





# Assessment of the relationship between seasonal meteorological variables and crop parameters in Senegal

July 2, 2019 Jenny Pirret and Joseph Daron

#### Contents

1	Intro	oduction	3						
2	Data	a and Methods							
	2.1	Meteorological Data	5						
	2.2	Crop Data	6						
	2.3	Correlation	7						
	2.4	Significant Difference of Mean Averages	7						
	2.5	Multivariate Analysis	8						
3	Res	sults	8						
	3.1	Crop Yield Correlation	8						
	3.2	Meteorological Parameter Correlation	9						
	3.3	Bivariate Correlation	10						
		3.3.1 Residuals	12						
		3.3.2 Observational Data	14						
		3.3.3 Time Period	14						
		3.3.4 JJA v JAS	16						
		3.3.5 Total Production and Area Harvested	17						
		3.3.6 Derived Metrics	19						
	3.4	Sea Surface Temperatures	19						
		3.4.1 ENSO	19						
		3.4.2 Cluster Analysis	22						
	3.5	Multivariate Analysis	24						
4	Disc	cussion	25						
5	Conclusions 27								

#### **Executive Summary**

Communities in the Sahel region of West Africa rely on seasonal rainfall in order to sustain livelihoods. Yet the evidence on how year-to-year climate variability impacts on key livelihoods in the region, such as those in agriculture and pastoralism, remains limited. Improving our understanding and quantifications of the relationships between seasonal climate and variables relevant to these sectors, can help in developing climate services to inform decision-making to reduce the risks of food insecurity in the Sahel.

This report presents the findings of research exploring the links between crop production and seasonal climate variability in Senegal. The study was conducted for the ASPIRE (Adaptive Social Protection: Information for enhanced REsilience) project, as part of the Weather and Climate Information Services for Africa (WISER) programme funded by the UK Department for International Development (DFID). ASPIRE aims to provide technical support and advice to the World Bank's Adaptive Social Protection Programme (ASPP) in the Sahel, which is providing funding and expertise to governments in six countries (Burkina Faso, Chad, Mali, Mauritania, Niger, and Senegal) to help design and implement adaptive social protection initiatives and systems.

The research presented contributes to wider efforts in ASPIRE assessing the feasibility of using seasonal forecasts to inform adaptive social protection programmes in West Africa. For example, a system could be envisaged whereby a forecast showing an increased likelihood of low seasonal rainfall could trigger a payment or actions to promote the use of drought-resistant crops ahead of the growing season. The system would require: a) skilful forecasts of relevant climatic parameters (an aspect being assessed in parallel research in ASPIRE), and b) significant causal relationships between the forecast parameters and specific crop parameters. The research presented here focuses on the second part, examining relationships between seasonal climate (season average temperature and season total rainfall) using past climate data, and country-wide crop data for the four main crops in Senegal: maize, millet, sorghum and rice.

For both season total precipitation and season average rainfall over the July-August-September period in Senegal, we find significant correlations with yields of maize, millet and sorghum, but not rice. We explore the sensitivity of the results to different climate datasets, meteorological parameters, crops parameters, and seasonal periods. We also explore links with key climate drivers and teleconnections, such as El Niño and sea surface temperatures in different regions of the world. Finally, using observational data, we combine temperature and precipitation to determine whether or not crop yield 'shocks' could be skilfully forecast.

The relationships found between seasonal climate and crop parameters are significant but modest. They provide a foundational basis for further work to examine the potential for providing crop-relevant information using seasonal forecasts. Coupled with improvements in seasonal forecasts, there is potential to provide information on timescales relevant to agriculture and food security decisions in Senegal.

#### 1 Introduction

The Adaptive Social Protection: Information for enhanced REsilience (ASPIRE) project aims to help countries prepare in advance of weather and climate 'shocks', through improved use and understanding of climate information, focusing on seasonal forecasts. Funded by the UK Department for International Development (DFID), the project aims to support and inform the World Bank's Adaptive Social Protection Programme (ASPP) in Sahelian West Africa. A key element of enabling adaptive social protection in the Sahel is to better understand the role of weather and climate variability in impacting dominant livelihoods. Agro-pastoralism is a key livelihood for communities across the region, and some areas have land that are appropriate for cultivation (Figure 1). The agriculture sector is mainly reliant on water from rainfall in the monsoon season (June to September) and variability in seasonal rainfall is thought to have a key influence on food security. A key objective of ASPIRE is to ascertain whether, how and where seasonal forecasts could be used to inform food security decisions in the Sahel, and thereby inform the ASPP, with particular focus on Senegal, Niger, Mali, and Burkina Faso.





