Global seasonal prediction fire danger maps

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ABSTRACT

The European Centre for Medium range weather forecast (ECMWF) on behalf of the Copernicus Emergency Management Service (CEMS) has recently widened the fire danger data offering in the Climate Data Store (CDS) to include a set of fire danger forecasts with lead times up to 7 months. The system incorporates fire danger indices for three different models developed in Canada, United States and Australia. The indices are calculated using ECMWF Seasonal Forecasting System 5 (SEAS5) and verified against the relevant reanalysis of fire danger based on the ECMWF Re-Analysis (ERA5). The data set is made openly available for the period 1981 to 2022 and will be updated regularly providing a resource to assess the predictability of fire weather at the seasonal time scale. The data set complements the availability of real time seasonal forecast provided by the Copernicus Emergency Management Service in real time.
Globally anomalous conditions for fire weather can be predicted with confidence 1 month ahead. In some regions the prediction can be extended to 2 months ahead. In most situations beyond this horizon, forecasts do not beat climatology. However an extended predictability window, up to 6-7 months ahead is possible when anomalous fire weather is the results of large scale phenomena such as the El Niño Southern Oscillation and the Indian Ocean Dipole, often conducive of extensive fire burning in regions such as Indonesia and Australia.

Background & Summary

Wildfires are processes that can be both beneficial and deleterious for the environment. On the one hand, uncontrolled fires make it often in the news as environmental disasters, causing destruction and loss of lives. On the other hand, fires have been happening since hundreds of million years ago (according to tests on fossil charcoal,[1]) and have a crucial role in the evolutionary path of many ecosystems[2]. In addition, controlled fires are very efficient for clearing agricultural land and for fire prevention and management, e.g. controlled burns create a discontinuity in the land depriving fires from fuel and interrupting potential propagation pathways[3]. Hence the importance of managing wildfires and prevent as much as possible that controlled and accidental burns rage out of control. Forecasting fire danger is key in fire prevention and protection measures as it improves readiness of fire professionals and allows timely and efficient allocation of resources[4].

Scientific literature shows that, besides well established fire danger forecasts with lead times of a few days[5,6], skilful predictions of fire danger is possible up to the seasonal time scale for Mediterranean Europe[7], United States[8,9] and Asia[10]. Seasonal forecasting of fire weather conditions throughout the world have been found to correlate with large scale climate patterns such as the El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole, implying that fire weather conditions can be predicted fairly accurately for various seasons and regions[11]. In Europe, forecasts for the eastern and south-eastern areas have shown to be fairly reliable 'paving the way to their operational applicability'[7].

The soil moisture and heat wave mechanism has been identified as an important source of predictability in Europe, along with atmospheric circulation patterns such as ENSO[12] and other atmospheric conditions such as triggering trade-offs between relative humidity and temperature[7,13,14], although the latter two deserves further investigations.

In 2018, ECMWF in collaboration with the Copernicus Emergency Management Service (CEMS), established the ECMWF Global Fire Forecasting (GEFF) system. This is an operational system that provides the fire community with pre-calculated fire danger indices based on models developed in Canada (Fire Weather Index,[15]), United States (U.S. Forest Service National Fire-Danger Rating System,[16] and Australia (McArthur Mark 5 Rating System,[17]). Using ECMWF weather forcings, GEFF produces fire danger reanalysis[18,19] as well as forecast products[5,6]. A set of seasonal forecast from SEAS5 is now available and span the period 1981 to 2022. The dataset will be updated regularly providing an up-to date resource to understand the predictability of landscape flammability regionally and through different decades. Seasonal forecast have monthly initial date and forecast horizon of 216 days corresponding to 7 months.

This data descriptor reports on the available dataset and makes a first assessment of the skill of the fire danger seasonal prediction using the available fire weather reanalysis data-set as reference[19]. The new dataset is particularly important to help decision makers and forestry agencies prepare for periods of potentially high fire activities. It is made available as a probabilistic model output, allowing to quantify uncertainties in the fire danger estimations. The seasonal estimates of fire indices are released under the Copernicus open data license, through the Copernicus Climate Data Store (CDS).

Methods

Seasonal forecasting is the attempt to provide useful information about the "climate" that can be expected in the coming months. A seasonal forecast is not a weather forecast: weather can be considered as a snapshot of continually changing atmospheric conditions, whereas climate is better considered as the statistical average of the weather conditions occurring in each season. The principal aim of seasonal fire danger forecast is then to predict the range of possible values which is most likely to occur during the next season. For the fire danger metrics this is achieved by coupling the GEFF model with ECMWF SEAS5 seasonal weather prediction outputs.

SEAS5 is a coupled atmosphere ocean system where the atmospheric component is the ECMWF IFS (Integrated Forecast System) model version 43r1[20]. This model version was introduced for medium-range forecasting on 22 November 2016. The horizontal resolution used for seasonal forecasts is T319 (0.4x0.4 degrees). SEAS5 uses the community ocean model NEMO (Nucleus for European Modelling of the Ocean) with a resolution of 0.25 degrees and 75 vertical levels (ocean model configuration ORCA025z75). The seasonal forecasts consist of a 51-member ensemble. The ensemble is constructed by combining the 5-member ensemble ocean analysis with SST perturbations and the activation of stochastic physics. The forecasts run for 7 months[20].

