#RC1

Overall

The paper presents a spatially explicit modeling approach for human-caused wildfire ignitions across various European regions. The study applies machine learning techniques, specifically Random Forest models, to analyze historical fire records and environmental variables such as land cover, population density, accessibility, and dead fine-fuel moisture content (DFMC). The results highlight that the most influential variables in predicting ignition probability are DFMC anomalies, proximity to the Wildland-Urban Interface (WUI), and road accessibility.

The study emphasizes the role of anthropogenic factors in fire ignition and provides valuable insights into human-caused wildfire ignitions. However, it faces challenges related to model generalizability, temporal dynamics, and policy application.

Thank you for your valuable comments. We have carefully addressed all your observations, and all replies are highlighted in **red** color. Additionally, we have incorporated a Supplementary Material section to provide further details to clarify data providers and overfitting analysis.

Major comments

- One major comment regarding this paper is that a big portion of the core of this study has been already published as a conference paper https://doi.org/10.23919/SpliTech58164.2023.10193249 with a high degree of overlap in content, methodology, and key findings of the current article under review. Here it seems that there is an extended and refined version of the previously published material, thus I leave it up to the editors to make a decision about that.

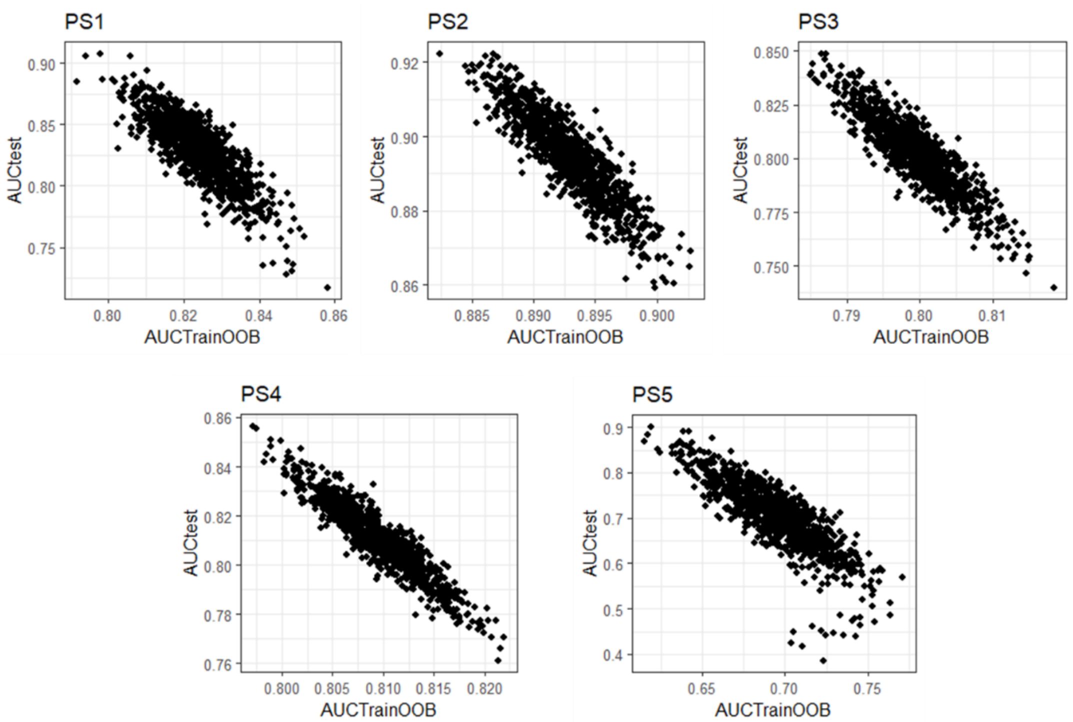
We appreciate the reviewer's observation. The conference paper the reviewer refers to was an early proof-of-concept focused on pilot sites with a preliminary dataset,limited predictors and incomplete formal analyses. The current manuscript substantially extends this work by expanding to a European-scale model, incorporating methodological advances such as the autocorrelation control (AC) term, DFMC mean and anomalies, and new anthropogenic variables, systematically comparing site-specific and full models. It also provides comprehensive cross-validation, performance analysis, and interpretation of spatial ignition patterns, while discussing broader implications, limitations, and operational applications. The conference paper is thus an early-stage presentation of one component, whereas this submission constitutes the complete study. This conference paper was already cited in the manuscript.

