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Modelling current and future forest fire susceptibility in north-eastern Germany

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Supplement

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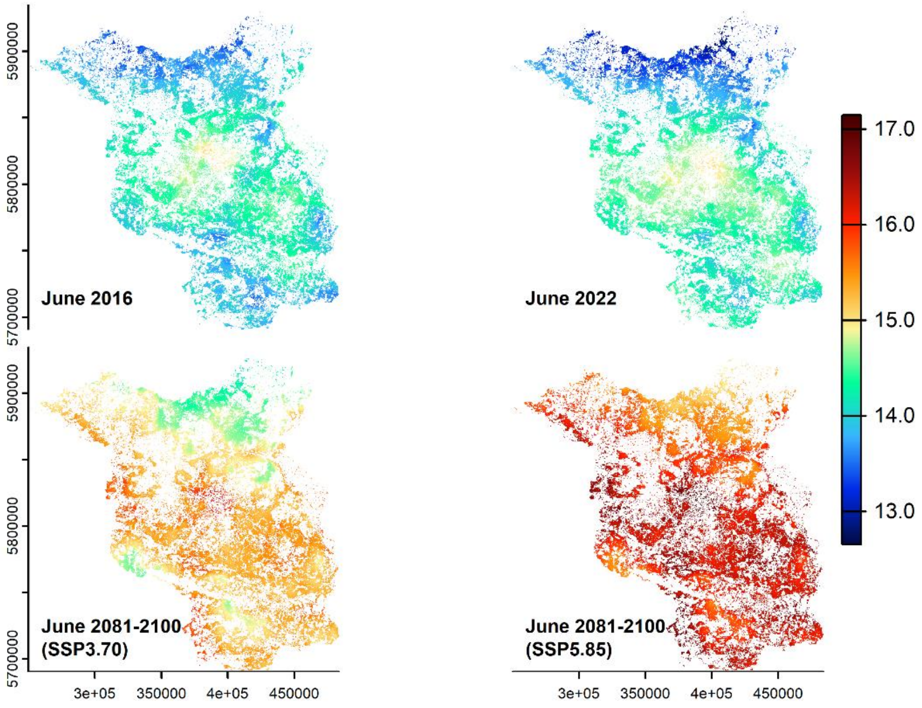


Figure S 1. 3-monthly aggregated air temperature (in °C) in June under the four scenarios. Data for June 2016 and June 2022: DWD Climate Data Center (CDC): Grids of monthly averaged daily air temperature (2m) over Germany, version v1.0. Data for June 2081-2100: Multi-annual monthly air temperature of GCM MPI-ESM1-2-HR (SSP3-7.0 and SSP5-8.5) from CMIP6 multi-model ensemble derived from WorldClim (2023).

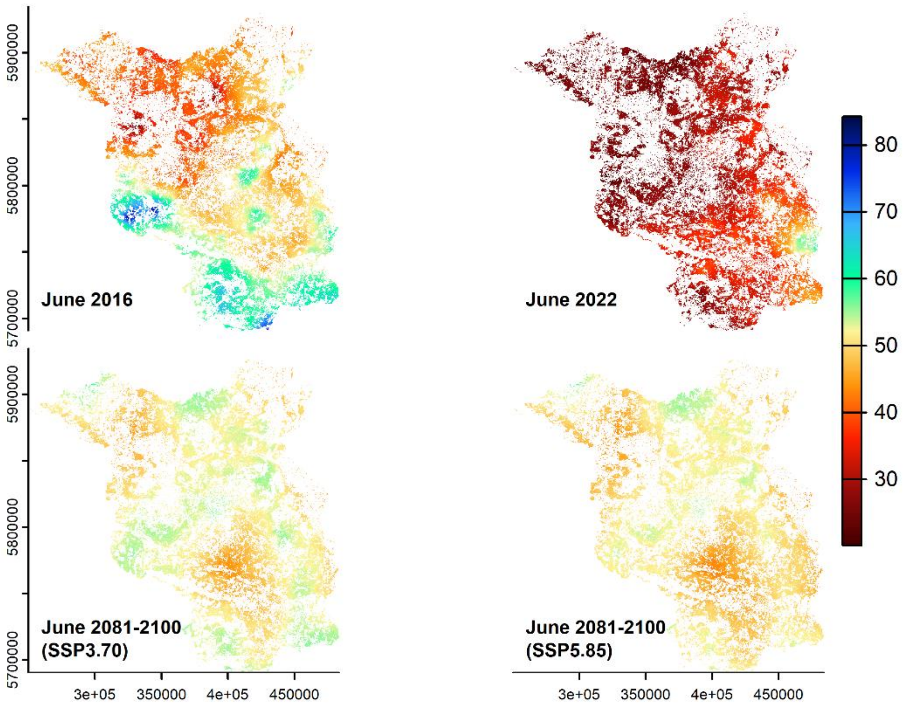


Figure S 2. 3-monthly aggregated precipitation sums (in mm) in June under the four scenarios. Data for June 2016 and June 2022: DWD Climate Data Center (CDC): Hourly station observations of precipitation for Germany, version v24.03. Data for June 2081-2100: Multi-annual monthly total precipitation (mm) of GCM MPI-ESM1-2-HR (SSP3-7.0 and SSP5-8.5) from CMIP6 multi-model ensemble derived from WorldClim (2023).

