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Reliability of fire danger forecasts for Czech agricultural and forestry landscapes

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Abstract

Background The increasing threat of fire caused by ongoing climate change requires accurate and timely prediction for the effective management of extreme fire situations. The limited research on the connection between fire danger metrics and the occurrence of wildfires in the forested and agricultural landscapes of the Czech Republic underscores the need to better understand how to properly quantify fire danger in the context of Central Europe. This study focused on assessing the accuracy of fire danger prediction with respect to the number of wildfires in different geographic regions of the Czech Republic and provided new insights into central European fire ecology.

Results We found that the fire season in the Czech Republic has two peaks, in spring and summer, with regional differences in the total number of wildfires. Analyses of fire danger via the Canadian Fire Weather Index (FWI) and Australian Forest Fire Danger Index (FFDI) for the years 2018–2022 revealed that the IFS numerical weather prediction model is the most suitable for conditions in the Czech Republic. A linear regression model showed a high predictive capability for the total number of wildfires in the Czech Republic, with an observed *R*-squared value of 0.81 and a mean absolute error (MAE) of 5.19 wildfires with a 95% confidence interval (CI) of 4.94–5.44. Additionally, the second model, which utilized a linear model with random effects to account for regional variability, had an *R*-squared value of 0.34 and an MAE of 1 wildfire (95% CI ± 3), indicating that the inclusion of regional correction coefficients (random effects) enhanced the prediction accuracy.

Conclusions This study provides key insights into fire danger prediction in relation to the number of wildfires. With this model, it is possible to predict how many wildfires may occur at specific values of the FWI and FFDI in individual regions (NUTS 3) of the Czech Republic. This information can be used for more effective readiness planning for human resources and fire equipment while also contributing to the enhancement of general knowledge in the field of fire science in the context of central Europe.

Keywords Czech Republic, Fire danger, FFDI, Fire occurrence, FWI, Number of wildfires, Prediction, Weather forecast

Resumen

Antecedentes La creciente amenaza de incendios de vegetación causados por el inminente cambio climático requiere de predicciones precisas en el tiempo para manejar efectivamente situaciones extremas causadas por incendios. Las limitadas investigaciones sobre la conexión entre las métricas del peligro de incendio y la ocurrencia de incendios en paisajes forestales y áreas agrícolas de la República Checa subrayan la necesidad de entender mejor cómo cuantificar apropiadamente el peligro de incendios en el contexto de Europa Central. Este estudio se enfocó en determinar

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la exactitud de la predicción del peligro de incendios con respecto al número de incendios en diferentes regiones geográficas de la República Checa y proveer de nuevas percepciones en la Ecología del Fuego del Centro de Europa.

Resultados Encontramos que la estación de fuegos en la República Checa tiene dos picos, en primavera y verano, con diferencias regionales en cuanto al número total de incendios. Los análisis del peligro de incendios a través del Índice de Peligro de Incendios Canadiense (FWI) y del Índice Australiano del Peligro de Incendios Forestales (FFDI) para los años 2018-2022 revelaron que el IFS, modelo de predicción numérica del tiempo meteorológico, es el más adecuado para las condiciones de la República Checa. Un modelo de regresión linear mostró una alta capacidad de predicción para el número total de incendios en la República Checa, con un R^2 observado de 0.81 y un error medio absoluto de (MAE) de 5,19 incendios con un intervalo de confianza del 95% (CI), de entre 4,94 y 5,44. Adicionalmente, el segundo modelo, que utilizó un modelo linear con efectos al azar para tener en cuenta la variabilidad regional, tuvo un R^2 de 0,34 y un MAE de 1 incendio (95%, CI ±3), lo que indica que la inclusión de coeficientes de correlación regionales (de efectos al azar) aumentó la exactitud de la predicción.

Conclusiones Este estudio provee de percepciones clave para la predicción del peligro de incendios en relación con número de incendios. Con este modelo, es posible predecir cuántos incendios pueden ocurrir con valores específicos del FWI y del FFDI en regiones individuales (NUTS 3) de la República Checa. Esta información puede ser usada para un planeamiento rápido más efectivo en cuanto a recursos humanos y equipamiento contra el fuego, mientras se contribuye al aumento del conocimiento general en el campo de la ciencia del fuego en el contexto de Europa Central.

Background

The issue of fire risk has become increasingly relevant worldwide, as climate change and other factors significantly affect the extent and intensity of forest and agricultural wildfires (e.g., Flannigan et al. 2009; Wasserman et al. 2023). Fire risk has become a key concern for environmental experts, firefighters, scientists, and decision-making authorities, as its proper understanding, assessment, and prediction are crucial for the prevention and management of catastrophic events. Wildfires have a significant impact on society and the environment (Kala 2023), not only in terms of immediate damage to property and endangerment of human lives but also in terms of long-term economic and ecological consequences. While some wildfires, such as those involving controlled burning, can be beneficial for ecosystems and, in certain ecosystems, play a crucial role in maintaining biodiversity and promoting the spread of specific plant species (e.g., Pausas et al. 2019), uncontrolled wildfires are associated with potential loss of biodiversity, loss of forest cover, and soil degradation. Therefore, forecasting and preventing wildfires are essential for environmental protection and sustainability, especially in areas where controlled burning is not a part of regular landscape management (e.g., Chu et al. 2023).

The Czech Republic, situated in Central Europe, has not yet experienced extensive wildfires such as those in other parts of the world (e.g., the USA, Canada, Siberia, or Australia). However, according to current studies (Trnka et al. 2020a, 2021; Možný et al. 2021; Hetzer et al. 2024), the risk of wildfires in this area is likely to increase, as evidenced by the growing number of wildfires in agricultural and forest landscapes (Ministry of the Interior - Directorate General of the Fire Rescue Service of the Czech Republic 2021; San-Miguel-Ayanz et al. 2022). In 2022, the Czech Republic faced its largest recorded wildfire in history, with over 1100 hectares burned in a national park (Kudláčková et al. 2023). Given these statistics and historical data, it is evident that climate change plays a role in increasing fire risk.

Trends in extreme temperatures and circulation types in the Czech Republic from 1961 to 2020 show a significant increase in the frequency of summer heatwaves, tropical days, and warm anomalies, alongside a decline in frost days and cold anomalies (Zahradníček et al. 2022). These changes are closely associated with a rising prevalence of anticyclonic circulation patterns, which favor warm and dry conditions, particularly in summer, while cyclonic patterns have become less frequent (Brázdil et al. 2022). Additionally, long-term temperature trends confirm a statistically significant warming, with the most pronounced increases occurring in summer months and in lower-altitude regions. This warming has been particularly evident since the 1990s, with the last decade (2011–2019) experiencing an accelerated rise in cumulative temperature sums and an increase in both maximum and minimum daily temperatures (Zahradníček et al. 2020). Similarly, changes in precipitation patterns reveal a decline in spring precipitation and an increase in summer precipitation, leading to a seasonal redistribution of moisture availability (Brázdil et al. 2021).

Understanding and predicting fire danger has become crucial for mitigating damage and saving human lives. Over the past century, widely used fire indices such as the Canadian Fire Weather Index (FWI, Van Wagner 1987) and the Australian Forest Fire Danger Index

(FFDI, McArthur 1967) have been developed to forecast fire danger. The European Forest Fire Information System (EFFIS) predicts fire danger via the FWI, which has been adapted to European conditions (EFFIS n.d.). In the Czech Republic, the Czech Hydrometeorological Institute (CHMI) provides a forecasting service that uses a simplified Fire Danger Index (Brázdil et al. 2015; Možný et al. 2021), which is part of the Integrated Warning Service System (SIVS). Since 2020, detailed information has been provided for both the SIVS service and the general public through the fire danger prediction system firerisk.cz (hereafter FireRisk), which has operated as a collaborative effort of the Global Change Research Institute of the Czech Academy of Sciences, Institute of Forest Ecosystem Research, Mendel University in Brno, and CHMI.

FireRisk offers detailed information on the environmental conditions that are important from the perspective of fire ignition and spread. The main layers of information displayed on FireRisk include fire danger prediction (based on a combination of FWI and FFDI), FWI and FFDI, prediction of fire ignition risk (based on 10-h dead fuel moisture content; Bradshaw et al. (1984); Cohen et al. (1985); Fire Weather Indices WIKI (n.d.)), and measurements of 10-h dead fuel moisture content (DFM10H) from a network of more than 100 stations. The main layers are also supplemented by additional layers, including temperature, wind speed, atmospheric stability, and others. In addition to the measurements of DFM10H, all other layers are based on weather forecasts, which are subject to significant uncertainty; therefore, relying solely on the outputs of one model is not practical (as in Krishnamurti et al. (2000)). FireRisk uses five numerical weather prediction (NWP) models (European Centre for Medium-Range Weather Forecasts Integrated Forecast System (IFS), American Global Forecasting System (GFS), Canadian Global Earth Model (CMC), French ARPEGE, and British Unified Model Global (GUM); more detailed information about the models is provided in Stepanek et al. (2018)). Combining multiple models with different resolutions and forecast lead time provides the opportunity to significantly reduce prediction errors while also providing the necessary level of uncertainty accompanying the forecast, which is a valuable tool for users. The portal provides forecasts for up to 9 days, which is crucial for crisis management planning. FireRisk operates year-round, and all main layers, including the FWI, are computed also during the winter months.

Each fire index has its own characteristics, and since they were not designed for the territory of Europe or the Czech Republic, predictions may vary. Uncertainty is also introduced by NWP models, which have different resolutions, forecast lead time, or other internal numerical computational models (e.g., Stepanek et al. 2018). Comparative analyses of fire indices and fire danger forecasts in the Czech Republic have been conducted by researchers such as Jurečka et al. (2019) and Trnka et al. (2020a), and this study was built upon and significantly expands upon these publications. Previous fire-related studies from the region have focused primarily on comparisons of fire indices and fire danger predictions with measured data (e.g., Jurečka et al. 2019 or Trnka et al. 2020a). Our study builds on these findings and significantly expands them by comparing fire danger to observed wildfires and developing a prediction model for estimating the number of wildfires in advance. This approach opens up opportunities for large improvements and innovations in fire preparedness and prevention in the Czech Republic.

