ADVANCES IN FOREST FIRE RESEARCH 2022

Edited by

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Construction and evaluation of Fire Forecasting Model based on IS4FIRES fire information system

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Keywords

Fire forecasting, IS4FIRES, Fire radiative power

Abstract

A challenging task of fire forecasting has been approached in climatological mode, i.e. for completely hypothetical meteorological scenarios (or for long meteorological archives) and without any relevant observational information on fires. This challenge has been approached by extending the methodology developed by FMI in collaboration with University of Latvia on the basis of statistical forecasting technique suggested by Main Geophysical Observatory (St. Petersburg). The technique was successfully applied to a wide variety of problems. The essence of the methodology is to establish a "static mapping", i.e. a set of non-linear statistical dependencies between a set of predictors (in the current case, meteorological parameters including cloud-to-ground lightning flash density, and fire danger indices) and the predicted variable - the fire radiative power FRP or its time-integral, fire radiative energy, FRE.

The methodology relies on a thorough investigation of the statistical properties of the data at hand and possible physics-based relations between the parameters. Therefore, the solution to the fire prediction problem started from investigating the statistical properties of the underlying datasets, first of all, MODIS FRP retrievals, which is presently the longest time series of FRP – over 20 years (2000 - present).

1. Introduction

Availability of satellite observations of active fires (Temperature Anomaly, TA, and Fire Radiative Power, FRP) allows for global fire detection in near-real-time. These data however tell very little about the fire pattern in (near) future: extrapolation of the observed patterns even over one day leads to large errors and moreover regional prediction of fire patterns for a few days turned out to be a challenging task (Di Giuseppe et al., 2017, 2016; Partanen and Sofiev, 2022). At the same time, quality and features of fire predictions largely determine the capabilities of downstream applications, such as atmospheric composition and air quality forecasts.

The current paper introduces a new fire prediction model, outlines its key features, and shows the first results.

2. Problem statement

The goal of the study is to construct a statistical model based on machine learning techniques for prediction of daily fire Radiative Power (FRP) released by vegetation fires at regional-to-global scales. The prediction time horizon is unlimited: the model should be able to operate at climate-relevant scales, both in past and future, using only meteorological predictions produced by weather forecasting and climate models.

The system is based on the Integrated System for Wildland Fires IS4FIRES (http://is4fires.fmi.fi, visited 20.08.2022), (Soares et al., 2015; Sofiev et al., 2012, 2009), which uses the FRP retrievals of MODIS instruments onboard of Aqua and Terra satellites and produces time- and space- resolving 4-D emission flux for 21 atmospheric pollutants.

3. Materials and methods

3.1. Input datasets

The detection procedure of Collection 6 of MODIS FRP fire products is based on an algorithm of (Wooster, 2003) that exploits the strong emission of mid-infrared radiation from fires. Details on the way the MODIS FRP is used by IS4FIRES are described in (Soares et al., 2015; Sofiev et al., 2009).

The ERA5 reanalysis (European Reanalysis v.5, https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5, visited on 21.08.2022) is a global meteorological dataset, which provides hourly estimates of atmospheric, terrestrial, and oceanic meteorological variables. The data cover the globe with a ~25km grid and resolve the atmosphere with 137 levels from the surface up to a height of ~80km. The current study uses the period 1980-2021.

Another source of meteorological information is ECMWF's Integrated Forecasting System (IFS) global forecast archive, with its advantage of the most recent modelling developments. Since 2018, ECMWF implemented a new lightning parameterization in IFS (Lopez, 2016) predicting total lightning flash density (in flashes km^{-2} day^{-1}). Together with height of convective cloud top and height of zero-degree wet-bulb temperature, it was used to calculate the cloud-to-ground lightning flash density following the approach of Price and Rind (1994). This parameter was used to simulate lightning as a major natural cause of wildland fires (Veraverbeke et al., 2017; Pérez-Invernón et al., 2021). The lightning data are currently available for the period since the lightning parameterization was implemented in IFS (mid-2018 – 2021).