As part of the ASPIRE project, we have explored the links between seasonal meteorological parameters and crop production. Seasonal forecasts were chosen as the focus of the ASPIRE project due to their potential for increasing the lead-time and success of early action in social protection decision-

making, thereby increasing the resilience of communities and capacities to respond in times of extreme climate conditions (e.g. droughts). Seasonal forecasts can also play an important role in influencing agricultural and pastoral decisions on the timescales necessary for planning at the household level (Sultan et al., 2005), though directly influencing decisions is challenging. These challenges can be divided into three main components: 1) the forecast; 2) its communication; and 3) the farmer's response (Hansen et al., 2011). Whilst acknowledging the importance of all components, it is the first part that the ASPIRE project has focussed on, to inform potential improvements to the forecast itself. The second part, on the communication of seasonal forecasts, refers to modes of communication (e.g. radio, internet) available to a farmer, as well as the disseminator's use of these channels to communicate key information. The third part, on the farmers response, encompasses their level of understanding and capacity to respond, and must acknowledge the costs of taking action to mitigate negative impacts even though such impacts are not certain to occur.

Hansen et al. (2011) frame the forecast component in the language used by Cash et al. (2003) and Meinke et al. (2006), stating the forecast must be credible, legitimate and salient. Credibility can be determined in part through forecast verification using historical forecasts and observations, which forms a key part of the ASPIRE project (Pirret et al., 2019, in preparation). Legitimacy considers the need for information to be impartial, from a trustworthy source and respectful of user values and requirements. ASPIRE is working to improve legitimacy through engaging with social protection stakeholders to understand the decision-making processes and identify entry points to enable adaptive social protection; that is, scaling up actions in response to climate information (e.g. a seasonal forecast). Engagement activities can improve the users' understanding and perception of the forecast, and are key in users making the most out of the service (Pope et al., 2017). Saliency refers to the relevance of the information communicated to the user and their decision-making context. This report aims to tackle one aspect of forecast saliency, by providing evidence on the relationships between seasonal meteorological parameters and the yields of major crops grown in the Sahel region of West Africa, thereby aiding the translation of seasonal information into more decision-relevant information.

The relationship between seasonal weather and crops is further complicated by a changing climate, as reported in detail by Hatfield et al. (2011). Higher  $CO_2$  concentrations will increase yields through increasing photosynthesis and spurring plant growth, but are expected to be offset in decreased yields due to changes in weather and climate. Furthermore, the nutritional content of crops is excepted to decrease under a changing climate (Smith and Myers, 2018). Increasing temperatures have different effects in different parts of the world, depending on whether it increases growing season length or whether it increases exposure to very high temperatures, as well as changing crop water requirements. Water availability will also be impacted by changes to precipitation induced by climate change, which also vary geographically. Some of these changes have already been observed (Taylor et al., 2017; Schroeer and Kirchengast, 2018).There are other potential impacts from the reaction of weeds, pests and disease to climate change. Furthermore, different crop species show different responses. Despite a changing climate, in this work we assume that the relationships between crops and weather are are

the same throughout the study period.

Our aim is to identify a parameter that can be readily understood by forecast users, can be used in assessing forecast skill, and is relevant to agriculture. Research was therefore conducted to examine if relevant meteorological metrics at the seasonal time-scale could be linked with key crop parameters, such as yield. Such metrics may then be applied to the outputs of seasonal forecasts, by communicating a forecast relevant to the users. An important interim step would be to assess the forecast skill in terms of the metric, to determine whether such a forecast would have significant skill (see Pirret et al., 2019, in preparation). Crop growth is physically linked to precipitation and temperature on short (Frieler et al., 2017) and long (Lobell et al., 2011) timescales. In this report, we aim to assess the links between crop parameters and both season total precipitation and season average temperature, based on past observational data for Senegal. Statistical tests are performed, to ascertain whether there were significant links between these seasonal weather parameters and crop yields. This report focusses on Senegal, one of the focus countries for the ASPIRE project, but the work can readily be repeated for other countries or groups of countries and some analysis has been conducted for Niger as part of ASPIRE.

#### 2 Data and Methods

We first discuss the meteorological and agricultural data, before discussing the main methods used in the analysis. These include: 1) calculating correlations and assessing their significance, including the cluster analysis technique from Davie et al. (2019), 2) determining whether there is a significant difference in mean average for two groups, and 3) following the work of Kent et al. (2017), whether the seasonal climate parameters are useful predictors for crop yield shocks.

#### 2.1 Meteorological Data

In this study we use 'WATCH Forcing Data – ERA-Interim' (WFDEI) data (Weedon et al., 2014), which interpolate the ERA-Interim (Dee et al., 2011) data onto a  $0.5^{\circ} \times 0.5^{\circ}$  grid with corrections for elevation and additional bias correction from observations including CRU (Harris et al., 2014) and GPCC (Becker et al., 2013). Temperature, precipitation and other variables data are available on a global grid for the years 1981 to 2013. WFDEI data were chosen for this work because both variables are available on daily and longer time periods. Using WFDEI data, we calculate season total precipitation and season average temperature for each point in Senegal, then average over the entire country to give one measure for precipitation and temperature, for each season. These measures are then correlated with crop yields.