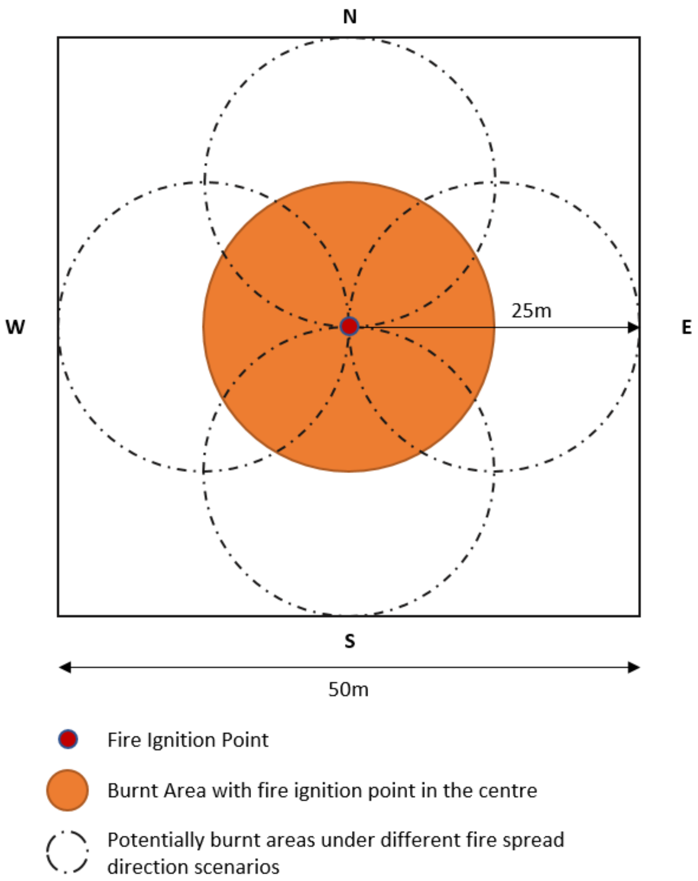


Figure S 3. Potential fire spread under different conditions. Own illustration.

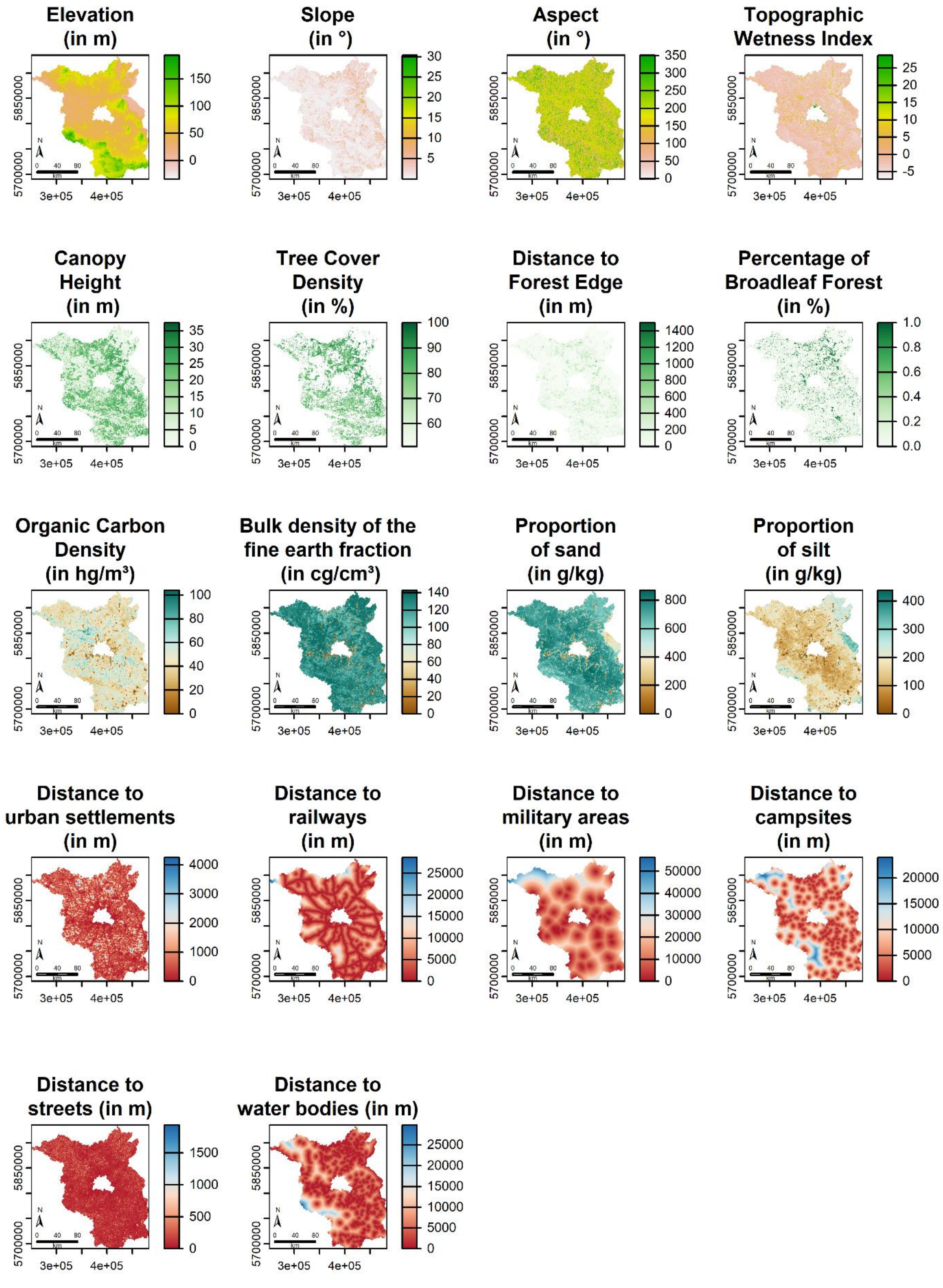


Figure S 4. Static predictors used for the forest fire susceptibility modelling. Data basis see Table 1.