3.2. Statistical procedures

The statistical methodology adapted to fire forecasting has its roots in the ground-setting works of Voeikov Main Geophysical Observatory for urban air pollution (Berlyand, 1991; Genikhovich et al., 2004). This approach has been adapted by the FMI team, in collaboration with University of Latvia, to a variety of tasks (Ritenberga et al., 2017, 2016; Sofiev et al., 2017). However, the statistical features of the fire problem represent an extreme case, which required more complicated arrangements.

Since the prediction of individual fire ignition is meaningless, the problem uses spatial and temporal averaging with adjustable kernels to catch the mean and/or upper percentiles of the fire events.

Apart from non-linear transformations described by Ritenberga et al., (2017, 2016) and Sofiev et al. (2017), the following additional transformation steps were implemented in order to cope with peculiarities of the fire prediction problem:

- MODIS detection limit was parameterized generally following the procedure of (Maier et al., 2013), who estimated it for FRP Collection 5 data in Australia. Modification of that analysis leads to a simple analytical parameterization of MODIS detection limit applicable over the globe.

- SEVIRI-based parameterization of diurnal FRP variation of IS4FIRES v.1.0 has been reviewed by adjusting the day-night spread but keeping the profile shape intact.

- Five popular fire danger indices (FDIs) have been reviewed and their coefficients re-optimized using MODIS fire detections as a fitting target: Fire Weather Index (Van Wagner and Pickett, 1985), Keetch-Byram drought index KBDI (Keeth and Byram, 1968), soil drought index SDI as quoted by (Kumar and Dharssi, 2015), McArthur grass fire danger index as presented by (Schreck et al., 2010).

- Due to episodic character of fires, the normalization step had to be skipped in the pre-processing and replaced with the post-processing alignment of distribution functions. This was realized as a point-by-point rescaling of quantile chart towards the 1:1 relation.

3.3. Input parameters for fire forecasting

The FDIs, both initial and after optimization, were accompanied by a set of basic meteorological variables, which had a theoretical possibility to influence the fire regime:

- temperature at 2m above the ground
- relative humidity at 2m above the ground
- soil skin temperature
- leaf area index for low vegetation

- leaf area index for high vegetation
- soil moisture content
- total cloud cover
- water-equivalent snow depth
- convective rain
- large-scale rain
- windspeed at 10 m above the ground
- day length in hours
- convective available potential energy CAPE
- cloud-to-ground lightning flash density.

All these variables were taken as daily-min, daily-mean and daily-max, while precipitation and lightning data were also used as daily-sum.

4. Results

4.1. Predicted fires and comparison with MODIS

The most-important predicted time series refer to the MODIS observation period, which allows for direct evaluation. For the comparison, the whole period 2000-2020 has been split to training and test subsets of days in proportion 70-30, so that the first 70% of days (approx..14 years) were taken as training and the last 30% of days (approx.. 6 years) were used for testing. This approach was used because: (1) for a global model the "year" term is ambiguous, (2) random split at daily level may facilitate "gap-filling" solutions between neighbouring days instead of time-agnostic predictions,

An example of predicted crop residue fires in Central Europe is shown in Figure 1. Red dots denote the actually observed FRP, blue small dots show the MODIS detection limit for the days when it did not see any fires. The FFM prediction is the brown line. An intriguing feature of these time series is that for the seasons of 2001 and 2002 FFM predicted very low fire intensity. For trees, these were indeed very weak years but for grasses and crop residues the season was among the strongest. The most-plausible explanation was the ignition irregularities: moderate conditions still allow for fires to go if they get ignited. Such sensitivity is characteristic for grass and shrubs fires, whereas forests are more resilient for fires unless conditions are strongly favourable for burning.

