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Skillful seasonal prediction of key carbon cycle components: NPP and fire risk

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Abstract

We investigate the skill of the GloSea5 seasonal forecasting system for two carbon cycle processes, which are strong contributors to global CO₂ variability: the impact of meteorological conditions on CO₂ uptake by vegetation (characterised by net primary productivity, NPP), and on fire occurrences (characterised by fire risk indices). Current seasonal forecasts of global CO₂ concentrations rely on the relationship with the El Niño–Southern Oscillation (ENSO), combined with estimated anthropogenic emissions. NPP and fire are key processes underlying that global CO₂–ENSO relationship: In the tropics, during El Niño events, CO₂ uptake by vegetation is reduced and fires occur more frequently, leading to higher global CO₂ levels. Our study assesses the skill of these processes in the forecast model for the first time. We use the McArthur forest fire index, calculated from daily data from several meteorological variables. We also assess a simpler fire index, based solely on seasonal mean temperature and relative humidity, to test the need for additional complexity. For NPP, the skill is high in regions that respond strongly to ENSO, such as equatorial South America in boreal winter, and northeast Brazil in boreal summer. There is also skill in some regions without a strong ENSO response. The fire risk indices show significant skill across much of the tropics, including Indonesia, southern and eastern Africa, and parts of the Amazon. We relate this skill to the underlying meteorological variables, finding that fire risk in particular follows similar patterns to relative humidity. On the seasonal-mean timescale, the McArthur index offers no benefits over the simpler fire index: they show the same relationship to burnt area and response to ENSO, and the same levels of skill, in almost all cases. Our results highlight potentially useful prediction skill, as well as important limitations, for seasonal forecasts of land-surface impacts of climate variability.

1. Introduction

Atmospheric CO₂ levels are often considered to be a ‘driver’ of changes in the climate system, particularly when considering projected changes over many decades. However CO₂ concentration is itself a function of both anthropogenic emissions and exchanges with the land and ocean. It is these natural fluxes, and in particular the three factors of heterotrophic respiration, vegetation productivity and fire variation, that dominate the interannual variability of CO₂ (Zeng et al 2005). It has been shown that CO₂ concentrations can be skillfully predicted from features of the climate system, such as the El Niño–Southern Oscillation (ENSO) together with an estimate of anthropogenic emissions (Jones et al 2001, Jones and Cox 2005, Betts et al 2016, 2018). However, seasonal forecasts based on global climate models could also be used to forecast components of CO₂ variability more directly. We aim here to investigate that possibility, for vegetation productivity and fire risk, in the context of the skillful ENSO-based CO₂ forecasts.

ENSO is the largest global mode of interannual variability and affects both the global climate and global carbon cycle (Rodenbeck et al 2018). El Niño and La Niña events occur every 2–7 years, when sea surface
temperatures (SSTs) in the equatorial Pacific are anomalously high or low, respectively, over a period of several months (e.g. Philander 1990, Trenberth 1997). The anomalies typically peak in boreal winter, but their impacts on the climate can last for many months. An El Niño event brings higher temperatures and reduced precipitation to the tropics. These conditions put vegetation and soils under stress, with implications for their large global stores of carbon: it leads to increased respiration, reduced assimilation of carbon, and increased fire risk (Kim et al 2016, Chen et al, April 2016).

The variation in vegetation carbon uptake/ emissions within a system can be assessed in terms of net primary production (NPP). This represents the amount of CO₂ that is taken in by vegetation, calculated as gross primary production (GPP, the total amount of carbon assimilated by plants) minus carbon lost through autotrophic respiration (Roxburgh et al 2005). Kim et al 2016 studied Earth System Models (ESMs) from CMIP5 and showed that the CO₂–ENSO relationship in the models is mostly due to variations in NPP: the increased temperature and reduced precipitation in the tropics due to an El Niño event leads to a reduction in NPP, which leads to an increase in atmospheric CO₂. They found that their ESM ensemble overestimated ENSO-related NPP anomalies, due to overestimating the temperature response to ENSO. However, the ESMs also tended to underestimate the carbon fluxes from fires, and from heterotrophic respiration, which adds to the uncertainty in the simulation of the CO₂–ENSO relationship.

Fire emissions in pan-tropical forests increased by over 100% during El Niño compared to La Niña from 1997 to 2016 (Chen et al 2017), and a one-third increase in fires in the Brazilian Amazon was recorded during the 2015/16 El Niño (Aragao et al 2018). The spike in fire emissions in 1997/98, associated with a large El Niño event, has been attributed to the burning of large areas of carbon-rich peatland in Indonesia (Page et al 2002), contributing between 0.81 Gt and 2.57 Gt of carbon to global annual emissions, the equivalent of 13%–40%.

Tropical forests are not typically at high risk of burning, due to high moisture levels. However, during years of strong drought such as during an El Niño, vegetation can dry out enough to burn. On top of a background of continued warming, these events may have increasing impacts on fire risk in the future (Fasullo et al 2018). An ignition source is also required to start a fire, either via anthropogenic or natural means (e.g. lightning), and with increased land use activities in recent decades, including the use of fire as a land-cleanup method, the risk of fire has also been increasing (Spessa et al 2015).

ENSO can be forecast with a high degree of skill using seasonal climate prediction systems (e.g. Barnston et al 2012, Ren et al 2019, and references therein). Bett et al (2016, 2018) used skillful ENSO predictions to successfully forecast the CO₂ concentrations at Mauna Loa, often regarded as a proxy for global levels. Their hybrid statistical–dynamical approach used a forecast of the Niño3.4 index of SSTs in the east Pacific, from the GloSea5 seasonal forecasting system, together with the observed CO₂–ENSO relationship and estimated anthropogenic emissions. Several authors have studied how the skill in forecasting ENSO can be used to forecast fires in different regions. For example, Chen et al (April 2016) examined how SST indices, including ENSO, can be used to forecast annual burnt area across the globe. Chen et al (2011) performed a similar study, focusing on South America. Spessa et al (2015) demonstrated that fire activity is negatively correlated with rainfall, and positively associated with deforestation in Indonesia. They use rainfall from a seasonal forecasting system to show that burnt and fire-affected area in Indonesia can be forecast at several months’ lead time, and that these results are strongly influenced by El Niño events. Mariani et al (2016) evaluated the correlation between ENSO and seasonal rainfall anomalies across Southeast Australia. They found a significant and persistent influence of El Niño on fire activity in the region on a decadal scale, mostly driven by an ENSO-related reduction in water availability. The increased activity is influenced not only by drier conditions in the austral summer and autumn of the fire season year, but also by water availability in the preceding winter and spring.

