



# Modelling current and future forest fire susceptibility in north-east Germany

Katharina H. Horn<sup>1</sup>, Stenka Vulova<sup>1</sup>, Hanyu Li<sup>1</sup>, Birgit Kleinschmit<sup>1</sup>

<sup>1</sup> Geoinformation in Environmental Planning Lab, Technical University of Berlin, Germany | 13<sup>th</sup> June, 2024

## 1 Introduction

Preventing and fighting forest fires has been a constant challenge in Germany in recent decades. Climate change and related drought events, paired with anthropogenic activities, have substantially magnified the intensity and frequency of forest fires. It is crucial to identify the conditions that cause the emergence and spread of forest fires to improve prevention and management. In this study, we use Random Forest (RF) machine learning algorithm to model current and future forest fire susceptibility (FFS) in the federal state of Brandenburg (Germany) at a spatial resolution of 50 metres for current conditions (2014-2022) and future scenarios (2081-2100).

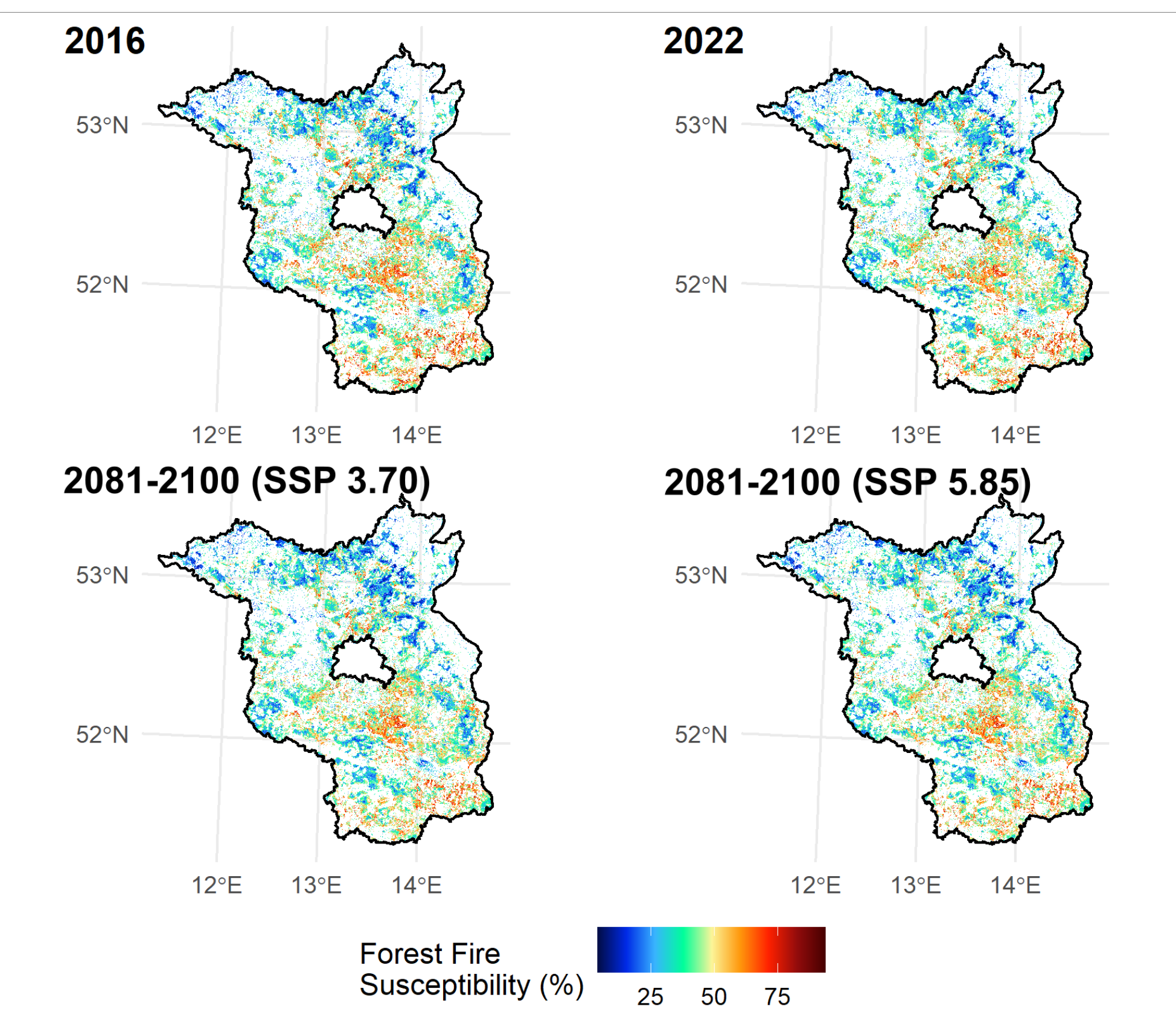


Figure 1. Forest fire susceptibility in Brandenburg (Germany) under current and future scenarios. <sup>1</sup>

## 2 Data

- Predictor variables for modelling: topography, climate, soil, vegetation, anthropogenic influences, land use and land cover
- Forest fire data provided by the Lower Forestry Authority of the State of Brandenburg (2023) [1]
- Selected scenarios:
  - a) Current scenarios: June 2016, June 2022
  - b) Future scenarios: June 2081-2100 under SSP 3.70 and SSP 5.85