Any coupled model that runs in seasonal forecast mode suffers from bias - the climate of the model forecasts differs to a greater or lesser extent from the observed climate[21]. Since seasonal forecast signals are often small, this bias needs to be considered, and must be estimated from a previous set of forecasts. Also, it is vital that users know the skill of a seasonal forecasting system if they are to make good use of it in real applications, and again this requires a set of forecasts from earlier dates.

A set of re-forecasts (otherwise known as hindcasts or back integrations or just referred as climatology) are thus made starting on the 1st of every month for the years 1981-2016. They are identical to the real-time forecasts in every way, except that the ensemble size is only 25 rather than 51. From 2016 to 2022 the ECWMF seasonal forecast provides the full range of 51 ensemble members.

The set of 1981-2022 seasonal forecast were used as atmospheric forcings to generate fire danger seasonal predictions using the GEFF model. The GEFF model is open source and available from a public repository under an APACHE2 license. The current version is 4.1. Data are archived in the Copernicus Climate data Store with several advantages: open access via a user friendly web interface and bulk access via a convenient API, integration with the CDS toolbox for performing server-side operations as well as shared visualisation and data analysis tools. Users can browse the available data catalogue without logging in, however registering an account is mandatory to download data. The CDS has a user-friendly web interface, ideal for the retrieval of small datasets while for larger data volumes users are encouraged to send data requests using the CDS API (`https://cds.climate.copernicus.eu/api-how-to`).

If users intend to retrieve the hindcast to asses long-term averages, the transfer of such large data volume could become prohibitive. In this case the use of the CDS toolbox is highly recommended and an example application is provided in the 'usage notes' section.

Data Records

The fire danger seasonal forecast dataset has a global coverage and a spatial resolution of about 0.25 degrees (about 35 km). Natively, data are laid out over an octahedral reduced Gaussian grid (O320), and archived as GRIB2, a standard format published by the World Meteorological Organisation[22]. Users can also request data in NetCDF format which implies an internal remapping data transformation. Data in NetCDF format are on a regular unprojected grid with spherical coordinates expressed in decimal degrees (EPSG:4326). Latitudes span the range from -90 to +90 degrees and are referenced to the equator. Longitudes are in the range from 0 to 360 degrees, referenced to the Greenwich Prime Meridian, consistently with other ECMWF products. Forecasts are issued monthly, on the 1st day of each month, with a leadtime of 216 days (about 7 months). The GEFF model, driven by SEAS5, outputs fire indices based on three systems:

- The Canadian Fire Weather Index[15];
- The U.S. Forest Service National Fire-Danger Rating System[16];
- The Australian McArthur Mark 5 Rating System[17].

For an in-depth description of the GEFF model, fire rating systems and indices, the reader is reminded to[5,6]. In the subsections below, the three systems are briefly described with the list of the available indices and subindices provided.

The FWI system

The Canadian FWI system describes the fire weather, the complex atmospheric conditions that can lead to a dangerous fire. It quantifies potential fire danger using temperature, relative humidity, wind speed, and 24-hr accumulated precipitation values measured at noon Local Standard Time (LST). The indices include measures of fuel moisture (Fine Fuel Moisture Code, Duff Moisture Code, and Drought Code), fire behavior indices (Initial Spread Index, Build Up Index, and Fire Weather Index) and indices related to ease of fire suppression (Danger Severity Rating). This is the index used by Environment Canada to assess short range fire danger and also monthly and seasonal fire danger outlooks.

The NFDRS system

The National Fire Danger Rating System (NFDRS) is widely used in the U.S. The fire danger is rated accordingly to static maps of fuel type and topography and considers weather as the main driver. It uses temperature, precipitation, relative humidity and cloud cover to estimate the moisture content of dead and live vegetation at different depth in the fuel bed. In turn, these allow to calculate the Ignition Component and contribute to the other indices such as the Spread Component, Energy Release Component and Burning Index. The National Fire Danger Rating System (NFDRS) is used in the U.S. by all federal and most state agencies (e.g. The U.S. Department of Agriculture, The National Wildfire Coordination Group, etc.).

The MARK5 system

The McArthur (MARK5) fire danger rating system is mostly used in Australia. It uses precipitation, temperature, relative humidity and wind speed to estimate the behaviour of fires burning on a typical Australian landscape. At first the Drought Factor is calculate to represent the effect of temperatures and precipitation on fuel availability. The drought factor is then used to calculate the Keetch-Byram Drought Index which measure soil moisture deficit. Lastly, the Fire danger Index, is calculated to quantify probability of fire occurrence, its intensity, and related difficulty of suppression. The McArthur (MARK5) fire danger rating system is mostly used in Australia, by rural fire authorities.

Technical Validation

Global skill

Seasonal fire danger forecasting is rather novel because, although the link between long-term fluctuations of Sea Surface Temperature and seasonal precipitation/drought patterns are scientifically proven in the tropics and to a lesser extent in the extra-tropics[23], the implications on seasonal fire danger is largely under-explored. As fire danger is, by definition, weather-driven a link with SST is expected to be detectable in terms of long-term averages (typically over one to three month).