In addition to the WFDEI data, precipitation data from the Climate Hazards group InfraRed Precipitation with Stations (CHIRPS) project were also used. CHIRPS data are estimated from satellite, adjusted using gauge and station data, to give gridded data from 1981 (Funk et al., 2015). Though only precipitation data are available, CHIRPS contains daily data for a long period of time and is widely used

in the Sahel. The CHIRPS rainfall is used to calculate season total rainfall averaged over Senegal for each year, in the same way as the WFDEI data.

We explore the links with the El Niño Southern Oscillation (ENSO), using the Oceanic Niño Index (ONI), produced by the Climate Prediction Center (NWS Climate Prediction Center, 2018). El Niño conditions defined as ONI greater than 0.5; La Niña has ONI less than -0.5; and otherwise conditions are described as neutral. Here, we use the index averaged over the previous December-January-February (DJF) compared to July-August-September (JAS) temperature or precipitation, because ENSO is typically strongest in DJF and teleconnection patterns take some time to have an effect. We then expand this work to explore links with sea-surface temperatures (SSTs) in ERA-Interim (Dee et al., 2011).

#### 2.2 Crop Data

Crop data come from the UN's Food and Agriculture Organisation (FAO, 2017). For a range of crops, yield, area cultivated and total production are available for each country, for every year back to the 1960s, but we use the data since 1981 to align with the meteorological observations. We concentrate our analysis on four major food crops, chosen based on FAO advice (FAO, 2019); historical crop yield data for Senegal is shown in Figure 2. The main growing season in Senegal runs from June to October, depending on crop type (FAO, 2019).



Figure 2: Yield data for the four major crops in Senegal, using data from the FAO. Note that the units for yield are 'hectograms per hectare' [hg/ht], so  $10^4$  hg/ht is one tonne per hectare.

As well as meteorological factors, there are important socio-economic influences on crop yields. The raw yields shown in Figure 2 steadily increase over time (most clearly seen for rice), due to incremental improvements in farming practices. Henceforth, we subtract a five-year rolling mean from the raw yield data, removing the slowly-changing trend to give a 'yield anomaly'.

#### 2.3 Correlation

Correlations between crop yield and seasonal meteorological variables are tested using Pearson's correlation coefficient (Rees, 2001, Section 14.2) and assessed for significance to test the hypothesis that there is no correlation between the two variables. This is done by calculating a test statistic (Rees, 2001, Equation 14.2), and comparing this to tabulated values for different degrees of freedom and significance levels ( $\alpha$ ). Correlation becomes significant at the  $\alpha = 0.05$  level when the test statistic exceeds a critical value, depending on the number of data points in the correlation (Rees, 2001, Section 14.3). For WFDEI data with 35 points, the critical value is 1.690, whereas for CHIRPS with 37 data points, it is 1.684.

Some preliminary results were obtained using boostrapping, which is a method used in statistics to test the accuracy of a metric. Here, we resample the data by removing two years at random (with replacement), and rerun the correlation tests. This is repeated 1000 times, which allows estimation of confidence intervals for the correlation coefficient and for the associated significance test, we calculate the percentage of the 1000 tests that exceed the threshold and exhibit significant correlation.

Further to testing the correlation, we also present regression lines on scatter diagrams. When performing regression analysis, we can assess the robustness of linear correlations by calculating the residuals; that is, the difference between the linear fit and the observed points. If there are systematic differences or a pattern to how the residuals are distributed, then a different type of regression might be more appropriate. We use linear regression as a starting point.

Correlation is also tested between crop yield anomaly and SSTs from ERA-Interim. SSTs have been linked to rainfall over the Sahel region (Rowell, 2011). Following the work of Davie et al. (2019) and Pope et al. (2019), regions of the global ocean where this correlation is significant are identified. The first step is to detrend SSTs by subtracting a linear trend from them, which allows for the slow increase in SSTs over the study period. The process then uses point-by-point correlation and image processing to establish contiguous geographical regions which contains points where the correlation is significant at the 90% level.

It should be noted that correlation does not imply causation; these are statistical relationships, and we leave exploration of physical reasons to future work. Here, we identify regions where detrended SSTs over December-January-February are significantly correlated with each crop's yield anomaly, with the aim of providing guidance to seasonal forecasters, indicating which ocean regions are related to crop yield. Future work should include assessing how much yield variability can be explained by SST variations in these regions, or finding the dynamical links that would explain causal relationships.

#### 2.4 Significant Difference of Mean Averages

In order to explore the links with ENSO, we separate the meteorological and crop data by whether it is in a year with El Niño, La Niña or neither, based on the ONI index discussed in Section 2.1. Within each of these three groups, we take mean values of season total rainfall and season average temperature. We test whether the means are significantly different using the Mann-Whitney test (Rees, 2001, Section

11.9). In the period 1979-2013, there are 11 years with El Niño in the preceding DJF, 12 have La Niña, and 12 are Neutral. We assume a null hypothesis that the means are not significantly different for the datasets being studied (Rees, 2001, Section 10.9).