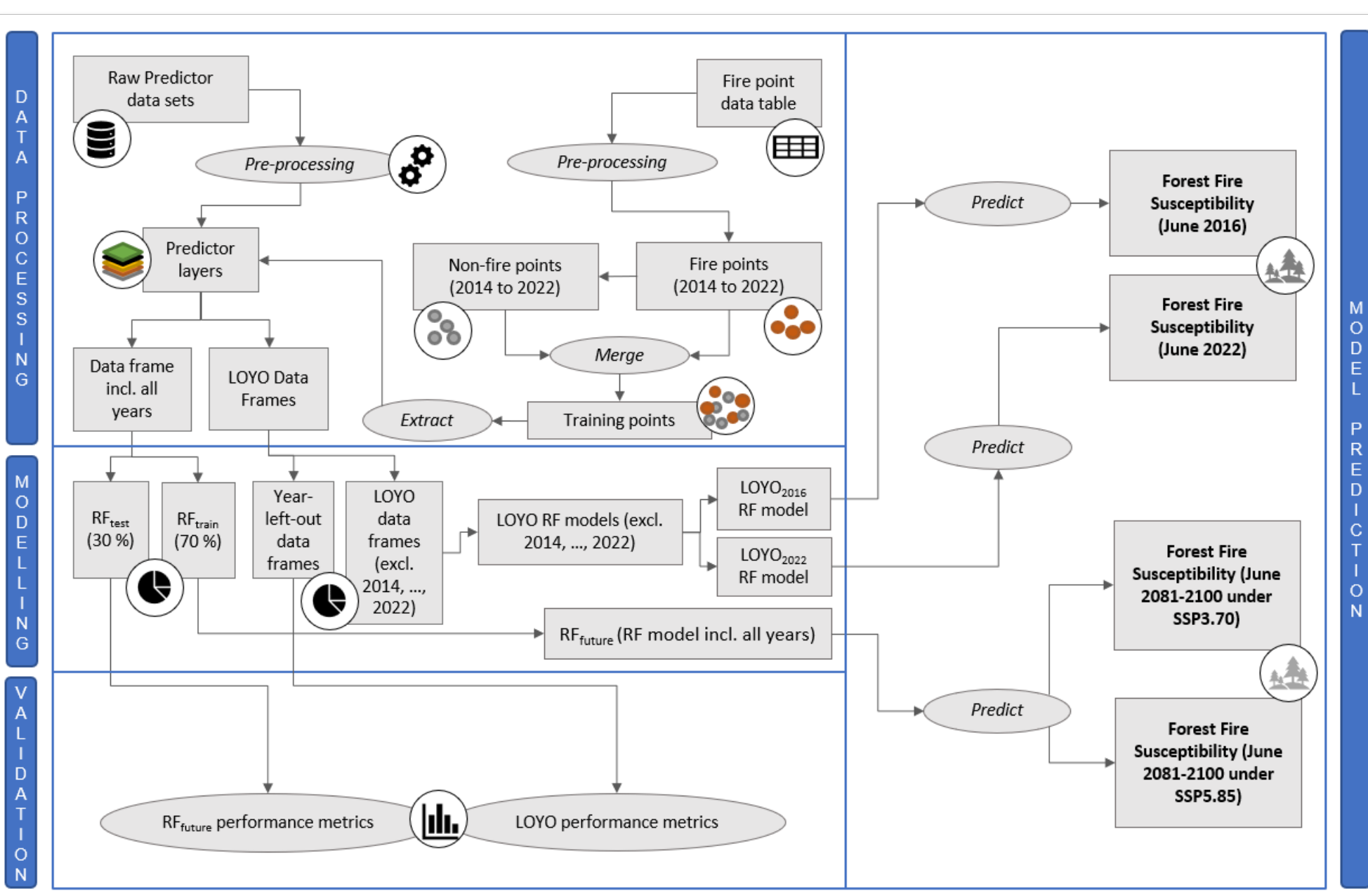


Figure 2. Workflow showing the main input data and methodological steps.

## 3 Methods

- Random Forest (RF) machine learning algorithm to model forest fire susceptibility
- Available data for modelling: 2014 to 2022
- RF<sub>future</sub> model to model future scenarios
- RF<sub>2016</sub> and RF<sub>2022</sub> model to model current scenarios

### Data split for model training

- 70% training, 30% testing for future scenario modelling using entire dataset
- Leave-one-year-out (LOYO) modelling to model current scenarios (2016 & 2022)

## 4 Results

### Model results

- Overview of the validation metrics

	Accuracy	Kappa	Precision	Recall	F1-Score	AUC
RF <sub>test</sub>	0.718	0.435	0.712	0.714	0.713	0.718
LOYO CV	0.695	0.388	0.702	0.654	0.676	0.694

### Variable importance

- Most important predictors: distance to urban settlements, percentage of broadleaf forest, and distance to railways (Fig. 3)