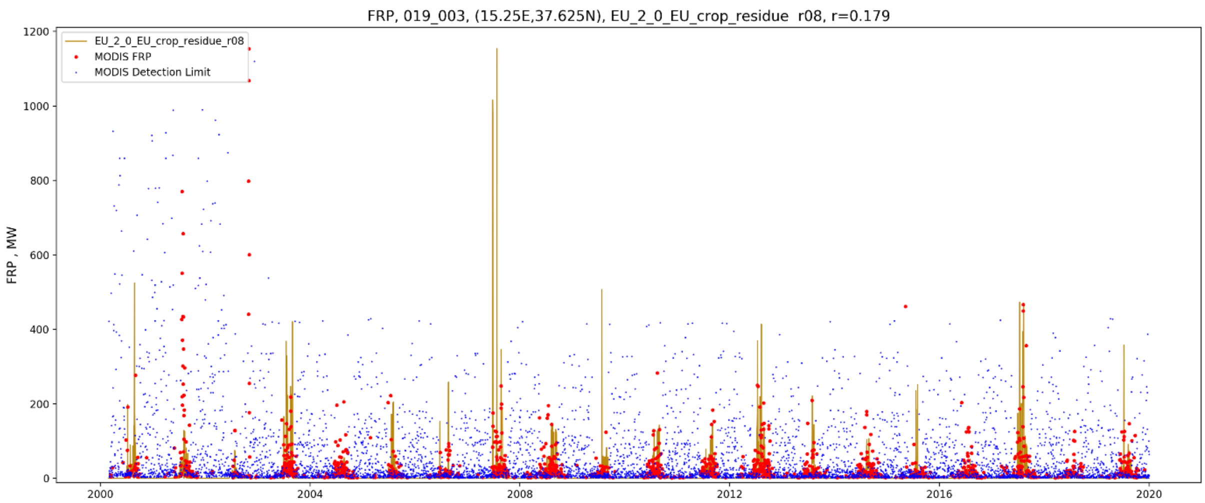

Figure 1. Example of time series for crop residue fires in Central Europe

4.2. Comparison with GFED v.4

Comparison with other fire emission databases is quite difficult because the new dataset has no direct analogies. However, one can compare, e.g., the distribution of total emission of IS4FIRES FFM and GFED v.4 (Figure 2). Since these datasets are based on different input (GFED is based on burnt area observations rather than on the actual-fire counts), direct comparison of the maps is not very informative due to random fluctuations of the fields. However, the qualitative comparison of the fire patterns reveals both good agreement and striking regional differences.

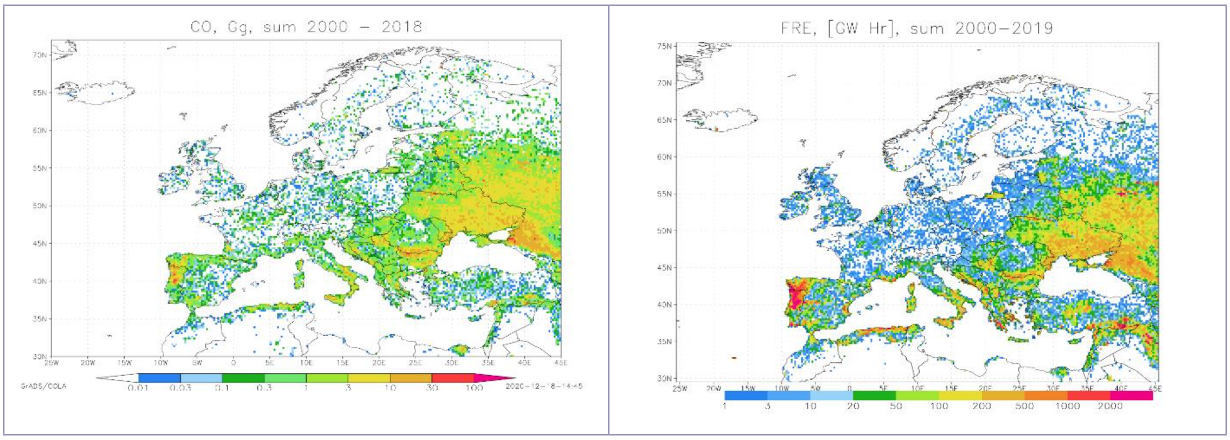

Figure 2. Left: Total CO emission from fires, GFED v.4, sum 2000-2018, Gg CO. Right: A predicted map of total FRE release 2000-2019 in Europe. Grid cell size is 0.25°×0.25°.

