in the predicted value. Large points vary less than 20% (low); medium-size points vary between 20 and 50% (medium); and small points vary over 50% (high) around the median.

Several works report a strong contribution of WAI to human-caused fires in Spain. Rodrigues et al. (2014a) investigated WAI's influence on fires over 5 ha burned in the period 1988-2011. They reported strong positive relationships all over Spain. Rodrigues and de la Riva (2014a) reported similar results. In the same line, other works (Chuvieco et al., 2010; Martínez-Fernández and Koutsias, 2011) reached similar conclusions. However, we detected a strong variability in the contribution of WAI across subsets (Figure 3). This may imply that the explanatory power of WAI may depend on fire size, season or time period. Rodrigues et al. (2016) suggest WAI might be losing performance over time because of forest management policies such as investment in social intervention programs in rural. According to our results WAI seems to be mostly related to small and large unintended fires during summer-past subsets. It also displays a positive relationship with small and large fall-winter fires during the past all over the north region, also observed in arson fires. Moving towards present WAI loses performance as a fire occurrence driver during spring-summer except for large unintended fires in the Southern Mediterranean region. In addition, WAI shows a strong positive relationship with large fall-winter arson fires in Northwest.

Overall, we can observe a stronger relationship with fall-winter fires that increases towards present days, in terms of significance and reduced uncertainty in the prediction. However, WAI losses performance during spring-summer months. Fall-winter fires in Spain are mostly intentional; up to 80% of them are linked to livestock burnings for the maintenance of pasture (Ganteaume et al., 2013; Leone et al., 2003). Fire has been traditionally the preferred means to eliminate agricultural residues, weeds or cleansing field's margins from hedges and shrubs. The increase in the contribution of WAI during winter-fall may be promoted by increased mechanization efficiency (Leone et al., 2009), burn disposal of agricultural byproducts (only allowed during this season).

Wildland-Urban Interface (Figure 4) has been commonly considered the most relevant human ignition indicator (Galiana-Martin et al., 2011; Martínez et al., 2009; Romero-Calcerrada et al., 2010; Vilar et al., 2016). In the early 90s WUI is clearly related to small-medium unintended and, to a lesser extent, arson fires. Like WAI, the contribution of WUI to fire occurrence towards present days was expected to drop. While this might be the case for spring-summer fires is not happening during fall-winter. A recent study by Modugno et al. (2016) indicate that "*the probability of large burned surfaces increases with diminishing WUI distance in regions with a strong peri-urban component as Cataluña, Comunidad de Madrid, Comunidad Valenciana*". Our results suggest the WUI appears to gain performance to explain fall-winter small fires, being significant in all the study area in unintended and arson fires in models for 2006-2010. In any case, the discrepancies between the studies may be linked to the difference in the scale of analysis (European *vs* national) or the spatial unit of analysis (NUTS 3 *vs* 10x10 km grid).

Additionally, some areas in the south are significant both in past and present medium arson fires, with the significant-positive area growing towards present. Therefore, WUI displays a stronger relationship during spring-summer in the past that shifts towards fall-winter in present years. Decreased contribution of WUI during spring-summer can be understood as a more sensible behavior of human beings in forest areas, thus as an increased concern about the environment. One of the cornerstones of fire prevention in Spain are awareness campaigns and other educational resources, which might be ultimately behind the observed behavior in WUI during spring-summer (article 44, Ley 43/2003, de 21 de noviembre, de Montes).

Demographic potential (Figure 5) is a variable linked to increased pressure of human beings on wildlands. However, opposite to WUI, DPT relates to urban areas rather than rural settlements and residential areas (Calvo and Pueyo, 2008; Rodrigues and de la Riva, 2014a; Rodrigues et al., 2016).

Demographic potential shows positive relationship in small-unintended past fires alone. The remaining combinations are either non-significant or significant negative. The only exception is a small region in NW for arson fall-winter fires in recent years. Considering this, we can conclude urban population is not an effective driver of wildfires. In previous works, changes in DPT were reported as a strong driver (Rodrigues and de la Riva, 2014a, 2014b), but used as a standalone value DPT no longer contributes as a fire occurrence driver. It was somehow related to small unintended fires in past subsets, but currently appears as a deterrent factor, i.e., fires do not occur near purely urban areas.

According to Figure 6, PLW Increases performance towards present. PWL are expected to be linked with unintended fires (Leone et al., 2003, 2009). They are usually related with accidental fires from sparks or lightning-bolt arcs reaching vegetated areas. We do observe a more consistent relationship of PWL and small unintended fires in past and medium-size in present. But significant relationships with arson fires are also detected, especially in models from 2006-2010. There is no clear explanation to this. It maybe that in some cases the corridors surrounding power lines are used as pathways leading to forest areas or that arsonists try to conceal intentional fires as unintended by starting fires in the neighborhood of power lines. On the other hand, why is the influence of PWL increasing? There are several reasons why power lines cause forest fires. The main one is the contact between vegetation and powerlines, either by directly touching or by fall of the towers or posts. Less frequent is the short circuit in stations or substations and transformers. Similar to fires triggered close to railways, the number of fires related with power lines appears to increase (MAPAMA, 2012; WWF, 2005) due to the lack of maintenance (cleansing) of vegetate areas around lines (WWF, 2005). Depending on the voltage, a buffer 45 to 100 meters wide must be cleared (Ferrer, 2012).

Railroads behave mostly the same as power lines do (Figure 7). The fact that most railroads depend on an electric power line source makes them like ordinary power lines. But, RRD are also associated mainly with accidental fires. For instance, hot coal transported in semi-open wagons may lead to fire ignitions. But while it is true that locomotives and wagons have been modernized, how is it that the ignition relationship increases instead of decreasing? The answer must be sought in two main aspects. On the one hand, improvement in infrastructure has not reached second-order or old railways, especially those crossing mountain areas. Secondly the lack of cleaning and maintenance of vegetation –especially herbaceous and grasslands– in zones around railways, where sparks, generally coming from the braking, generates potential ignition sources when the environmental conditions are favorable (WWF, 2005).

Forest tracks are a proxy for accessibility to forest areas. Locations and forest enclaves easy to reach are prone to fire occurrence; in particular, arsonist leverage accessibility to forest (Leone et al., 2003). According to Figure 8, TRK is related to arson fires during past-spring-summer models, and to small fires during winter. Same as other factors depicting human pressure on wildlands (WUI), TRK losses importance towards present, even becoming negative related, i.e., fires tend to occur far from forest tracks, except for unintended large fires, perhaps due to increased recreational use of forest areas (MAGRAMA, 2014).

It is commonly agreed areas under any kind of protection or special management are expected to experience lower fire occurrence, given the extra effort to prevent or suppress fires (Chuvieco et al., 2010). In this sense, NPA (Figure 9) acts as a deterrent factor associated to increased concern about the environment. Bearing this in mind, NPA should display negative relationships (Leone et al., 2003). Figure 8 shows non-significant relationship during past-spring-summer models, becoming an actual deterrent factor towards present days, but only in small and medium size fires. Overall NPA gains significance towards present as a restraining driver (Rodrigues et al., 2016). However, it is noteworthy its positive relationship with arson fires in the Northwest region, possibly due to conflicts with new management in protected areas (Hovardas, 2012) or even arsonist targeting valuable resources.