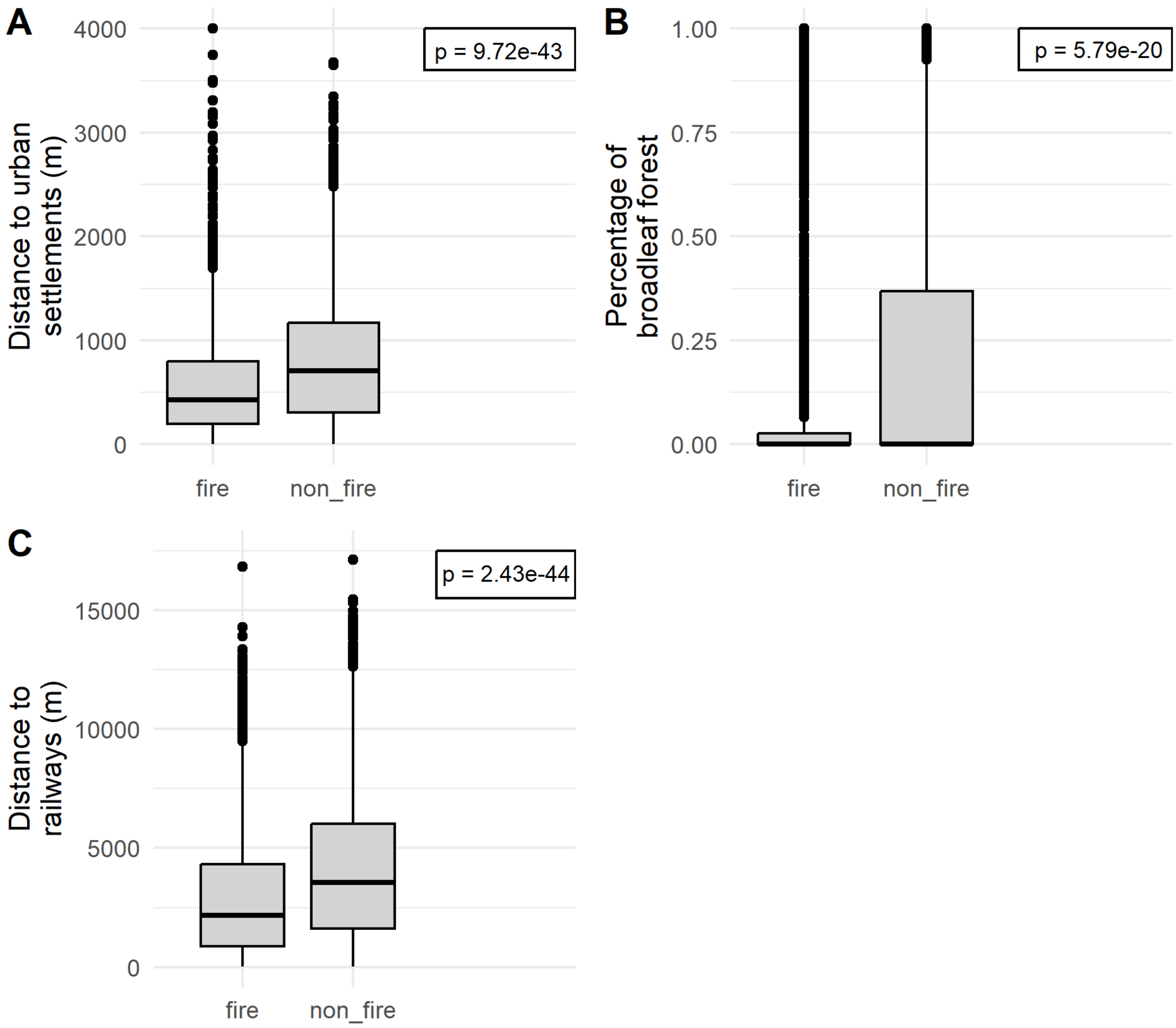


Figure S 5. Boxplots of three different predictors of forest fire susceptibility.

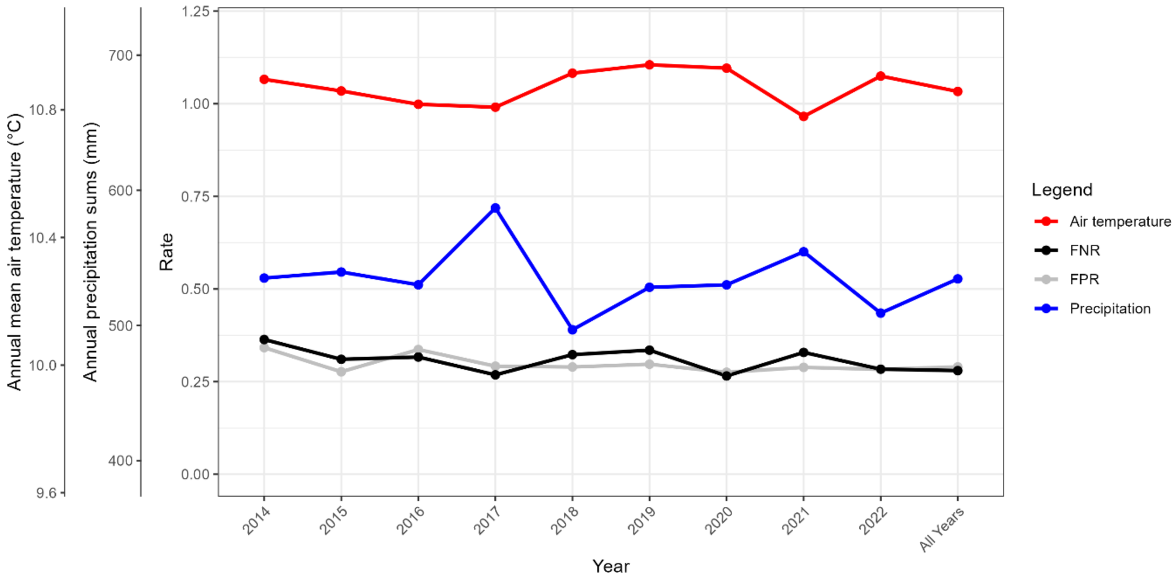


Figure S 6. False Positive Rate (FPR) and False Negative Rate (FNR) of the RF models for each year (2014 to 2022) and all years combined. In order to analyse the influence of climate parameters on the FNR and FPR, the graph additionally shows annual means of monthly precipitation and annual mean air temperatures. These were computed based on data by the DWD Climate Data Center (CDC): Grids of monthly averaged daily air temperature (2m) over Germany, version v1.0 and DWD Climate Data Center (CDC): Hourly station observations of precipitation for Germany, version v24.03.

