

Modelling Current and Future Forest Fire Susceptibility in north-east Germany

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Supplement

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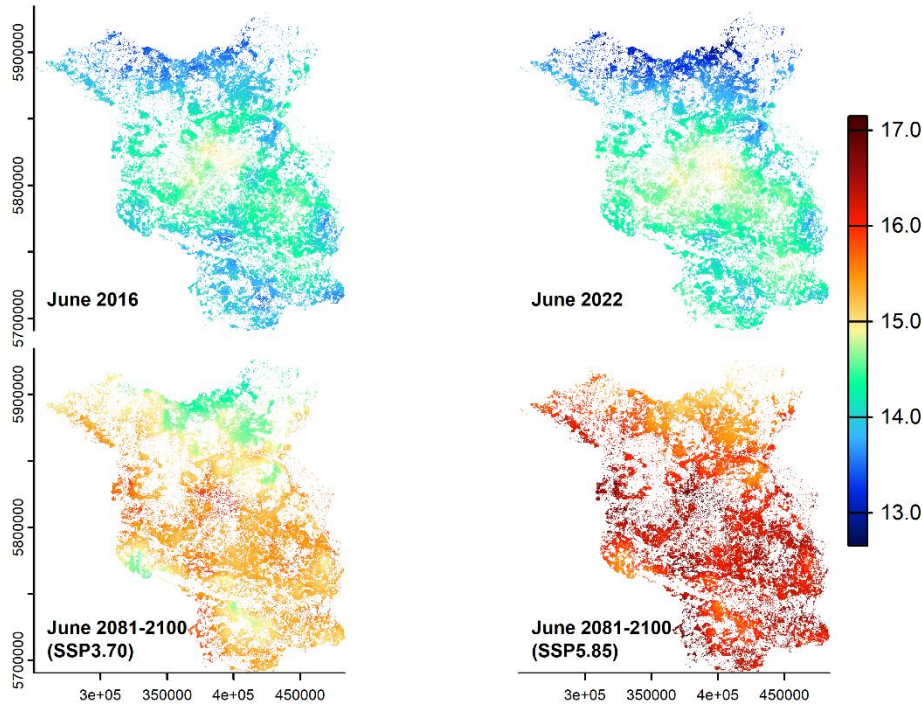


Figure S 1. 3-monthly aggregated air temperature (in °C) in June under the four scenarios. Data for June 2016 and June 2022: DWD Climate Data Center (CDC): Grids of monthly averaged daily air temperature (2m) over Germany, version v1.0. Data for June 2081-2100: Multi-annual monthly air temperature of GCM MPI-ESM1-2-HR (SSP 3.70 and SSP 5.85) from CMIP6 multi-model ensemble derived from WorldClim (2023).