Being able to skillfully forecast fire risk or NPP at long lead times is of course useful in itself, not just as part of forecasting global CO₂ variations. Human-relevant impacts of weather and climate variability such as these are often described using complex physical or statistical models, requiring driving data from several different quantities at sub-daily time resolution. These can be effective for short-term forecasting (e.g. weather timescales, Giuseppe et al 2020) and for case studies of past events or historical climatology. However, for seasonal climate forecasting, this kind of comprehensive impact modelling is usually not effective: using a metric based on fewer variables, driven by data averaged over longer timescales, will tend to be less noisy and more skillful. Bett et al (2019) demonstrate this explicitly in the context of wind and solar energy generation in Europe, following similar work by Palin et al (2016) and Clark et al (2017). A balance therefore has to be made between capturing the processes necessary to forecast the interannual variability of the quantity of interest, without simply adding complexity to a model where there is insufficient skill. In the context of the interannual variability of crop yield, Williams and Falloon (2015) demonstrated that the driving data to their crop model can be simplified: replacing some variables with climatologies, and reducing the temporal resolution of others, did not reduce the predictability. In the context of fire forecasting, Turco et al (2018) looked at combinations of precipitation, evapotranspiration and temperature as predictors for seasonal forecasts of burnt area. They found that using a solely precipitation-based metric was the best choice.
The GloSea5 seasonal forecasting system is based on a coupled climate model, which includes simulation of the land surface and vegetation in its component model JULES (Joint UK Land Environment Simulator, Best et al 2011, Clark et al 2011). Although GloSea5 does not include a coupled carbon cycle, NPP is calculated internally by JULES. Fire risk indices can also be calculated offline, based on GloSea5 forecast model output. We are therefore able to examine how well the same seasonal forecasting system used by Betts et al (2016, 2018) can directly model separate elements of the carbon cycle.

In this paper we assess the skill of GloSea5 for forecasting NPP and the McArthur Forest Fire Danger Index (McArthur 1966, Luke and McArthur 1978) in the Tropics, and explain this with reference to the skill in the underlying meteorological variables. We also investigate a simple fire index based only on temperature and relative humidity, to understand the impact of using fewer and simpler quantities in the calculation of fire risk on seasonal time scales.

We describe the data sets, methods and calculations we use in our analysis in section 2. Section 3 describes our results, firstly validating our observation-based data, then considering seasonal forecast skill. We discuss our conclusions in section 4.

2. Data and analysis methods

In this section we describe how the fire risk indices and NPP are defined, and how they are calculated for our observation-based reference values. We then describe the GloSea5 seasonal forecasting system, and how we use that to calculate hindcast-based values of the fire indices and NPP.

2.1. Fire risk indices

Fire indices are used operationally in many fire-prone regions to help risk reduction and planning. A wide variety of indices have been developed to quantify fire risk, recently reviewed by de Groot et al (2015). Although they are usually tuned to specific regions, some have been used successfully in global-scale climate simulations (e.g. Betts et al 2015, Burton et al 2018), including the two we consider here: the McArthur index and the Angström index.

The McArthur Forest Fire Danger Index Mark 5 was first developed for Australia, and is calculated on a daily basis, integrating information on past rainfall leading up to each day (Noble et al 1980):

\[ I_M = 1.275 f^{0.967}_{drt} \exp \left( \frac{T_{C,\text{max}}}{T_{A0}} - \frac{RH_{\text{ RH},\text{min}}}{RH_{A0}} + \frac{W}{W_{A0}} \right), \]

where \( T_{C,\text{max}} \) is the maximum daily temperature in °C, \( RH_{\text{ RH},\text{min}} \) is the daily minimum relative humidity as a percentage and \( W \) is the daily mean wind speed in m s\(^{-1}\). The scale constants are \( T_{A0} = 29.5858 \) °C, \( RH_{A0} = 28.9855 \% \), and \( W_{A0} = (42.735/3.6) \) m s\(^{-1}\). The Keetch and Byram (1968) drought index \( f^{drt}_{drt} \) has a maximum limit of 10 (Sirakoff 1985), and is given by

\[ f^{drt}_{drt} = \min \left[ 0.191 (a_{\text{restore}} + 104) \frac{(N + 1)^{1.5}}{3.52(N + 1)^{1.5} + R - 1}, 10 \right] \]

where \( N \) is the number of days since the last day with rainfall, and \( R \) is the amount of rainfall on that day in mm.

The restore amount, \( a_{\text{restore}} \), is the amount of water needed to restore the water content of the soil to field capacity, given in the range 0–200 mm. Given the difficulty in obtaining global soil moisture observations, we remove the soil moisture dependence entirely, by setting \( a_{\text{restore}} \) to a constant value of 120 mm, as used in Golding and Betts (2008). We have tested the effect of this simplification on correlations of seasonal means in appendix A.

The McArthur fire index is used particularly in Australia, South Africa and Spain (de Groot et al 2015), but it has also been shown to strongly correlate with satellite estimates of actual fire occurrence in the Amazon (Hoffmann et al 2003), and Golding and Betts (2008) used it in their study of Amazonian fire risk under future climates. Note that the McArthur index is defined such that higher values indicate greater risk.