Figure S 6 illustrates the False Positive Rate (FPR) and False Negative Rate (FNR) of the RF models. The grey and black lines show the FPR and FNR, respectively. The red line illustrates the mean air temperature per year, computed based on monthly mean air temperatures. The blue line shows mean precipitation sums per year, based on monthly precipitation sums.

The figure shows that across the years, FPR and FNR only differ slightly. Whereas air temperature and precipitation values change more substantially across all years, this did not appear to significantly influence the FPR and FNR. These results underline that the model was not so sensitive to changing weather conditions. Therefore, it can be assumed that the model has more of a spatial than temporal influence. This means that the model is better at distinguishing where forest fires may occur but has more difficulties to understand forest fire prone weather conditions. This drawback could be addressed by future research that could for example utilise a Long Short-Term Memory (LSTM) model. By introducing an internal memory unit known as the 'cell state' and three gate units: the forget gate, input gate, and output gate, LSTM is able to process short and long-term meteorological trends and the subsequent effects on forest fire susceptibility more adequately.

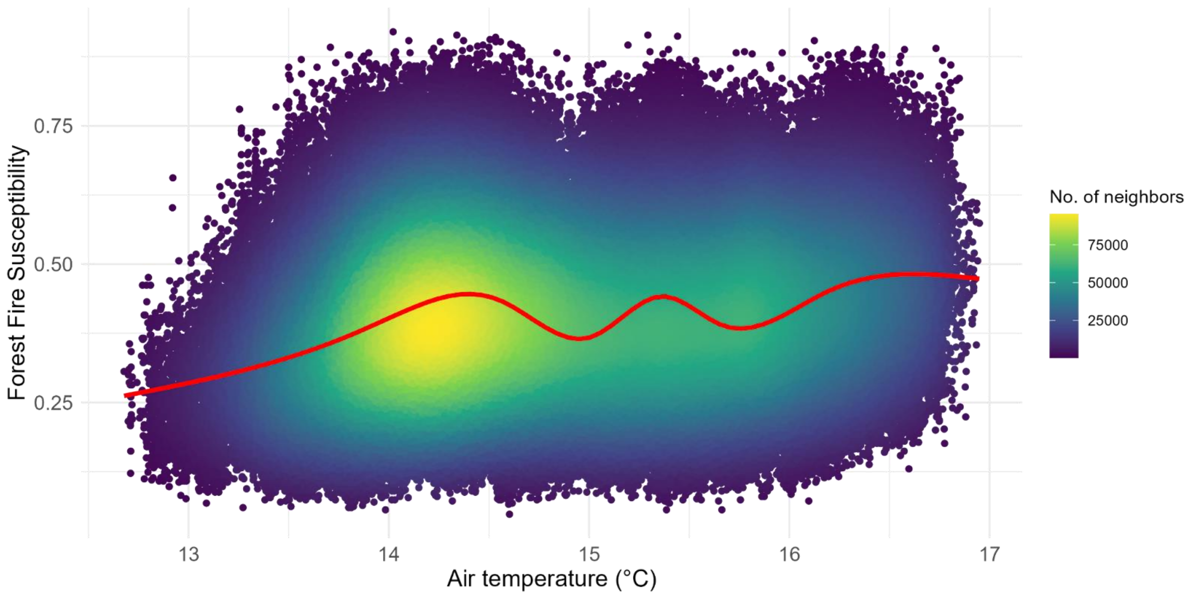


Figure S 7. Partial dependence plot for air temperature and forest fire susceptibility. To compute this plot, a random subset of 100,000 pixels from each of the four FFS predictions (2016, 2022, 2081-2100 under SSP3-7.0 and SSP5-8.5) was combined (400,000 data points in total). Data for June 2016 and 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 (SSP3-7.0 and SSP5-8.5) from CMIP6 multi-model ensemble derived from WorldClim (2023).