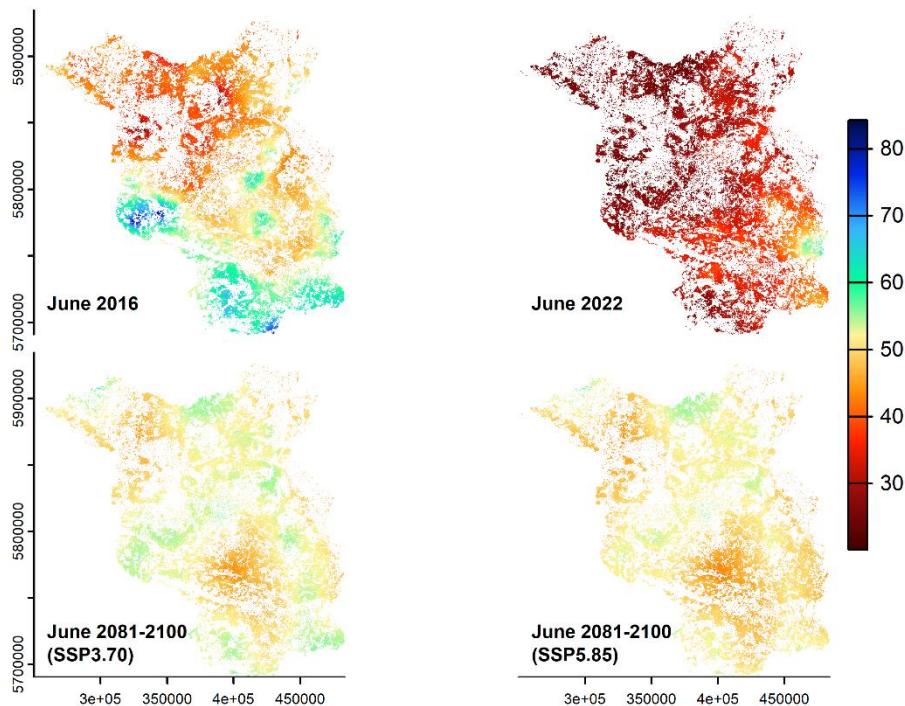


Figure S 2. 3-monthly aggregated precipitation sums (in mm) in June under the four scenarios. Data for June 2016 and June 2022: Hourly station observations of precipitation for Germany, version v24.03. Data for June 2081-2100: Multi-annual monthly total precipitation (mm) of GCM MPI-ESM1-2-HR (SSP 3.70 and SSP 5.85) from CMIP6 multi-model ensemble derived from WorldClim (2023).

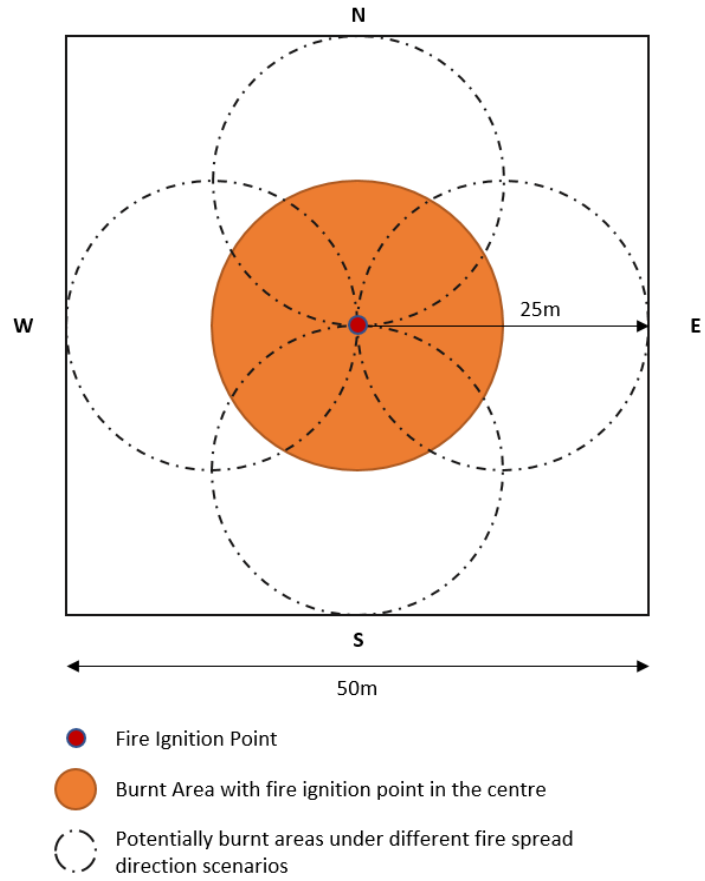


Figure S 3. Potential fire spread under different conditions.