The Angström index has a much simpler definition:

\[ I_A = \frac{RH_{\text{ RH}}}{RH_{A0}} + \frac{T_C - T_{A0}}{T_{A0}}, \]

where \( RH_{\text{ RH}} \) is daily mean relative humidity as a percentage, and \( T_C \) is the daily mean temperature in °C. The scale constants are \( RH_{A0} = 20 \% \), \( T_{A0} = 10 \) °C and \( T_{A1} = 29 \) °C, following Eastaugh et al (2012); other constants are also in use, e.g. Skvarenina et al (2004) and Holsten et al (2013). Since this equation is linear, it can also be used with monthly or seasonal mean relative humidity and temperature values. Note that smaller values of the Angström index indicate greater fire risk.

The Angström index was developed in the first half of the Twentieth Century in Sweden, and has been used throughout the Scandinavian Peninsula (Hamadeh et al 2017), but has had success in other countries such as
Slovakia (Skvarenina et al. 2004), Taiwan (Lin 1995), Germany (Holsten et al. 2013), Austria (Arpaci et al. 2013) and Brazil (Alves White et al. 2013).

We calculate observation-based reference values of both fire indices, using the WFDEI reanalysis data set (WATCH Forcing Data methodology applied to ERA-Interim, Weedon et al. (2011, 2014), using CRU precipitation). This covers land points only, on a 0.5° grid. We calculate the reference Angström index from monthly mean temperature and relative humidity. We calculate the reference McArthur index using daily maximum temperature, daily minimum relative humidity, daily mean windspeed, and daily precipitation. We use a near-zero threshold for daily precipitation (10^{-8} mm), but we have also tested a higher level (5 mm) following Keetch and Byram (1968). The seasonal-mean results from using either threshold using the WFDEI data are very highly correlated.

Although these fire indices do not account for available fuel in their quantification of fire risk, we mask out gridcells where the fraction of bare soil is \( \geq 0.5 \), following Gilham (2014). This removes regions without substantial amounts of vegetation to burn.

It is important to understand how the fire risk indices we consider here relate to actual fire occurrence. In principle, there could be significant differences: the fire indices do not explicitly account for fuel availability or chance of ignition, for example. These indices are based solely on meteorological factors, as opposed to human factors. We use observations of burnt area to quantify fire occurrence, using v4.1s of the Global Fire Emissions Database (GFED, Giglio et al. 2013, Randerson et al. 2017), which includes an experimental adjustment for small fires (Randerson et al. 2012, van der Werf et al. 2017). The GFED data starts in 1997, later than the WFDEI and seasonal forecast data sets we use.

2.2. Net primary productivity

Net primary productivity is calculated from the carbon assimilated by photosynthesis minus the carbon lost by respiration. This quantity is not directly observable. At the site level, eddy correlation techniques can be used to measure net ecosystem exchange, which incorporates both NPP and soil respiration. Field-based measurements can give accurate NPP data on a small scale, but it is difficult to estimate NPP on larger scales due to sparse observation networks (Pachavo and Murwira 2014). Satellite products exist (e.g. MODIS NPP, Zhao et al. 2006, Heinsch et al. 2006), but these are themselves based on models, and they can be contaminated by cloud cover—particularly relevant in the Tropics. The MODIS NPP data is only available from 2000, which would give too short a period to robustly assess the skill of seasonal forecasts.

To avoid these problems, and for greater internal consistency, we calculate our observation-based reference values of NPP using JULES driven by the WFDEI reanalysis data. In JULES, NPP depends strongly on soil moisture (Clark et al. 2011, Harper et al. in prep). Soil moisture depends on evaporation and transpiration, which in turn depend on vegetation cover and atmospheric conditions (in particular, temperature and humidity, with wind also being a factor). NPP in JULES also has a strong dependence on temperature (Clark et al. 2011), via both photosynthesis and respiration.

Modelled primary productivity in JULES has been evaluated against a number of observational datasets, and is shown to successfully reproduce interannual variability of GPP on global scales, while on a regional scale GPP in the tropics was biased to higher values than observed (Slevin et al. 2017).

The JULES configuration used for our WFDEI-driven simulations is based on ‘JULES-C’ as used in the Global Carbon Budget annual assessments (le Quéré and assessed for its ENSO response characteristics (Bastos et al. 2018). In the present application the dynamic vegetation model was switched off and the vegetation cover prescribed using the International Geosphere and Biosphere Programme (IGBP) land classification dataset, which was processed as part of the WFDEI project. The soil ancillary was generated by the Central Ancillary Program (Dharmasiri et al. 2009) on the WFDEI grid, using the Brooks and Corey (1964) parameterisation. The topographic index data was from HydroIrk (ERSO Archive 2017). The model was forced with global CO\(_2\) from NOAA.\(^4\)

2.3. Seasonal forecasts

We use data from the GloSea5 seasonal forecast system (MacLachlan et al. 2015) in its Global Coupled 2.0 (GC2) configuration, based on the Hadley Centre General Environment Model version 3 (HadGEM3-GC2, Williams et al. 2015). This coupled climate model uses an atmospheric grid of 0.83° longitude by 0.55° latitude, with a well-resolved stratosphere and a 0.25° ocean grid. The land surface model component is the GL6.0 configuration of JULES (Best et al. 2011, Walters 2017). We use a hindcast data set comprising 24-member ensemble forecasts of the December–January–February (DJF) and June–July–August (JJA) seasons each year, initialised around 1st November and 1st May respectively. The hindcasts are produced for the 20 years of 1992–2011 for the JJA and 1992/93 to 2011/12 for the DJFs. While the skill of different GloSea5 outputs has been evaluated in a variety of

\(^4\) [https://data.giss.nasa.gov/modelforce/ghgases/Fig1A.ext.txt](https://data.giss.nasa.gov/modelforce/ghgases/Fig1A.ext.txt), downloaded from [https://data.giss.nasa.gov/modelforce/ghgases/](https://data.giss.nasa.gov/modelforce/ghgases/), based on Hansen et al. (2007).
different contexts and applications, of particular relevance here is that GloSea5 has very high levels of skill in forecasting ENSO (MacLachlan 2015), and in forecasting rainfall in the tropics (Scaife et al 2017, 2019). Note that the version of JULES used within GloSea5 is less recent than the one we use to calculate observation-based NPP (see previous subsection).