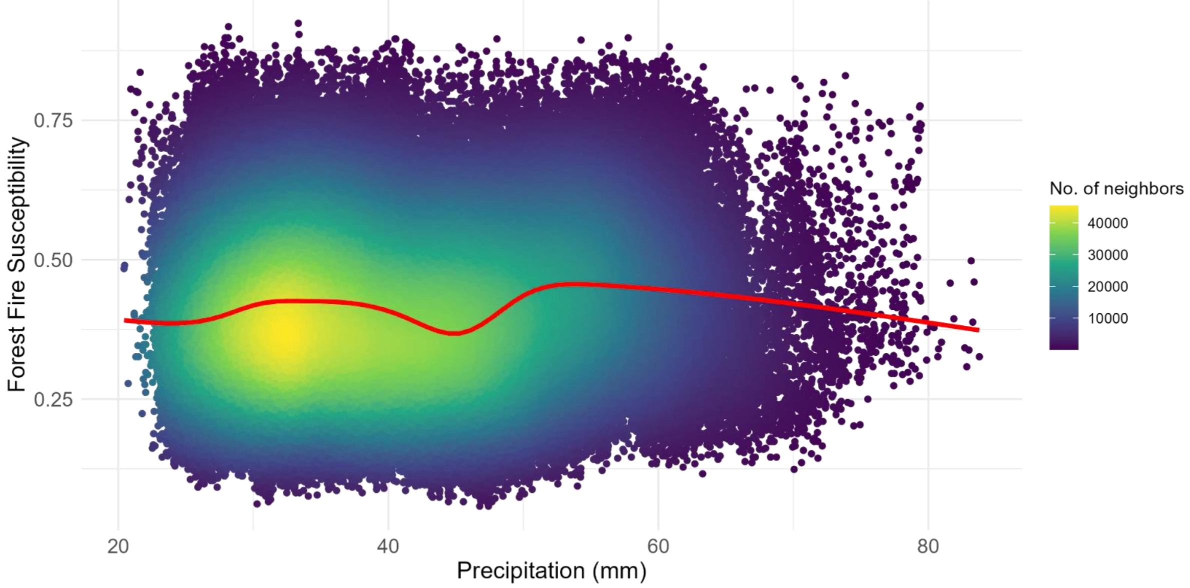
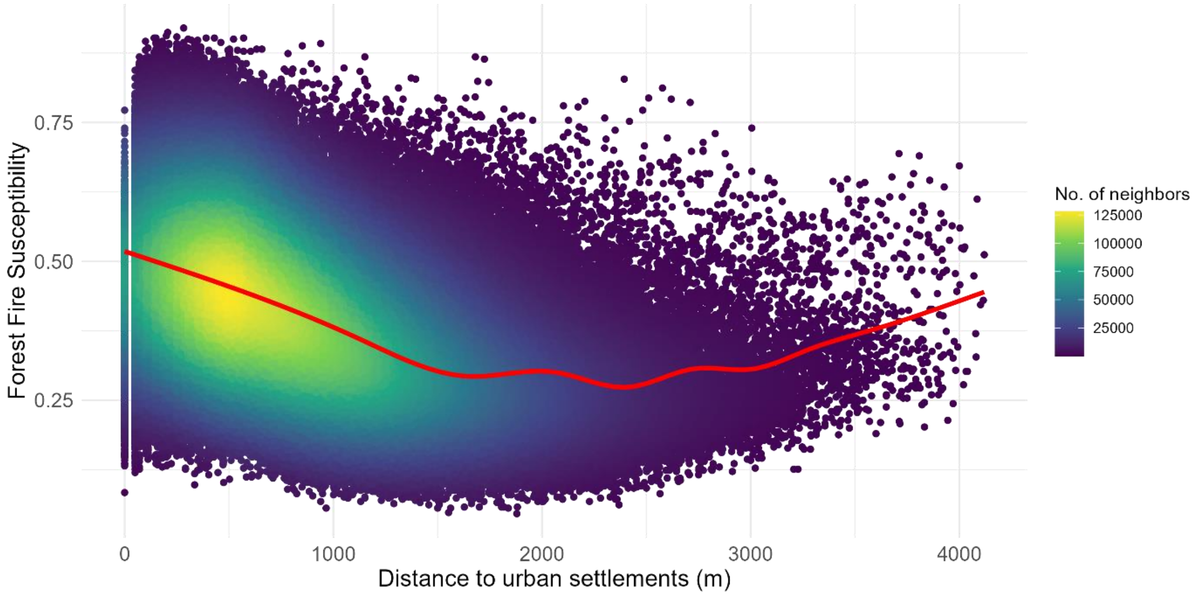
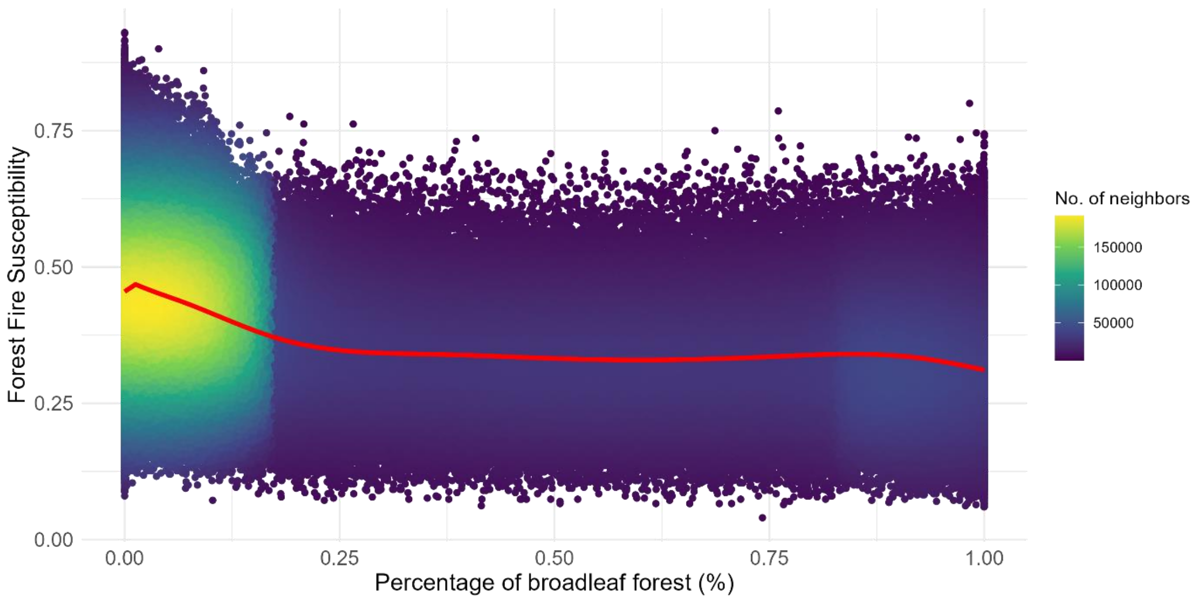


Figure S 8. Partial dependence plot for precipitation and forest fire susceptibility. To compute this plot, a random subset of 100,000 pixels from each of the four FFS predictions (2016, 2022, 2081-2100 under SSP3-7.0 and SSP5-8.5) was combined (400,000 data points in total). Data for June 2016 and June 2022: DWD Climate Data Center (CDC): 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 (SSP3-7.0 and SSP5-8.5) from CMIP6 multi-model ensemble derived from WorldClim (2023).

Figures S 7 and S 8 show the partial dependence plots for the dynamic variables and the predicted FFS. Fig. S 7 underlines that when air temperatures are higher, the FFS increases as well.

Fig. S 8 shows that higher or lower precipitation sums did not substantially increase or decrease FFS, indicating that precipitation did not play a significant role for the FFS predictions.