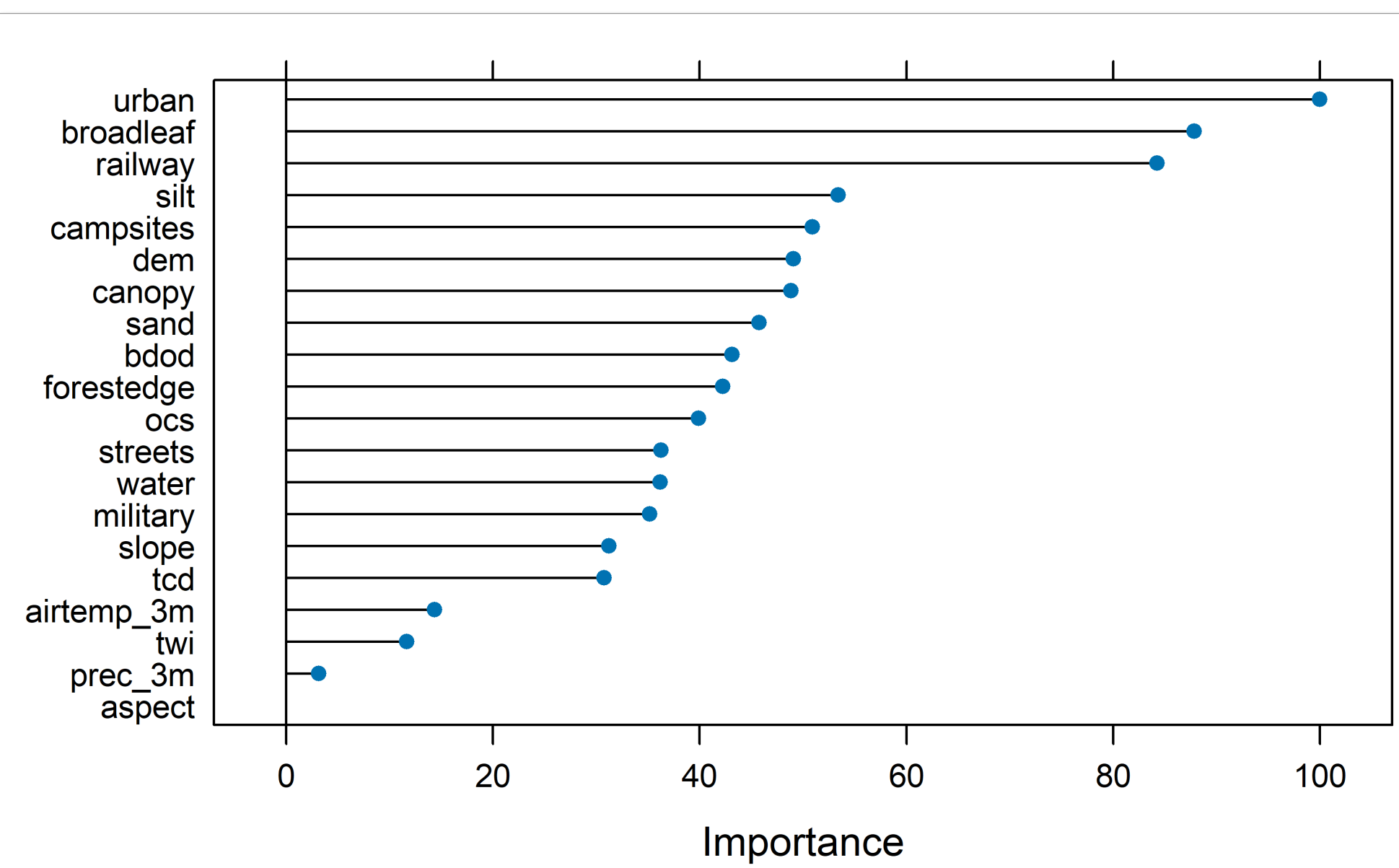


Figure 3. Variable importance of the different predictors based on the RF<sub>future</sub> model.

### Forest fire susceptibility (FFS)

- High FFS in the southern part of Brandenburg (Fig. 1)
- Low FFS in the northern part of Brandenburg (Fig. 1)
- FFS anomalies show negative values in southern part of Brandenburg in the future and positive values in the southeast compared to reference scenario 2016 (Fig. 6)