The main goal of this study is to determine whether and with what reliability we can predict the number of wildfires on the basis of fire danger forecasts for agricultural and forestry landscapes in the Czech Republic. To achieve this goal, we addressed the following objectives:

(i) To investigate the fire danger from 2018 to 2022
(ii) To evaluate the accuracy of fire danger prediction forecasts derived from five selected NWP models with fire danger calculated from observed weather station data
(iii) To analyze the number of wildfires in agricultural and forest landscapes
(iv) To explore how the number of wildfires relates to fire danger indices and other weather variables using statistical modeling

The results of this study will lead to a better understanding of the relationships among wildfire occurrence, fire danger, and other factors, which can improve the precision of wildfire occurrence predictions, ultimately significantly enhancing the utility and effectiveness of FireRisk.

Methods

Study area

The total area of the Czech Republic is approximately 78 871 km^2 and is characterized by diverse environments, including mountain ranges, plains, and river valleys. According to the Czech Statistical Office (Český statistický úřad 2021), at the beginning of 2021, the proportion of forests to the total area of the Czech Republic was approximately 34%, with agricultural land accounting for 32%. The Czech landscape is traditionally associated with agricultural activity, with the majority of arable land being used for cereal grains (approximately 54%), fodder crops (21%), and oilseed (15%). Grazing land and other landscape elements also constitute a significant part of the area.

In recent years, an increasing trend in the occurrence of wildfires has been observed in the Czech Republic (Ministry of the Interior - Directorate General of the Fire Rescue Service of the Czech Republic 2021), primarily due to the influence of climate change (Trnka et al. 2021; Možný et al. 2021). More extreme temperatures, drought, and changes in precipitation patterns may create conditions conducive to fire ignition and rapid spread in vegetation that is drier and more susceptible to burning. According to the San-Miguel-Ayanz et al. (2024), during the period 2008–2010, an average of 572 forest wildfires per year, with a total burnt area of 156 hectares per year, was recorded. In contrast, during the period 2018–2020, these averages increased to 2025 forest wildfires per year, covering a total area of 499 hectares annually. Notably, the largest wildfire recorded in history occurred in 2022, when more than 1100 hectares of Bohemian Switzerland National Park burned (Kudláčková et al. 2023). Specifically, during the analyzed period, it was determined that 50% of forest wildfires were due to negligence, while 36% were directly caused by human activities (San-Miguel-Ayanz et al. 2024).

Input data

To determine the accuracy of the forecasts, we compared the values calculated from the actual measurements from meteorological stations in the Czech Republic with the forecasted values from the NWP models. Specifically, we focused on comparing fire indices, meteorological elements, and other variables that were calculated both from actual meteorological data (further referred as observed data, see below) and from the NWP models (further referred as NWP data, see below). These comparisons allowed us to evaluate the differences between the forecasted and observed values, which is crucial for understanding the reliability and accuracy of the NWP models in predicting fire danger.

We obtained observed meteorological data for input calculations from the weather station network of the CHMI from 2018 to 2022. Daily data were interpolated across the entire Czech Republic using a regression kriging method that incorporates geographic coordinates, elevation, and other terrain characteristics as predictors, resulting in a 500 m resolution grid. To ensure that station measurements are accurately reflected in the final maps, an additional layer of interpolated residuals (computed from station locations) was incorporated into the model. All input data were transformed into raster layers with the same projection and spatial resolution to facilitate subsequent data processing and analysis. From these data, we obtained the FWI and its components (Fine Fuel Moisture Code (FFMC; the moisture content in the surface litter and other fine fuels, which influences the ease with which these materials can ignite; range 0–101 (cured)), Duff Moisture Code (DMC; the moisture content in loosely compacted organic layers, known as duff, and is important for understanding how deeply a fire can burn; range 0–∞, 150 rarely seen), Drought Code (DC; reflects the moisture content in deep, compact organic layers and is used to assess the long-term drying effects on these layers; range 0–∞, 1000 rarely seen), Initial Spread Index (ISI; combines the effects of wind speed and FFMC to estimate the potential rate at which a fire could spread; range 0–∞), and Build-Up Index (BUI; integrates DMC and DC to provide an estimate of the total amount of fuel available for combustion; range 0–∞)) according to Van Wagner (1987), FFDI (McArthur 1967), dead fuel moisture 10-h (DFM10H; according to Bradshaw et al. (1984), Cohen et al. (1985), and Fire Weather Indices WIKI (n.d.)) from the FireRisk database (www.firerisk.cz). From the SoilClim model (Hlavinka et al. 2011; Trnka et al. 2020b), we used data on the Relative Soil Moisture Content 0–10 cm (RSMC; in %; where 0 is the wilting point, 100 is the field capacity), Drought Intensity 0–40 cm (DI; range 0 (extreme drought) to 6 (no drought); indicating the severity of drought conditions), Soil Moisture Deficit 0–40 cm (SMD; in mm, deviation of the soil moisture content from 1961 to 2010), and Drought Factor (DF; as a input component used in the FFDI, which represents the dryness of the fuel and soil, as described McArthur 1967). Hereafter, we collectively refer to the above-mentioned meteorological variables and sub-components of fire danger indices in this study as “observed fire danger/weather variables” or “observed data/values.”

We computed forecasted variables (hereafter referred to as “NWP fire danger/weather variables” or “NWP data/values”) from five NWP models (IFS, GFS, CMC, ARPEGE, and GUM; more detailed in Stepanek et al. (2018)). The outputs of all the NWP models were computed from D0, i.e., the forecast on the current day, up to a X-day lead time. The IFS, GFS, and CMC models provide forecasts up to a 9-day lead time, whereas the GUM model provides data only up to a 6-day lead time, and the ARPEGE model provides data up to a 3-day lead time. For analyses, we used spatial daily data with a resolution of 500 × 500 m for the Czech Republic from 2018 to 2022.

We obtained the number of recorded wildfires during this period from the database of the Fire Rescue Service of the Czech Republic (FRS CR; Fire Rescue Service of the Czech Republic n.d.-b). Each wildfire in the dataset is represented as a single point location, with latitude and longitude coordinates recorded. The temporal resolution includes the exact day, month, and year of the fire occurrence; however, no further details on the ignition time are available. The accuracy of these records depends on the reporting methodology, and minor uncertainties may arise due to manual data entry, rounding errors, or limitations in the recording process. Additionally, the dataset provides only point locations of wildfires, without information on the burned area. To prepare the data for analysis, we intersected the wildfire locations with a land cover map to classify them into agricultural or forest landscapes. This spatial overlay allowed us to categorize wildfires based on their surrounding environment. Only wildfires occurring outside built-up areas were included.

We divided the data analysis into four categories on the basis of our previously defined objectives. We conducted the analyses using the Python programming language and R software. Data formatting and manipulation were conducted in Python pandas (McKinney 2010), and shapely library (Gillies et al. 2024) and the R package dplyr (Wickham et al. 2023). Plots were created using the ggplot2 (Wickham 2016) R package. We performed statistical analyses at a significance level of alpha = 0.05, which is described further in the upcoming sections. We carried out Geographic Information System (GIS) analyses via ArcGIS 10.6 software (ESRI, Redlands, CA, USA).

Data analysis

Investigation of observed fire danger and fire-related variables

The first step in the analysis of fire danger involved the summarization and exploratory analysis of relevant data on observed fire danger/weather variables. To provide a general overview of the input data for the selected area and timespan, we conducted exploratory data analysis and presented basic statistical measures (minimum, maximum, mean, SD, confidence intervals (CIs)) using data from all days within the selected period from 2018 to 2022. During this analysis, we also calculated the 25%, 50%, 75%, 90%, and 95% percentiles of the FWI to determine values for selected fire danger classes. These metrics were computed from the original data, i.e., from data for each cadastral area (i.e., for each municipality and surrounding land). This analysis, based on cadastral unit-level data, is presented in table.

We utilized geospatial layers in GEOTIFF format, with each file representing a specific day from 2018 to 2022. The analysis included data from all days of the year to provide a comprehensive overview of fire danger trends. Each spatial file and each element were averaged for the entire country and recorded in a table corresponding to the specific day. These values were then used for the calculation of basic statistical indicators (minimum, maximum, mean, value distribution, monthly distribution, etc.) and subsequently presented graphically. The Results section presents the average extent and patterns of values for the territory of the Czech Republic during the analyzed period of observed fire danger variables (Figs. 1, 2, and 3).

Evaluation of NWP fire danger forecasts

The second objective aimed to evaluate the accuracy of the FWI and FFDI forecasts from five selected NWP models by comparing them with the observed FWIs and FFDIs calculated from spatially interpolated meteorological station data. Mean daily values of FWI and FFDI during fire season (derived from a later analysis) for whole study area (Czech Republic) were analyzed for the period 2018–2022. We compared NWP data for each model and day up to a 9-day lead time (D0 to D9), except for models ARPEGE up to D3 and GUM up to D6. For each forecasted day and model, we compared the NWP values of the FWI and FFDI to observed FWI and FFDI values calculated from the station-measured data. We conducted a comparative analysis of the NWP models, focusing on revealing the impact of the lead time on the accuracy of the fire danger estimates.

We divided the 9-day forecasts of the NWP models into three time intervals (D7 to D9, D4 to D6, and D0 to D3) because of the different lead times of the NWP models. For each time interval and each model, we calculated the following metrics: absolute accuracy (measured by the mean absolute error (MAE)), variability in prediction accuracy (measured by the standard deviation (SD)), and forecasting tendency, indicating systematic overestimation/underestimation of predictions (measured by bias, the difference between the NWP-predicted and observed values). While MAE provides an overall measure of the prediction error magnitude, SD indicates the consistency of the model's prediction accuracy, and bias highlights systematic overestimation or underestimation tendencies.

The best NWP model is considered the one with the lowest values of the MAE and SD. In the context of applicability of this study in real life scenarios, overall model accuracy is prioritized over concerns of systematic over- or underestimation (bias). In the results, we emphasize different aspects of used metrics depending on the context of evaluation. For the best model, we conducted further accuracy analysis for each month of the fire season.