4.3. Model improvements by the inclusion of lightning data

Incorporation of lightning into the list of predictors, on average, increased correlation with MODIS time series for the same region by 2-10% even with the very limited training dataset (2 years of FRP observations). The improvement is spatially distributed (Figure 3) depending on thunderstorm activity, fire frequency, and anthropogenic ignitions. Figure 4 shows an example of the impact of lightning predictor inclusion on the FFM predictions: a few fires in late July 2021 were missed by the original model while the model with the lightning input was able to predict them.

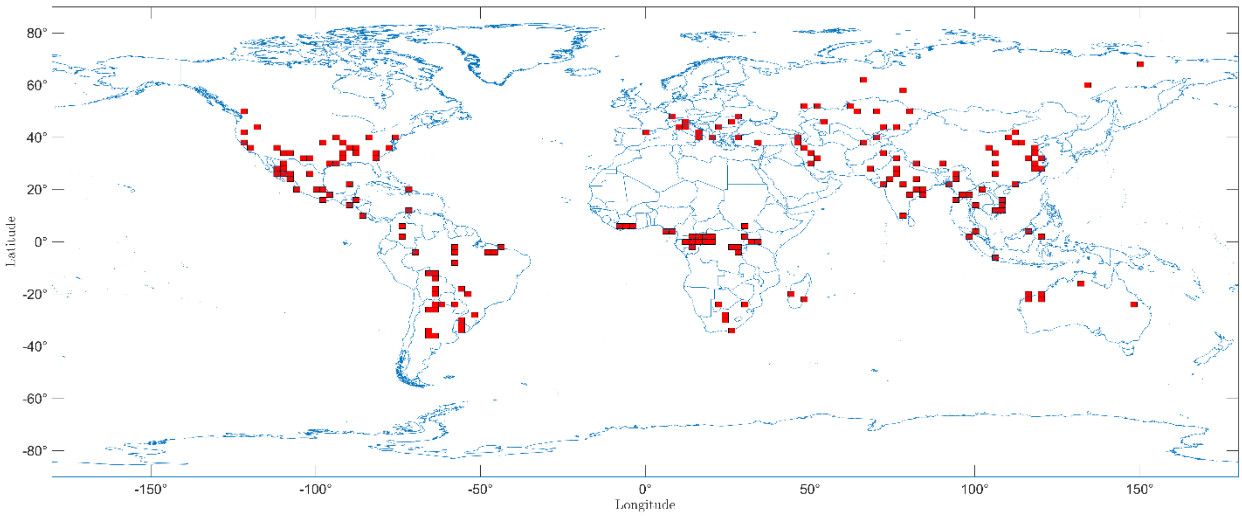

Figure 3. Map of model grid cells with statistically significant contribution of the cloud-to-ground lightning flash density to a predictor. Grid cell size is 2°×2°.