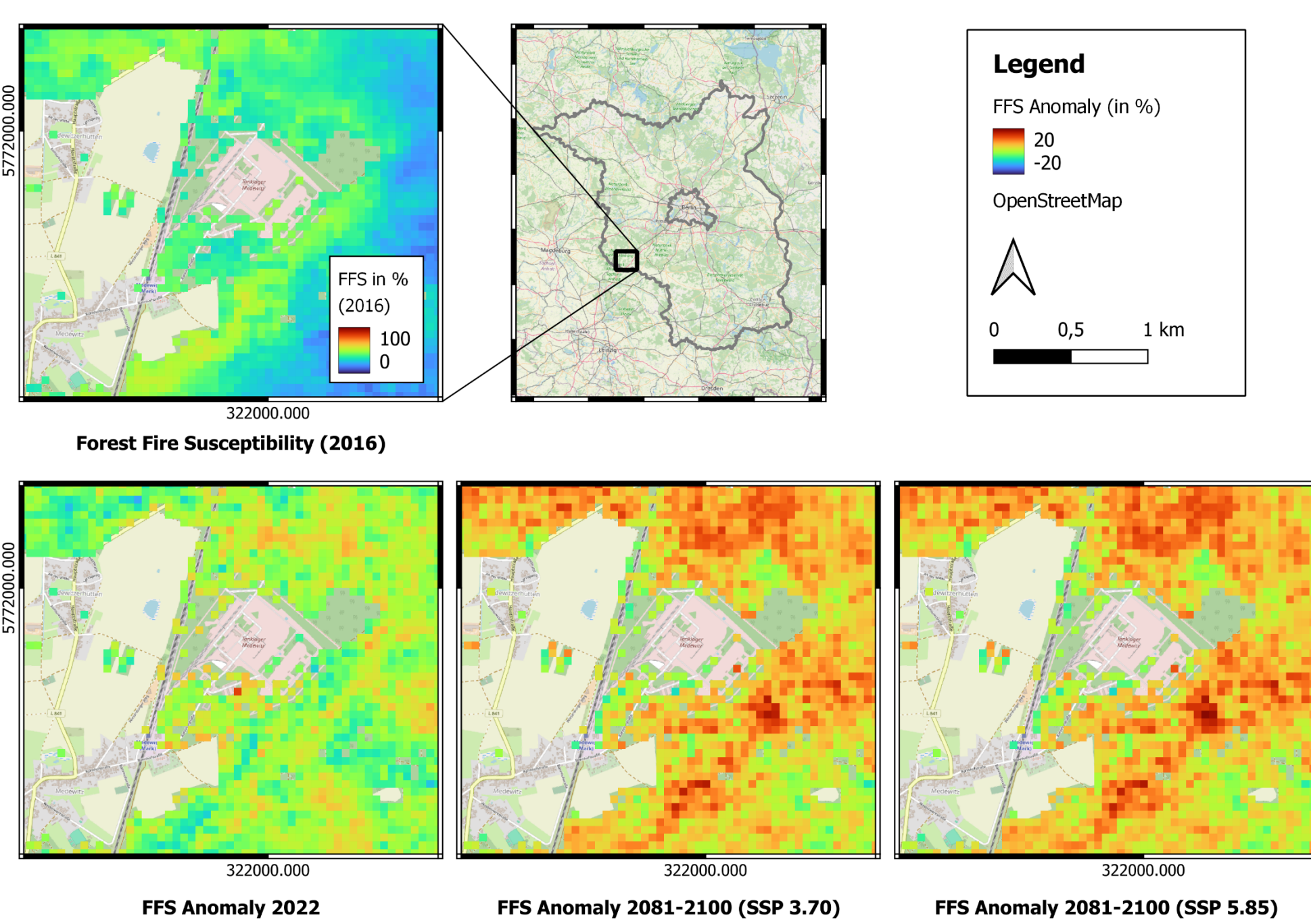


Figure 4. Detailed maps of future FFS increase in the municipality of Medewitz (Brandenburg). <sup>1,2</sup>