In relation to this analysis, we determined the parameters that influence the NWP FWI and FFDI prediction the most (i.e., "feature importance"). This analysis involved computing the Spearman correlation (Corder et al. 2014) coefficient (as the data do not follow a normal distribution) between the differences in either the FWI or FFDI from reality (observed data) and the differences in selected meteorological parameters (air temperature maximum (T_{max}), relative humidity

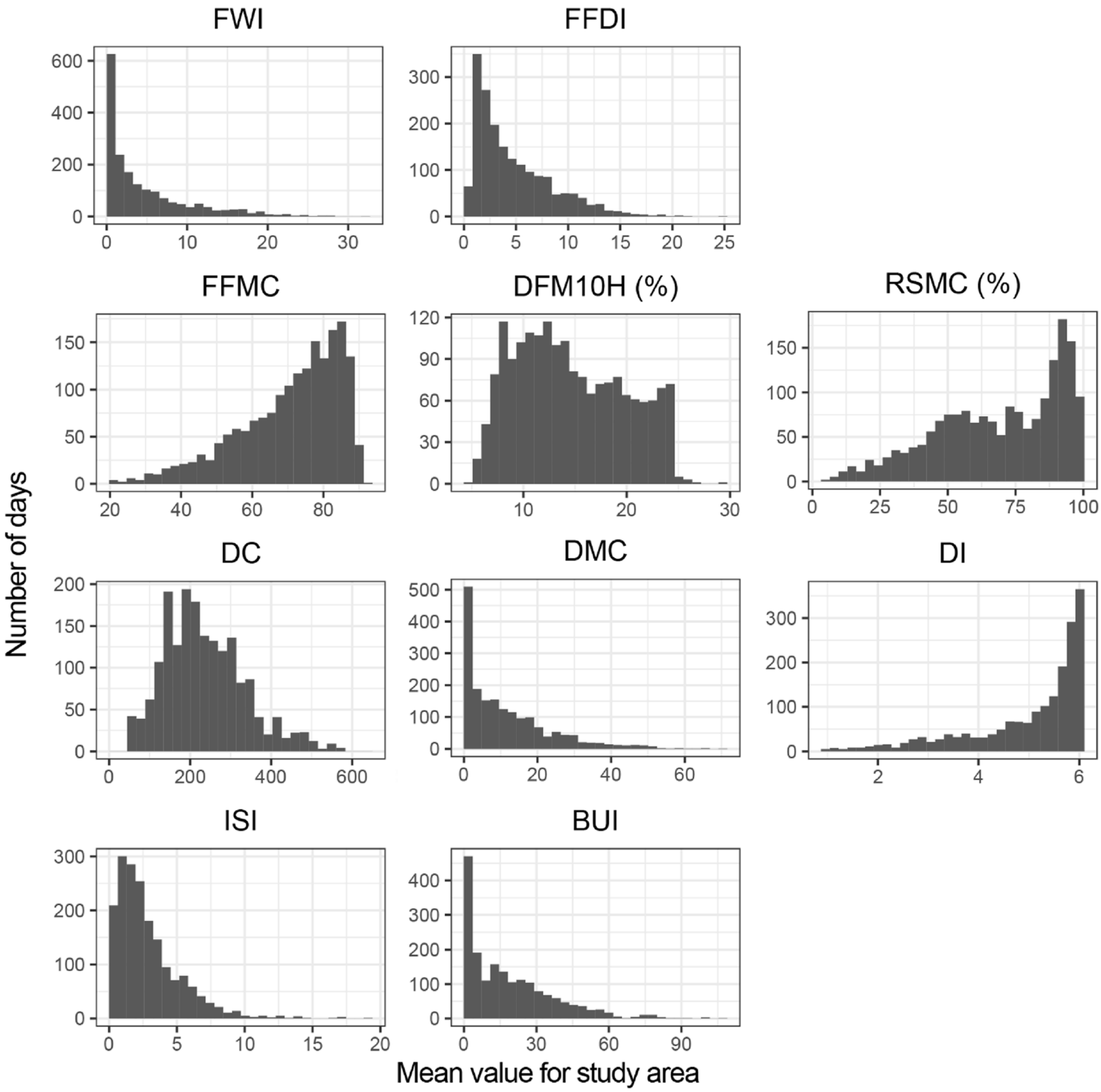


Fig. 1 Histogram of the frequencies of selected variables from 2018 to 2022. Most variables are unitless unless explicitly indicated in the plot titles. FWI—Fire Weather Index, FFDI—Forest Fire Danger Index, FFMC—Fine Fuel Moisture Code, DFM10H—Dead Fuel Moisture Code 10-h, RSMC—Relative Soil Moisture Content, DMC—Duff Moisture Code, DI—Drought Intensity, ISI—Initial Spread Index, BUI—Build-Up Index

minimum (RH_{min}), precipitation, wind speed, and DF from reality).

Analysis of wildfire occurrence

This section aimed to provide a general overview of wildfire occurrence in the Czech Republic from 2018 to 2022 based on data obtained from FRS CR. We determined the fire season and described the seasonal pattern based on the analysis of wildfire occurrence in individual months. The fire season was defined based on months with the highest wildfire occurrence, as observed in historical wildfire data for the Czech Republic from 2018 to 2022. We also computed basic statistical metrics for the number of wildfires. The specific results of this analysis are presented later in the Results section. Additionally, we identified high-risk areas in the Czech Republic at the regional level

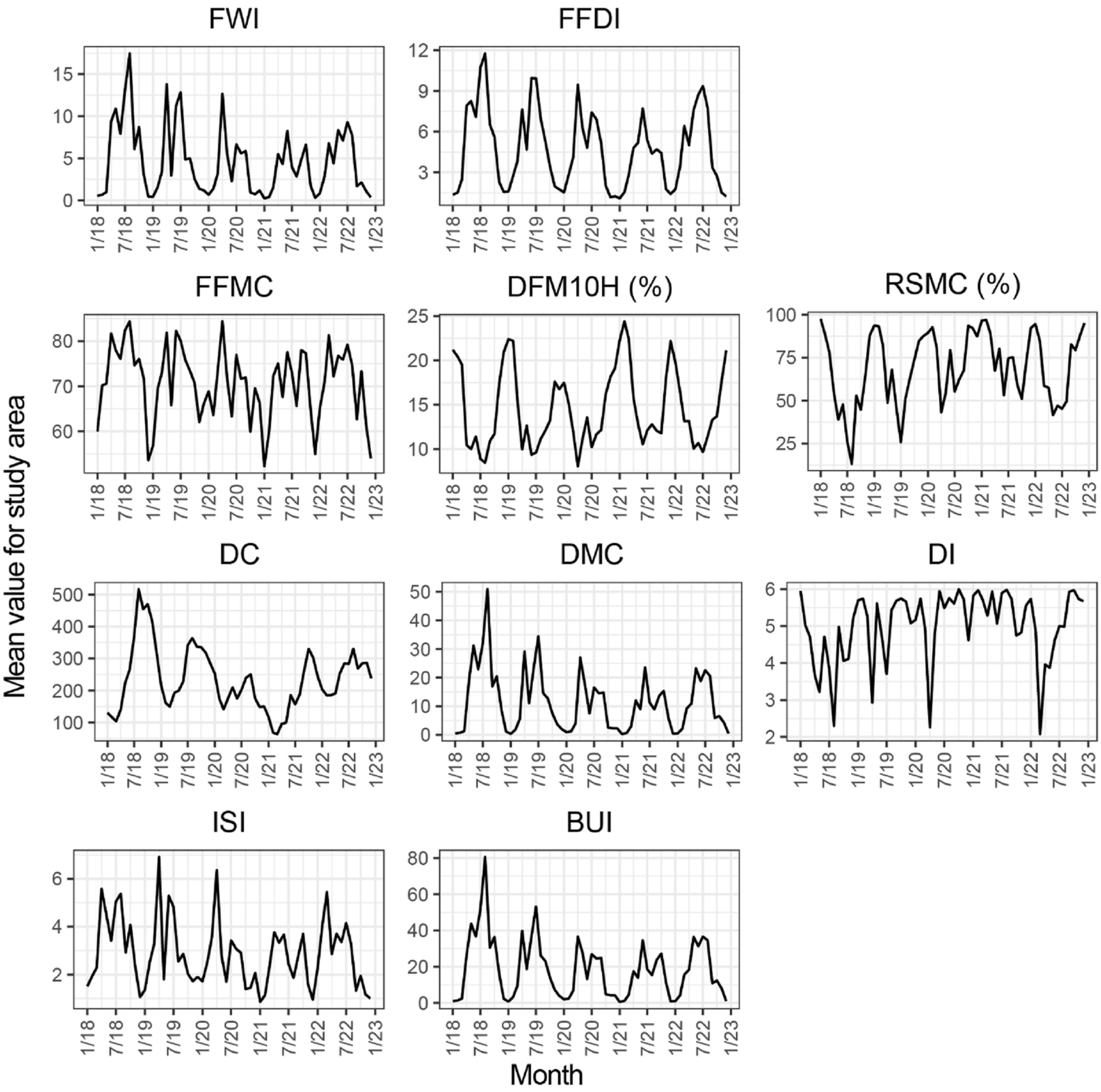


Fig. 2 Average daily values of the examined variables for whole study from 2018 to 2022 in the Czech Republic. Most variables are unitless unless explicitly indicated in the plot titles. FWI—Fire Weather Index, FFDI—Forest Fire Danger Index, FFMC—Fine Fuel Moisture Code, DFM10H—Dead Fuel Moisture 10-h, RSMC—Relative Soil Moisture Content, DMC—Duff Moisture Code, DI—Drought Intensity, ISI—Initial Spread Index, BUI—Build-Up Index

(Nomenclature of Units for Territorial Statistics (NUTS 3)).

Wildfire occurrence prediction

In this section, we analyzed the dependence of the number of recorded wildfires on observed fire danger/weather variables for the entire period under study. We used linear regression analysis and linear regression analysis with random effects to examine these relationships (see below).