As seasonal forecast becomes more skilful, they are gaining relevance as support to decision-making processes in a wide range of sectors, such as energy, agriculture, water and risk management[?]. A first assessment of the forecast skill is then provided to understand the usability of this data-set in a real time applications. The global skill metrics presented are provided as monthly means and using the ensemble mean as best prediction outcome. Also the FWI is chosen as an example as this is one of the most used metric to predict fire danger in global systems[24,25]. Results are similar for other metrics.

Both bias and root mean square error are used for assessing model performance (figure 1 and 2), as they capture different aspects. Bias helps identify consistent deviations from the true values, while RMSE provides an overall measure of accuracy, considering both bias and the spread of errors. They provide insights into the systematic errors and overall quality of the model's predictions compared to the reference value identified as ERA5 fire danger reanalysis[26]. A positive bias indicates an over-prediction the opposite for negative bias. Biases tend to increase for more distant prediction while they have similar spatial distribution as they typically diagnose the systematic deficiency of the underlying weather forecast model.

When the bias and the RMSE are of the same magnitude of the signal of interest which is typically in the order of 10 units for the fire weather index, then using the prediction is equivalent to employing a climatology. It is then evident from figures 1 and 2 that on average after month 2 most of the areas interested by changes in landscape flammability display errors that would make the direct use of fire danger value unsuitable for advance warnings if based on warning levels.

To extend the prediction seasonal forecasts often utilize the concept of anomalies. Anomalies are deviations from the long-term average conditions and are useful to identify the early establishment of danger conditions. The Anomaly Correlation Coefficient (ACC) is one of the most widely used measures in the verification of spatial fields. It expresses the spatial correlation between a forecast anomaly relative to climatology, and the verifying analysis anomaly relative to climatology. ACC represents a measure of how well the forecast anomalies have represented the observed anomalies and shows how well the predicted values from a forecast model "fit" with the real-life data. ACC values lie between +1 and -1. Where ACC values approach +1 there is good agreement and the forecast anomaly has had value. Below around 0.5 the forecast errors are similar to those of a forecast based on a climatological average. When ACC is around 0 there is poor agreement and the forecast has had no value. Figure 3 represents the anomaly correlation for the fwi seasonal forecast system during the hindcast period (1981-2022) for all the forecasts and valid for month 1 to 4. It highlights that there is good skill in detecting anomalous conditions a month ahead almost everywhere. In few regions anomaly conditions can be predicted 2 months.

Extended predictability

El Niño Soutern Oscillation (ENSO) is a climate pattern characterized by the warming of the surface waters in the central and eastern tropical Pacific Ocean and often leads to a shift in rainfall patterns, resulting in reduced precipitation in Southeast Asia, including Indonesia. This can create drier-than-normal conditions, especially in peatland areas, making them more susceptible to fires[27]. The conditions established by strong El Niño conditions exacerbates landscape flammability but are human activities that play a significant role in igniting fires. In Indonesia, particularly in the regions of Sumatra and Kalimantan, land clearing practices such as slash-and-burn agriculture, illegal logging, and peatland drainage for agriculture have been responsible for extensive burning in the past[28]. Release of large amounts of smoke and pollutants into the atmosphere have affected air quality not only within Indonesia but also in neighboring countries, such as Malaysia and Singapore, generating international health emergencies[29].

The establishment of a positive or negative ENSO are usually monitored using a Multivariate index (MVI) obtained by extracting the leading combined Empirical Orthogonal Function (EOF) of five different variables over the tropical Pacific basin (30S–30N and 100E–70W). During strong positive and negative ENSO seasonal prediction of fire weather is enhanced up to 7 ahead (figure 4) as a results of the enhanced predictability of these large scale patterns at the seasonal time scale[30]. Efforts to mitigate the impact of fires during ENSO events in Indonesia could therefore benefit from an early warning system at this time scale as they could be issued with sufficient advance time. This could help enforcing land management practices, implement fire prevention and suppression measures, and raise awareness about the environmental and health hazards associated with burnings[31].

A similar phenomenon is the Indian Ocean Dipole (IOD) that occurs in the Indian Ocean, characterized by the difference in sea surface temperatures (SST) between the western and eastern parts of the ocean. The IOD has been known to influence weather patterns in various regions, including southern and eastern parts of Australia. During positive IOD events, there is typically a reduction in rainfall in these regions, leading to drier-than-normal conditions. There is still debate if there is a direct influence between the IOD and the Australian fires as a clear signal is often hindered by changing land management practices, fuel availability, and human activities[32]. Figure 5 shows the FWI anomalies over South east Australia for the 2013 -2022 period in relation to the occurrence of the Indian Ocean Dipole as measured by the Dipole mode Index (DMI). The DMI is defined as the difference between the SST anomalies of Western (10S-10N and 50E-70E) and Eastern (10S-0N and 90E-110E) Equatorial Indian Ocean regions.