Calculating the Angström fire index from the hindcast data is reasonably straightforward. As already discussed, the Angström index is linear, so its seasonal mean values can be calculated directly from monthly mean forecast output. In contrast, the McArthur index can only be approximated by the forecast data. Although daily maximum temperature and daily mean wind speed were available, the daily minimum relative humidity was not stored when the forecasts were made, so we have used the daily mean in that case. A second difficulty is in the calculation of the drought factor: the number of days since there has been any rainfall could be longer than the forecast lead time in some locations (e.g. before 25th Oct, 1st Nov or 9th Nov for the DJF forecasts). Those cases are masked out of our calculations.

To make an initial assessment of the forecast skill, we will be using the simple interannual Pearson correlation between the seasonal mean, ensemble mean hindcast data, and the reference data derived from observations. Using the ensemble mean ensures that we are maximising the predictable signal from the ensemble; having skill in the ensemble mean is a necessary first step before examining more complex skill metrics based on the distribution of ensemble members.

We are not applying any bias correction to any of the hindcast data. While the Pearson correlation is not sensitive to overall seasonal-mean biases, the fact that there are many absolute thresholds in the fire index definitions means that model biases could still affect the results. We are also not detrending any of the data when assessing its skill. While it is often informative to understand how much of a skillful forecast comes from a trend versus other processes, in our case it is just as relevant to know that the model is able to reproduce an observed trend. Studies detailing the ability of a seasonal forecast to produce a useful climate service for a particular user would require more detailed consideration of biases and trends, as well as probabilistic skill assessment. For this initial study, of how well the initialised climate model on its own can capture the processes necessary for forecasting relevant components of the carbon cycle, we simply test the correlation.

3. Results

We first show how tropical NPP and fire risk behave under El Niño and La Niña conditions in our observation-based data sets. This provides important context for the subsequent subsections on their performance within the GloSea5 hindcasts. For consistency, all plots cover the same 20-year period and two seasons as the hindcast (1992/93–2011/12, DJF and JJA), unless noted otherwise.

Figure 1(a) shows, for meteorological context, the mean anomalies of seasonal rainfall totals under El Niño and La Niña conditions, based on the Oceanic Niño Index’ (ONI): A season is labelled as being El Niño if its seasonal mean value is $>0.5$ K; and as La Niña if its ONI $<-0.5$ K. We classify DJFs and JJAs separately according to their own ONI values. There are clear regions of enhanced or reduced precipitation across the Tropics, with impacts in different regions at different times of the year, reflecting the changes in atmospheric circulation induced by the ENSO events.

3.1. NPP and fire index relationship with El Niño

Figure 1(b) shows the response of NPP to El Niño and La Niña events in DJF and JJA. There are regions of both reduced and enhanced productivity in each case. The response matches that of precipitation in water-limited regions of northern South America in DJF, and in Africa in both seasons. The NPP signal in northeastern Brazil in JJA is not reflected in the precipitation response, but is reflected in variables that affect soil moisture via evaporation. There is no NPP signal in Indonesia in JJA despite the clear precipitation response, likely due to vegetation in the region not being water limited.

Similar composite maps are shown for the McArthur and Angström fire indices in figure 1(c) and (d). These follow the precipitation response more closely, with enhanced fire risk in northern South America, southern Africa and northwestern Australia in DJF, and in Indonesia and eastern India in JJA El Niños. As with NPP, there are some additional responses not seen in the precipitation, such as in the Sahel, the Horn of Africa and India in DJF, and northern Australia in JJA.

3.2. Fire index relationship with burnt area

Figure 2(a) shows the ENSO response in the observed burnt area data. For consistency with our other results, we only use the period up to the end of the GloSea5 hindcast data set, i.e. the 15 years of 1997/98 to 2011/12 for DJF, and

5 https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php.
1997–2011 for JJA. As the GFED data set is based on very high resolution observations of individual fires, this data is much more spatially varied than the meteorology-based data shown previously (all our figures use data regridded to match the GloSea5 data). Nevertheless, there are clear similarities with the fire risk indices, particularly in northern South America, the Sahel and northwest Australia in DJF. It is important to note that the two seasons we focus on here do not necessarily correspond to the peak fire seasons around the world; for completeness, we show the burnt area ENSO response in the other two seasons, and the climatologies of all four seasons, in appendix B.

To clarify the relationship between burnt area and the fire risk indices, figure 2(b) maps the correlation of their seasonal mean time series. This shows that, in almost all the regions where the fire indices respond strongly to ENSO, they are well correlated with observed burnt area (although a noticeable exception is northern Australia in JJA). This gives us confidence that the fire indices give a reasonable estimate of fire risk.

One of the most important features seen in figure 1(c), (d) and figure 2 is that there is very little difference between the results for the McArthur and Angström fire indices: they both perform equally well/poorly in terms of following the interannual variability of burnt areas in the tropics. This is backed up by plotting the correlation between the two fire indices themselves (figure 3): they are very highly (anti-)correlated, with values $r < -0.8$ in most places for both seasons, over the 20-year period we consider here. The additional complexity in modelling fire risk that goes into the McArthur index does not seem important for most regions of the tropics for forecasting seasonal means.