The Standardized Precipitation-Evapotranspiration index (Figure 10) is the only factor selected as potential driver in every single subset according to the GLM simulations (Table 2). However, same as other factors, its contribution in GWLR models is not always found significant. SPEI has been previously explored in models of burned area size Europe (Camiá and Amatulli, 2009; Piñol et al., 1998; Trigo et al., 2016; Turco et al., 2013; Urbieta et al., 2015). In fact, our results suggest stronger relationship with large fires. To our knowledge there is no prior analysis of SPEI as an ignition or occurrence driver, at least in Spain. Overall, SPEI shows negative relationship (the higher the drought the higher the probability of occurrence) with occurrence, both during fall-winter and spring-summer. In turn, SPEI's influence seems to increase towards present. For instance, models for spring-summer large fires arouse SPEI as significant driver in 2006-2010 but not during 1988-1992. One of the most streaking results is SPEI's influence during winter. Fall-winter conditions are usually considered as unfavorable when it comes to fire triggering. We are aware that our SPEI is calculated using a long temporal span (60 months) but apparently drought anomalies also influence fall-winter fires to a certain degree maybe due to the increased length of the main fire season (Jolly et al., 2015).

3.3. Implications in wildfire modeling

Most models dealing with human-caused fire occurrence are based on large historical datasets, often disregarding fire size or motivation (Chuvieco et al., 2012; Martínez et al., 2013, 2009; Rodrigues and de la Riva, 2014b; Rodrigues et al., 2014; Vilar et al., 2016). However, according to the literature there is a clear difference in drivers of natural, accidental and arson fires (Leone et al., 2003). Our results suggest differences in the contribution of the analyzed drivers across the modeled subsets of size, season, and cause. These are usually put together when modeling fire occurrence. Bearing in mind the noticeably differences reported in this study, doing so might not be the best practice, at least when the main goal is investigating the relationship among occurrence and factors. For instance, WAI is largely related to small spring-summer fires and strengthens its role in fall-winter fire occurrence.

From a predictive standpoint, we also find differences in the performance of models. Figure 11 shows a summary of the AUC from the Leave-one-out cross-validation. As we can see, performance varies according size, season and period. Overall, we find lower performance towards 2006-2010; particularly high in large fires. In addition, fall-winter models tend to perform best, especially in large fires. Moreover, models of arson fires slightly outperform those of unintended fires.

3.4. Implications for forest management

According to Badia et al. (2002) forest fire policy overreacted to the waves of wildfires during the 90s, overemphasizing suppression to the detriment of prevention; but over the years, the balance between suppression and prevention is slowly accomplished (MAPAMA, 2012). In fact, prevention measures appear to be working to a certain degree given the overall drop in the explanatory performance of WUI and WAI (Fox et al., 2015; Rodrigues et al., 2016), two of the most important variables associated to wildfires in Spain (Martínez et al., 2009, 2004b; Rodrigues et al., 2014) and Mediterranean environments (Vilar et al., 2016). For instance, there is investment in social intervention programs in regions with high percentage of fires triggered by accidents due to the use of fire in rural districts of Asturias, Cantabria, Castilla y León or Galicia. Notwithstanding, it is necessary to go a step further and actively involve those clusters of individuals most associated with high accident rates (WWF/Adena, 2016).

On the other hand, climate plays a determinant function, which appears to grow towards present (Figure 10). According to Rodrigues et al. (2016), models disregarding environmental conditions steadily loss performance over time. In this work, we identified SPEI as one of the most important indicators of fire occurrence. Indeed, it is better found in large fire models (Camiá and Amatulli, 2009; Piñol et al., 1998; Trigo et al., 2016; Turco et al., 2013; Urbieta et al., 2015) but, In any case, SPEI is also linked to the occurrence of small and medium fires. This suggests climate not only influences ignition in the usual way (the drier the likelier to trigger) but also arsonist may be targeting favorable conditions for fire ignition. In this regard, it is noteworthy the contribution of SPEI to fall-winter fires. Fall-winter is a season theoretically unfavorable to fire ignition, but with persistent dry conditions fires can occur and become uncontrolled (WWF, 2005). For instance, 2015 and 2017 were years with intense fall-winter fire activity tied to an extended dry period after summer, thus promoting larger fires (68% of large fires in 2017 triggered during winter; ADCIF, 2017), matching the expected lengthening in fire season according to Jolly et al (2015). Therefore, management strategies must encourage compelling considerations for fall-winter fires. For instance, the policy managing burning permits for plot cleansing and maintenance must be revised. It should target promoting a different strategy for the removal of agricultural residues (centralized dumping and disposal; use as soil fertilizer or biomass). Moreover, forest fire crews and on watch personnel must be active thorough most of the year and not only during the main fire season, i.e., spring-summer months (Costafreda-Aumedes et al., 2018).

Finally, natural plus unintended fires account for less than 50% of fires in Spain (Table 1), with the remaining proportion of fires attributed to arson fires. Fire cause is usually neglected or disregarded in most fire modeling approaches given the challenge that poses associating arson motivations to traditional fire drivers (Leone et al., 2003; Martínez et al., 2009, 2004a; Rodrigues et al., 2016). Nonetheless, little is known about the actual motivations or factors around arson wildfires. For instance, the European fire database lists as unknown the deliberately started fires reported from the Spanish database compiled in the European Forest Fire Information System, due to the lack of detail on motivations (Camia et al., 2013). Intentional fires have grown in number towards present, particularly during fall-winter season. They appear to be associated to areas close to residential areas in forest enclaves (WUI) during spring-summer and somehow related to infrastructures such as railroads and powerlines which might be indirectly providing accessibility. Moreover, large arson fires in the present are positively related to NPA which suggest arsonist try to burn valuable recreational resources.

4. Conclusions

In this work we explore past and present subsets of fire size, cause and season to determine whether fire triggering of wildfires factors vary depending on fire features and time. The study is developed using GWLR to integrate insights into underlying spatial patterns into the temporal perspective.

Our results confirm the non-stationary nature of wildfire drivers in Spain. Results suggest that temporal and spatial differences in fire features do exist. For instance, intentional fires in present models are no longer related to accessibility. Moreover, arsonist might be now targeting favorable climate conditions according the SPEI outputs. In the same line, human-related factors are losing performance towards present days in favor of climate-related drivers.

From a modeling perspective, considering fire events altogether disregarding fire features (season, cause and size) is not fully recommended. The behavior of fire drivers not only evolved temporally but varies as well across the analyzed subsets of occurrence.

Finally, management policies should be adapted to reflect the different behavior observed in the subsets. Moreover, considering the increasing importance of climate-related drivers, activities targeting fuel management and preventive silviculture must be encouraged. On the other hand, the loss of performance of human-related factors might be reflecting the success of prevention measures during the study period.