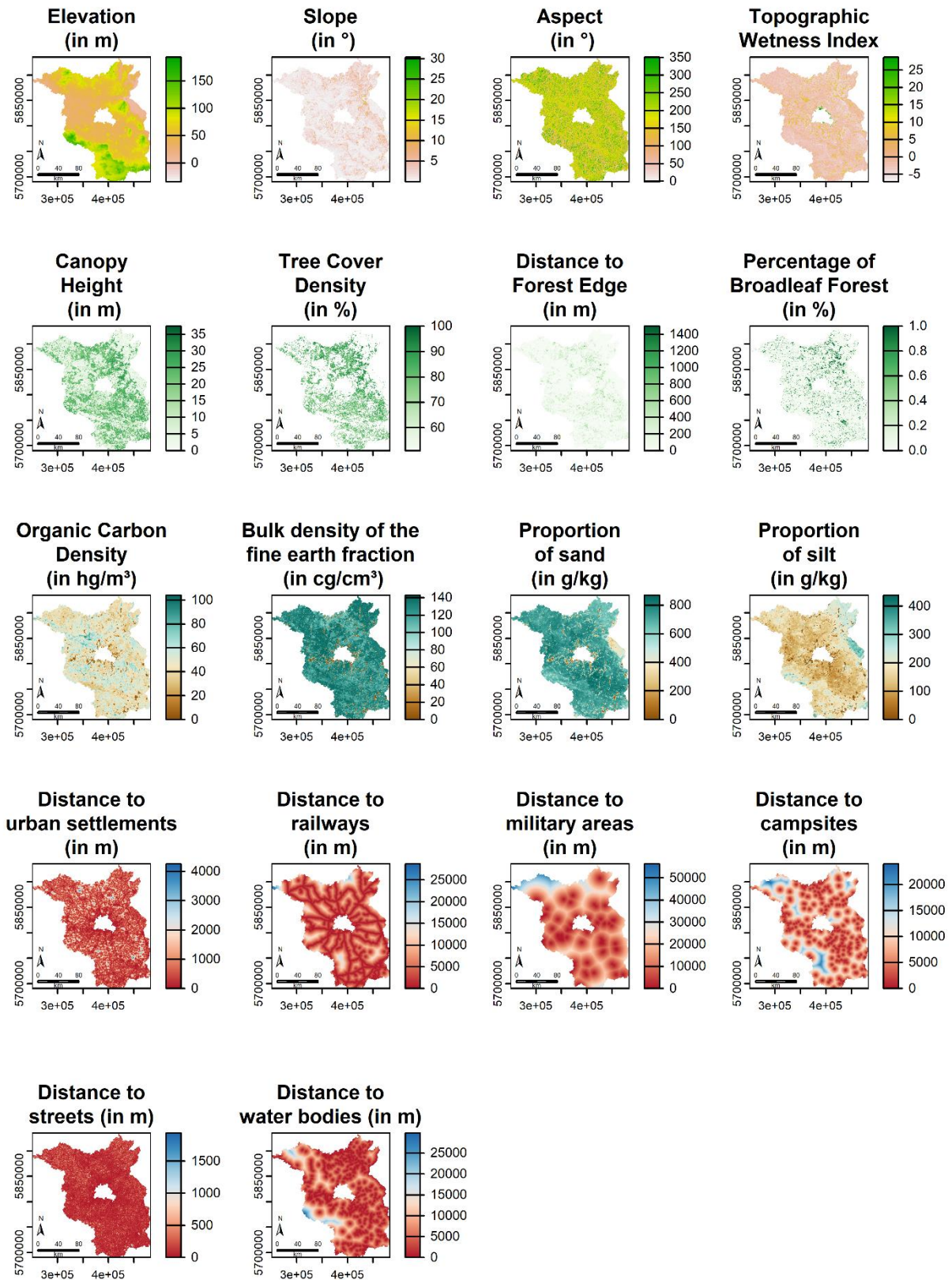


Figure S 4. Static predictors used for the forest fire susceptibility modelling. Data basis see Table 1.