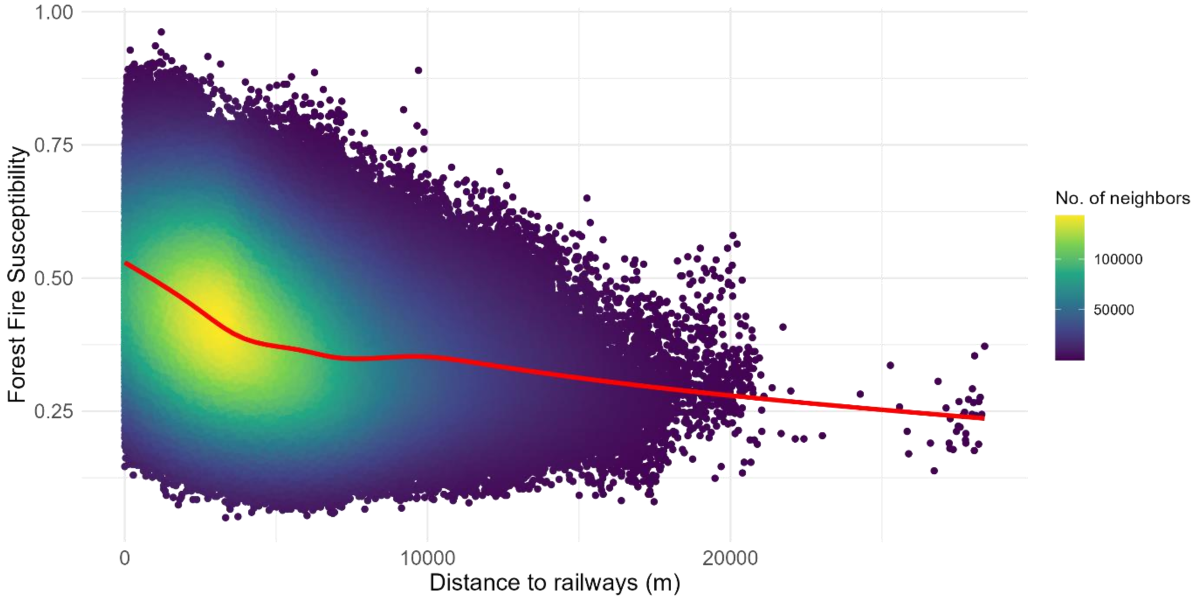


Figure S 9. Partial dependence plot for the three most important predictors and FFS. Similarly to Fig. S 7 and S 8, a subset of 100,000 pixels was extracted from each prediction (2016, 2022, 2081-2100 under SSP3-7.0 and SSP5-8.5) to compute the partial dependence plots.

The partial dependence plots of the three most important predictors and the related FFS (Fig. S 9) show the relation between the parameter and the FFS. With an increasing distance of up to ~2500 m from urban settlements, an increasing distance to railways, and an increasing percentage of broadleaf trees, FFS decreases.

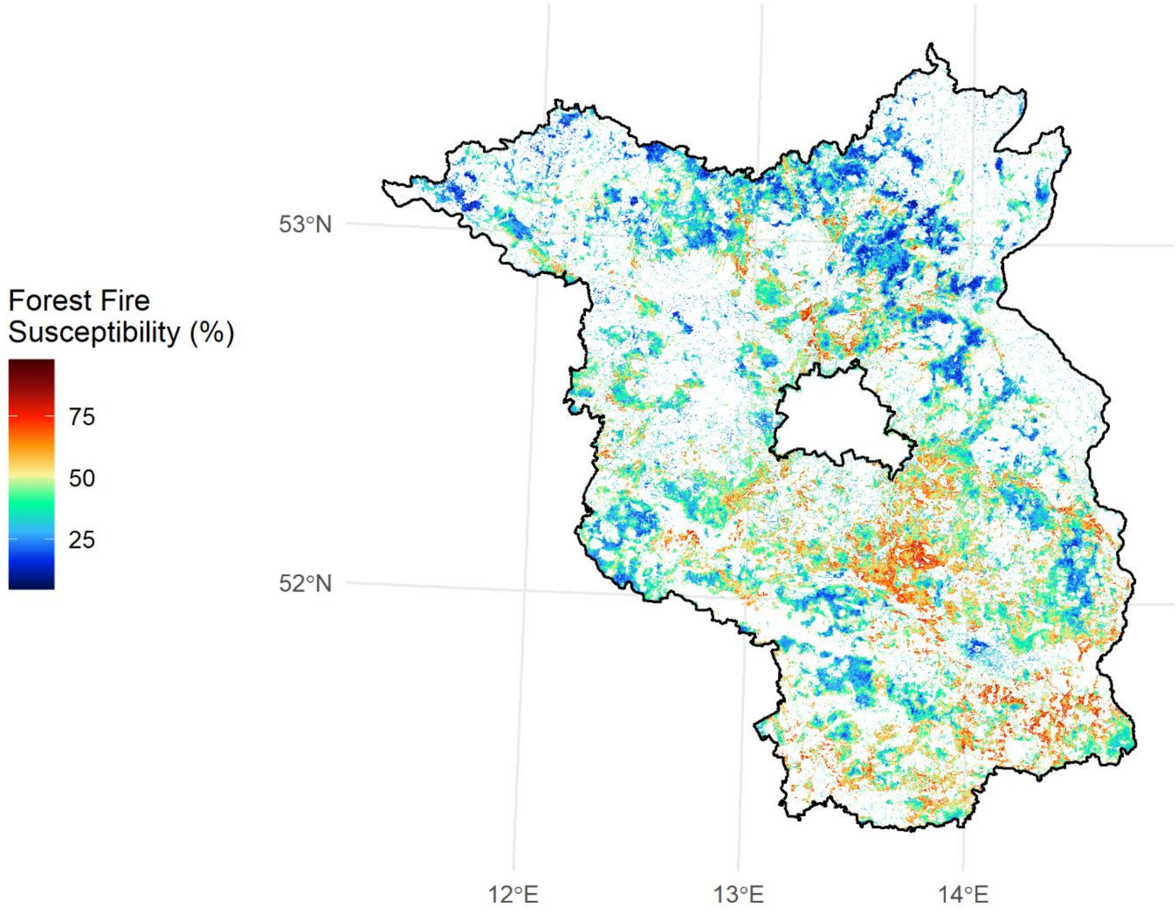


Figure S 10. Predicted forest fire susceptibility in June 2081-2100 (SSP3-7.0) excluding projected land cover data. Border layer © 2018-2022 GADM.