Figure 1. Each set of 4 panels shows the mean anomalies of observation-based data for a given quantity for El Niño and La Niña DJF and JJA seasons, with respect to the climatology for that season. (a) WFDEI precipitation. (b) NPP from WFDEI-driven JULES runs. (c) McArthur fire index calculated from WFDEI data. (d) Angström fire index calculated from WFDEI data. Note that the colour scheme has been switched in this case to be consistent with orange indicating greater fire risk. DJF climatologies are calculated for the 1992/93–2011/12 period, and JJA climatologies for the 1992–2011 period.
3.3. Seasonal forecasting skill

In the following figures, we show seasonal forecast skill maps, for NPP (Figure 4) and the McArthur and Angström fire indices (figure 5). Figure 6 shows the skill of their underpinning meteorological variables: temperature, precipitation, relative humidity and wind speed.

3.3.1. NPP and its components

In DJF, there is skill in NPP forecasts (figure 4) in equatorial South America, Africa, India and the Indochinese Peninsula. However, air temperature, precipitation, relative humidity and wind speed all show greater skill over much larger areas of South America in DJF (figure 6), particularly in the region from the Venezuelan coast south to the Amazon river. This is a good demonstration of how skill in the underlying variables does not map directly on to skill in the compound variables. In India and Indochina, the high correlation in NPP seems more related to temperature, with Indochina in particular not showing widespread skill in relative humidity or precipitation. These are also regions where NPP does not show a clear ENSO response in DJF.

In JJA, the correlation between reanalysis-forced NPP and GloSea NPP is high in northern Venezuela, northeastern Brazil, eastern Africa and northern Australia. These regions show a clear response to El Niño in JJA (figure 1(b)). The NPP skill shown could have useful applications, such as for agricultural production in northeast Brazil. In this region, the main contributor to the high skill is likely to be the depletion in soil moisture due to evapotranspiration, affected by relative humidity and wind speed, which both show skill in this area.

3.3.2. Fire indices and their components

There are large areas of skill in both DJF and JJA for the McArthur fire index, with very similar patterns seen for the Angström index skill (figure 5). The areas of skill largely correspond to where the fire indices in these seasons
respond strongly to ENSO (figure 1c and d). Comparing with the skill of the meteorological variables (figure 6), it is clear that the skill patterns are very similar to those of relative humidity and, to a lesser extent, wind speed and precipitation. The temperature skill patterns differ, but temperature is more skillful generally, over broader areas, partly due to its trend. This points to the key processes needed for forecasting fire risk being simply a measure of dry and hot conditions.

Finally, we estimate the skill of GloSea5 in forecasting burnt area, using a fire index or a single meteorological variable as a linear predictor (i.e. simply the correlation between a variable from the GloSea5 hindcast and the observation-based burnt area data). Figure 7 shows the Pearson correlation for each of these variables with burnt area. Here, a strong positive or negative correlation indicates that the variable could be used as a skillful predictor. Although the skill is clearly reduced compared to forecasting the fire indices or meteorological variables themselves, there are nevertheless some coherent large-scale regions that suggest useful levels of skill: northern South America, southern Indochinese Peninsula, northwestern Australia in DJF; northeastern Brazil, east Africa and Indonesia in JJA. It also appears that, to a large extent, just using a single meteorological variable could provide skillful forecasts of fire risk in some regions.

As expected from our examination of the observation-based data, the additional complexity of the McArthur index does not significantly improve the forecast skill, either of the fire indices themselves, or of actual burnt area.
4. Discussion and conclusions

This study has examined the seasonal forecasting skill of two key processes that contribute to the interannual variability of global CO$_2$ levels: fire risk and net primary productivity. While we expect that hybrid dynamical–statistical forecasts (e.g., based on ENSO, similar to Betts et al. 2016, 2018) will still be the best approach to forecasting global CO$_2$, our investigation is useful for highlighting underlying capabilities in the climate model used for our seasonal forecasts. We highlight where the forecasts do and do not have skill, in different regions and at different times of the year, in order to determine whether the skill is in the key regions and seasons that contribute to the CO$_2$ variability. The regional distribution of skill can also inform approaches to seasonal forecasting, and, in principle, the development of climate services for agriculture and fire risk management.

The seasonal forecast skill for the NPP modelled explicitly in GloSea5 is significant for large areas of the Tropics, including where NPP responds strongly to ENSO. Some of the regions where it is skillful are well-placed for forecasting crop yield, such as northeast Brazil.

The fire indices we have considered also show significant skill across much of the Tropics. However, we have also demonstrated, in observations as well as in terms of seasonal forecast skill, that on seasonal-mean time scales there is no benefit to using the detailed McArthur fire index over a simple indicator of hot and dry conditions—the Angström fire index. Any benefits from having a more detailed, carefully-calibrated fire index, as might be seen on weather-forecasting time scales, are lost when averaging over a season. The resulting skill picks out large-scale features in common across both indices: areas where it becomes anomalously dry and hot at similar times. We have demonstrated that there are several regions where burnt area itself could be forecast skillfully, based either on a fire risk index, or perhaps even on a single meteorological variable.

A third process, which is not considered here, but is also an important contributor to the interannual variability of terrestrial carbon emissions, is heterotrophic respiration. This is currently modelled within the GloSea5 system but not available as an output variable. Model heterotrophic respiration includes a factor that depends explicitly on soil temperature, and a factor that depends explicitly on soil moisture (Clark et al. 2011). An interesting extension to this work would be to look at whether the GloSea5 system can skillfully predict these two factors, and how much of this skill can be captured for seasonal means using a simple combination of meteorological variables such as air temperature, precipitation and wind speed.

Here, we have focused on the terrestrial components of the carbon cycle that are known to dominate the interannual variability of atmospheric CO$_2$ (Jones et al. 2001). However, the ocean plays a smaller, but still
significant, opposing response to the land for a typical El Niño event, of approximately 25% of the land magnitude. A logical next step towards developing a physically-based seasonal atmospheric forecast would be to assess the skill of both terrestrial heterotrophic respiration (as discussed above) and the air–sea flux of carbon. Ocean biogeochemistry is not currently included in the GloSea5 forecast system, although the related UK Earth System Model (UKESM, Sellar et al 2019) does include an ocean biogeochemistry model, MEDUSA. However, it is computationally very expensive, and including it in forecasts may not add predictive skill. This again implies that a more parsimonious approach, through understanding the seasonal drivers of ocean carbon exchange, is likely to yield better results.