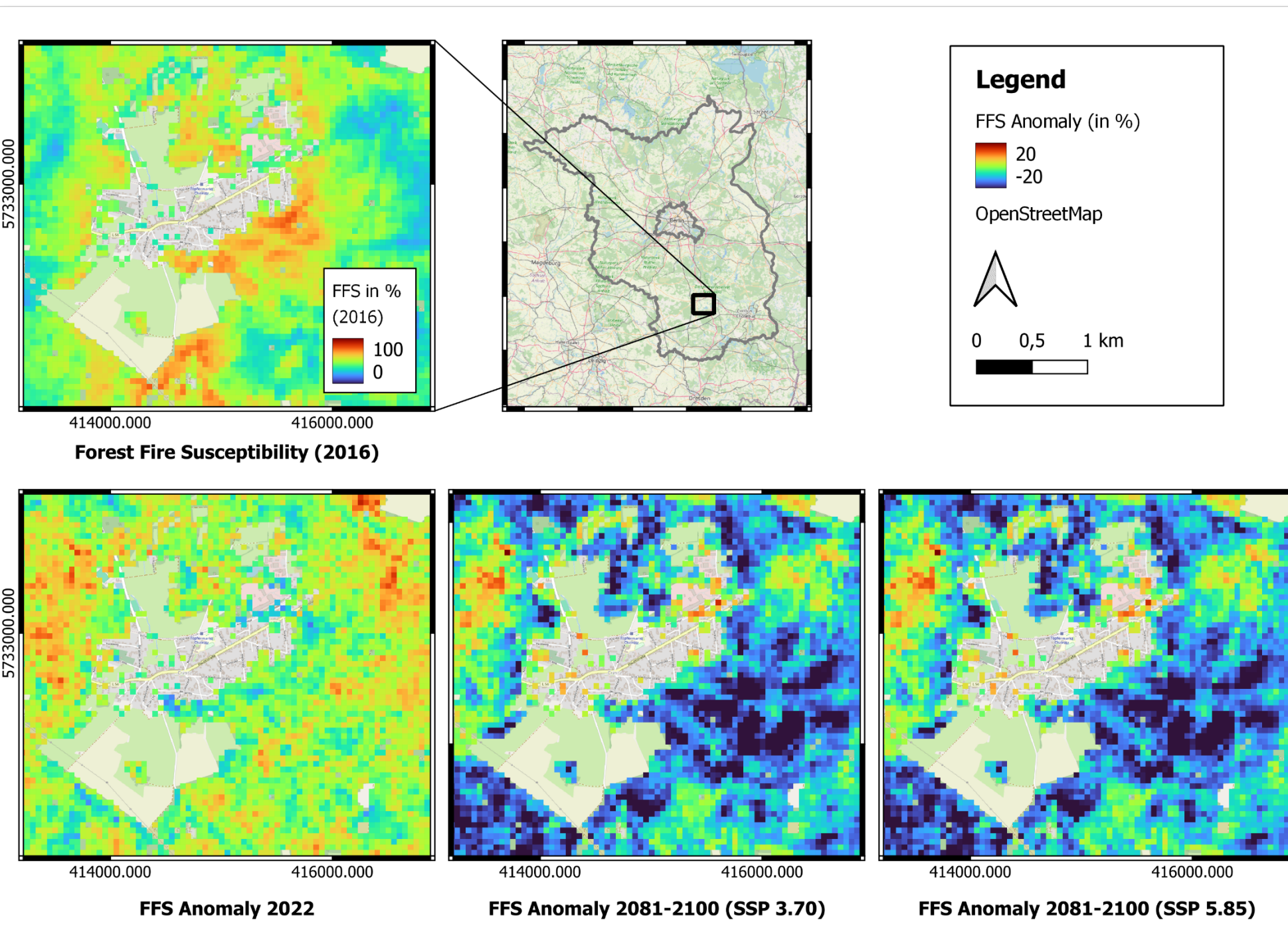