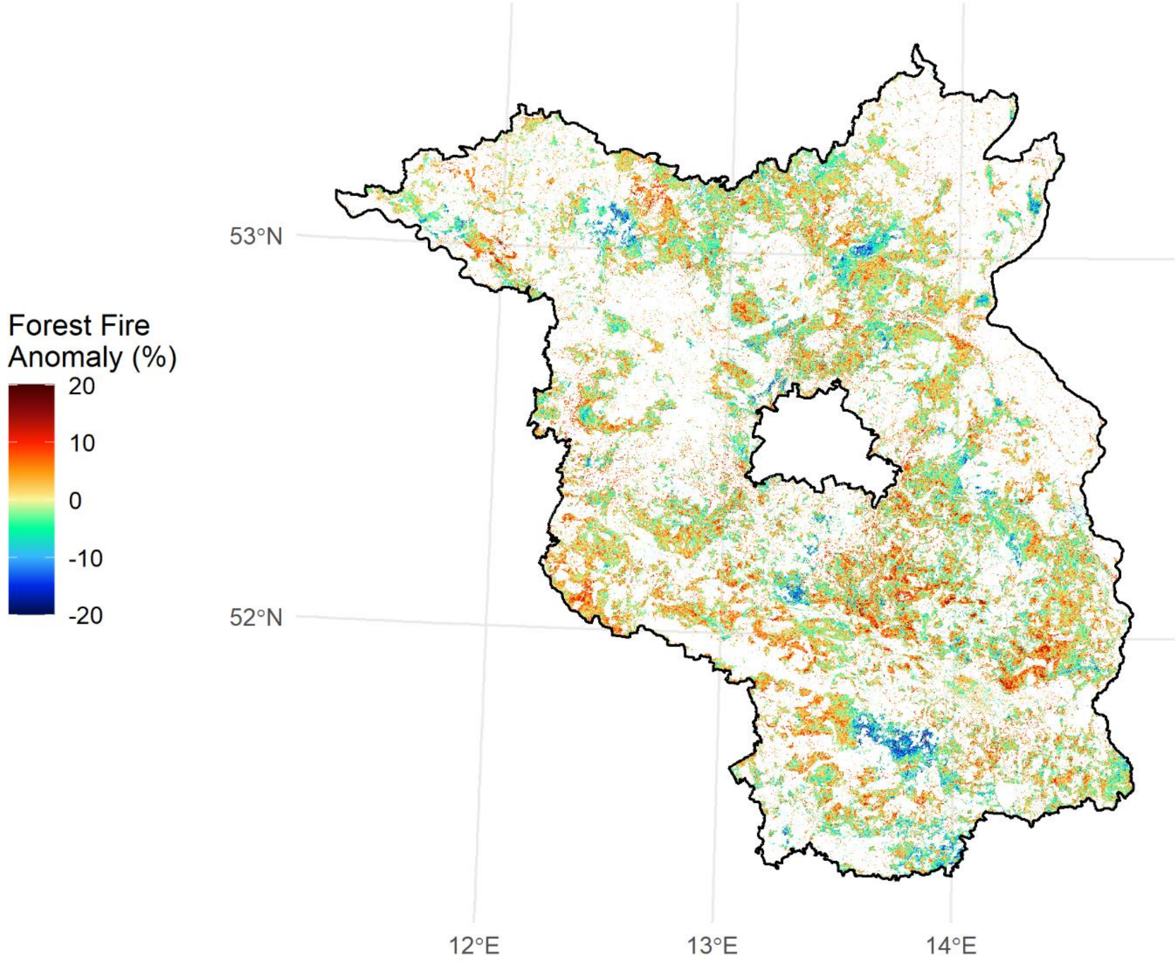


Figure S 11. Forest fire anomaly in June 2081-2100 (SSP3-7.0) excluding projected land cover data compared to the reference scenario of June 2016. Border layer © 2018-2022 GADM.