- Although the study acknowledges spatial autocorrelation effects, does not fully resolve them, leading to reduced model performance in regions with fewer fire records (e.g., Attica). This undermines the reliability of the model when applied to areas with limited historical data, reducing its effectiveness for wildfire prediction.

We appreciate this observation. To address spatial autocorrelation (SAC), we incorporated an autocorrelation control term into all models, which reduced Moran’s I to non-autocrrelated levels in most realizations. However, in data limited regions like Attica, some residual SAC persisted, likely contributing to lower AUC values. We acknowledged that limited historical ignitions constrain generalization and promote overfitting in lines 420-423

- In this study the authors develop separate models for different pilot sites and then compare them to a full model. While this approach helps capture local variations, it may lead to overfitting within specific regions, limiting the model’s ability to generalize ignition likelihood across broader areas. Although the authors discuss some of these aspects (e.g., Section 4) they could provide a more detailed discussion and clearly state all the limitations of their approach.

Thank you for your observation- To assess potential overfitting, we compared the AUC obtained from Out-of-Bag (OOB) predictions—model predictions with reserved sample for OOB error calculation —with the AUC based on independent test samples. As expected, the OOB AUC was consistently lower than the test AUC across pilot sites. This result aligns with previous evidence showing that OOB-based AUC tends to underestimate model performance (https://doi.org/10.1371/journal.pone.0201904). The only exception was PS5, where approximately half of the models showed test AUC < OOB AUC, suggesting some degree of overfitting. We attribute this not to the inclusion of EDF per se, but to the reduced sample size available at PS5, which increases the instability of model estimates (please see figure below). In this sense we caution on these issues in sections 3.1(L253-254) and 4.4.1 (L423-424) and added the below figure in supplementary material.



- For further improvement: Although the authors state some of these issues in Section 4.4, their study focuses on static environmental and anthropogenic variables but does not incorporate seasonal or real-time human activity variations (e.g., increased tourism in summer, agricultural burning periods). Since human behavior significantly influences fire ignition, integrating temporal dynamics would improve model accuracy.

In lines 426 to 430 we acknowledge that seasonal human activities, such as tourism peaks or agricultural burning periods, can influence ignition patterns. However, since exact ignition dates are not known for some pilot sites, we cannot include variables tied to specific days or seasons, just as we could not incorporate daily DFMC. Additionally, our objective was to develop a spatially explicit model, where all predictors vary continuously across the study area. Most seasonal or real-time human activity variables are represented by unique values, lacking spatial variation. Including such non-spatial predictors would compromise the spatial resolution of the model and distort cross-site comparisons. For this reason, we focused on spatially explicit variables available consistently across Europe.

- Although the temporal coverage is short in most areas, did the authors consider any temporal trends in DFMC?

Yes, we did. While the temporal coverage was indeed short in some pilot sites, we accounted for temporal patterns in DFMC by including the anomaly relative to the DFMC baseline as predictors. This allowed us to capture short-term deviations from typical seasonal conditions, which are often critical for ignition occurrence. Given the limited number of years available in certain regions, modelling long-term temporal trends was not feasible without compromising robustness.

Minor comments

- Line 28: AUC abbreviation is not introduced earlier.

Done

- Line 105: Needs to be revised-error message.

Corrected

- Line 115: Maybe "seasonal" instead of "annual"?

Changed

- Lines: 104-116: Some references to the related statements are necessary here.

Added

- Lines 128-132: The native resolution of the fuel type is missing here.

The fuel type layer does not have a single native resolution, as it is derived from a combination of several products. The final resolution, consistent with the other variables, is 100 m. We clarified this in the revised version (section 2.3.4 – L183-189).

- Lines 183-185: Could the authors be more specific about the terms reclassifying and merging? Does this also involve any regrid method and if yes, which one?