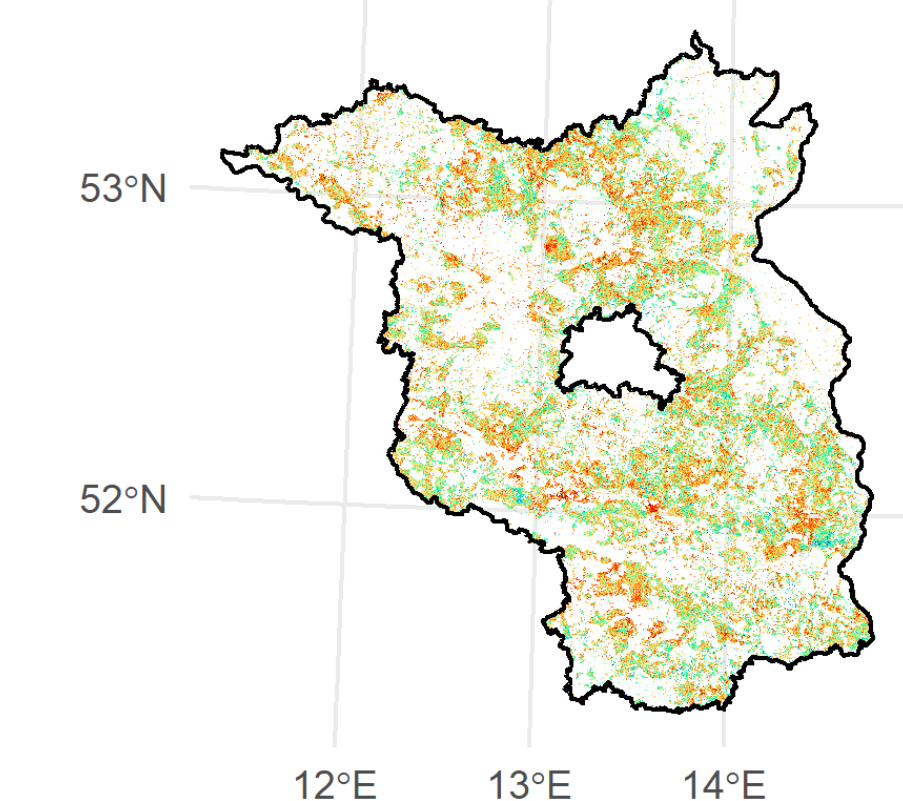