#### 2.5 Multivariate Analysis

Following the work of Kent et al. (2017), we also explore multivariate correlation; i.e. the links between crop yield, temperature and precipitation. Kent et al. analyse the links between climate and the risk of severely low production for maize, concentrating on the major 'breadbasket' regions in China and the USA. Concentrating on reductions of at least 1 tonne per hectare on yield, they aim to link such 'yield shocks' with thresholds in temperature and rainfall, using large-scale observed data averaged over the summer season. They apply the thresholds to climate model data that covers 1981 to 2015, with the model is run repeatedly to give 1400 simulations of present climate following the method of Thompson et al. (2017). This gives a wider range of potential weather scenarios than in historical, observational data alone.

In our study, multivariate analysis is firstly done by plotting season total precipitation against season average temperature, with the points coloured by the crop's yield, as per Kent et al. (2017, Figure 2c). Secondly, we calculate the Heidke skill score using the observed season total precipitation and season average temperature as predictors. This tests whether a temperature above or precipitation below the threshold was a significantly skilful predictor for a yield shock. The skill score is then plotted for a range of temperature and precipitation thresholds, as per Kent et al. (2017, Figure 2a). Given the range of crops used, we define a yield shock as exceeding one standard deviation of the mean yield anomaly.

#### 3 Results

In this section we first compare how the four main crops in Senegal are related to each other, and then how seasonal average temperature and seasonal total precipitation are correlated. We then move on to bivariate correlation (Section 3.3), assessing the links between crop yields and season total rainfall or season average temperature. These results are tested for robustness through residual analysis and sensitivity to changing the meteorological observation dataset, time period, season definition and crop variable. The relationship between the meteorological variables, crop yields and SSTs is then explored (Section 3.4), before moving on to correlation between all three variables: crop yields, seasonal average temperature and seasonal total precipitation (Section 3.5).

#### 3.1 Crop Yield Correlation

We might expect that the yield would be correlated across all crops, since external factors affect yield in a similar way; for example, drought stress would reduce yields of all crops in the region. Figure 3 shows positive correlations are found for most combinations of crops. Although correlations are

modest, they are shown to be significantly different from zero using a one-sided t-test. The correlation between Sorghum and Maize is slightly below the threshold for significance and Sorghum and Rice is substantially below the threshold. Rice is grown in paddy fields, so we might expect rice to have different sensitivities to external factors compared to the other cereal crops.



Figure 3: Scatter plots comparing the yields of four major crops with each other, using FAO data over Senegal. In the top-right corner are the Pearson's correlation coefficient for each pair of crops, and a significance test for the correlation ('sig test') that exceeds 1.690 for significant correlation.

#### 3.2 Meteorological Parameter Correlation

It is also noteworthy that the two meteorological parameters – season average temperature and season total precipitation – are significantly correlated. Figure 4 shows this using WFDEI data, and illustrates

the negative correlation. Therefore, warmer seasons tend to be drier and cooler seasons wetter. This also means that any correlations found between crop yields and either of these variables are not mutually exclusive, and so multivariate correlation will be explored in Section 3.5.



Figure 4: Scatter plot of WFDEI JAS season total precipitation against season average temperature.

#### 3.3 Bivariate Correlation

Figure 5 shows significant correlations between meteorological variables and crop yield data for Senegal. The correlation between yield anomaly and season total precipitation is positive, meaning that wetter years tend to give higher crop yields. For season average temperature, the correlation is negative, so warmer years tend to be associated with lower yields. Against season total precipitation, significant correlation is found with sorghum, millet and maize yield anomalies, and nearly with rice yield anomaly. The bootstrapping shows that the correlation is accurate to  $\pm 0.12$  for sorghum,  $\pm 0.11$  for millet,  $\pm 0.13$ for maize, and  $\pm 0.16$  for rice, and that more than two-thirds of the bootstrapping results yield statistically significant correlation for sorghum, millet and maize.

In the case of season average temperature, the correlation is again significant for sorghum, millet and maize but not for rice. The bootstrapping shows that the correlation is accurate to  $\pm 0.14$  for sorghum,  $\pm 0.17$  for millet,  $\pm 0.18$  for maize, and  $\pm 0.16$  for rice, which are larger errors than for precipitation. In terms of the correlation's significance, again more than two-thirds of the bootstrapping results yield significant correlation for sorghum, millet and maize. These initial results are promising in terms of finding a meteorological metric that could be used to provide a relevant seasonal forecast to agriculture. However, in both season total precipitation and season average temperature the relationships are modest and their robustness needs to be assessed – the focus of the next section.



#### WFDEI Season Total Precipitation

Figure 5: Testing the correlation between crop yield anomalies (from FAO data) and (top) season total precipitation or (bottom) season average air temperature, using WFDEI data over Senegal in July-August-September. If the significance test exceeds a magnitude of 1.690, the correlation is statistically significant.