We aggregated the data using majority vote for categorical variables and mean for numerical variables. In the case of the Global Forest Canopy Height product, used to generate fuel models, which is originally at 30 m resolution, we aggregated it to 90 m using the mean value and then resampled it to match the 100 m grid defined for the other variables. Please see further clarifications in section 2.3.4, L183-189.

- Line 191-194: Is this daily-mean or daily-max DFMC? Could you please clarify what do you mean by aggregating daily values to annual products? Furthermore, could the authors specify the time scale of the 5th percentile and the anomalies? Are these multi-year daily climatological values or something else?

We thank the reviewer for this question. To clarify, we calculated the monthly-mean DFMC values, derived from Monthly reanalysis data from ERA5 (https://developers.google.com/earth-engine/datasets/catalog/ECMWF_ERA5_MONTHLY), which were then aggregated into annual products. Additionally, we computed the mean DFMC over the period 1991–2021 and the annual anomalies (Z-scores) to capture interannual variability. Regarding the 5th percentile, we acknowledge that this was mistakenly mentioned in the manuscript and has now been removed. Please see changes in section 2.3.5 - L198.

- Lines 239-240: Needs to be revised-error message.

Done

- Line 258: needs to be revised.

Done

- Lines 259-276: Could authors provide some further explanation for the limited importance of DFMC in PS4 and especially in PS5? Is this related only to the more frequent low DFMC conditions compared to the northern sites?

We believe so. As the reviewer noted, in the Mediterranean basin low DFMC conditions are very frequent in summer time, which reduces their explanatory power in the models. In addition, other human-related drivers exert a stronger influence on ignition patterns in the Mediterranean region, in contrast to northern Europe where climatic variability plays a more dominant role. Please see new clarifications in section 3.2, L287-290.

- Could the authors provide some explanation for the limited role of fuel type as a predictor? The study finds that fuel type is not a significant factor in human-caused ignitions, which contradicts existing research. This could indicate potential data quality issues or model design limitations. A sensitivity analysis on fuel-related variables would clarify this discrepancy.

Fuel type is not widely used in fire susceptibility research. Concretely, this review paper (Chicas, Østergaard and Nielsen J., 2022. – www.doi.org/10.1007/s11069-022-05495-5) points out that fuel type is used as predictor only in 5 research articles from the 94 analyzed and only in 3 has explanatory power.

In our case, the main causes of ignition in southern Europe are primarily driven by anthropogenic actions and tend to occur near roads and in agricultural-forest interface areas. This results in ignitions predominantly occurring in the same fuel types (grasslands, shrublands, or areas with low tree density, dominated by fine fuels which facilitate ignition).

Regarding modeling, fuel models did not provide significant explanatory power, similarly to findings in another study (Gelabert et al., 2024 - https://www.tandfonline.com/doi/full/10.1080/19475705.2025.2472864). Fuel types are more used to predict fire spread rather than ignition, as ignitions mainly occur in areas with fine fuels.

- The study uses multiple terms for similar human-related ignition factors (e.g., "human pressure on wildlands," "accessibility," "population influence"). Standardizing terminology throughout the paper would improve clarity and coherence.

We appreciate the reviewer's suggestion. However, the terms used in the manuscript are deliberately employed to represent standardized causal factors that have been widely recognized in the literature. Each term reflects a conceptual category that can be characterized through different variables. This approach follows established frameworks, such as those proposed by Leone et al. (2003) (http://dx.doi.org/10.1142/9789812791177_0006) where multiple human-related drivers are grouped under broader thematic concepts.

- Figures illustrating ignition probability (Fig. 4) distributions lack sufficient annotation or explanation (e.g., annotations of subfigures). Enhancing the clarity of these visuals would make the findings more accessible. Furthermore, the colobar for the probabilities could be revised to better communicate the results.

In the revised manuscript, we have incorporated a new version of the ignition probability maps (Fig. 4) in which the results are represented by quintiles. This approach improves interpretability and highlights the relative distribution of probabilities more clearly. We have also revised the figure annotations and subfigure labels to enhance clarity, and updated the colorbar using breaks to better communicate the probability values.