We constructed a linear model (Chambers 1992; referred to as Model CZE) for predicting the total number of wildfires on the basis of daily data for the whole study area (i.e., total wildfire count for each day) and a

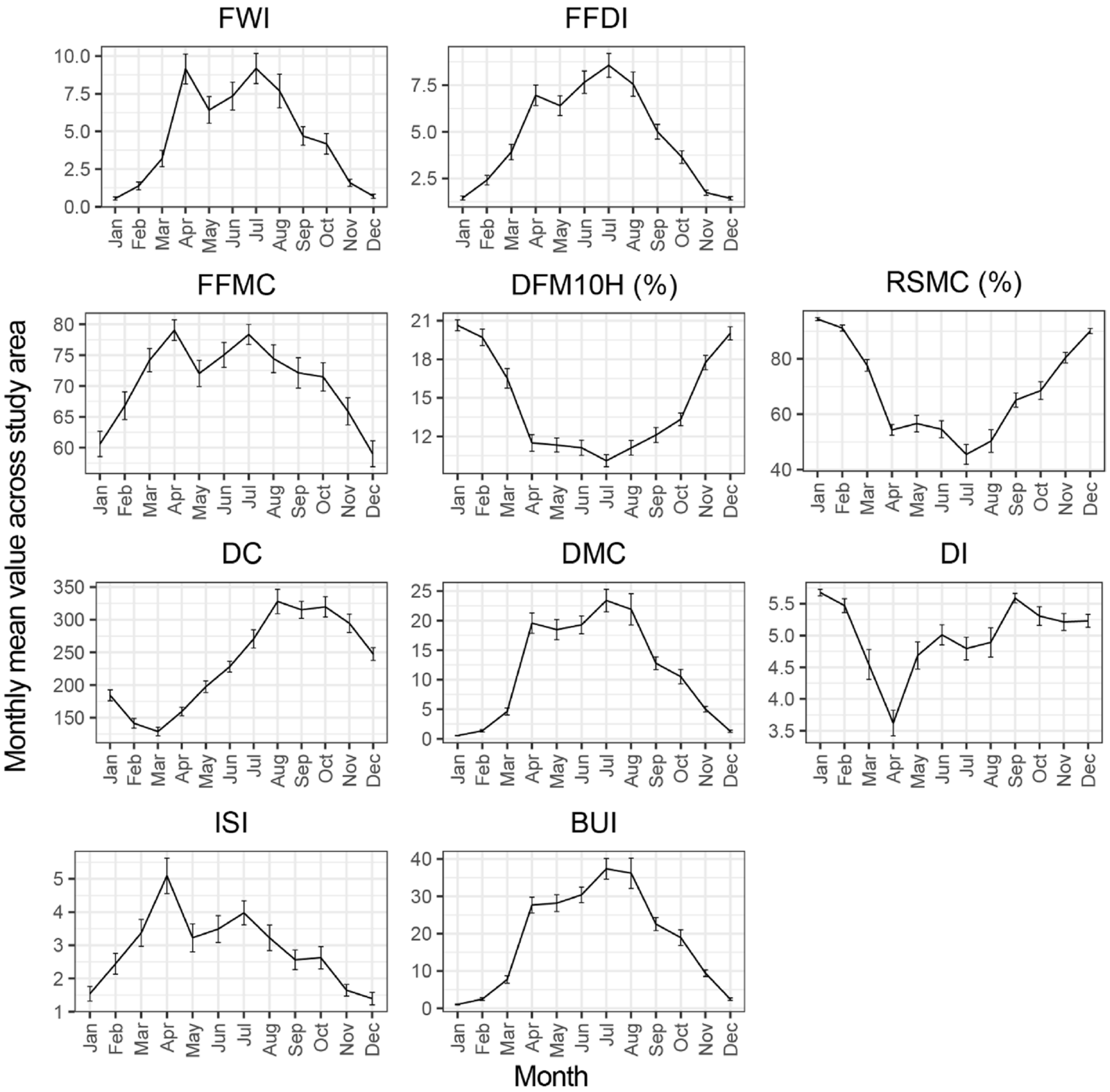

FWI FFDI FFMC DFM10H (%) RSMC (%) DC DMC DI ISI BUI

Fig. 3 Course of average variables from 2018 to 2022 within individual months in the Czech Republic. Error bars depict 95% confidence intervals. Most variables are unitless unless explicitly indicated in the plot titles. FWI—Fire Weather Index, FFDI—Forest Fire Danger Index, FFMC—Fine Fuel Moisture Code, DFM10H—Dead Fuel Moisture 10-h, RSMC—Relative Soil Moisture Content, DMC—Duff Moisture Code, DI—Drought Intensity, ISI—Initial Spread Index, BUI—Build-Up Index

linear model with random effects (Chambers 1992; further referred to as Model NUTS 3), where administrative areas at the NUTS 3 level were taken as random effects for model intercepts. We selected parameters for both models on the basis of the variance inflation factor (VIF) value (as some predictors were expected to be highly correlated with each other) and *P* value of each predictor via backward selection (excluding predictors with high VIF values and nonsignificant predictors first). The fire danger indices were intentionally included in the model, as their ability to predict the number of wildfires was assessed.

Results

Investigation of observed fire danger and other fire-related variables

A basic statistical overview of the analyzed observed data is presented in Table 1, summarizing key variables

Table 1 Statistical information of the variables of interest for the Czech Republic during the study period 2018–2022 (MIN—minimum, MAX—maximum, SD—standard deviation, CI—confidence intervals, FWI—Fire Weather Index, FFDI—Forest Fire Danger Index, DFM10H—Dead Fuel Moisture 10-h, FFMC—Fine Fuel Moisture Code, DMC—Duff Moisture Code, DC—Drought Code, ISI—Initial Spread Index, and BUI—Build-Up Index)

Variable	**MIN**	**MAX**	**Mean**	**SD**	**CI**	**Percentile (%)**						
						5	**10**	**25**	**50**	**75**	**90**	**95**
FWI	0.00	111.29	4.68	6.47	0.00	0.01	0.06	0.37	1.65	6.81	13.89	18.57
FFDI	0.26	53.20	4.74	4.07	0.00	0.74	0.95	1.62	3.37	6.78	10.58	12.95
DFM10H	2.76	34.52	14.58	6.37	0.00	6.53	7.39	9.52	12.75	19.25	24.63	24.63
FFMC	2.08	94.09	70.75	17.16	0.01	34.44	44.19	61.34	76.79	83.99	87.33	88.56
DMC	0.00	169.26	11.60	13.72	0.01	0.05	0.18	1.44	6.96	16.73	29.81	39.51
DC	0.00	974.40	235.08	139.85	0.06	12.87	48.66	131.26	229.54	326.11	415.56	477.25
ISI	0.00	262.70	2.88	3.06	0.00	0.03	0.17	0.92	1.97	4.02	6.50	8.29
BUI	0.00	220.03	18.77	20.74	0.01	0.08	0.32	2.61	12.26	27.94	46.73	60.10

such as the FWI, FFDI, and other moisture- and drought-related parameters from 2018 to 2022 for original input data (per cadastral unit level). The majority of recorded FWI and FFDI values are on the lower end of the scale (the mean values for the FWI 4.68 and FFDI 4.74), but occasional spikes indicate periods of increased fire danger. The maximum recorded values (FWI 111.29, FFDI 53.20) highlight that extreme conditions do occur, although they are less frequent.

Fuel moisture indicators, such as FFMC, DMC, and DC, reveal that surface and deeper fuels generally retain enough moisture to reduce fire ignition and spread under normal conditions. However, the data also indicate periods of significant drying, especially in the deeper organic layers, as reflected by the high maximum DMC (169.26) and DC (974.40) values. This suggests that during prolonged dry spells, the risk of persistent and severe fires increases.

Figure 1 further illustrates these patterns, showing that most distributions are heavily right-skewed, meaning low values dominate, but occasional extreme values occur. This pattern is particularly evident FWI and FFDI, where most values remain low, yet high extremes are present. In contrast, DFM10H and DC exhibit more symmetrical (bell-shaped) distributions, indicating a broader range of observed values rather than strong skewness toward low or high extremes.

The variability in these fire danger indices is further highlighted by the standard deviations and confidence intervals, which indicate significant fluctuations across different regions and times. This variability underscores the need for continuous monitoring and localized fire risk assessments to effectively manage and mitigate potential fire hazards in the Czech Republic.

In summary, fire danger in the Czech Republic fluctuates over time. While most recorded values remain low, occasional high-risk periods occur, particularly during dry conditions. This underscores the importance of proactive fire management strategies, such as the allocation of firefighting resources, enforcing fire bans during high-risk periods, and informing public awareness campaigns to reduce human-caused ignitions.

As a result of the exploratory analysis, we found that values of average daily FWI in the Czech Republic ranged from 0 to 18 during the study period, and average daily FFDI values ranged from 1 to 12 (Fig. 2). The highest values were reached in the summer months (especially in 2018), whereas the lowest values were observed in the winter months (especially in 2021). Figure 2 shows the course of all variables of interest for each day of the study period (daily averages for the entire Czech Republic). The other variables followed similar seasonal patterns, peaking during warmer months and dipping during colder periods.

The seasonality for each variable is further illustrated in Fig. 3, where we averaged daily values into monthly values and across the years of the analysis (averages from values for individual months from all analyzed years). This analysis revealed two peaks of fire danger, occurring in the spring (March–April) and summer (July–August) months. Additional variables were added to contextualize their relationship with fire danger. High values in the summer months were also observed for the parameters FFMC, DMC, ISI, and BUI, whereas the opposite was true for other parameters (DFM10H, DI—inverted scale, also extreme). A minor exception was the parameter DC, which presented the highest values in the autumn months.

Table 2 Mean absolute error (MAE) of the numerical weather prediction (NWP) models for the Fire Weather Index (FWI) and Forest Fire Danger Index (FFDI) with corresponding statistical indicators (SD—standard deviation, SE—standard error, CI—confidence interval) for individual forecast intervals. Shaded cells indicate the lowest MAE and SD for NWP models across the forecast intervals

day of forecast	NWP	N	FWI MAE	SD	SE	CI	FFDI MAE	SD	SE	CI
D7–D9	CMC	3582	4.26	5.55	0.09	0.18	2.81	5.22	0.09	0.17
	GFS	3594	4.43	4.52	0.08	0.15	2.88	6.95	0.12	0.23
	IFS	3656	4.30	4.46	0.07	0.14	2.42	2.26	0.04	0.07
D4–D6	CMC	3617	3.27	5.30	0.09	0.17	2.37	5.39	0.09	0.18
	GFS	3622	3.29	3.46	0.06	0.11	2.20	4.97	0.08	0.16
	GUM	2827	3.25	7.04	0.13	0.26	2.52	6.61	0.12	0.24
	IFS	3669	2.84	3.37	0.06	0.11	1.71	1.74	0.03	0.06
D0–D3	ARPEGE	4857	2.26	4.20	0.06	0.12	1.56	3.53	0.05	0.10
	CMC	4825	1.99	4.67	0.07	0.13	1.73	4.49	0.06	0.13
	GFS	4852	2.15	2.38	0.03	0.07	1.66	4.18	0.06	0.12
	GUM	4876	2.25	6.37	0.09	0.18	2.19	6.33	0.09	0.18
	IFS	4892	1.74	2.04	0.03	0.06	1.10	1.05	0.02	0.03

Evaluation of fire danger NWP models

The analysis of the MAE between the NWP values of fire danger and observed values revealed a significant influence of the lead time, and the MAE decreased with a shorter lead time. Closer to the current day (D0), there is notably higher accuracy in forecasting fire danger (Table 2). Considering the varying lead times of the models, the forecasts were divided into three time intervals (D0 to D3, D4 to D6, D7 to D9).