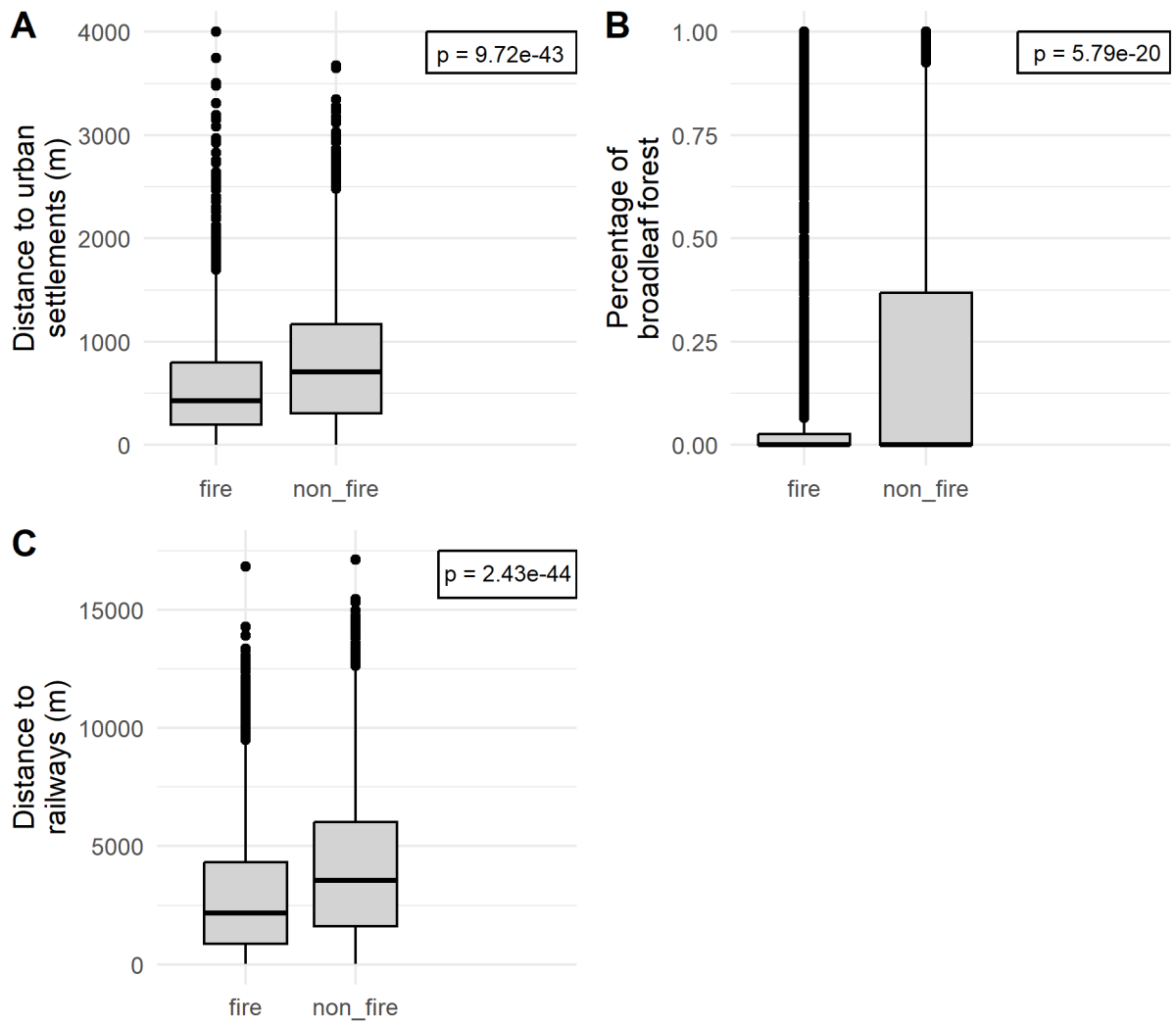


Figure S 5. Boxplots of three different predictors of forest fire susceptibility.

Table S 1. Statistics of burnt area (ha) in Brandenburg between 2014 to 2022.

	Minimum	1 st Quartile	Median	Mean	3 rd Quartile	Maximum
Burnt area (ha)	0	0.015	0.05	1.326	0.223	422.0

Results based on data provided by Lower Forestry Authority of the State of Brandenburg (2023)

Table S 2. Cause of forest fires in Brandenburg between 2014 to 2022.