© Crown Copyright 2019, Met Office



#### 3.3.1 Residuals

Figure 6 shows the residuals (the difference between the linear fit and the observed points) for season total precipitation and season average temperature. Here, we return to WFDEI data and focus on the three crops which have significant correlations, as shown in Figure 5. Across both meteorological variables and all three crops, visual inspections shows that the residuals are randomly distributed either side of the x-axis, indicating that linear regression is appropriate.



Residual analysis: Season Total Precipitation

Figure 6: Residual analysis for the correlation between the four major crops in Senegal (Maize, Millet, Rice Sorghum) with two climate parameters (season total precipitation, season average temperature).

#### 3.3.2 Observational Data

CHIRPS data is also used to explore the results' sensitivity to meteorological observational dataset. Table 1 reports the Pearson's correlation coefficients and the result of the significance tests, comparing crop yield and season total precipitation from both WFDEI (as seen in Figure 5) and CHIRPS (not shown). Comparing between CHIRPS and WFDEI precipitation, some notable differences emerge. For sorghum, maize and rice, the correlation is weaker in the CHIRPS data than that found with WFDEI, but the correlation is similar for millet. This means that significant relationships exist between CHIRPS precipitation and yield anomaly for millet and sorghum, but not for rice or maize. This is unexpected given the broad similarity between the two datasets (Figure 7). One potential reason is the differences between CHIRPS and WFDEI rainfall in 2002, which was a year with a particularly low maize yield (Figure 2).

	Season Total Precipitation					
Crop	WF	DEI	CHI	RPS		
	Pearson   Sig. test		Pearson	Sig. test		
Sorghum	0.3621	2.0922	0.3003	1.7245		
Millet	0.4830	2.9703	0.4799	2.9961		
Maize	0.4028	2.3701	0.2615	1.4842		
Rice	0.2831	1.5892	0.1892	1.0555		

Table 1: Testing whether correlations are sensitive to the observational dataset used by comparing the correlation between Senegalese crop yield and season (JAS) total precipitation, from WFDEI and CHIRPS data. If the significance test exceeds 1.690 (WFDEI) or 1.684 (CHIRPS), the correlation is statistically significant.



Figure 7: Comparing season total rainfall for CHIRPS and WFDEI over Senegal.

#### 3.3.3 Time Period

The relationships between season total precipitation and yield anomaly can be assessed qualitatively by comparing time series of the crop yield anomalies and country-averaged, seasonally-totalled precipitation over the period 1981 to 2011. Figure 8 implies that there is a stronger degree of similarity



Figure 8: Time series plots that compare FAO crop yield (cyan) and WFDEI precipitation (blue) over Senegal.

between precipitation and yields for sorghum, maize and millet compared to rice, which is reflected in the correlation tests for these crops (Figure 5).

Since the early 1990s, the observational record has improved and West Africa's precipitation has recovered from the multi-year regional drought of the 1980s. Whether the correlation has strengthened in more recent years is tested in Table 2, which reports the results of the correlation analysis from Figure 5 covering 1981 to 2013, and comparing them to similar analysis performed for 1993 to 2013. For precipitation, the correlation is stronger and is now significant for all four crops in the more recent period. For temperature, the results are more mixed but the correlation is now only significant for rice and not for sorghum, millet or maize. Given this loss of significant correlation, the rest of this report will use the longer data period. Furthermore, the short period over which we consider the data means that we cannot exclude the possibility that these correlations have changed due to random chance or other factors such as changes to land management strategies. However, if future work in concentrating solely on precipitation or precipitation-derived variables, careful consideration should be given to the data period used.

	Season Total Precipitation				Season Average Temperature			
Crop	Crop 1981-2013		1993-2013		1981-2013		1993-2013	
	Pearson   Sig. test   Pearson   Sig. tes		Sig. test	Pearson	Sig. test	Pearson	Sig. test	
Sorghum	0.3621	2.0922	0.4570	1.9896	-0.4271	-2.5436	-0.3598	-1.4933
Millet	0.4830	2.9703	0.5597	2.6159	-0.3267	-1.8614	-0.3416	-1.4075
Maize	0.4028	2.3701	0.4806	2.1223	-0.3736	-2.1687	-0.3961	-1.6709
Rice	0.2831	1.5892	0.6858	3.6493	-0.1435	-0.7809	-0.4335	-1.8631

Table 2: Assessing the sensitivity to change in time period (1981-2013 v 1993-2013) of correlation between crop yield and season (JAS) total precipitation or season average temperature, using WFDEI data over Senegal. If the significance test exceeds a magnitude of 1.690, the correlation is statistically significant.