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Table 1. *Total of fire occurrences per period, season, ignition source, and fire size. First parentheses show percentage within year; second parentheses shows percentage within season.*

	1988-1992		**2006-2010**	
Spring-summer	**Unintended**	**Arson**	**Unintended**	**Arson**
<1 Ha	3854 (9.5) (15.5)	6376 (15.7) (25.7)	8319 (14) (26.8)	13351 (22.5) (43)
1-100 Ha	2927 (7.2) (11.8)	10859 (26.7) (43.8)	2768 (4.7) (8.9)	6367 (10.7) (20.5)
>100 Ha	149 (0.4) (0.6)	644 (1.6) (2.6)	104 (0.2) (0.3)	161 (0.3) (0.5)
	6930 (17.0) (27.9)	**17879 (44) (72.1)**	**11191 (18.9) (36)**	**19879 (33.6) (64)**
Fall-winter	**Unintended**	**Arson**	**Unintended**	**Arson**
<1 Ha	1314 (3.2) (8.3)	3234 (8) (20.4)	5366 (9.1) (19)	9994 (16.9) (35.5)
1-100 Ha	1992 (4.9) (12.6)	8991 (22.1) (56.7)	2689 (4.5) (9.5)	9796 (16.5) (34.8)
>100 Ha	73 (0.2) (0.5)	263 (0.6) (1.7)	36 (0.1) (0.1)	288 (0.5) (1)
	3379 (8.3) (21.3)	**12488 (30.7) (78.7)**	**8091 (13.7) (28.7)**	**20078 (33.9) (71.3)**
TOTAL	**10309**	**30367**	**19282**	**39957**

Table 2. *Summary of variable significance (p < 0.05) across subsets from GLM. Number of selected variables reported between parentheses. Bold font indicates variables significant in GWLR. Effective number of parameters in GWLR models reported between brackets. WAI: Wildland-Agricultural interface; WUI: Wildland-Urban interface; DPT: Demographic potential; PWL: power lines; RRD: railroads; TRK: forest tracks; NPA: natural protected areas; SPEI: Standard Precipitation-Evapotranspiration index.*

		1988-1992		**2006-2010**	
		Unintended	**Arson**	**Unintended**	**Arson**
Summer	<1Ha	***WAI***, *WUI*, ***DPT***, *PWL*, *RRD*, ***SPEI*** *(6)[3]*	***WAI***, ***WUI***, ***RRD***, *TRK*, ***SPEI*** *(5) [4]*	***WUI***, ***DPT***, ***PWL***, *RRD*, ***TRK***, ***NPA***, ***SPEI*** *(7) [6]*	***WUI***, ***PWL***, ***RRD***, ***NPA***, ***SPEI*** *(5) [5]*
	1-100 Ha	*WUI*, ***PWL***, ***RRD***, ***SPEI*** *(4) [3]*	***WAI***, ***WUI***, ***PWL***, ***RRD***, ***TRK***, ***SPEI*** *(6) [6]*	***WUI***, *PWL*, ***RRD***, ***TRK***, ***NPA***, ***SPEI*** *(6) [5]*	***PWL***, ***RRD***, ***SPEI*** *(3) [3]*
	>100 Ha	*WAI*, ***WUI***, ***PWL***, ***TRK***, ***SPEI*** *(5) [4]*	***WUI***, ***DPT***, ***RRD***, ***TRK***, ***SPEI*** *(5) [5]*	***WAI***, ***DPT***, *PWL*, ***SPEI*** *(4) [3]*	***DPT***, ***PWL***, ***TRK***, ***SPEI*** *(4) [4]*
Winter	<1Ha	***WAI***, ***WUI***, ***RRD***, *TRK* *(5) [3]*	***WAI***, ***RRD***, *TRK*, ***NPA***, ***SPEI*** *(5) [4]*	*WUI*, *PWL*, *RRD*, ***NPA***, ***SPEI*** *(5) [2]*	***WAI***, *WUI*, ***DPT***, ***PWL***, ***RRD***, ***TRK***, ***NPA***, ***SPEI*** *(8) [7]*
	1-100 Ha	***PWL***, ***NPA***, ***SPEI*** *(3) [3]*	***WAI***, ***WUI***, ***DPT***, ***PWL***, ***RRD***, ***NPA***, ***SPEI*** *(7) [7]*	***WAI***, ***DPT***, *PWL*, *RRD*, ***TRK***, ***NPA***, ***SPEI*** *(7) [5]*	***WAI***, ***WUI***, ***PWL***, ***RRD***, ***TRK***, ***NPA***, ***SPEI*** *(7) [7]*
	>100 Ha	***WAI***, ***DPT***, ***PWL***, ***RRD***, ***SPEI*** *(5) [5]*	***WAI***, ***SPEI*** *(2) [2]*	***WAI***, *TRK*, *NPA*, ***SPEI*** *(4) [2]*	***DPT***, ***PWL***, ***RRD***, ***NPA*** ***SPEI*** *(5) [5]*

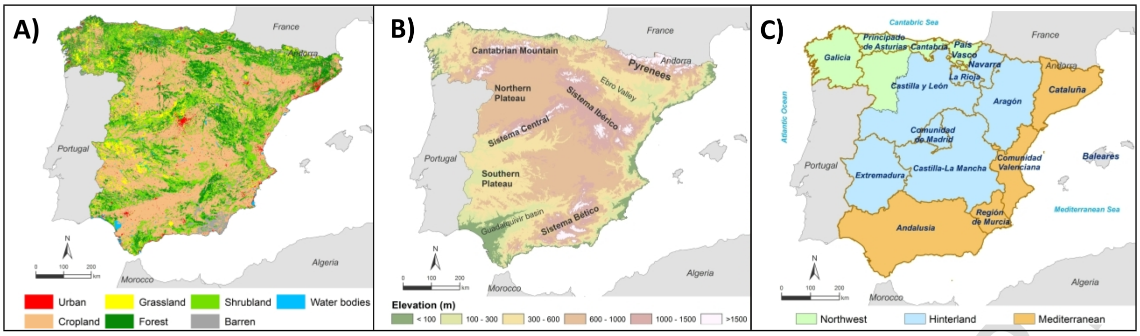

Figure 1. *Study area. A) Land use/cover from Corine Land Cover 2000; B) Relief; C) Administrative division.*