For the longest lead time forecasts of FWI (D7 to D9), the most accurate NWP models were the CMC and IFS (MAEs of 4.26 and 4.30, respectively, with a lower SD for the IFS). For mid-range lead times (D4 to D6), the most accurate model was IFS (MAE = 2.84, SD = 3.37), as well as in the shortest lead time (D0 to D3), with MAE = 1.74 and SD = 2.04 for the forecast of the FWI. For the FFDI, the IFS model performed best in all mentioned lead time intervals (D7 to D9—MAE = 2.42, SD = 2.26; D4 to D6—MAE = 1.71, SD = 1.74; D0 to D3—MAE = 1.10, SD = 1.05), as detailed in Table 2. These results suggest that among the analyzed NWP models used for forecasting fire danger, the most accurate (lowest MAE and smallest SD) is the IFS model.

Higher MAEs were recorded for the FWI, and within individual lead times, there was less variability in the MAEs between the models. With respect to the FFDI, greater variability in the MAE between models was revealed within individual lead times (Fig. 4). The average MAEs at D9 were 4.70 for the FWI and 2.88 for the FFDI (SDs of 4.98 and 4.96, respectively), whereas at D1, the MAEs were 1.94 for the FWI and 1.59 for the FFDI (SDs of 3.81 and 3.87, respectively).

The analysis of bias for FWI revealed that some NWP models systematically overestimated fire danger, e.g., for prediction for D0 to D3, IFS and ARPEGE showed average biases of 0.62 and 0.44, respectively, whereas others underestimated it—CMS and GUM; average biases of − 0.43 and − 0.82, respectively. Notably, the lowest systematic mean bias for FWI prediction showed GFS model (0.24 for D0 to D3, − 0.14 for D4 to D6, and 0.08 for D7 to D9), which was lowest absolute value in all cases. Conversely, for the FFDI, it was revealed that all NWP models systematically underestimated fire danger (Fig. 5). In case of FFDI, the highest mean absolute bias across all lead days showed GUM model (− 2.25), lowest absolute bias IFS (− 0.48).

For the best-performing model, IFS, we analyzed the accuracy of the forecasts separately for each month (Fig. 6). The highest monthly MAEs for the FWI and FFDI forecasts were more pronounced during the summer months (June–August), where we also observed the greatest differences in the MAEs for individual lead times (D0 to D9). Similar to the previous analyses, the errors gradually decrease with shorter lead times. The results suggest that NWP forecasts of the FWI and FFDI are more accurate and reliable for short-term forecasts.

Within this analysis, we also analyzed the feature importance (i.e., which meteorological parameter has the greatest influence on FWI and FFDI prediction). We

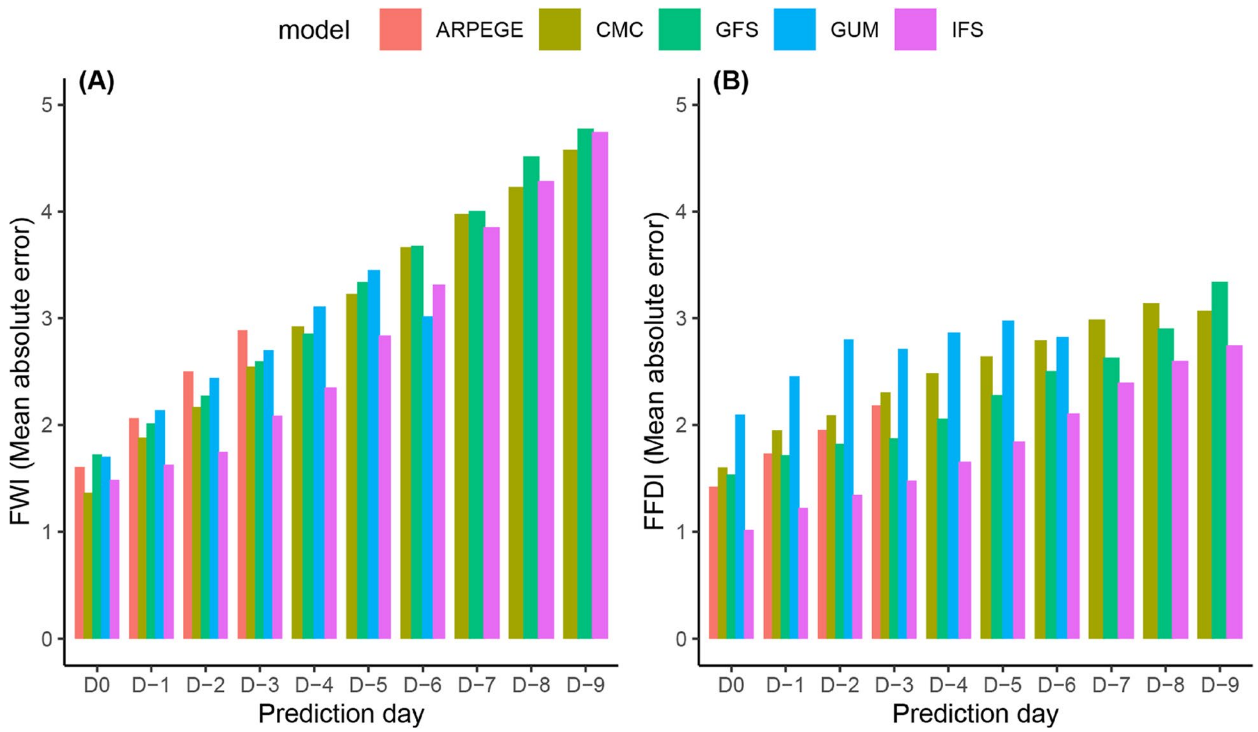


Fig. 4 Mean absolute error (MAE) of the Fire Weather Index (FWI; **A**) and Forest Fire Danger Index (FFDI; **B**) values on individual forecast days compared with the actual measured day. Five numerical weather prediction (NWP) models were used from 2018 to 2022

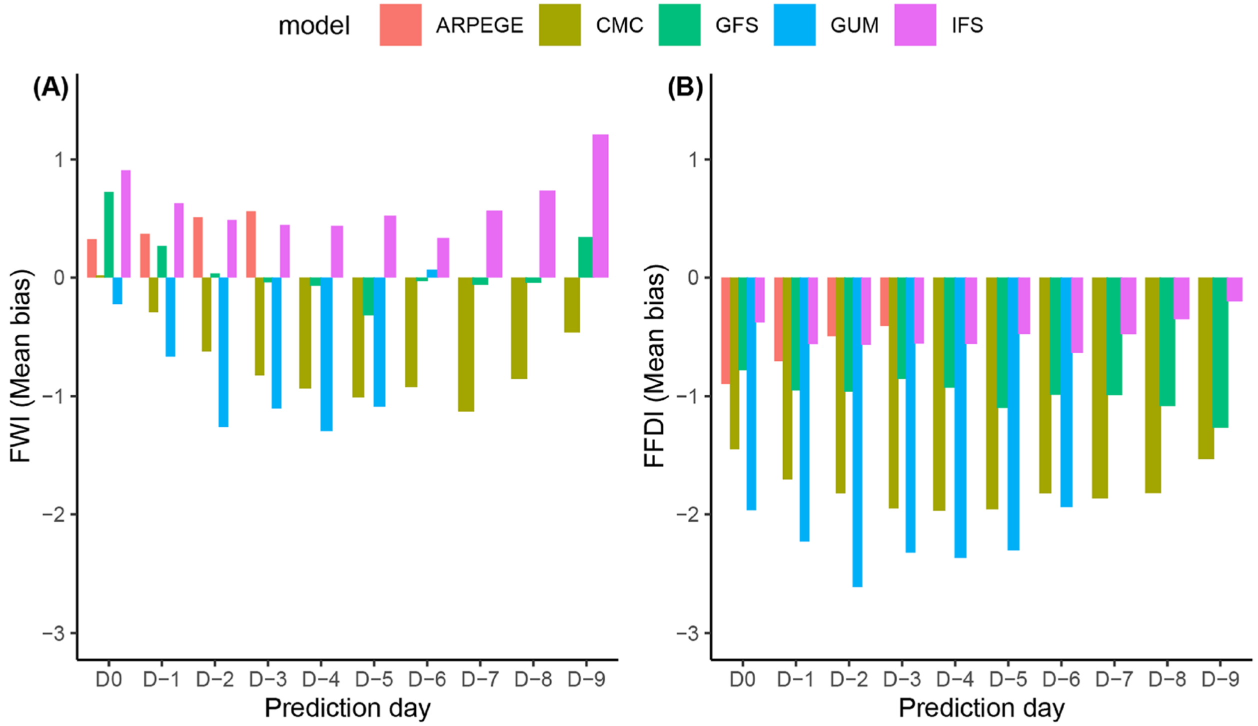


Fig. 5 Mean bias of the Fire Weather Index (FWI; **A**) and Forest Fire Danger Index (FFDI; **B**) on individual forecast days (D0 to D9) compared with the actual days from 2018 to 2022