The 2019-2020 Australian bushfire season is commonly referred to as the "Black Summer" in Australia. It was an exceptionally devastating and prolonged period of bushfires that occurred from late 2019 to early 2020. The fires had a severe impact on various parts of Australia, causing widespread destruction, loss of human lives, and significant damage to wildlife and the environment. The Black Summer fires were characterized by their unprecedented scale, intensity, and duration. They also occurred in a period of strong Indian Ocean Dipole which is a contributing factors to enhance the predictability of the anomalous fire danger conditions

In the aftermath of the Black Summer fires, efforts were made to assess the damage, and implement measures to prevent and mitigate future fire seasons' impacts. The 7 month predictability window for this extreme event could be relevant to help implementing sustainable practices to protect against future fire disasters.

Usage Notes

In this section, we describe two typical workflows to retrieve and explore seasonal data using exclusively the Copernicus CDS API and toolbox. In order to replicate the work, users should ahead over to the CDS website (`https://cds.climate.copernicus.eu/cdsapp#!/home`) and register an account (`https://cds.climate.copernicus.eu/user/register?destination=%2F%23!%2Fhome`). Once an account is created, and the user logs in, the seasonal fire forecasts can be found by typing relevant keywords in the search box, e.g. 'fire danger indices seasonal data'. The web page dedicated to the seasonal fire forecasts is divided into three tabs: the 'overview' tab shows a concise description of the data; the 'download data' tab contains a data request form; the 'documentation' tab contains in depth information about the dataset and originating systems. At the top of the page, another set of tabs allow users to explore other datasets, applications, requests and the toolbox.

Download global fire danger forecast maps

The seasonal forecast of the Fire Weather Index issued on 2019-01-01 with 1 month lead time, are used as example files. Downloading these data is rather straight forward using the CDS web interface. The registered user needs to tick a few boxes to specify the index, period of interest and type of data, then click on a ‘Download’ button. For larger data requests, the use of the CDS API is recommended. Below an example script is provided.

```
import cdsapi

c = cdsapi.Client()

c.retrieve(
    ’cems-fire-seasonal-reforecast’,
    {
        ’format’: ’grib’,
        ’variable’: ’fire_weather_index’,
        ’system_version’: ’4_1’,
        ’year’: ’1991’,
        ’month’: ’09’,
        ’leadtime_hour’: [
            ’12’, ’36’, ’60’,
            ’84’, ’108’, ’132’,
            ’156’, ’180’, ’204’,
            ’228’, ’252’, ’276’,
            ’300’, ’324’, ’348’,
            ’372’, ’396’, ’420’,
            ’444’, ’468’, ’492’,
            ’516’, ’540’, ’564’,
            ’588’, ’612’, ’636’,
            ’660’, ’684’, ’708’,
        ],
    },
    ’download.grib’)
```

Plotting data using the CDS toolbox

To harness the power of the CDS, users are invited to familiarise with the CDS Toolbox. This is an interactive environment that allows to process and plot data without necessarily downloading them. This is particularly useful for users with limited bandwidth and/or unstable connections. The toolbox is designed to develop python applications that can be shared with other users, hence streamlining collaborative research and development. The script below can be pasted in the toolbox editor to generate a static map of the Fire Weather Index (as they are shown in the EFFIS and GWIS platform) that can be exported and used for reports and publications.

```
import cdstoolbox as ct
# Magics plot configuration dictionary
MAP_CONFIG = {
    ’contour’: {
        ’contour_level_selection_type’: ’level_list’,
        ’contour_level_list’: [0, 5.2, 11.2, 21.3, 38, 50, 150],
        ’contour_shade’: ’on’,
        ’contour_label’: ’off’,
        ’contour_shade_method’: ’area_fill’,
        ’contour_shade_colour_method’: ’list’,
        ’contour_shade_colour_list’: [’#84F07F’, ’#FFEB3C’, ’#FFB00C’,
                                      ’#FA4F00’, ’#B40000’, ’#280923’],
        ’contour’: ’off’,
        ’legend’: ’on’,
    },
```

```
    'legend': {
        'legend_text_colour': 'black',
        'legend_text_font_size': 0.4,
        'legend_display_type':'continuous',
    }
}
# Initialise the application
@ct.application(title='Fire Weather Index 2020-07-01', fullscreen=True)
@ct.output.figure()
def application():
    # Retrieve full resolution FWI data for a single date
    data = ct.catalogue.retrieve(
        'cems-fire-historical-v1',
        {
            'product_type': 'reanalysis',
            'variable': 'fire_weather_index',
            'dataset_type': 'consolidated_dataset',
            'system_version': '4_1',
            'year': '2020',
            'month': '07',
            'day': '01',
            'grid': '0.5/0.5',
        }
    )
    # Plot the data using the defined configuration MAP_CONFIG on a dynamic map
    plot = ct.map.plot(data, **MAP_CONFIG)

    return plot
```

Code availability

The fire indices have been generated using the open source GEFF modelling system v4.1(`https://git.ecmwf.int/projects/CEMSF/repos/geff`). The code to reproduce the results of this manuscript is openly available on a public repository: `https://github.com/fdg10371/Jupyter_notebooks`.

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Author contributions statement

C.V., F.D.G., J. S-M. and G. L. conceived the experiments. S.V. and F.W. established the data governance for the dataset. C.B. produced the data and carried out the archival of indices on the Climate Data Store. P.M. developed version 4.1 of the GEFF model used to produce the data. F.D.G. analysed the data and wrote the first version of the manuscript. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.