Figure 5. Detailed maps of future FFS decrease in the municipality of Crinitz (Brandenburg). <sup>1,2</sup>

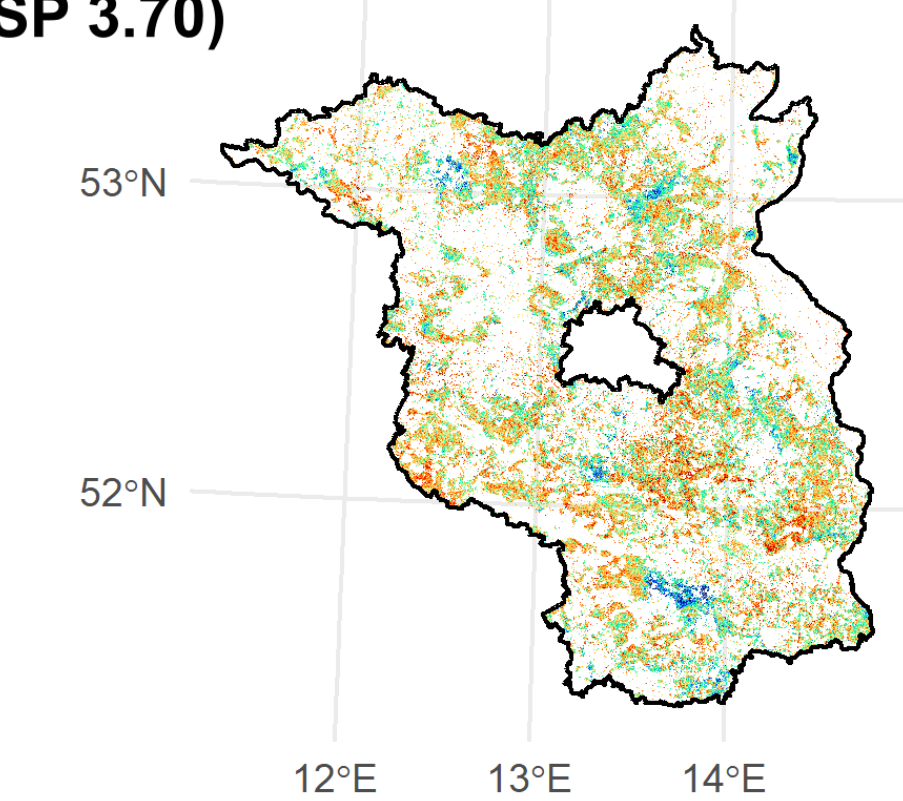
<sup>1</sup> Border layer © 2018-2022 GADM

<sup>2</sup> Base Map © OpenStreetMap contributors 2024. Distributed under the Open Data Commons Open Database License (ODbL) v1.0