#### 3.3.4 JJA v JAS

	Season Total Precipitation				Season Average Temperature			
Crop	JJA		JAS		JJA		JAS	
	Pearson	Sig. test	Pearson	Sig. test	Pearson	Sig. test	Pearson	Sig. test
Sorghum	0.4928	3.0497	0.3621	2.0922	-0.3642	-2.1059	-0.4271	-2.5436
Millet	0.4926	3.0485	0.4830	2.9703	-0.0907	-0.4905	-0.3267	-1.8614
Maize	0.5931	3.9670	0.4028	2.3701	-0.3349	-1.9143	-0.3736	-2.1687
Rice	0.2630	1.4681	0.2831	1.5892	0.0027	0.0143	-0.1435	-0.7809

Table 3: Assessing the sensitivity to change in definition of season (June-July-August v July-August-September) of correlation between crop yield and season total precipitation or season average temperature, using WFDEI data (1981-2013) over Senegal. If the significance test exceeds a magnitude of 1.690, the correlation is statistically significant.

Here we test sensitivity to the months chosen for the analysis. In Senegal, the main rainy season covers June to September, which is also when crops are typically sowed and grown, with harvesting beginning in September and continuing into November, although for rice harvesting may continue into

January (FAO, 2019). However, the forecasts produced at the PRESASS regional climate outlook forum typically cover two three-month periods: June-July-August (JJA) and July-August-September (JAS). Table 3 shows that there are some differences in the degree of correlation between crop yield and the meteorological parameters, depending on whether JJA or JAS is used. For season total precipitation, the correlation is generally stronger when JJA is used, but not for rice yield where the correlation remains non-significant. For season average temperature, the correlation is weaker for JJA with only two crops now having significant correlation, compared to three for JAS. On balance, more crops show significant correlation for JAS than JJA.

#### 3.3.5 Total Production and Area Harvested

The FAO supply three variables for each country: yield, total crop production and area harvested. Figure 9 shows time series for total production and area harvested, which like yield show a gradual upward trend. Therefore, detrended data (subtracting a 5-year running mean) was used to explore the correlation between each of these and the seasonal meteorological parameters. The results in Table 4 show significant correlation for all four crops with both total precipitation and average temperature. That correlation is found between rainfall or temperature and rice production or harvested area but not yield is unexpected, because yield is simply production divided by area. However, as yield is the amount of crop grown on a given area, it measures how efficiently the crops grew, which is likely to be most strongly influenced by the weather. Furthermore, production and area harvested are more likely to be influenced by short-term socio-economic factors, such as subsidies for particular crops and availability of land.

	Season Total Precipitation								
Crop	Yie	eld	Total Pro	oduction	Area Harvested				
	Pearson	Sig. test	Pearson	Sig. test	Pearson	Sig. test			
Sorghum	0.3621	2.0922	0.4635	2.8171	0.3891	2.2743			
Millet	0.4830	2.9703	0.5707	3.7428	0.5634	3.6721			
Maize	0.4028	2.3701	0.4234	2.5168	0.3239	1.8433			
Rice	0.2831	1.5892	0.5369	3.4273	0.5298	3.3642			
		Sea	ason Averag	e Temperat	ure				
Crop	Yie	Sea	ason Averag Total Pro	e Temperat	ture Area Ha	arvested			
Crop	Yie Pearson	Sea eld Sig. test	ason Averag Total Pro Pearson	e Temperat oduction Sig. test	ture Area Ha Pearson	rvested Sig. test			
Crop Sorghum	Yie Pearson -0.4271	Sea eld Sig. test -2.5436	ason Averag Total Pro Pearson -0.5085	e Temperat oduction Sig. test -3.1802	ure Area Ha Pearson -0.4100	arvested Sig. test -2.4205			
Crop Sorghum Millet	Yie Pearson -0.4271 -0.3267	Sea eld Sig. test -2.5436 -1.8614	ason Averag Total Pro Pearson -0.5085 -0.4083	e Temperat oduction Sig. test -3.1802 -2.4090	ure Area Ha Pearson -0.4100 -0.4333	arvested Sig. test -2.4205 -2.5890			
Crop Sorghum Millet Maize	Yie Pearson -0.4271 -0.3267 -0.3736	Sea eld Sig. test -2.5436 -1.8614 -2.1687	ason Averaç Total Pro Pearson -0.5085 -0.4083 -0.3783	re Temperat oduction Sig. test -3.1802 -2.4090 -2.2004	ure Area Ha Pearson -0.4100 -0.4333 -0.3315	arvested Sig. test -2.4205 -2.5890 -1.892			

Table 4: Exploring the correlation between crop yields, total production or area harvested and [top] season total precipitation and [bottom] season average temperature, based on WFDEI data from JAS 1981-2013. If the significance test exceeds a magnitude of 1.690, the correlation is statistically significant.



Figure 9: Using data from the FAO, [top] Total crop production and [bottom] Area harvested for the four main crops in Senegal over the years 1981-2016.