Figures & Tables

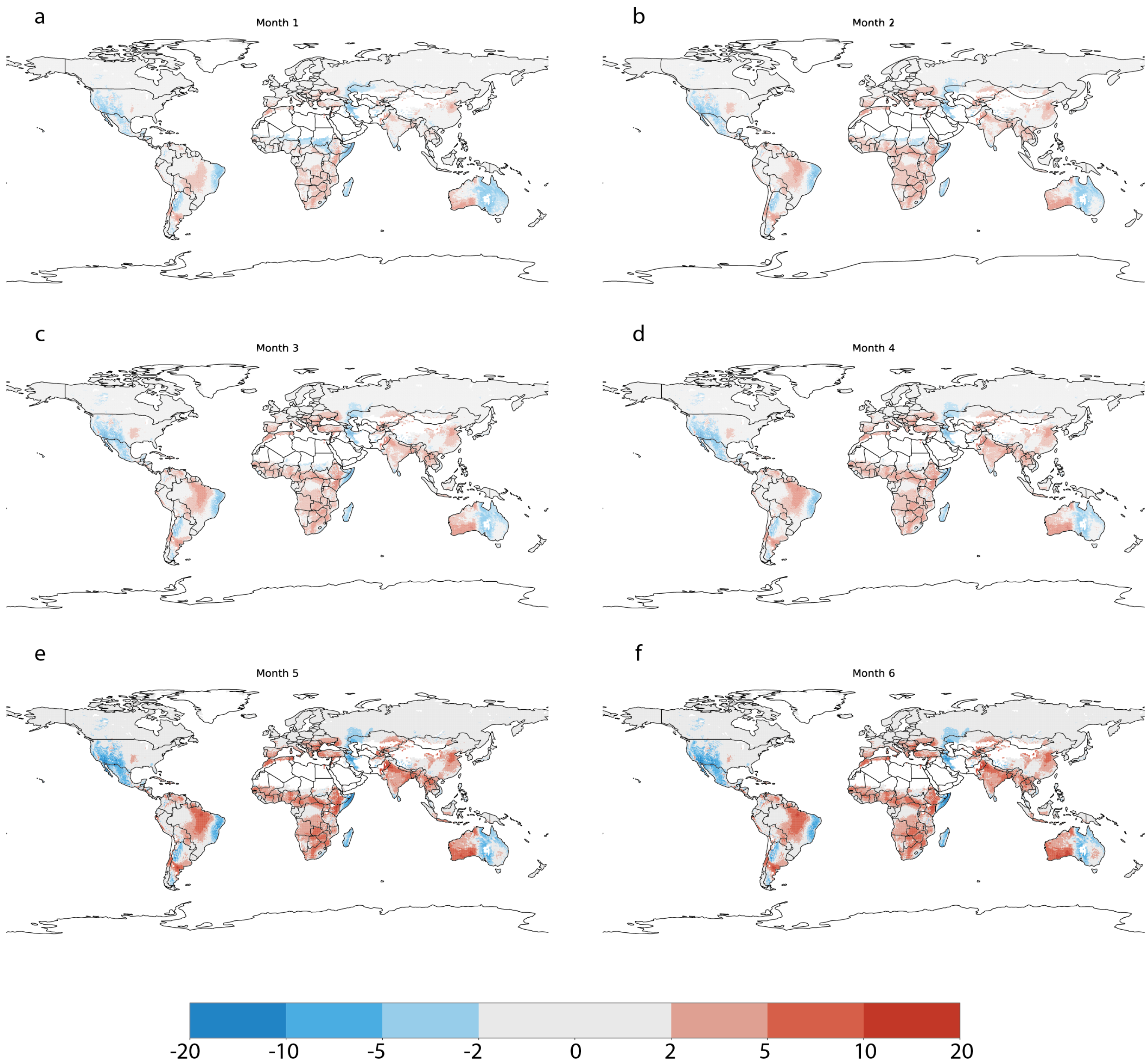

Figure 1. Bias as the average deviation or difference between the predicted monthly values and the observed values here provided by reanalysis simulations. It provides information about the tendency of the model to consistently overestimate or underestimate the true values. The average is performed for the ensemble mean and for all the months in the 1981-2020 period. Panel a to f provides the 7 months forecast horizon available.