## 2022



## 2081-2100 (SSP 3.70)



## 2081-2100 (SSP 5.85)

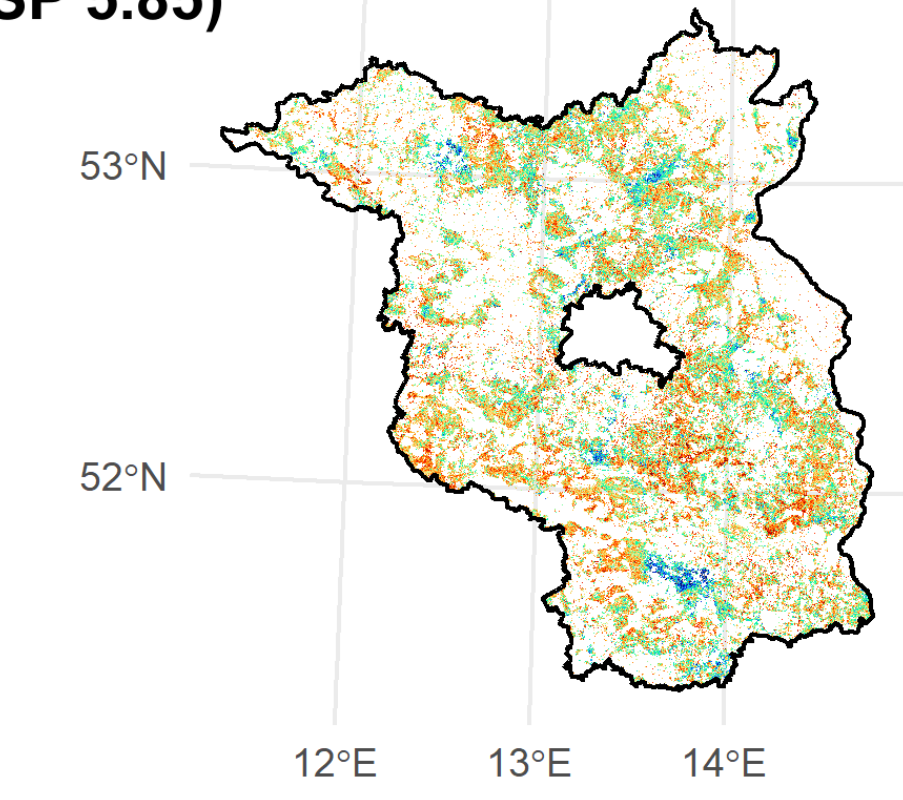


Figure 6. FFS anomalies in Brandenburg (Germany) compared to the reference scenario of June 2016. <sup>1</sup>

## 5 Discussion

The results reflect that climatic variables did not have a significant influence on the model performance (Fig. 3) due to low geospatial variation of meteorological data. This may differ when analyzing FFS on an (inter-)national scale [2,3,4]. In contrast, anthropogenic parameters appear to be more significant on a regional scale. The statistics of causes of forest fire emergence support this, highlighting that most forest fires in Brandenburg emerged from human negligence or malicious arson [1, also see 2,5].

## 6 Strategies for forest fire management

- Growth of mixed forests instead of monocultural pine forests
- Enhanced protection measures in forests close to urban settlements and forest edges
- transnational forest fire prevention strategies

## 7 Conclusion

This study predicted FFS on a regional scale under different scenarios using RF. Future FFS is expected to increase compared to the 2016 reference scenario. Extreme events such as droughts can significantly intensify FFS, underlined by the highest mean FFS value in 2022. The results can serve forest managers and environmental planners in the prevention of forest fires in the region.

## Acknowledgements

This research is funded by the Einstein Research Unit 'Climate and Water under Change' (CliWaC) from the Einstein Foundation Berlin (ERU-2020-609).

## References

- [1] Lower Forestry Authority of the State of Brandenburg. (2023). Waldbranddaten der Jahre 2010 bis 2022 [Data].
- [2] Busico, G., Giuditta, E., Kazakis, N., & Colombani, N. (2019). A Hybrid GIS and AHP Approach for Modelling Actual and Future Forest Fire Risk Under Climate Change Accounting Water Resources Attenuation Role. Sustainability, 11(24), 7166. <https://doi.org/10.3390/su11247166>
- [3] He, W., Shirowzhan, S., & Pettit, C. J. (2022). Gis and Machine Learning for Analysing Influencing Factors of Bushfires Using 40-Year Spatio-Temporal Bushfire Data. ISPRS International Journal of Geo-Information, 11(6), 336. <https://doi.org/10.3390/ijgi11060336>
- [4] Li, H., Vulova, S., Rocha, A. D., & Kleinschmit, B. (2024). Spatio-temporal feature attribution of European summer wildfires with Explainable Artificial Intelligence (XAI), Science of The Total Environment, 916, 170 330. <https://doi.org/10.1016/j.scitotenv.2024.170330>
- [5] Gnilek, A., & Sanders, T. (2021). Forest fire history in Germany (2001-2020). Advance online publication. <https://doi.org/10.3220/PB1636643380000>