Our results are a clear demonstration of the different kinds of analysis required when considering seasonal climate prediction, compared to weather forecasting studies, which require confidence at forecasting individual fire events; or climate projection timescales, where longer-term feedbacks are crucial. When forecasting seasonal means, simplicity is important. An impacts model that requires driving data from many input variables, at high temporal resolution, is unlikely to result in any benefit in terms of skill; much simpler metrics based on one or two variables on monthly-to-seasonal timescales are likely to be a more efficient way of achieving skillful forecasts. Palin et al (2016) and Bett et al (2019) have demonstrated this point in the very different contexts of seasonal forecasting for transport and energy sector impacts in Europe.

This also applies to interactive models, like JULES’ fire model INFERNO (Mangeon et al 2016, Burton et al 2019): While INFERNO adds value at climate projection timescales, where feedbacks between atmospheric CO2 and vegetation distributions are important, it is unlikely that including INFERNO in the GloSea system would give increased skill at forecasting burnt area at seasonal timescales, given the current level of skill of the relevant meteorological variables.

Development of climate services, for crop yield or fire risk, would require more detailed assessments, considering bias correction and probabilistic forecast calibration, similar to the study by Bedia et al (2018) on seasonal forecasting fire risk in the Mediterranean. Although they used the Canadian Fire Weather Index, which is similar in complexity to the McArthur index used here, they also found that their regions of good skill were closely linked to skill in forecasting relative humidity. Being able to use simpler impacts metrics could greatly simplify the development and production of seasonal climate services for forecasting fire risk. However, it could be the case that, operationally, the most important quantity to forecast is not the seasonal mean, but rather the number of high fire risk days within the season, or some other threshold-based quantity. This should be determined in conjunction with the relevant stakeholder as part of the co-development of the forecast service, as demonstrated by Turco et al (2019): they describe the development of a climate service prototype for probabilistic forecasts of the burnt area in Catalonia being above a user-defined threshold.

Our study is intended to be a starting point for investigating model capability for seasonal forecasting of carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components. There are of course many limitations: The NPP reference data are reanalysis-driven model runs; it was necessary to approximate the carbon cycle components.

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Appendix A. Soil moisture dependence of McArthur fire index

Throughout this paper we have used a simplified McArthur fire index, based on the McArthur Forest Fire Danger Index Mark 5, but with a constant restore amount \( h_{\text{restore}} \) in the drought factor (equation (2)). We have
tested using an explicit soil moisture ($\theta$) dependence by calculating $a_{\text{restore}}$, as the amount of water needed to restore the top 1 m of soil to field capacity ($\theta_{\text{FC}}$, at $-0.01$ MPa), as a fraction of the difference between field capacity and soil moisture wilting point ($\theta_{\text{W}}$, at $-1.5$ MPa), rescaled to be in the interval 0–200 mm:

$$
a_{\text{restore}} = \begin{cases} 
0 & \text{for } \theta \geq \theta_{\text{FC}} \\
200 \left( \frac{\theta_{\text{FC}} - \theta}{\theta_{\text{FC}} - \theta_{\text{W}}} \right) & \text{for } \theta_{\text{W}} < \theta < \theta_{\text{FC}} \\
200 & \text{for } \theta \leq \theta_{\text{W}}
\end{cases}
$$

(A.1)

This formulation has been informed by Holgate et al. (2017) and Walsh et al. (2017).

We used the daily soil moisture from the same WFDEI-driven JULES simulations we ran for our reference NPP calculations, to calculate a new McArthur fire index data set for testing.

Despite the restore amount showing significant regional variation (Figure A1), the seasonal mean McArthur index based on varying soil moisture, and the simplified index using a constant restore amount, are very highly correlated (figure A2).

**Appendix B. Burnt area seasonal climatologies throughout the year**

Figure B1 shows the climatological seasonal mean fields for burnt fraction of gridcells, covering all four seasons: DJF and JJA as in the body of this paper, plus March–April–May (MAM) and September–October–November (SON). This illustrates the regional distribution of the peak fire season throughout the year.

Figure B2 shows, for completeness, the response of the burnt fractions to ENSO, as in figure 2(a), but for MAM and SON.
Figure B1. Maps of the climatological seasonal mean values of burnt fraction of grid cells, for all four seasons as labelled. As with other burnt area figures, we use the 15 years from 1997/98–2011/12.

Figure B2. As figure 2(a), but for the other seasons, MAM and SON, as labelled.

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References

Alves White B L, Secundo White L A, Ribeiro G T and Martins Fernandes P A 2013 Development of a fire danger index for eucalypt plantations in the northern coast of Bahia, Brazil Revista Floresta 43 601–10

Aragão L et al 2018 21st century drought-related fires counteract the decline of Amazon deforestation carbon emissions Nat. Commun. 9 536

Arpaci A, Eastaugh C S and Vacik H 2013 Selecting the best performing fire weather indices for Austrian ecoregions Theor. Appl. Climatol. 114 393–406

Barnston A G, Tippett M K, L’Heureux M L, Li S and DeWitt D G 2012 Skill of real-time seasonal ENSO model predictions during 2002–11: Is our capability increasing? Bull. Am. Meteorol. Soc. 93 631–51

Bastos A et al 2018 Impact of the 2015/2016 El Niño on the terrestrial carbon cycle constrained by bottom-up and top-down approaches Philosophical Transactions of the Royal Society B: Biological Sciences 373 20170304

Bedia J, Golding N, Casanueva A, Iturbide M, Buontempo C and Gutiérrez J M 2018 Seasonal predictions of fire weather index: paving the way for their operational applicability in Mediterranean Europe Clim. Serv. 9 101–10