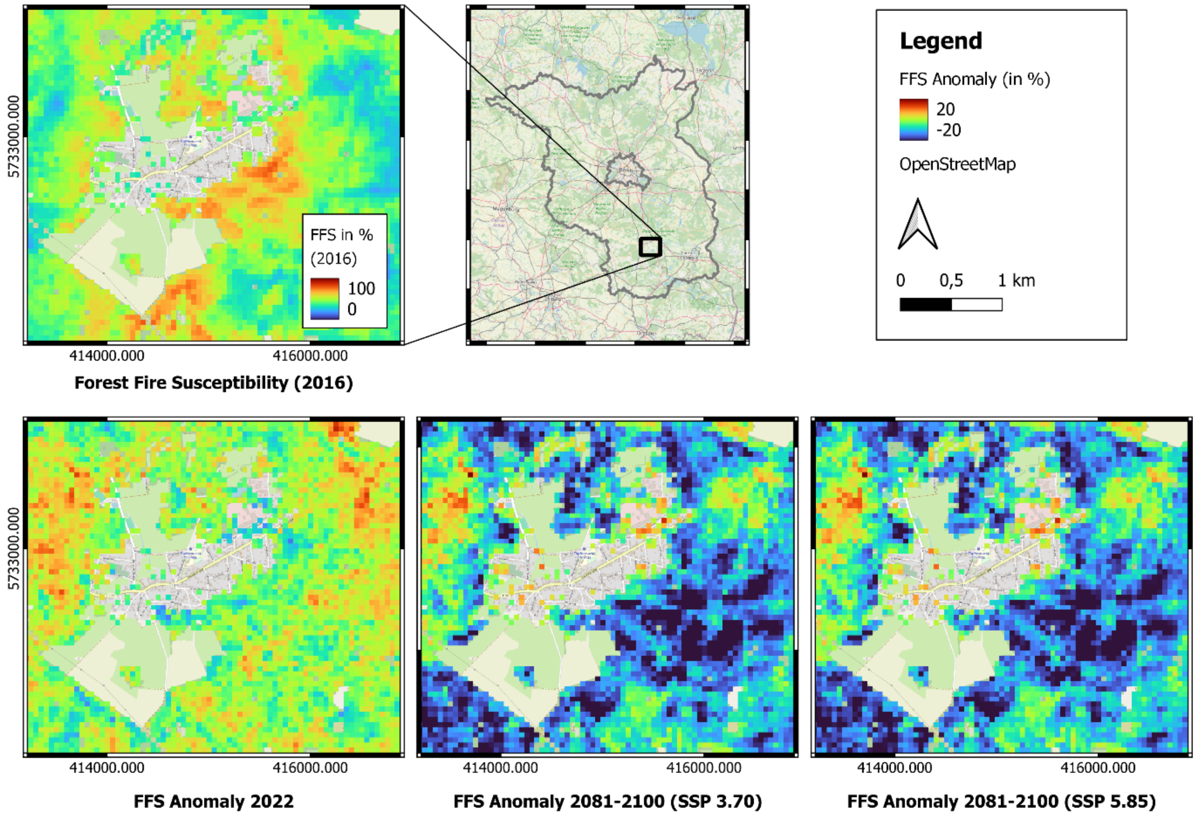


Figure S 12. Detailed maps of FFS anomalies in the municipality of Medewitz (Brandenburg). Base Map © OpenStreetMap contributors 2024. The future scenarios were computed excluding projected land cover data. Distributed under the Open Data Commons Open Database License (ODbL) v1.0, Border layer © 2018-2022 GADM.

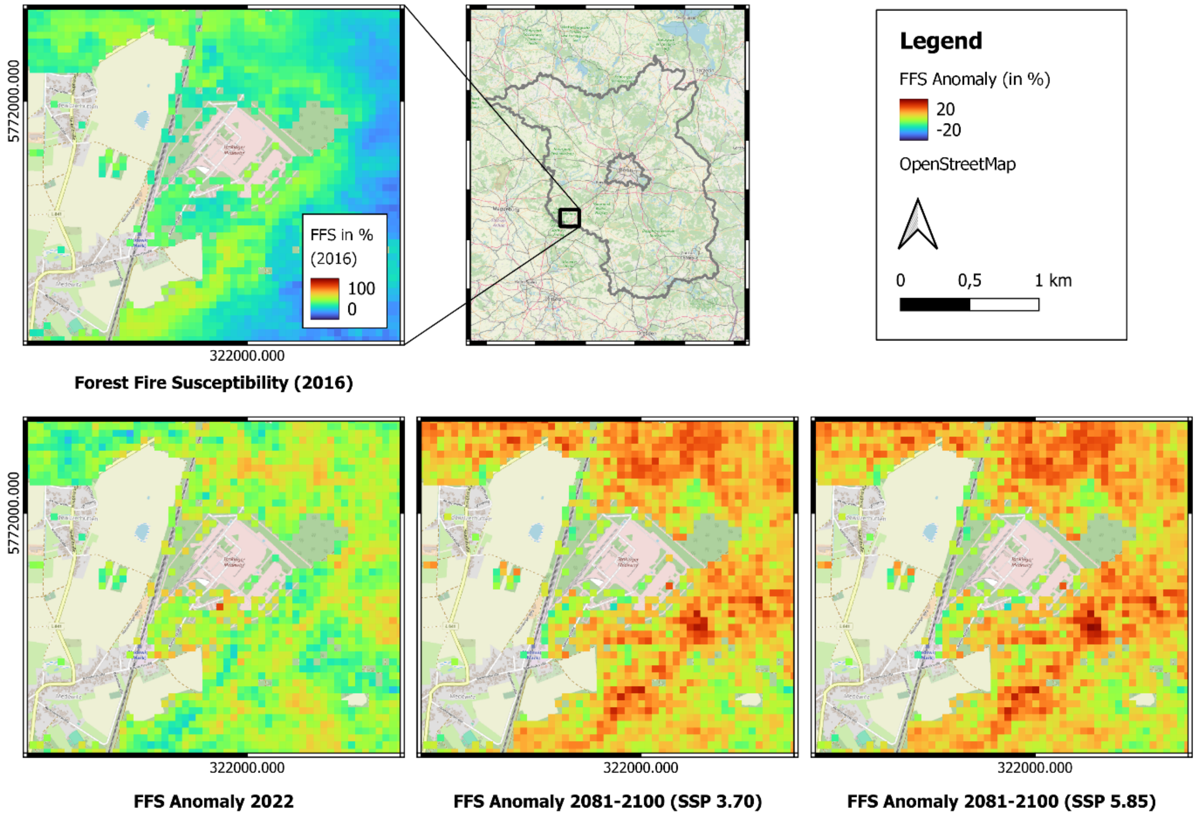


Figure S 13. Detailed maps of FFS anomalies in the municipality of Crinitz (Brandenburg). The future scenarios were computed excluding projected land cover data. Base Map © OpenStreetMap contributors 2024. Distributed under the Open Data Commons Open Database License (ODbL) v1.0, Border layer © 2018-2022 GADM.

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

	Minimum	1st Quartile	Median	Mean	3rd 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	$Recall = \frac{TP}{TP + FN}$
$\boldsymbol{F_\beta}$-Score	$F_\beta = (1 + \beta^2) * \frac{\text{Precision} * \text{Recall}}{(\beta^2 * \text{Precision}) + \text{Recall}}$

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	∑
fire	487	187	674
non_fire	194	520	714
∑	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.*

Table S 7. Overview of the scenario's key variables used for the analysis of FFS in Brandenburg.

SSP	Time period	GCM	Land cover data	Mean air temperature *(June 2081-2100)* (°C)	Mean precipitation sum *(June 2081-2100)* (mm)
3-7.0	June 2081-2100	MPI-ESM-1-2-HR (Gutjahr et al. 2019)	"Current" land cover data (OpenStreetMap Contributors, 2023)	19.1	57.6
5-8.5				20.4	53.7
5-8.5 *			Future land cover data (2050) (Esri Environment, 2021)	20.4	53.7