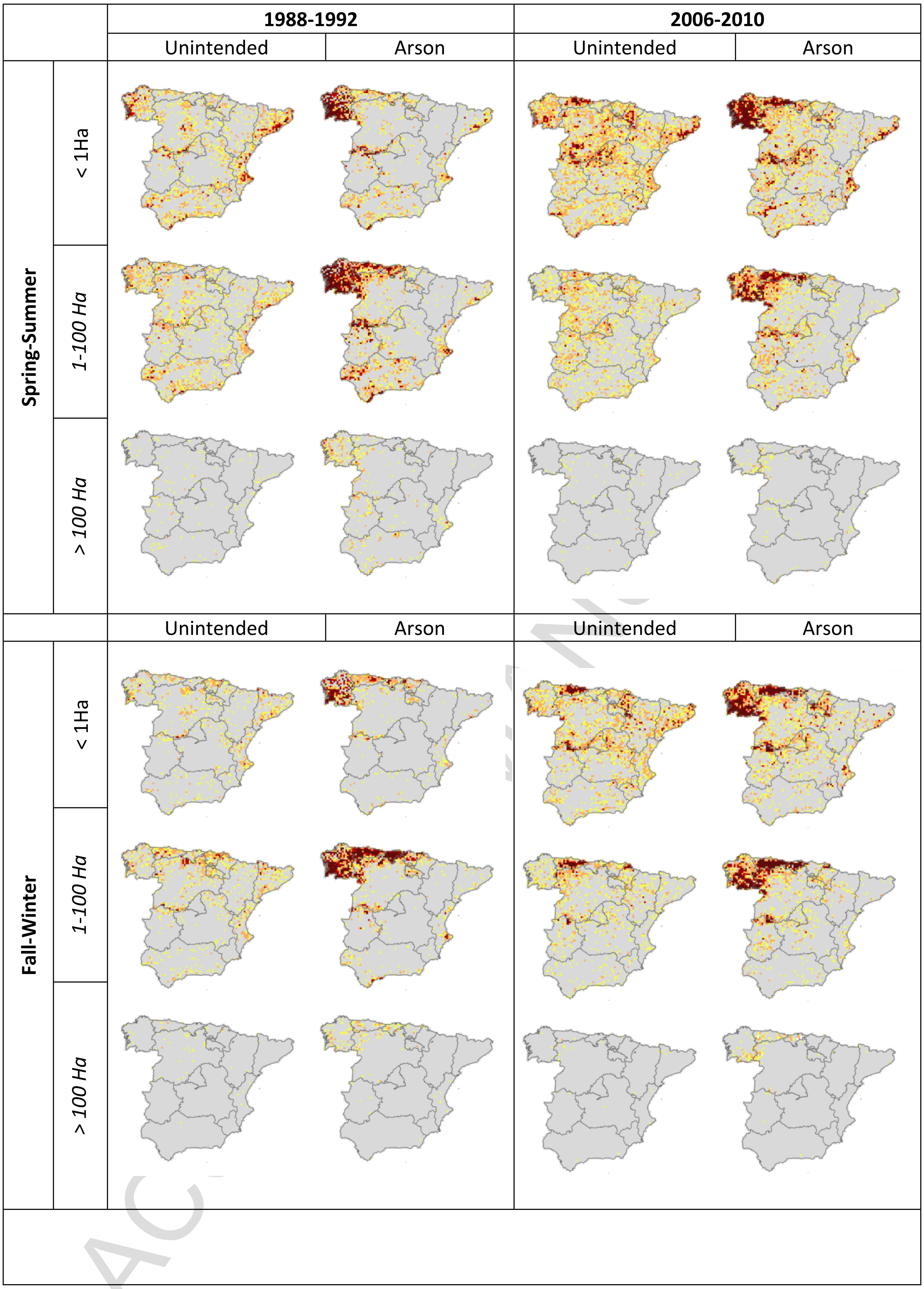

Figure 2. *Spatial distribution of wildfire occurrence.*

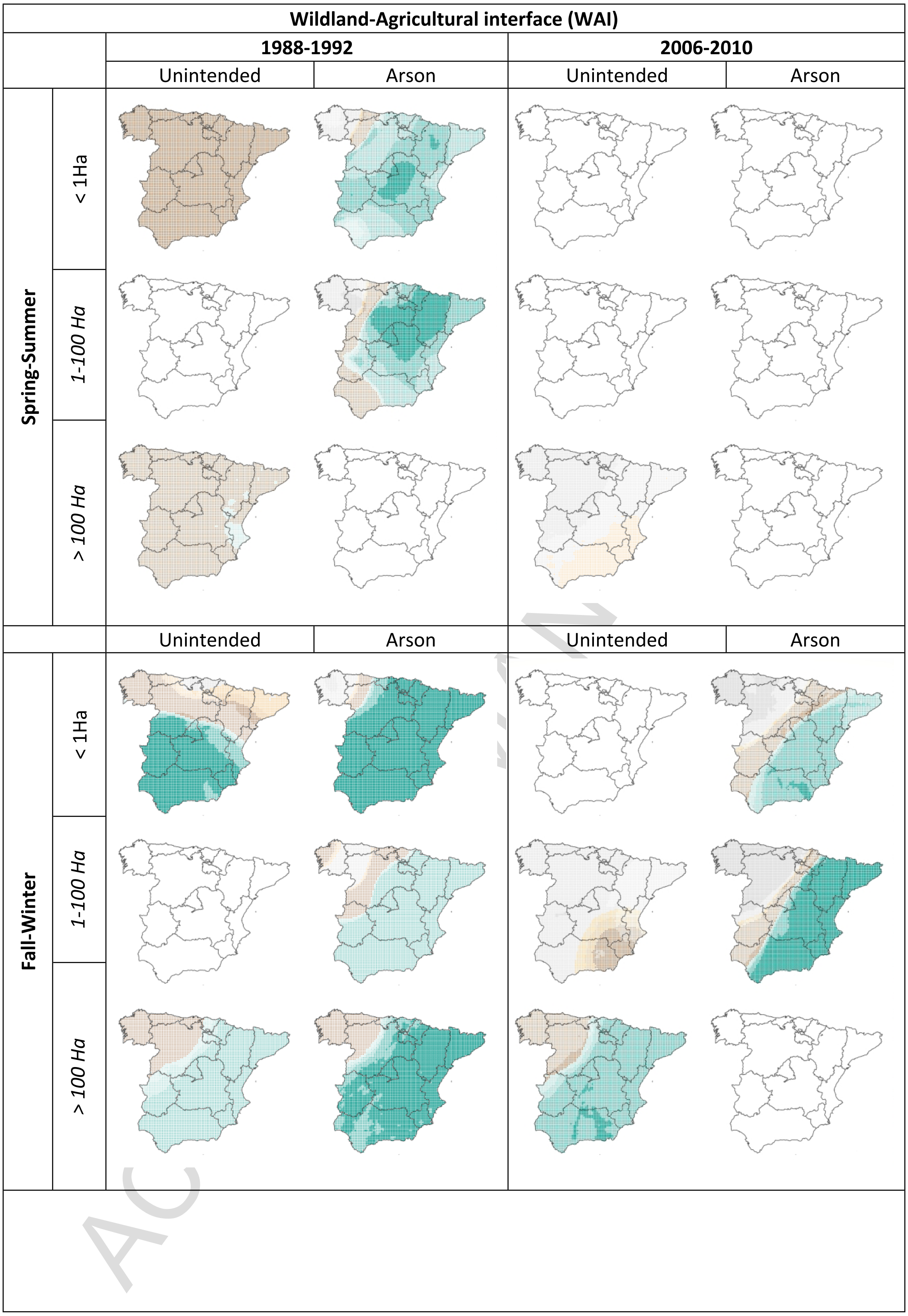

Figure 3. *Spatial pattern of significance level and explanatory sense of WAI. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.*

Significance level:

Uncertainty:

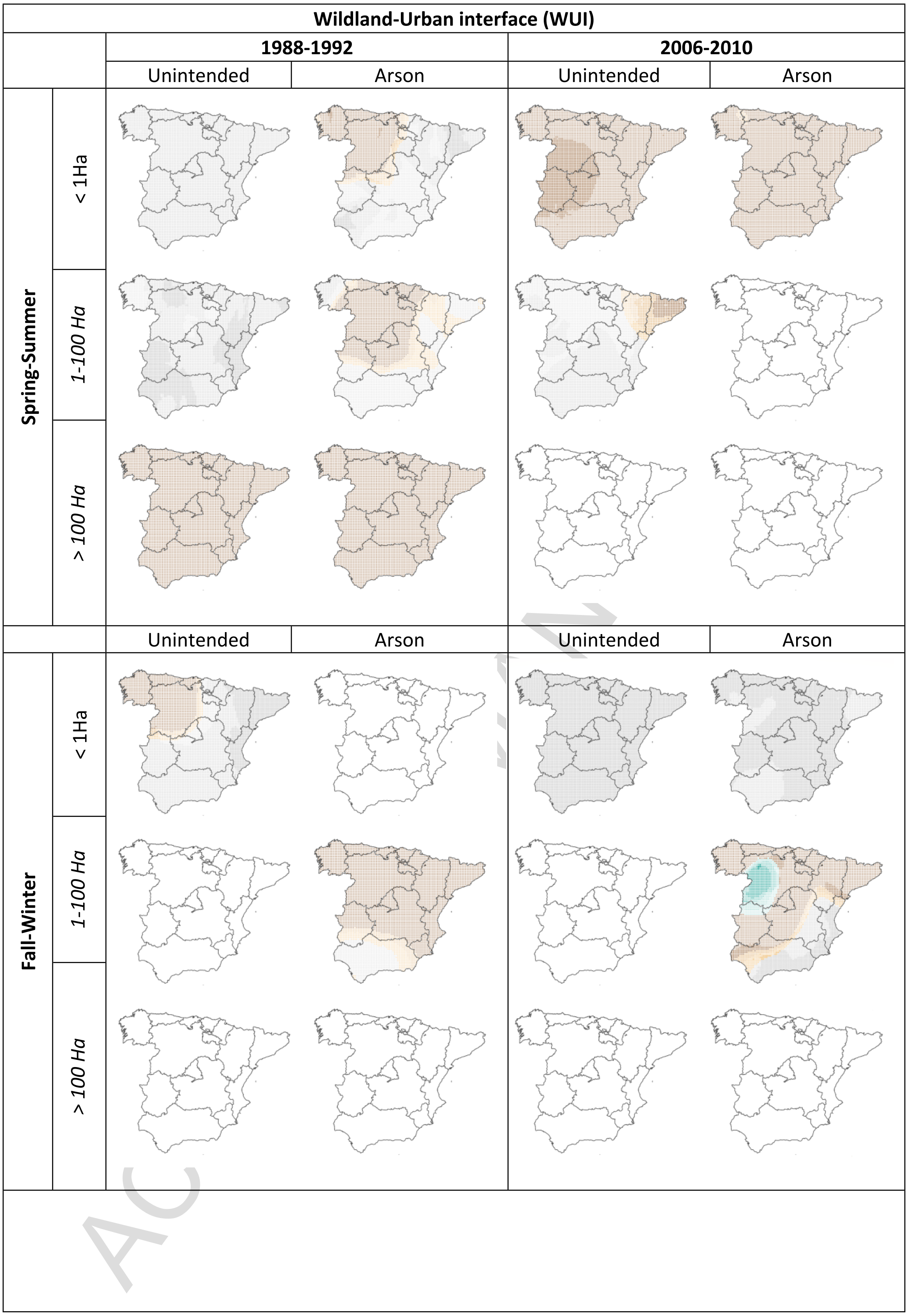

Figure 4. *Spatial pattern of significance level and explanatory sense of WUI. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.*

Significance level:

Uncertainty:

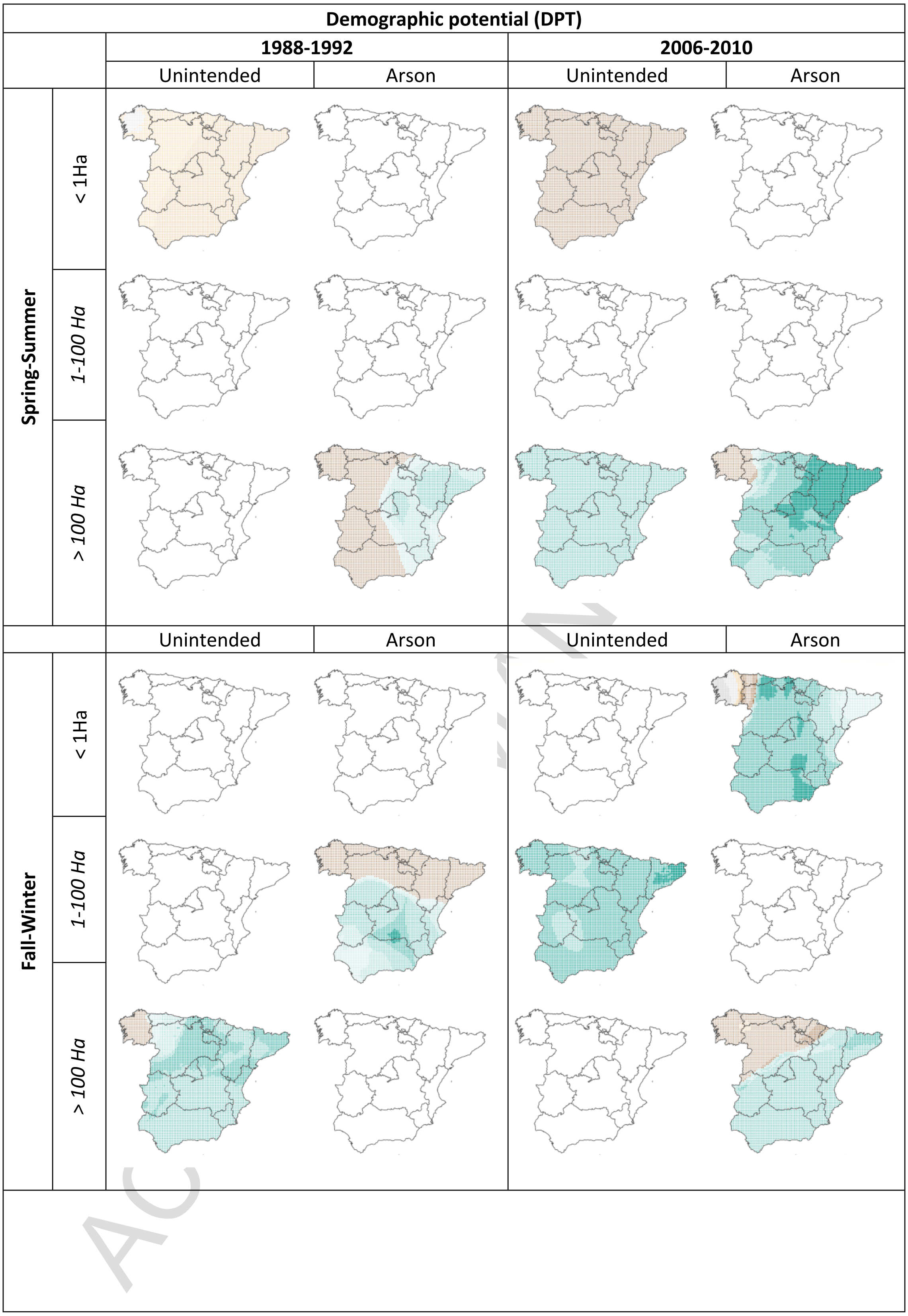

Figure 5. *Spatial pattern of significance level and explanatory sense of DPT. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.*

Significance level: Uncertainty:

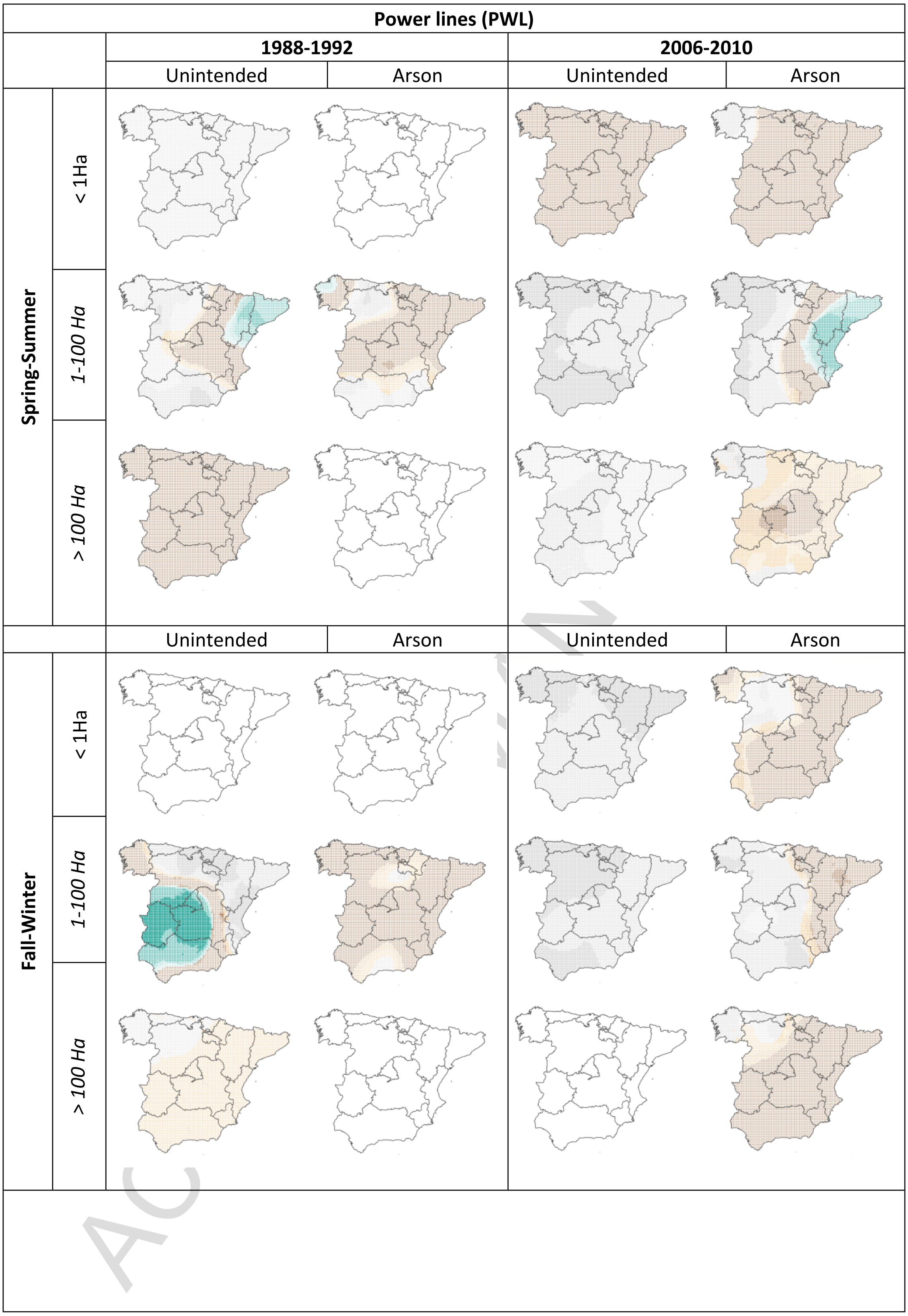

Figure 6. *Spatial pattern of significance level and explanatory sense of PWL. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.*

Significance level:

Uncertainty:

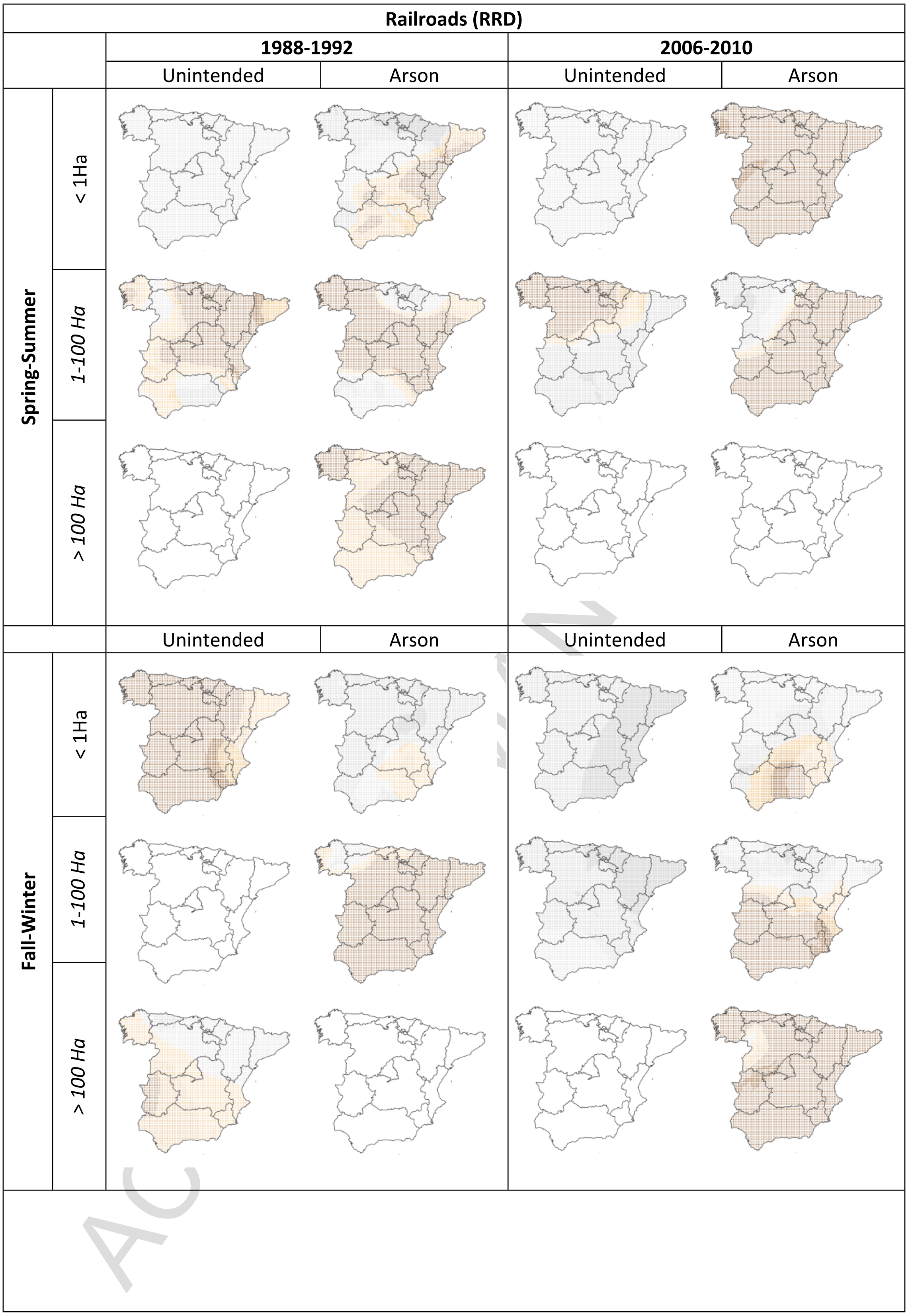

Figure 7. *Spatial pattern of significance level and explanatory sense of RRD. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.*

Significance level:

Uncertainty:

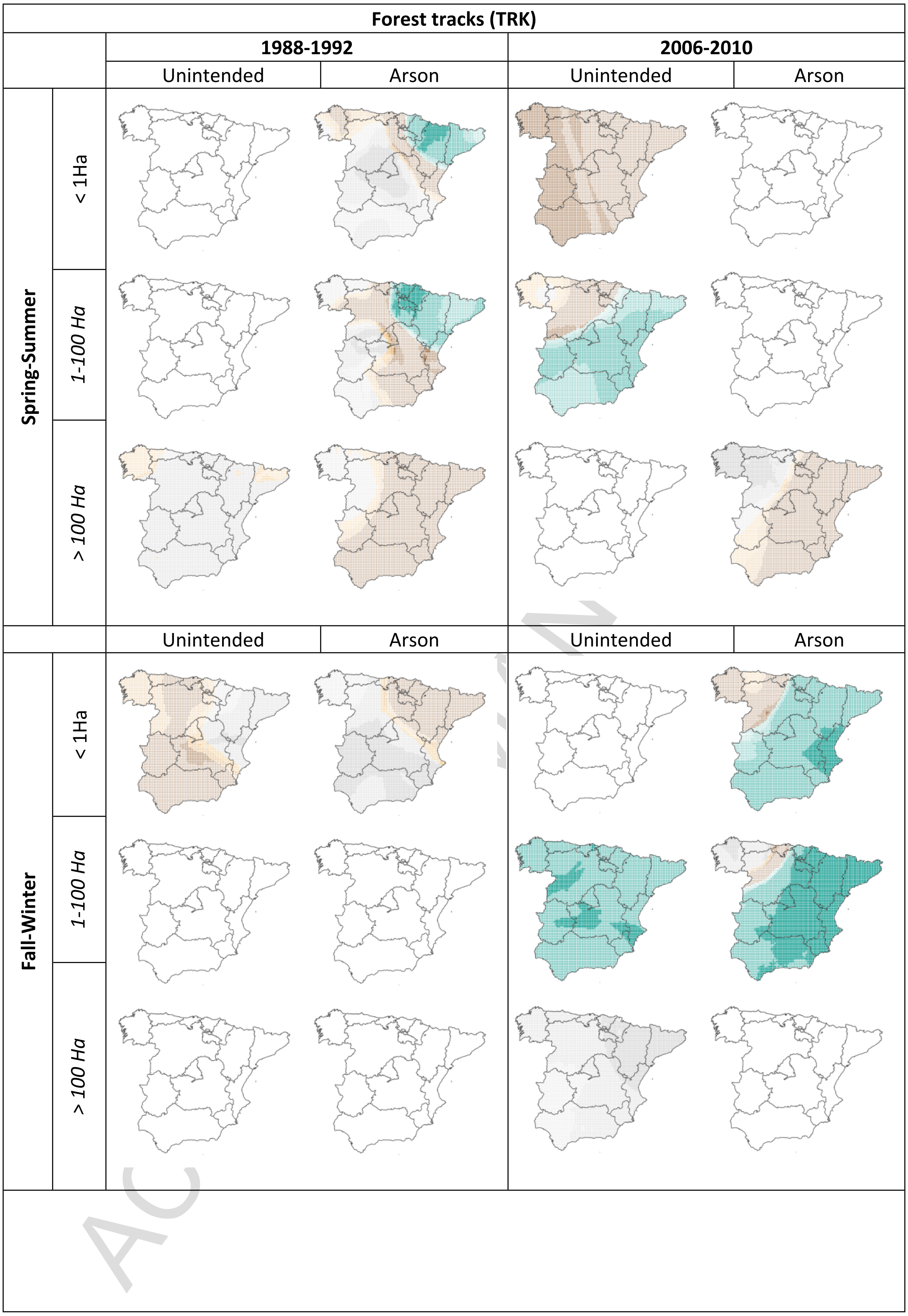

Figure 8. *Spatial pattern of significance level and explanatory sense of TRK. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.*

Significance level:

Uncertainty:

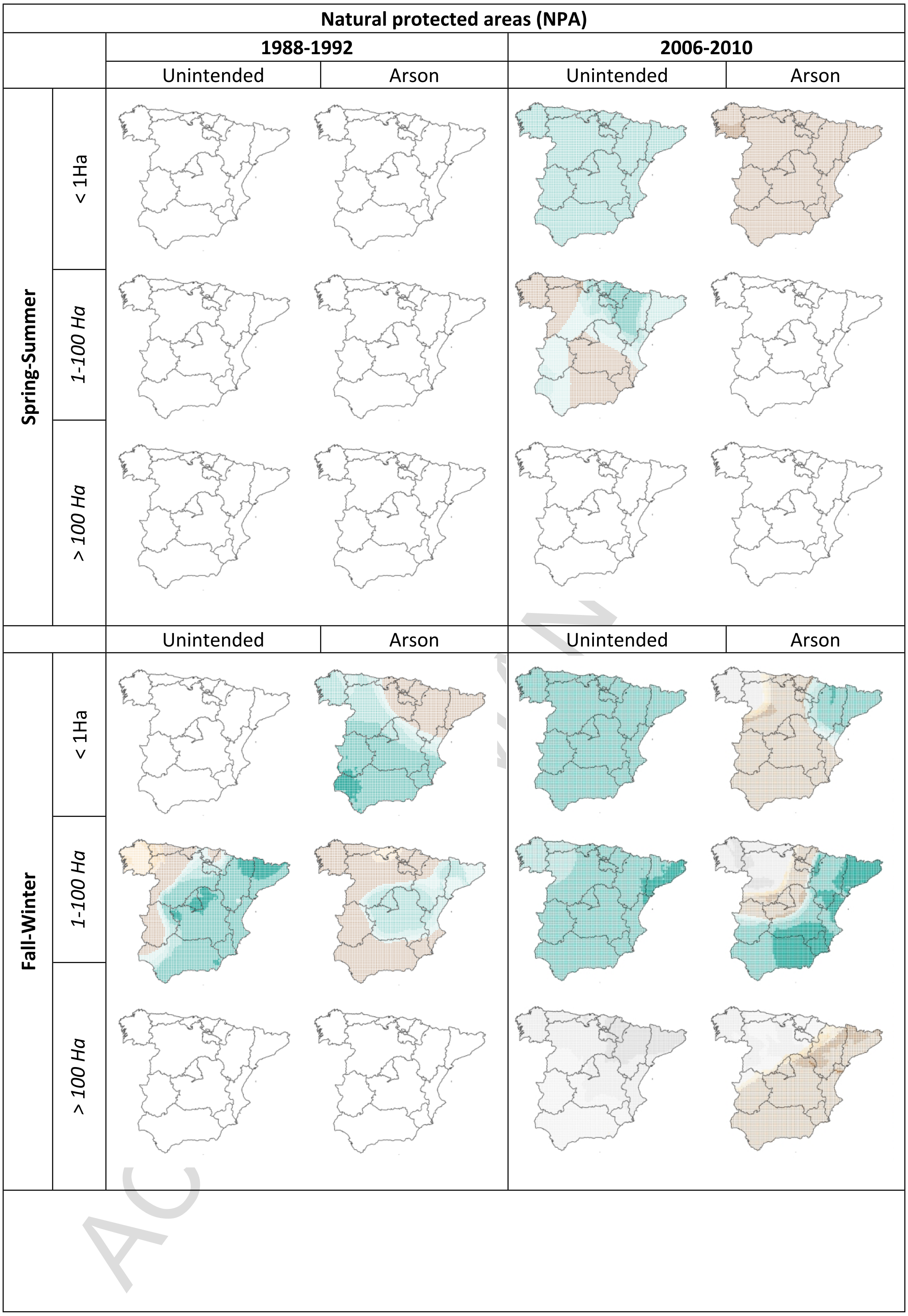

Figure 9. *Spatial pattern of significance level and explanatory sense of NPA. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.*

Significance level:

Uncertainty:

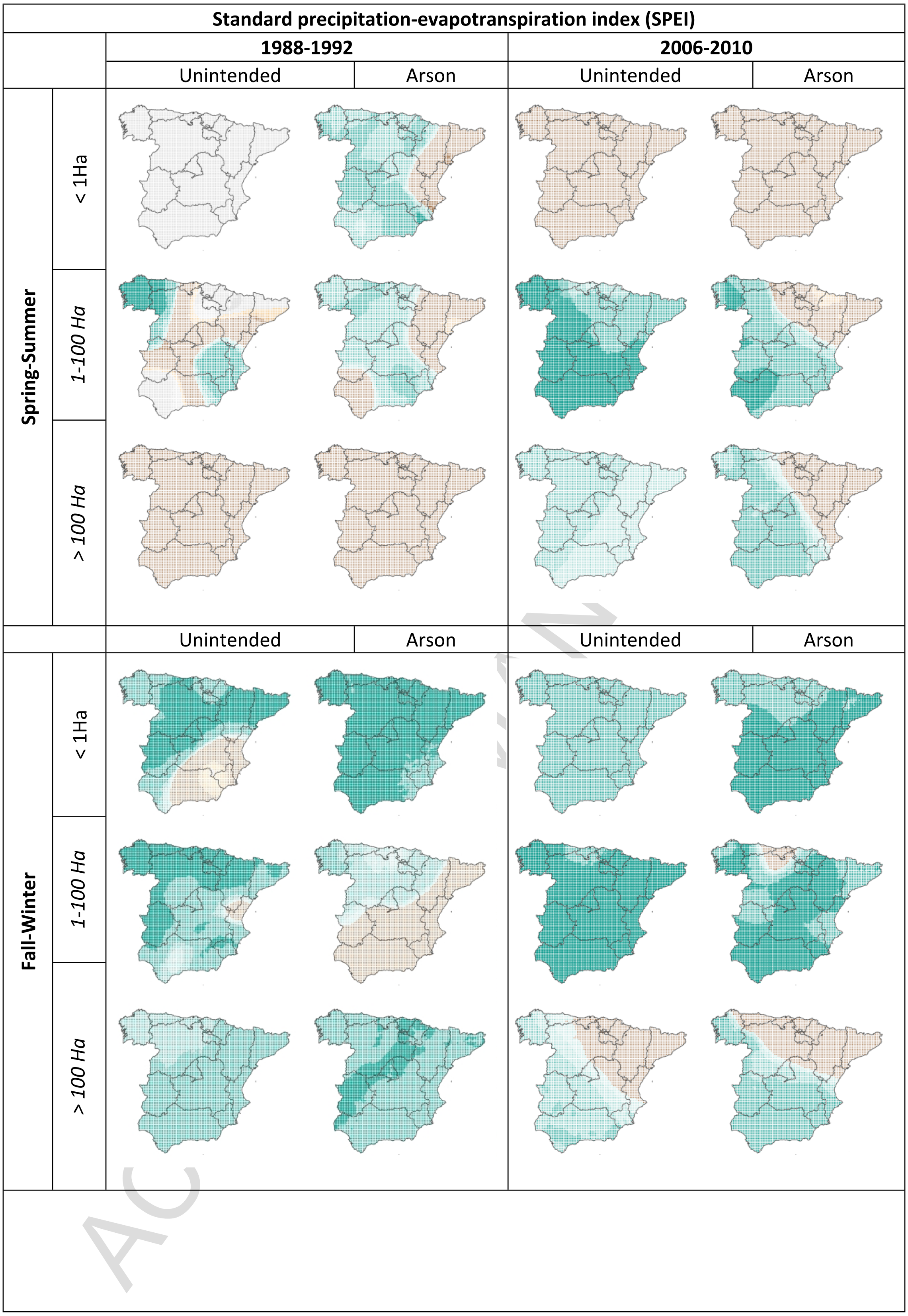

Figure 10. *Spatial pattern of significance level and explanatory sense of SPEI. Blank maps indicate no contribution. Dot color represents significance level and explanatory sense. Dot size represents the level of uncertainty according to MAD.*

Significance level:

Uncertainty:

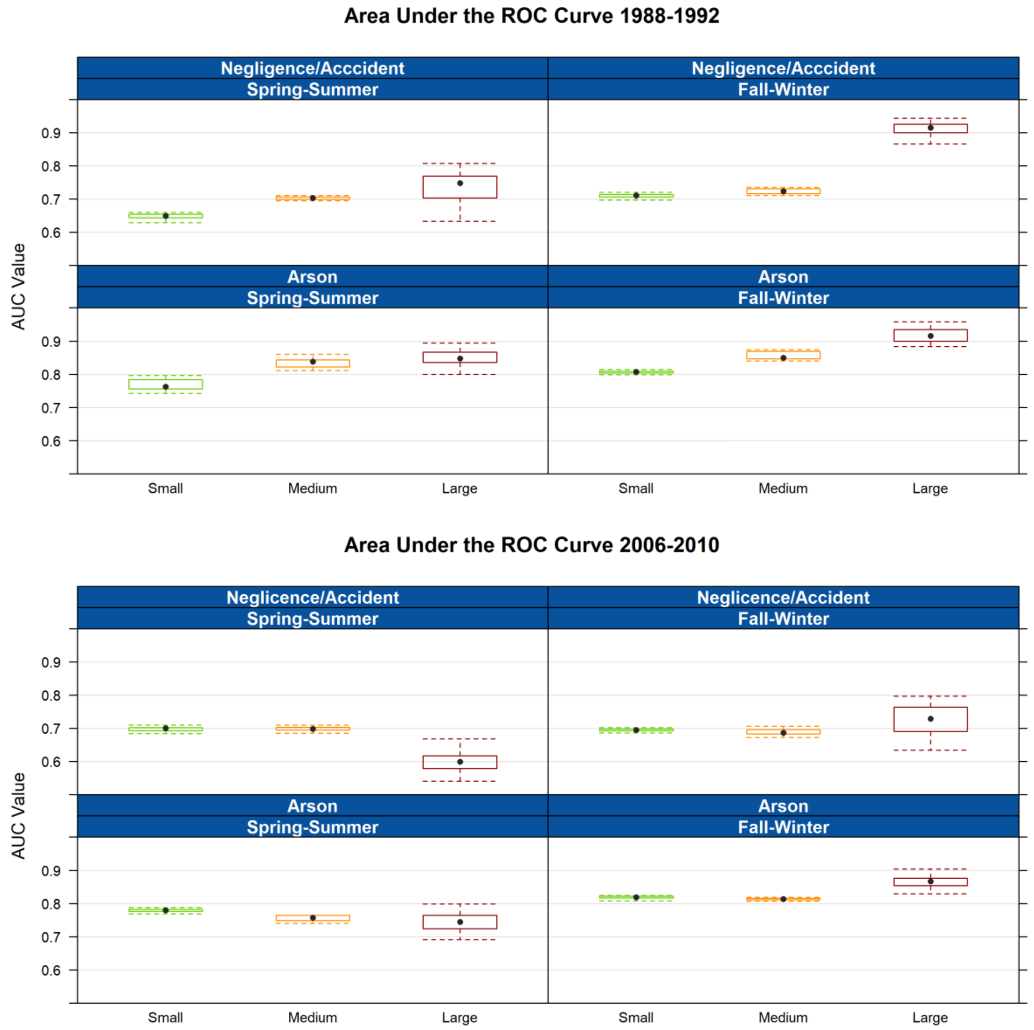

Figure 11. Predictive performance according to the Area Under the Receiver Operator curve.

Highlights

- We explore drivers of wildfire ignition in relation to size, cause and season.
- Human-related factors are losing performance towards present days.
- We report noticeable differences in the performance of models across scenarios.
- Management policies should adapted to the different behavior of winter fires.
- Drought is strongly tied to fire ignition, regardless the ultimate size of fires.