Cause of fire	Number
Unknown causes	919
Intentional arson	556
Unexplained ignitions	376
Lightning strike	157
Self-ignition of old ammunition	57
Open fires	44
Tools & vehicles	36
Ignitions on other public roads	24
Inadequate extinguishing of old fires	19
Burning buildings, equipment, facilities, vehicles (kfz)	18
Traffic operation	18
Arson by children	16
Smoking	16
Burning of waste or areas	6
Ignitions on highways	6
Smoking by employees	3
Military	1

Data provided by Lower Forestry Authority of the State of Brandenburg (2023)

Table S 3. Formulas for the calculation of the validation metrics for the RF modelling.

Validation Metric	Formula
Accuracy	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$
Precision	$Precision = \frac{TP}{TP + FP}$
Recall	$Recall = \frac{TP}{TP + FN}$
F_{β} -Score	$F_{\beta} = (1 + \beta^2) * \frac{Precision * Recall}{(\beta^2 * Precision) + Recall}$

The validation metrics were computed using the results of the confusion matrix that shows the distribution of correctly classified pixels (true positives (TP) and true negatives (TN)), as well as wrongly classified pixels (false positives (FP) and false negatives (FN)). The formulas shown in Table S 3 rely on formulas provided by Bradley (1997).

Table S 4. Confusion matrix of the RF model (based on RF_{test} testing data).

Prediction	fire	non_fire	Σ
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fire	487	187	674
non_fire	194	520	714
Σ	681	707	1388

Table S 5. Overview of the performance metrics of the LOYO RF models.

LOYO model (year left out)	Accuracy	Kappa	Precision	Recall	F1-Score	AUC
2014	0.646	0.288	0.658	0.565	0.608	0.643
2015	0.700	0.397	0.717	0.625	0.668	0.698
2016	0.674	0.347	0.662	0.672	0.667	0.674
2017	0.720	0.440	0.708	0.720	0.714	0.720
2018	0.692	0.382	0.710	0.632	0.699	0.691
2019	0.683	0.365	0.704	0.618	0.658	0.682
2020	0.728	0.455	0.722	0.742	0.732	0.728
2021	0.688	0.373	0.712	0.607	0.655	0.686
2022	0.721	0.442	0.727	0.703	0.711	0.721
Mean of all years	0.695	0.424	0.702	0.654	0.676	0.694

Table S 6. Overview of significance test results (Wilcoxon test) of the predictor variables.

Predictor	P-value (Wilcoxon test)	Significance (p <= 0.05)
Distance to urban settlements	9.72e-43	significant
Percentage of broadleaf forest	5.79e-20	significant
Distance to railways	2.43e-44	significant
Silt	1.14e-07	significant
Distance to campsites	4.06e-05	significant
Elevation	0.861	not significant
Canopy height	0.022	significant
Sand	0.51	not significant
Bulk density of the fine earth fraction	3.7e-09	significant
Distance to forest edge	0.000687	significant
Organic carbon density	1.4e-09	significant
Distance to streets	0.76	not significant
Distance to water bodies	0.0691	not significant
Distance to military sites	0.784	not significant
Slope	2.15e-07	significant
Tree cover density	0.000389	significant
Air temperature (3-monthly aggregated)	0.144	not significant
Topographic wetness index	0.202	not significant
Precipitation (3-monthly aggregated)	0.0823	not significant
Aspect	0.00624	significant

Wilcoxon test was carried out to check the significance of the different predictor variables. The test provides information on the singularity of the input classes (in this case fire and non-fire). The closer the p-value gets to 0, the higher the significant difference between the two classes. Usually, p-values < 0.05 reflect a high significance. Higher p-values are usually considered to be non-significant. In this case, e.g., distance to urban settlements, percentage of broadleaf forest, and distance to railways show a high significance meaning that the non-fire and fire points significantly differ considering those predictor variables.