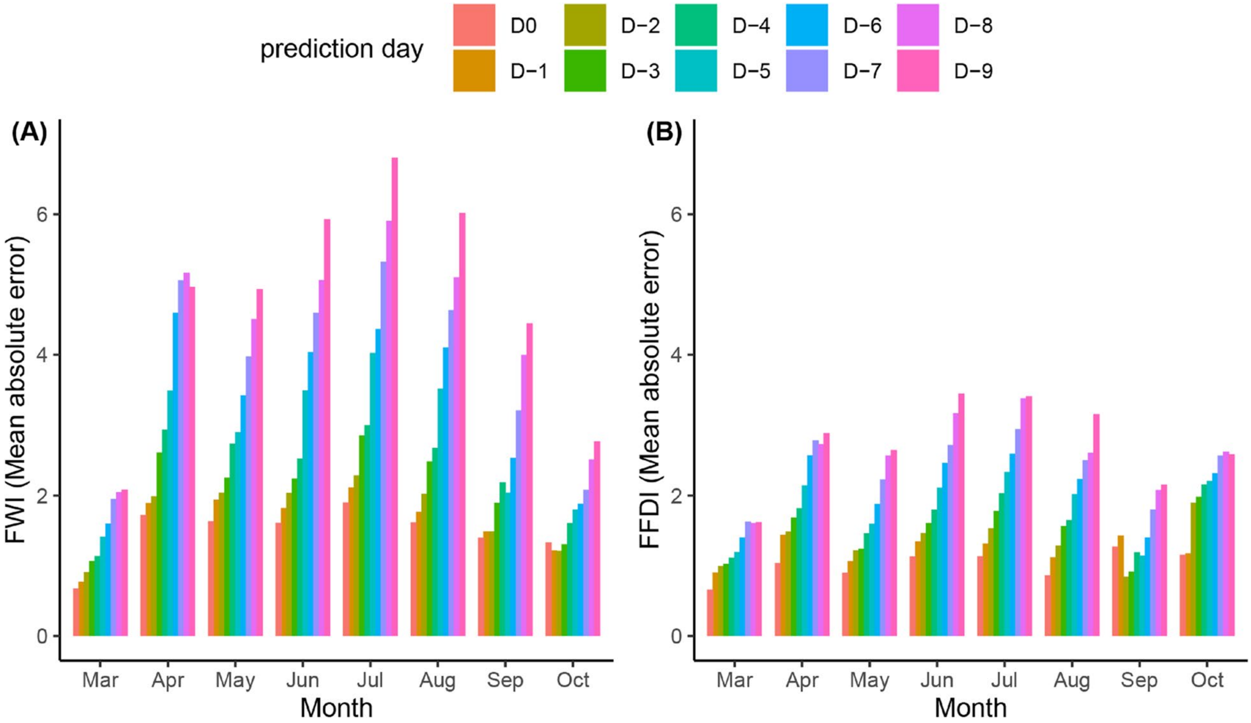


Fig. 6 Monthly mean absolute errors of the Fire Weather Index (FWI; **A**) and Forest Fire Danger Index (FFDI; **B**) during the 2018–2022 fire season via the IFS model

assessed the effects of each parameter (T_{max}, DF, RH_{min}, precipitation, and wind speed) by calculating the Spearman correlation coefficient between the differences in the observed and NWP data and the values of each meteorological parameter.

For FWI, the highest influence was observed for RH_{min} (Spearman cor. coef: − 0.47), followed by precipitation in mm (− 0.44), wind speed (0.38), and T_{max} (0.27). RH_{min} also has the greatest influence on the accuracy of FFDI prediction (− 0.83), followed by T_{max} (0.61), wind speed (0.35), and the DF (0.18). The parameters were ordered by the absolute value of the Spearman correlation coefficient, and negative values represented the negative influence of the FWI (FFDI) with increasing values of the parameters.

Analysis of wildfire occurrence

From the available data, we were able to identify the main periods of wildfire occurrence and fire seasonality. The fire season was determined based on a clear and consistent seasonal increase in wildfire occurrences across the study period (2018–2022). The fire season begins in March and ends at the end of October, depending on current temperatures and dry conditions. During this timeframe, there were, on average, approximately 500 fire department interventions monthly related to wildfires in forest and agricultural landscapes. The highest numbers of interventions were recorded in spring (March–April) and summer (July–August), when fire department units responded to an average of up to 1000 wildfires monthly. The data indicated that the fire season during the analyzed period experienced two distinct peaks (Fig. 7). According to the available data, wildfires were slightly more common in agricultural landscapes than in forest landscapes (16,459 compared with 14,534 during the study period).

A higher incidence of wildfires per square kilometer on agricultural land occurred in the Ústecký and Liberecký regions. For forestland, the highest incidence of wildfires was found in the Ústecký, Liberecký, and Středočeský regions and Kraj Vysočina, followed by the Jihomoravský region. In both cases, the capital city, Prague (Hlavní město Praha region), recorded the highest number of wildfires, with extreme values of 4.80 km^2 for agricultural land and 11.79 km^2 for forestland (Fig. 8). The highest number within the regions was recorded in the Středočeský and Ústecký regions (Fig. 9).

Fire occurrence in the context of fire danger and other variables

The predictability of the number of wildfires in the Czech Republic on the basis of fire indices and

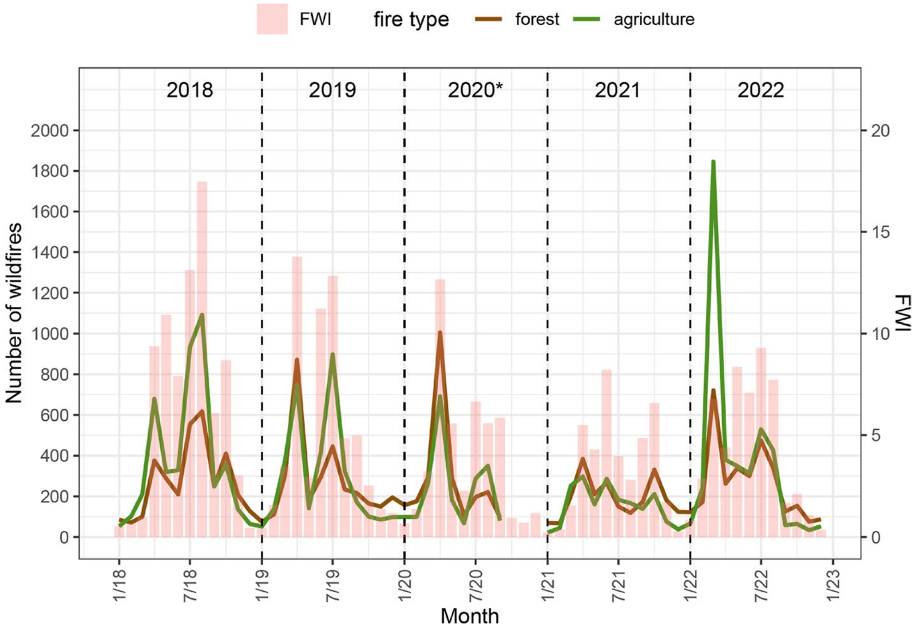


Fig. 7 Number of wildfires in agricultural and forest landscapes from 2018 to 2022 in the Czech Republic in the context of the Fire Weather Index (October–December 2020 data missing)

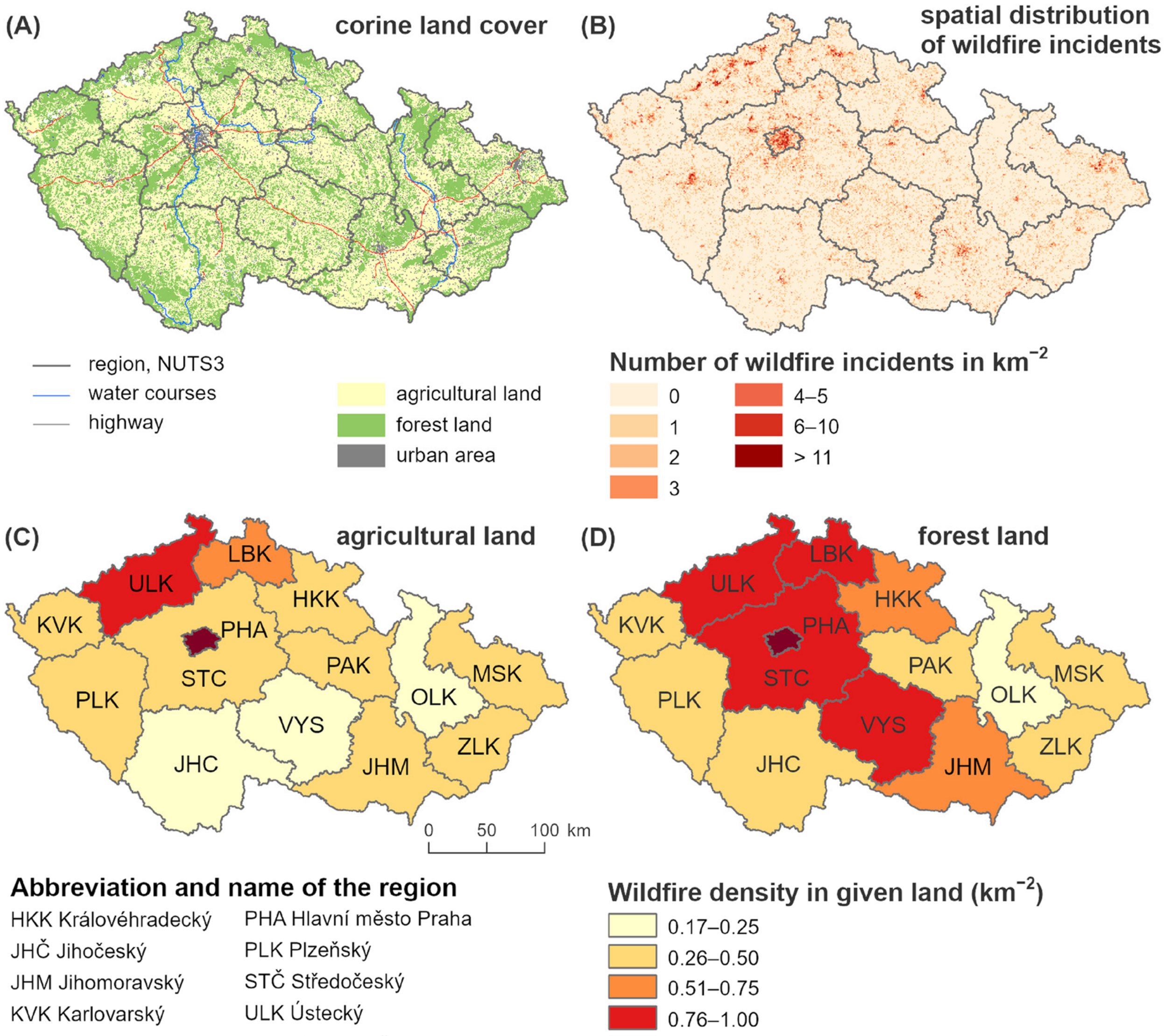
meteorological variables was assessed via a linear model with zero intercept. Daily data throughout the entire study period (not only during fire season) were used for the model. The final model (Model CZE; Table 3) was constructed via backward selection and parameter removal on the basis of the VIF score from the full model containing all meteorological and fire index parameters (variables). Finally, we removed the variable (RH_{min}) with low effect (coefficient estimate), which did not notably affect R-squared value (still 0.81 after rounding). During parameter selection, we aimed to maintain FWI and FFDI in the model, as firstly, these parameters are directly or indirectly computed from other predictors, and thus, it could be assumed that they contain information from other parameters. Second, in this work, we aimed to assess the usability of these parameters in practice.