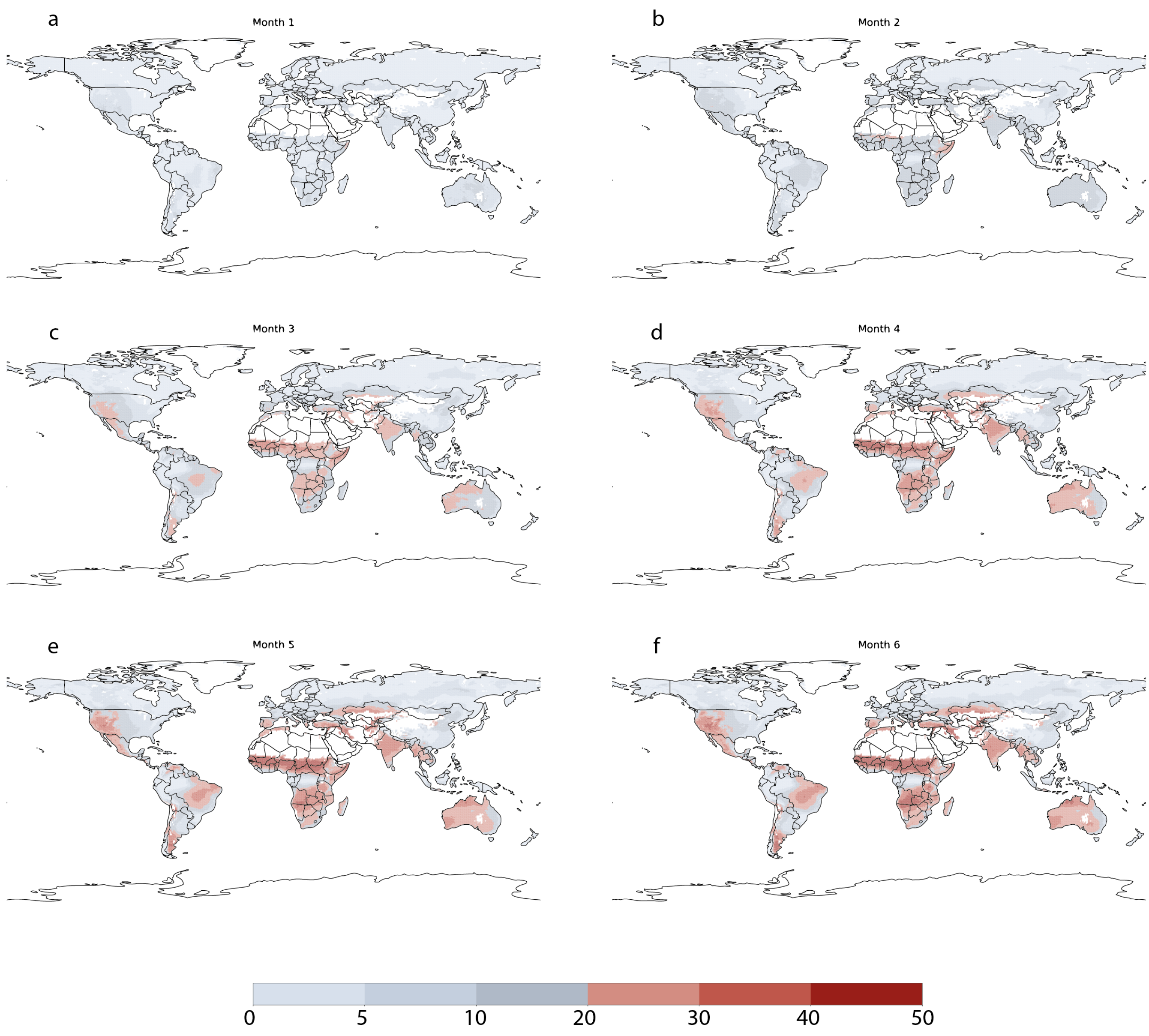

Figure 2. Same as figure 1 but for the RMSE

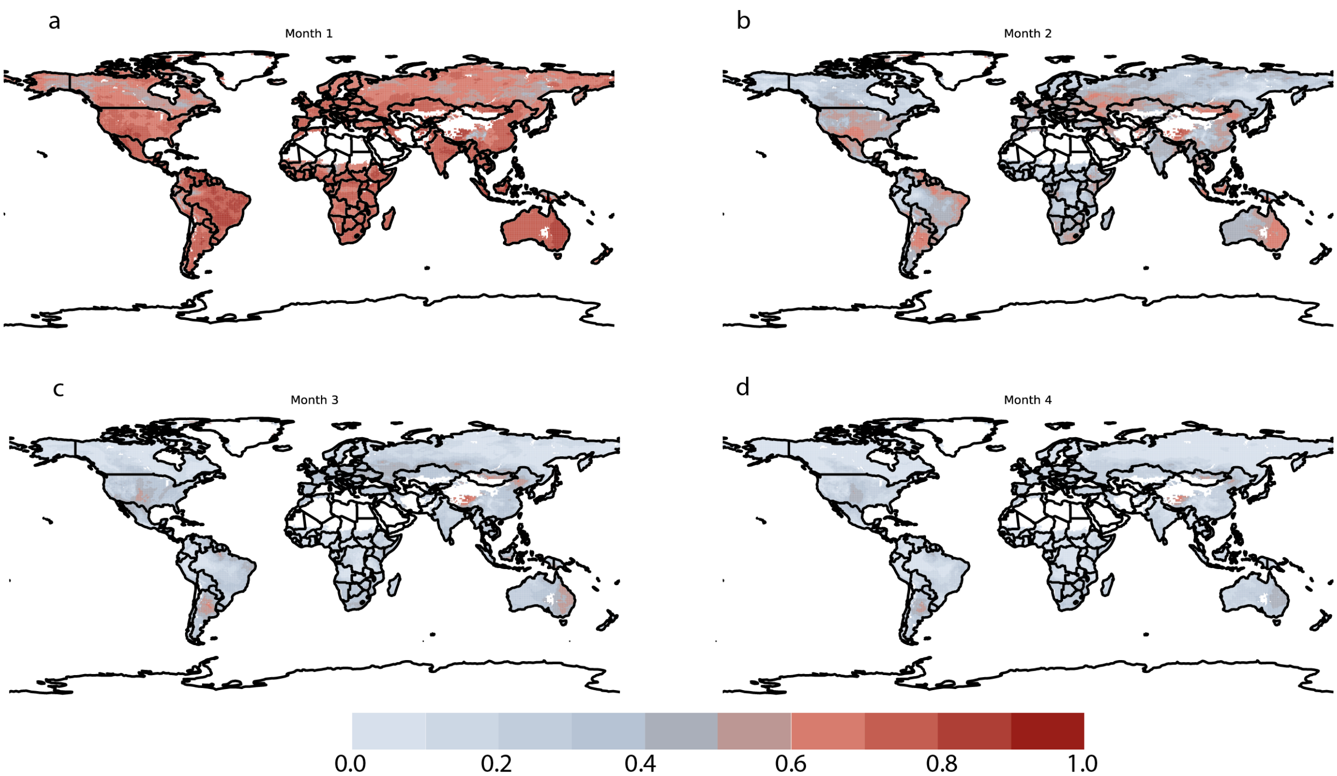

Figure 3. Anomaly correlation for the fwi seasonal forecast system during the hindcast period (1981-2022) for all the the forecasts and valid for month 1 to 4.

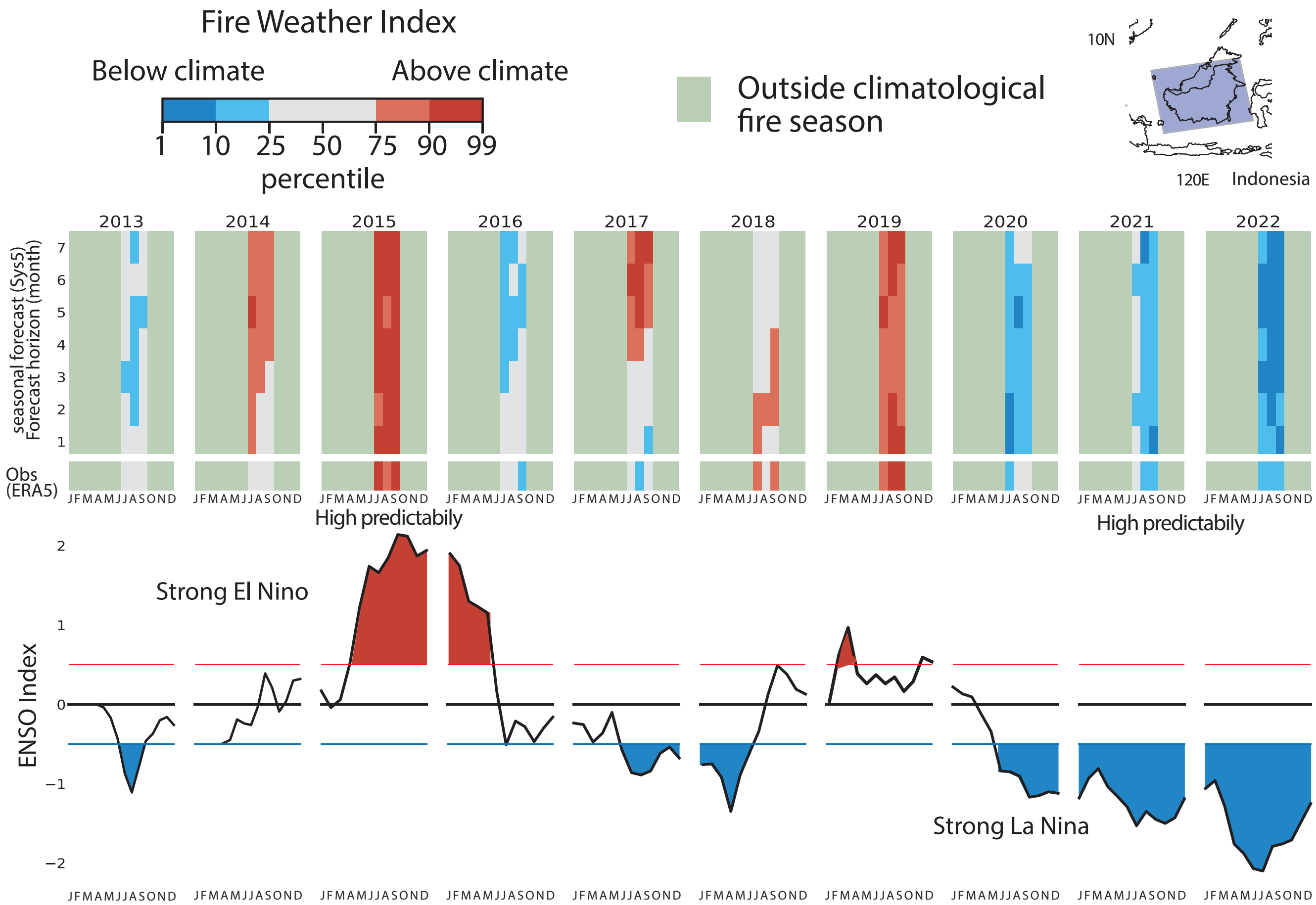

Figure 4. Prediction of fire danger anomalous conditions between 2013 and 2022 over Indonesia. Months are classified as above or below the climatic mean using percentiles compared to the climatological mean. Observed anomalies are compared to the forecast for increasingly longer lead times to highlight the predictability of anomalous conditions. Months outside the traditional fire season are masked out.They are months with average FWI lower then a third of the maximum yearly value. The ENSO index helps identifying years of strong positive and negative anomalies with established El Niño La Niña conditions. These years corresponds to period of high predictability when anomalous conditions could be predicted up to 7 months before.