Best M J et al 2011 The joint UK land environment simulator (JULES), model description—part 1: energy and water fluxes Geosci. Model Dev. 4 677–99

Betts R A, Golding N, Gonzalez P, Gornall J, Kahana R, Kay G, Mitchell L and Wiltshire A 2015 Climate and land use change impacts on global terrestrial ecosystems and river flows in the HadGEM2-ES earth system model using the representative concentration pathways Biogeosciences 12 1317–38

Betts R A, Jones C D, Knight J R, Keeling R F and Kennedy J J 2016 El Niño and a record CO₂ rise Nat. Clim. Change 6 806–10

Betts R A, Jones C D, Knight J R, Keeling R F, Kennedy J J, Wiltshire A J, Andrew R M and Aragão L E O C 2018 A successful prediction of the record CO₂ rise associated with the 2015/2016 El Niño Philosophical Transactions of the Royal Society of London B: Biological Sciences 373 20170301

Brooks R H and Corey A T 1964 Hydraulic properties of porous media Hydrology papers 3 Colorado State University (https://doi.org/10.31223/osf.io/kzwcx)

Burton C, Betts R A, Jones C D and Williams K 2018 Will fire danger be reduced by using solar radiation management to limit global warming to 1.5°C compared to 2.0°C? Geophys. Res. Lett. 45 3644–52

Burton C, Betts R, Cardoso M, Feldpausch T R, Harper A, Jones C D, Kelley D I, Robertson E and Wiltshire A 2019 Representation of fire, land-use change and vegetation dynamics in the Joint UK Land Environment Simulator vn4.9 (JULES) Geosci. Model Dev. 12 179–93
Chen Y, Randerson J T, Morton D C, DeFries R S, Collatz G J, Kasibhatla P S, Giglio L, Jin Y and Matliger M E 2011 Forecasting fire season severity in South America using sea surface temperature anomalies Science 334 787–91
Chen Y, Morton D, Andelna N, van der Werf G, Giglio L and Randerson J 2017 A pan-tropical cascade of fire driven by El Niño Southern Oscillation Nat. Clim. Change 7 906–11
Chen Y, Morton D, Andelna N, Giglio L and Randerson J T 2016 How much global burned area can be forecast on seasonal time scales using sea surface temperatures Environ. Res. Lett. 11 045001
Clark D B et al 2011 The Joint UK Land Environment Simulator (JULES), model description—Part 2: carbon fluxes and vegetation dynamics Geosci. Model Dev. 4 701–22
Clark R T, Bett P, Thornton H and Scaife A 2017 Skilful seasonal predictions for the European energy industry Environ. Res. Lett. 12 024002
de Groot W J, Wotton B M and Flannigan M D 2015 Wildland fire danger rating and early warning systems Wildfire Hazards, Risks and Disasters ed J F Shroder and D Paton (Elsevier: Oxford) 11 pp. 207–228 978-0-12-410434-1
Dharssi I, Vidale P L, Verhoef A, Macpherson B, Jones C and Best M 2009 New soil physical properties implemented in the Unified Model at PS18 Technical Report 528 Met Office, Exeter, UK (https://digital.nmla.metoffice.gov.uk/IO_01baed78-35d1-426d-aad0-883578b495b5)
Eastaugh C S, Arpaci A and Vacik H 2012 A cautionary note regarding comparisons of fire danger indices Nat. Hazards Earth Syst. Sci. 12 927–34
EROS Archive and 2017 Digital Elevation - HYDRO1K. A global hydrologic database derived from 1996 GTOPO30 data. USGS (https://doi.org/10.5066/P7pp8w40)
Fasullo J T, Otto-Bliesner B L and Stevenson S 2018 ENSO’s changing influence on temperature, precipitation, and wildfire in a warming climate Geophys. Res. Lett. 45 9216–23
Giglio L, Randerson J T and van der Werf G R 2013 Analysis of daily, monthly, and annual burned area using the fourth-generation Global Fire Emissions Database (GFED4) Journal of Geophysical Research: Biogeosciences 118 317–28
Gilham R 2014 Met Of...
Golding N and Betts R 2008 Fire risk in Amazonia due to climate change in the HadCM3 climate model: potential interactions with deforestation Global Biogeochem. Cycles 22 GB4007
Hamadeh N, Karouni A, Daya B and Chauvet P 2017 Using correlative data analysis to develop weather index that estimates the risk of forest fires in Lebanon & Mediterranean: Assessment versus prevalent meteorological indices Case Study: Fire Safety 7 8–22
Hansen J et al 2007 Dangerous human-made interference with climate: A GISS model study Atmos. Chem. Phys. 7 2287–312
Heinsch F A et al 2006 Evaluation of remote sensing based terrestrial productivity from MODIS using regional tower eddy flux network observations IEEE Trans. Geosci. Remote Sens. 44 1908–25
Hoffmann W A, Schroeder W and Jackson R B 2003 Regional feedbacks among fire, climate, and tropical deforestation J. Geophys. Res. 108 4721
Holgate C M, van Dijk A I J M, Cary G J and Yebra M 2017 Using alternative soil moisture estimates in the McArthur forest fire danger index International Journal of Wildland Fire 26 806
Holsten A, Dominic A R, Costa L and Kropp J P 2013 Evaluation of the performance of meteorological forest fire indices for German federal states For. Ecol. Manage. 287 123–31
Jones C D and Cox P M 2003 On the significance of atmospheric CO2 growth rate anomalies in 2002–2003 Geophys. Res. Lett. 32 L14816
Jones C D, Collins M, Cox P M and Spall S A 2001 The carbon cycle response to ENSO: a coupled climate–carbon cycle model study J. Climate 14 4113–29
Keech J and Byram G 1968 A drought index for forest fire control Research Paper SE-38 US Department of Agriculture Forest Service (https://www.srs.fs.usda.gov/pubs/rp/rp_se038.pdf)
Kim J-S, Kug J-S, Yoon J-H and Jeong S-J 2016 Increased atmospheric CO2 growth rate during El Niño driven by reduced terrestrial productivity in the CMIP5 ESMs J. Climate 29 8783–8805
le Quéré C et al 2018 Global carbon budget 2018 Earth System Science Data 10 2141–94 Lin C-C 1995 Study on the predicting system of forest fire danger rating in a Southern African savanna Int. J. Appl. Earth Obs. Geoinform. 30 217–26
Page S, Siegent F, Riley J, Boehm H, Jaya A and Limin S 2002 The amount of carbon released from peat and forest fires in Indonesia during 1997 Nature 420 61–5
Palin E J, Scaife A A, Wallace E, Pope E C D, Arribas A and Brookshaw A 2016 Skilful seasonal forecasts of winter disruption to the UK transport system J. Appl. Meteorol. Clim. 55 325–44
Philander S G 1990 El Niño, La Niña, and the Southern Oscillation (International Geophysics 46) (New York: Academic) (https://www.sciencedirect.com/books/inter...
Randerson J T, Chen Y, van der Werf G R, Rogers B M and Morton D C 2012 Global burned area and biomass burning emissions from small fires Journal of Geophysical Research: Biogeosciences 117 G04012
Randerson J, van der Werf G, Giglio L, Collatz G and Kasibhatla P 2017 Global Fire Emissions Database version 4.1 (GFEDv4) (https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1293)
Ren H-L et al 2019 Seasonal predictability of winter ENSO types in operational dynamical model predictions Clim. Dynam. 52 3869–90
Roddenbeck C, Zaehe S, Keeling R and Heimann M 2018 History of El Niño impacts on the global carbon cycle 1957–2017: a quantification from atmospheric CO₂ data Philosophical Transactions of the Royal Society B-Biological Sciences 373 20170303