The model revealed that the fire indices FWI and FFDI are sufficient predictors and produce relatively reliable predictions. The observed model R-squared value is 0.81, with coefficients of both parameters (FWI: 0.75, FFDI: 2.12) being highly significant (the null hypothesis is that the coefficient is equal to zero). The MAE of the model is 5.19 wildfires, with a 95% CI of 4.94–5.44. It should be mentioned that the model was constructed with emphasis on easy usability in practice, and future efforts should definitely be put into a deeper study of possibilities of model occurrences modeling. In its current form, the model includes two predictors that are naturally correlated. However, for practical reasons, we have decided to present the model in this way. First, both predictors are among the key metrics of the FireRisk portal, making them readily available for use. Second, omitting one of them increases the MAE (FWI only model: R-squared value = 0.74, MAE 95% CI: 5.73–6.32, FFDI only model: R-squared value = 0.80, MAE 95% CI: 5.21–5.72).

Model NUTS 3 (Table 4) used a linear approach with random effects to predict the number of wildfires in the Czech Republic. This model incorporated fire indices (FWI and FFDI), as these predictors showed as sufficient in previous case, along with NUTS 3 information as random effect. The random effects of final model are viewed as "regional correction coefficients" to adjust for regional variability. The model's conditional R-squared value of 0.34 and MAE of 1 wildfire (95% CI ± 3) indicate that while the FWI and FFDI are significant predictors, the inclusion of regional corrections enhances prediction accuracy.

Discussion

Wildfires in the Czech Republic are currently not as extensive and frequent as those in southern Europe (San-Miguel-Ayanz et al. 2022); however, climate change is altering climatological conditions in this region, leading



Data source: Data ArcČR © ČÚZK, ČSÚ, ARCDATA PRAHA 2023; FRS CR; CORINE Land Cover 2018. European Union's Copernicus Land Monitoring Service information, European Environment Agency. doi.org/10.2909/960998c1-1870-4e82-8051-6485205ebbac. (Accessed on 07.10.2024)

Fig. 8 Corine land cover (**A**) and the spatial distribution of wildfire incidents (**B**; km^{-2}) in the context of wildfire density in agricultural (**C**) and forest (**D**) landscapes in individual regions of the Czech Republic from 2018 to 2022 (number of detected wildfires km.$^{-2}$ of agricultural or forestland in each region; October–December 2020 data missing)

to increased fire risk (Trnka et al. 2020a; Možný et al. 2021; El Garroussi et al. 2024). Fire indices are used to better understand and predict fire danger. In the Czech Republic, information on the assessment of fire indices in a broader context has been lacking. This study aimed to fill this gap by analyzing data from 2018 to 2022, evaluating the accuracy of selected NWPs, and examining the number of recorded wildfires in the context of various influencing variables.

Fire danger analysis

Understanding the average daily values of the fire indices FWI and FFDI has allowed for a better comprehension of seasonal dynamics in the Czech Republic (Fig. 2). The average daily FWI values reach lower levels than, for example, those in Portugal (Carvalho et al. 2011; Andrade et al. 2023) or Greece (Ntinopoulos et al. 2022), while they are similar, for instance, to those in Sweden (Krikken et al. 2021). However, considering the expected

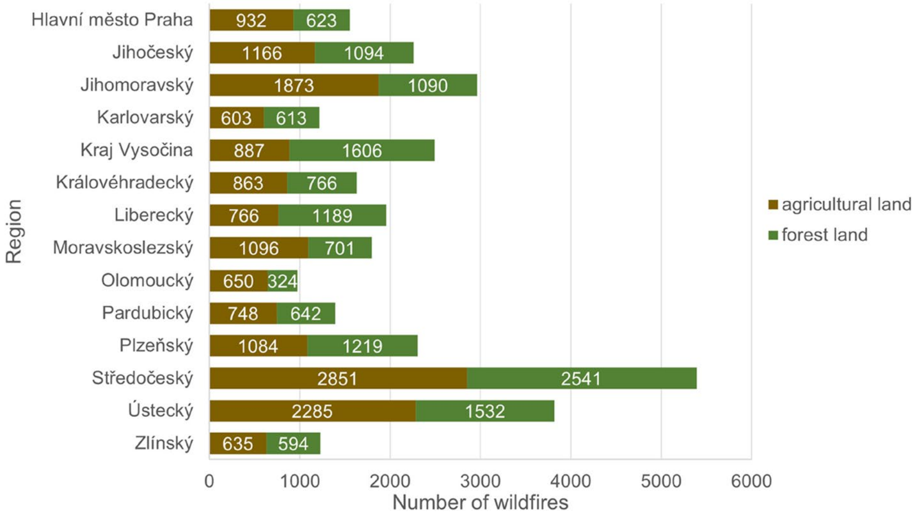


Fig. 9 Number of wildfires in the regions of the Czech Republic from 2018 to 2022 (October–December 2020 data missing)

changes in climatic parameters due to climate change, such as increasing temperatures and more frequent droughts, the current lower FWI levels could increase in the future, potentially leading to higher fire danger. The FWI percentiles (Table 1) defined in this study can be put into context with an alternative approach synthesizing thresholds from previous studies and review literature, as proposed by Kudláčková et al. (2024), providing a complementary perspective on fire danger classification in Central Europe but also in a broader global context. This highlights the importance of understanding the influence of meteorological factors on the reliability of fire danger forecasts, as these factors are likely to become increasingly critical in the context of a changing climate.

A temporal analysis revealed two seasonal peaks of fire danger in the spring and summer months, similar to patterns identified on the basis of the number of wildfires, in other countries, such as Portugal (with significant summer peaks, Silva et al. 2023) or Poland (Borucka 2019). Overall, Europe has two peaks in the fire season in terms of burned area, both in the spring and summer months (Copernicus n.d.). As shown in Fig. 3, the early peak in spring is likely dominated by wind-driven wildfires, as indicated by the high ISI, which is strongly influenced by wind speed. In contrast, summer wildfires are more likely driven by drought conditions, as reflected by the concurrent decrease in DI.

Other variables, such as FFMC, DMC, ISI, and BUI, presented high values during the summer months, reinforcing their relationship with fire danger. Conversely, the parameter DC reaches its highest values at the end of summer and during the autumn months, which may be explained by the soil moisture in the deeper layers reacting with a delay compared with that in the surface layer, and this variable has a time lag of approximately 52 days (Van Wagner 1987). In the context of the literature, our findings support the understanding of seasonal fluctuations and the significance of various meteorological factors in influencing fire danger.

Table 3 Results of a linear model (Model CZE) for predicting the total number of wildfires in the Czech Republic (SE—standard error)

Model CZE	***R*-squared: 0.81**		
Parameter	**Coefficient**	**SE**	***P* value**
FWI	0.746	0.074	< 0.001
FFDI	2.113	0.083	< 0.001

Accuracy of NWP models

The accuracy of the fire danger forecasts was evaluated by comparison with the actual measured values. MAE, SD, and bias were selected as metrics for assessing the forecast success. The values of the five NWP models were analyzed to identify the most accurate model, determine the highest seasonal uncertainty, and conduct further evaluation.

The results indicated that the NWP models demonstrate varying levels of accuracy depending on the lead time (Fig. 4). Shorter lead time led to a significant reduction in the MAE and increased forecast accuracy, particularly closer to the current day (D3 to D0) for all the models (Table 2; likewise, Kendzierski et al. 2018 or Sun et al. 2019). The IFS model predicted the FWI and FFDI with the lowest MAE and SD in all the lead time intervals

Table 4 Results of a linear model with random effects (Model NUTS 3) for predicting the total number of wildfires for regions in the Czech Republic. CI—confidence interval

Model NUTS 3	***R*-squared: 0.34**		
Parameter	**Coefficient**	***P* value**	
FWI	0.092	< 0.001	
FFDI	0.174	< 0.001	
Region	**Correction coefficient**	**Estimation error (fire count)**	**Estimation error 95% CI**
Hlavní město Praha	−0.891	1.049	0.048
Jihočeský kraj	0.118	1.110	0.080
Jihomoravský kraj	0.041	1.296	0.082
Karlovarský kraj	−0.364	0.684	0.038
Kraj Vysočina	0.088	1.207	0.098
Královéhradecký kraj	−0.310	0.800	0.098
Liberecký kraj	0.019	0.924	0.053
Moravskoslezský kraj	−0.159	0.907	0.060
Olomoucký kraj	−0.723	0.806	0.040
Pardubický kraj	−0.555	0.846	0.046
Plzeňský kraj	0.154	1.003	0.053
Středočeský kraj	1.566	2.183	0.127
Ústecký kraj	0.690	1.533	0.089
Zlínský kraj	−0.563	0.829	0.046

(Table 2). For this reason, it was identified as the most accurate model for forecasting fire danger in the Czech Republic for the study period, as we have prioritized overall model accuracy (MAE, SD) over systematic over- or underestimation (bias). This model was also evaluated as the most successful in forecasting meteorological variables in studies by Stepanek et al. (2018) or Bláhová et al. (2024), with a focus on the accuracy of forecasts of soil moisture and drought intensity. The IFS model and two other models (different from those in this study) were evaluated, for example, in the context of wind speed (wind energy). However, the IFS model had smallest SD but was not explicitly identified as the "best" model for the given study (Kalverla et al. 2018).

The bias analysis revealed that all the NWP models tended to either overestimate or underestimate fire danger, depending on the lead time and the specific model used (Fig. 5). For the FFDI method, there is a systematic underestimation of fire danger, whereas for the FWI method, models both underestimate (CMC, GUM) and overestimate (IFS, ARPEGE) the forecast, depending on the NWP model used. Notably, the GFS model exhibited the lowest bias among all models on average. This may indicate that the GFS model benefits from a more balanced treatment of key meteorological inputs compared to other models; however, its accuracy was not the best observed in this study. The NWP model outputs could be improved by accounting for biases as shown by, for example, Worsnop et al. (2021).

During the analysis of the average monthly MAE with the best NWP model IFS, we identified the highest errors in the summer months (June–August). During this period, there is a noticeable tendency for models to deviate from the actual values, which is likely due to naturally higher values of fire indices during this time and the complexity of atmospheric conditions during the summer months (uncertainty in storm forecasts). The issue and improvement of short-term precipitation forecasts have been addressed, for example, by Wang et al. (2016). As observed in previous analyses, errors decrease with shorter lead times. This pattern suggests that NWP models for FWI and FFDI tend to be more accurate and reliable for short-term forecasts, possibly because of their better ability to adapt to current conditions in the short term and the greater certainty of predictive elements compared with the actual day (D0). However, for practical use, the selected model (IFS) can also be utilized up to 9 days in advance, and the model's accuracy is sufficiently high even within this time frame (Table 2).