#### 3.3.6 Derived Metrics

As well as taking the direct output from the WFDEI project, we have also tested derived metrics such as 'rain days' against crop yields. For each year in the period of interest, the number of days when rainfall exceeds a threshold (here, 1mm) are counted for each point in Senegal, and this number is then averaged over the entire country. These are then compared to the crop yields, giving the correlation coefficients and significance tests shown in Table 5. For maize, millet and sorghum, the correlations are weaker than those for seasonal total precipitation, but for rice the correlation is stronger. The correlations are significant for millet, maize and rice but not sorghum. This suggests that for maize, millet and sorghum, the total rainfall in a season is more important than how it is distributed throughout the season. However, this result should be interpreted with caution, because it is possible that crops are more sensitive to rainfall distribution in the earlier stages of their development. For rice, the rainfall distribution might be more significant than the total amount, perhaps due to its growth in paddy fields.

Crop	Number of Rain Days		
	Pearson	Sig. test	
Sorghum	0.2613	1.4578	
Millet	0.3763	2.1875	
Maize	0.3226	1.8352	
Rice	0.3173	1.8015	

Table 5: Assessing the correlation between each crop's yield and the number of rain days in JAS. A rain day is defined as a day with more than 1mm of rainfall, calculated using WFDEI precipitation data for 1981-2013. If the significance test exceeds 1.690, the correlation is statistically significant.

#### 3.4 Sea Surface Temperatures

#### 3.4.1 ENSO

The El Niño Southern Oscillation (ENSO) is a key influence on climate at seasonal timescales across the globe (Met Office, 2016). Here, we assess whether there is correlation between an ENSO index and season total rainfall, season average temperature, or crop yields in Senegal. First, we classify each year in the sample according to whether the ENSO state in the preceding DJF was El Niño, La Niña or Neutral. We calculate the mean JAS rainfall and temperature, and test whether the means for each ENSO state were significantly different from each other using the Mann-Whitney test (Rees, 2001, Section 11.9); the results are shown in Table 6. The temperatures vary little between the three categories. For rainfall, it is interesting to note that El Niño and La Niña years show similar results, with

	Season Total Precipitation	Season Average Temperature
El Niño	540.1 mm/season	$28.32^{\circ}C$
Neutral	482.1mm/season	$28.30^{\circ}C$
La Niña	523.0 mm/season	$28.28^{\circ}C$

Table 6: Season (JAS) total precipitation and season average temperature for each of the three ENSO groups, separating the years 1981-2013 by ONI index value.

the main differences found when comparing to Neutral conditions.

Table 7 shows the results of the Mann-Whitney test (Section 2.4), giving a test statistic and a p-value. The null hypothesis, that the means are not significantly different, cannot be rejected at the 5% level because the p values exceed 0.05. The differences between the means are not significant for either season total precipitation or season average temperature.

	Season Total Precipitation						
	El Niño v La Niña	El Niño v Neutral	La Niña v Neutral				
Test Statistic	69.0	35.0	49.0				
p-value	0.3407	0.0849	0.1150				
	Season Average Temperature						
	El Niño v La Niña	El Niño v Neutral	La Niña v Neutral				
Test Statistic	71.0	51.0	69.0				
p-value	0.3817	0.4027	0.4883				

Table 7: Results of the Mann-Whitney test on the mean values given in Table 6.

In case the categorisation of the ENSO index is limiting the analysis, we also tested correlation on the values of ONI with season total precipitation (Pearson = -0.06, sig test = -0.36) and with season average temperature (Pearson = 0.16, sig test = 0.99). The correlations are both only weak and insignificant. Furthermore, Figure 10 shows the same data as used in Figure 5 but with the points coloured by ENSO category, in order to assess qualitatively whether there is any grouping between crop yields and precipitation or temperature, based on ENSO index; however, no such grouping is apparent. Testing whether the mean yield or yield anomaly for each of the four crops divided into El Niño years, La Niña years, and Neutral years gives no significant differences, meaning that ENSO does not significantly influence crop yields in Senegal. This is to be expected, given the weak links between ENSO and West African rainfall. However, links have been found with SSTs in other areas and the West African monsoon (Rodríguez-Fonseca et al., 2011), so in the next section we will continue to explore the links with crops yields.



Season Total Precipitation

Figure 10: Plot of WFDEI [top] season (JAS) total precipitation or [bottom] season average temperature data against FAO crop yield data, coloured by ENSO index (Red = El Niño, Yellow = Neutral, Blue = La Niña).

#### 3.4.2 Cluster Analysis

Following the work of Davie et al. (2019) and Pope et al. (2019), we explore correlation between global SSTs from ERA-Interim and crop yields in Senegal. Figure 11 shows regions where SSTs are significantly correlated with yield anomaly (that is, yield minus a 5-year moving average). Only correlation significant at the 90% level is shown, with positive correlation hatched and negative correlation left plain.

We notice that maize doesn't follow any expected pattern, but shows correlation with SSTs in the Southern Ocean. This is unlikely to have physical causes, because SSTs vary little in the Southern Ocean, but have a chance correlation with maize yields in Senegal. We therefore exclude correlation found in the Southern Ocean from the discussion.