Roxburgh S H, Berry S L, Buckley T N, Barnes B and Roderick M I 2005 What is NPP? inconsistent accounting of respiratory fluxes in the definition of net primary production Functional Ecology 19 378–82

Scaife A A et al 2017 Tropical rainfall, Rossby waves and regional winter climate predictions Q. J. R. Meteor. Soc. 143 1–11

Scaife A A et al 2019 Tropical rainfall predictions from multiple seasonal forecast systems Int. J. Climatol. 39 974–88

Sellars A A et al 2019 UKESM1: description and evaluation of the U.K. Earth System Model Journal of Advances in Modeling Earth Systems 11 4513–58

Sirakoff C 1985 A correction to the equations describing the McArthur forest fire danger meter Australian Journal of Ecology 10 481–481

Skvarenina J, Mindas J, Holecy J and Tucek J 2004 Analysis of the natural and meteorological conditions during two largest forest fires in the Slovak Paradise National Park InternationalScientific Workshop on Forest Fires in the Wildland–Urban Interface and Rural Areas in Europe: an integral planning and management challenge Ed G Xanthopoulos (Athens, Greece, 15–16 May 2003) pp 25–36 (http://www.fria.gr/WARM/warmProceedings.htm)

Slevin D, Tett S F B, Exbrayat J-F, Bloom A A A and Williams M 2017 Global evaluation of gross primary productivity in the JULES land surface model v3.4.1 Geosci. Model Dev. 10 2651–70

Spessa A C, Field R D, Pappenberger F, Langner A, Engilbert S, Weber U, Stockdale T, Siegert F, Kaiser J W and Moore J 2015 Seasonal forecasting of fire over Kalimantan, Indonesia Natural Hazards and Earth System Sciences 15 429–42

Trenberth K E 1997 The definition of El Niño Bull. Am. Meteorol. Soc. 78 2771–8

Turco M, Jerez S, Doblas-Reyes F J, AghaKouchak A, Llasat M C and Provenzale A 2019 Skilful forecasting of global fire activity using seasonal climate predictions Nat. Commun. 9 2718

Turco M, Marcos-Matamoros R, Castro X, Canyameras E and Llasat M C 2019 Seasonal prediction of climate–driven fire risk for decision-making and operational applications in a Mediterranean region Sci. Total Environ. 676 577–83

van der Werf G R et al 2017 Global fire emissions estimates during 1997–2016 Earth System Science Data 9 697–720

Walsh S F, Nyman P, Sheridan G J, Baillie C C, Tolhurst K G and Duff T J 2017 Hillslope-scale prediction of terrain and forest canopy effects on temperature and near-surface soil moisture deficit International Journal of Wildland Fire 26 191

Walters D et al 2017 The Met Office Unified Model Global Atmosphere 6.0/6.1 and JULES Global Land 6.0/6.1 configurations Geosci. Model Dev. 10 1487–520

Weedon G P, Gomes S, Viterbo P, Shuttleworth W J, Blyth E, Osterle H, Adam J C, Bellouin N, Boucher O and Best M 2011 Creation of the WATCH forcing data and its use to assess global and regional reference crop evaporation over land during the twentieth century J. Hydrometeorol. 12 823–48

Weedon G P, Balsamo G, Bellouin N, Gomes S, Best M J and Viterbo P 2014 The WFDEI meteorological forcing data set: WATCH forcing data methodology applied to ERA-Interim reanalysis data Water Resour. Res. 50 7905–14

Williams K D et al 2015 The Met Office Global Coupled model 2.0 (GC2) configuration Geosci. Model Dev. 8 1509–24

Williams K E and Falloon P D 2015 Sources of interannual yield variability in JULES-crop and implications for forcing with seasonal weather forecasts Geosci. Model Dev. 8 3987–97

Zeng N, Mariotti A and Wetzel P 2003 Terrestrial mechanisms of interannual CO₂ variability Global Biogeochem. Cycles 19 GB1016

Zhao M, Running S W and Nemani R R 2006 Sensitivity of moderate resolution imaging spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalysers Journal of Geophysical Research: Biogeosciences 111 G01002