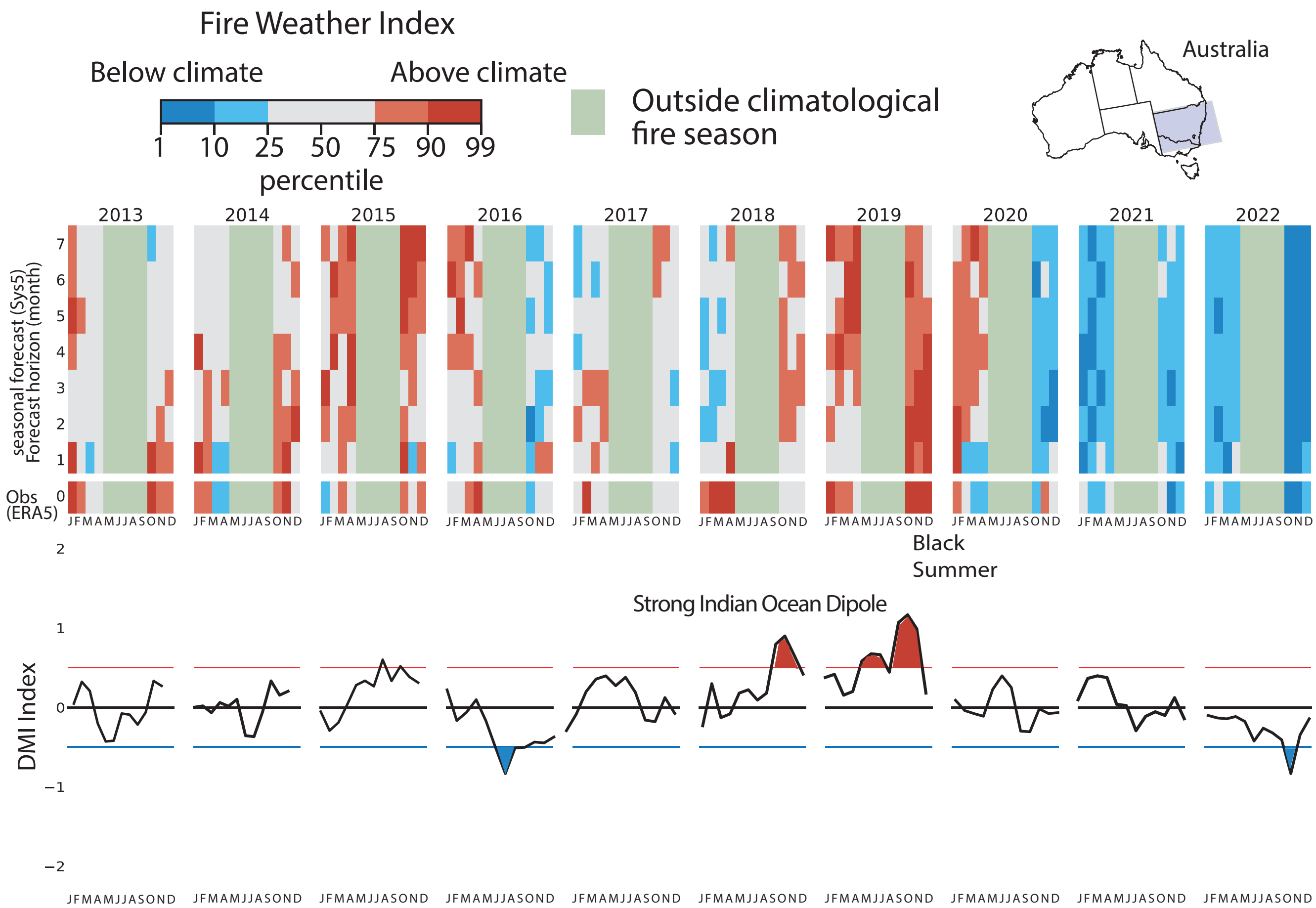

Figure 5. Prediction of fire danger anomalous conditions between 2013 and 2022 over New Welsh in Australia. Months are classified as above or below the climatic mean using percentiles. Observed anomalies are compared to the forecast for increasingly longer lead times to highlight the predictability of anomalous fire weather conditions. Months outside the traditional fire season are masked out.They are months with average FWI lower then a third of the maximum mean yearly value. The Dipole mode index (DMI) helps identifying years of strong positive and negative anomalies with established Indian Ocean Dipole conditions. DMI >0.5 were recorded during the 2019 Black summer when anomalous conditions could be predicted up to 7 months before.