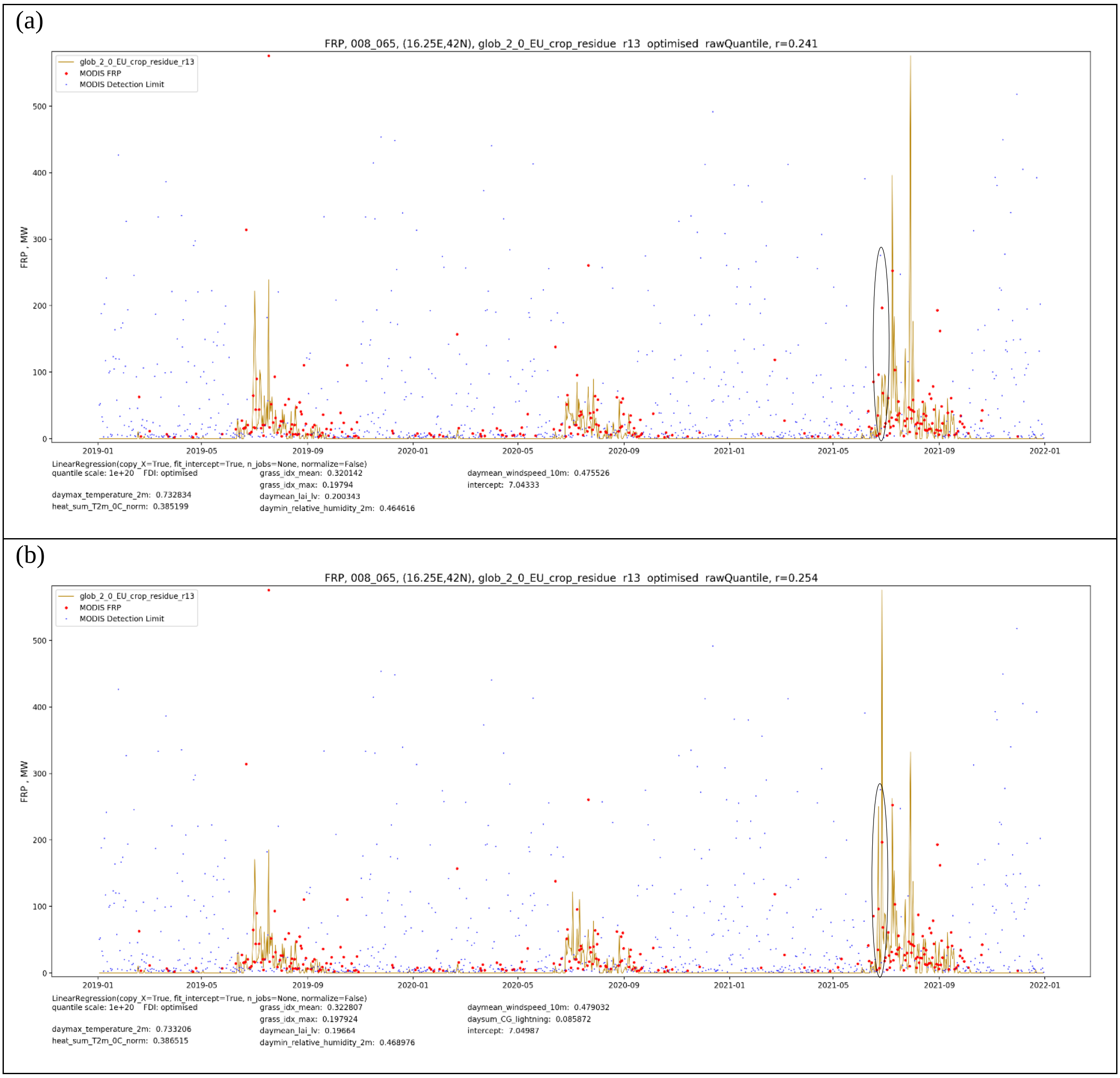

Figure 4. Example of the impact of lightning predictor inclusion on time series for crop residue fires in Central Italy. Panel (a) shows FRP by FFM trained with no lightning data compared to MODIS observations. Panel (b) shows FRP by FFM trained on the same meteorological predictors adding lightning predictions. The black ellipse denotes the area of improvement.

5. Conclusions

The current Fire Forecasting Model version 1.0 is the first practically applicable model capable of reproducing the main features of the fire seasons in Europe and, with some reservations, over the globe. Its time series seem to satisfy the requirements of the climatological-scale applications.

The main unresolved issue refers to handling the strongly non-Gaussian distribution function of FRP. The current approach ensured formal identity of the distribution functions and allowed usage of the data in downstream applications but left the core of the problem unresolved. This topic is closely related to the MODIS detection limit, which is partly behind the unusual features.

6. Acknowledgements

The work has been performed within the scope of H2020 EXHAUSTION (https://www.exhaustion.eu, grant No 820655), FirEUrisk (https://fireurisk.eu/, grant No 101003890), and Academy of Finland HEATCOST (grant No 334798) projects.

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