In the evaluation, we found that among the meteorological input parameters for calculating fire indices, RH_{min} has the greatest influence on forecast accuracy for both indices. Following RH_{min}, precipitation ranks second for the FWI, whereas T_{max} ranks second for the FFDI. Wind speed ranks third for both indices, and temperature has the least impact on the FWI forecast, whereas DF has the least impact on the FFDI forecast. Our findings differ from those of Dowdy et al. (2010), where outputs are most sensitive to wind speed, followed by RH and then temperature. The differences between our results and those of Australia are due mainly to the contrasting climate, vegetation, and fire dynamics between the two regions. Australia's dry, warm climate with frequent droughts makes wind speed a critical factor, as it quickly spreads wildfires through flammable vegetation. In the Czech Republic, the temperate and more humid climate means that RH and precipitation have greater impacts on fire danger, as moisture availability plays a greater role in fire behavior. Additionally, variable local humidity conditions in the Czech Republic further emphasize the influence of RH on wind speed, unlike the more uniform dry conditions considered in Australian studies.

Wildfire occurrence

The analyzed data on the number of wildfires and corresponding firefighting interventions in the Czech Republic during the studied period indicate a fire season lasting 8 months (March–October), with two distinct peaks (Fig. 7). This pattern is also reflected in the fire danger assessed by fire indices. During the analyzed period, there were, on average, 500 wildfires per month in the identified season, with nearly double the number of incidents occurring during the spring and summer peaks.

The scale of wildfires in the Czech Republic remains relatively moderate compared with that in countries such as Portugal or Greece, where wildfire activity is significantly more intense (e.g., San-Miguel-Ayanz et al. 2022, 2023). For example, the average annual burned area in the Czech Republic from 2010 to 2020 was 375 hectares, which is substantially lower than that in Mediterranean countries, where annual burned areas can reach tens of thousands of hectares. However, the severity of wildfires can vary greatly within the region, as demonstrated by the significant event in Bohemian Switzerland National Park in 2022, where more than 1100 hectares burned—the largest wildfire in Czech history (detailed in Kudláčková et al. (2023)). This exceptional event will significantly impact future statistics, highlighting the potential for severe wildfires even in areas that typically experience small wildfires.

This event strongly contrasts with typical wildfire sizes in the Czech Republic, highlighting the potential for extreme wildfire events even in regions traditionally considered at lower risk. For comparison, the wildfire in Bzenec in 2012 burned approximately 165 hectares, which, while substantial for the Czech context, is still far below the devastation seen in 2022. These events underscore the importance of understanding and preparing for potential shifts in fire regimes, particularly in the context of climate change, which is expected to increase the frequency and severity of wildfires across Europe (Andrade and Bugalho 2023).

Regarding the input data from the FRS CR, it is necessary to consider their potential uncertainty in accuracy and the total number of records (Špulák 2022). Therefore, it is essentially impossible to precisely determine the burned area of each wildfire in forest and agricultural landscapes in the Czech Republic. However, the average annual burned areas in the Czech Republic are available from the Joint Research Centre Repository (e.g., San-Miguel-Ayanz et al. 2022, 2023).

Compared with neighboring countries, the Czech Republic generally experiences fewer and smaller wildfires. However, the increasing occurrence of extreme weather events, coupled with historical precedents such as the Bohemian Switzerland wildfire, suggests that fire risk could increase in the future, necessitating more robust fire management strategies. These strategies may include enhancing early warning systems, improving fire detection and monitoring through remote sensing, implementing new fuel management practices, and strengthening inter-agency coordination for wildfire response. Public awareness campaigns and integrating fire risk into land-use planning can also help. Additionally, strategically placing mobile water sources, such as large IBC tanks, in fire-prone areas ensures rapid water availability, especially in remote locations.

The analysis of wildfire counts revealed a higher number of wildfires per square kilometer recorded in Central and Northwestern Bohemia (Fig. 8). In absolute numbers, the highest number of fire incidents is found in the Středočeský, Ústecký, and Jihomoravský regions (Fig. 9). These regions can be characterized as long-term drier areas than the remaining country in terms of drought monitoring (Bartošová et al. 2022; Meitner et al. 2023).

Prediction of fire occurrence

The Model CZE was used to predict the number of wildfires in the Czech Republic on the basis of fire danger forecasts and variables. The predictors for this model were the FWI and FFDI. This model demonstrated an R-squared of 0.81 and an MAE of 5.19 wildfires per day. The coefficients of these indices are statistically significant ($P < 0.001$). Thus, the FWI and FFDI form the basis for predicting the number of natural wildfires in a given region on the basis of fire risk forecasts (Table 3).

A similar topic was addressed by Carvalho et al. (2008), where the relationship between the FWI and the number of wildfires in Portugal was examined via forward stepwise regression (the R-squared values ranged from 0.36 to 0.77). Additionally, Jurečka et al. (2019) reported an R-squared value of 0.77 when using FWI and FFDI with z scores. Our model's accuracy, measured by an MAE of 5.19 with a 95% confidence interval of 4.94–5.44, confirms its ability to accurately estimate the number of wildfires. This value provides a useful quantitative indicator of the model's expected prediction error.

Model NUTS 3, with an R-squared of 0.34, incorporates regional correction coefficients (model intercepts as random effects in the model), which account for regional differences and improve prediction accuracy, resulting in a lower MAE of ± 1 wildfire (95% CI ± 3 wildfires). The variability in the coefficients across regions in Model NUTS 3 can be largely attributed to human activity. Wildfire occurrence is notably higher in exposed areas, near cities and major roads, while paradoxically, it is lower in more remote, less accessible areas (Možný et al. 2021).

Both models have statistically significant coefficients for the FWI and FFDI, highlighting their importance in predicting wildfire occurrence. Model CZE is simpler and better at explaining overall variability, whereas Model NUTS 3 provides more accurate regional predictions.

This can offer highly beneficial insights for regional headquarters in the Czech Republic, as each region primarily handles interventions within its own territory (Fire Rescue Service of the Czech Republic n.d.-a). Models were also selected so that predictions for a given area could be easily calculated using only the model formula.

Next steps

Model CZE and NUTS 3 represent valuable tools for predicting wildfires in the Czech Republic and provide a foundation for further research and the implementation of effective wildfire prevention measures and environmental protection strategies. These models allow us to estimate the likely number of wildfires on a given day, leading to more efficient use of human resources and firefighting equipment by the FRS CR. Moreover, the use of weather forecast information and meteorological elements allows firefighters to make more accurate tactical decisions, leading to more effective incident management and the minimization of damage (i.e., Rapp et al. 2021).

However, we are aware of potential shortcomings and inaccuracies in the data (previously discussed—missing data and the accuracy of input data from the FRS CR database; Špulák 2022), which may have affected the accuracy of the models. Further research should explore additional variables and refine the model to increase its accuracy and applicability on a larger scale (local administrative unit (LAU 1)). One possible improvement is the integration of soil moisture information into fire risk forecasts. This combination could lead to better predictions of wildfire occurrence and burned area (Krueger et al. 2022). In the Czech Republic, drought, as well as fire risk (firerisk.cz), is continuously monitored (intersucho.cz), and the available in situ dead fuel moisture measurement network offers the possibility to explore this integration in the future. Another potential improvement in predicting the number of wildfire incidents is the use of neural networks, which the authors plan to continue investigating in a follow-up article. This approach was already tested by Sadatrazavi et al. (2022) to improve wildfire prediction accuracy.

These results can provide important information for the enhancement and calibration of NWP models, especially during periods with greater deviations, such as the summer months. Improving forecast accuracy during these periods can strengthen the ability of the models to provide relevant and reliable information about fire danger. Given the best results in the first 3 days of the forecast, it is advisable to consider optimizing the NWP model for these longer periods. The tendency of the NWP models to overestimate the FWI and FFDI values underscores the need for calibration adjustments. The significant variability of deviations among models on individual days for the FFDI highlights the need for further investigation of the factors influencing this variability. In future research, we will extend our analysis by testing ensemble-based forecasts for predicting wildfire, further refining the predictive capabilities of our system.

In conclusion, the current statistical models (Model CZE and NUTS 3) provide a solid framework for predicting fire danger, but further research and the integration of new data sources will be key to enhancing its predictive power and utility. This ongoing effort to develop and improve models significantly contributes to the field of fire science, thereby improving wildfire prevention and response capabilities in the Czech Republic.

Conclusions

This study contributes to a deeper understanding of the dynamics of fire danger in the Czech Republic and provides relevant information for the prevention of and response to forest and agricultural wildfires in the region. We identified the IFS as the most accurate NWP model for predicting fire danger. On the basis of these data, we determined that the main fire season lasts from March to October, with two peaks occurring in spring and summer. The highest number of wildfires was identified in Central and Northwest Bohemia in agricultural and forest landscapes.

The analysis of variable percentiles in fire danger forecasts provided data to improve the accuracy of website firerisk.cz, which offers fire danger forecasts. The creation of a new Model NUTS 3 allows for the prediction of fire occurrences on the basis of specific FWI and FFDI values in individual regions of the Czech Republic (NUTS 3). This model has significant potential for improving emergency planning for human resources and the availability of fire equipment.

The study revealed the extent to which fire danger is predictable and identified the timescale of fire danger prediction reliability. This study also demonstrated the relationship between forecasts and the occurrence of wildfires. This approach has a substantial effect on the utility of the firerisk.cz system, especially for land management entities such as foresters and farmers, as well as for the FRS CR.

Overall, the methodology provided a clear framework for analyzing the relationships between fire indices and meteorological variables, enabling a deeper understanding of the factors influencing fire occurrence. These insights are broadly significant for fire science, as they contribute to better fire prediction and prevention, thereby enhancing safety and environmental protection in the Czech Republic.

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Authors' contributions
All authors contributed to the study conception and design. JB, RL, and LK carried out the material preparation, data collection, and analysis. LK wrote the initial version of the manuscript, and all authors provided feedback on earlier manuscript. All the authors have read and approved the final manuscript.

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Data availability
The datasets generated and/or analyzed during the current study are not publicly available because they are owned by a third party and the terms used prevent public distribution, but they are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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