With the exception of maize, the crops show negative correlation with SSTs off the west coast of Africa, meaning lower SSTs give higher yields. While physical explanations are beyond the scope of the current work, future work might analyse the mechanism that links SSTs off west Africa and crop yields in Senegal, and explore whether the SSTs can be used to inform seasonal forecasts.

In terms of potential links to ENSO, some differences appear between the crops: Sorghum appears to be linked to SSTs across the eastern Pacific region where ENSO is active, but the correlation is negative meaning that El Niño conditions give lower yields and La Niña give higher yields. Millet yield anomaly is correlated with SSTs to the north of this, and rice with SSTs to the south. This indicates that variability in Senegal's crop yields is not clearly correlated with SSTs in the ENSO region, but there are links with SSTs in the tropical Pacific. Figure 11 also hints that there is a link between crop yields and SSTs in the Indian Ocean, but no coherent regions emerge. This is unexpected, given that previous work demonstrates significant links between SSTs in several ocean basins and Sahelian rainfall (Rowell, 2011), but it might be that the dynamical relationships are different in Senegal compared to the Sahel as a whole. Further work could explore how the SSTs in the Indian and tropical Pacific Oceans dynamically influence crop yields in Senegal, though exploration of the meteorology that links them such as pressure patterns and associated changes in wind.

## (a) Sorghum (b) Millet **7**7 Ş Š. (c) Maize (d) Rice

Figure 11: Regions with significant correlation between SSTs and detrended yield for (a) Sorghum, (b) Millet, (c) Maize and (d) Rice. Colours indicate the different regions with significant correlation. Positive correlation is hatched and negative correlation is left unhatched. Based on the work of Davie et al. (2019).



#### 3.5 Multivariate Analysis

As per Kent et al. (2017, Figure 2c), Figure 12 shows the season total precipitation against average temperature, with points coloured by yield anomaly. There is a general trend towards negative yield anomalies in drier and warmer years, with positive yield anomalies in the wetter and cooler years. However, this is far from a clear relationship, for example both the best and worst years for millet occur with near-average precipitation. This is likely due to the much smaller amount of data we use, compared to Kent et al. (2017) who use climate model data. Another reason may be that there are factors influencing crop yields in Senegal other than the meteorological factors analysed here. It could be that the crops are more sensitive to different parameters and/or factors unrelated to the climate.



Figure 12: Scatter plots of season (JAS) total precipitation against season average temperature, with the points coloured by yield anomaly for [top-left] Sorghum, [top-right] Millet, [bottom-left] Maize, and [bottom-right] Rice. Based on Kent et al. (2017), Figure 2c.

We also calculated the Heidke skill score for a range of thresholds, as per Kent et al. (2017, Figure 2a), with the results in Figure 13. This gives a skill score for predicting a yield shock (that is, a crop reduction of at least one standard deviation), given temperature above and precipitation below a range of thresholds. Here, we are exploring whether there is a temperature or precipitation threshold, which can be used to skilfully forecast a yield shock. Figure 13 shows that this depends on the chosen crop. For maize, higher temperatures and lower precipitation show greater skill than the reverse, as

expected. For sorghum and millet, there is higher skill for lower precipitation, and to a lesser extent higher temperatures. Rice shows no skill in either, but this is unsurprising given that it has generally shown the weakest links with weather parameters in this work so far. In general, the skill is much weaker than that found by Kent et al. (2017), perhaps because the current work has fewer years' data to analyse meaning any relationship is less well-defined. Here, we analyse a different region to that used in Kent et al., and its different sensitivities mean a difference in skill is expected. Future work may wish to consider quantifying the uncertainty in order to assess whether the skill score is statistically significant, following the method of Kent et al..



Figure 13: The Heidke skill score for a range of temperature and precipitation thresholds, for [top-left] Sorghum, [top-right] Millet, [bottom-left] Maize, and [bottom-right] Rice. Based on Kent et al. (2017), Figure 2a.

#### 4 Discussion

This work finds evidence for some statistically significant associations between crop yields and parameters for seasonal climate in Senegal, providing a basis for evaluating the potential of seasonal forecasts to provide information relevant to crop production at the national scale. The correlations are significant for maize, millet and sorghum, but not for rice. This is reinforced by the results of the bootstrap analysis.

The absence of a relationship between seasonal rainfall and rice production could be due to a number of factors, including a reduced sensitivity to meteorological influences from growing rice in paddy fields. Importantly, the correlations for maize, millet and sorghum are modest, highlighting that other factors are relevant to variability in yields, such as management practices and other non-climate factors, as well as time-varying sensitivities due to the different growth stages of vegetation. Furthermore, correlation does not mean causation, which is particularly relevant to considering the SSTs results; we do not consider the physical interpretation of links, but exploring this with a focus on Senegal might be the subject of future work. Nevertheless, there is evidence of links between crop yields and SSTs in the nearby Atlantic region.

Though the JAS season was chosen as the primary period of interest, results show stronger correlations between crop yield and season total precipitation for the JJA season, though weaker correlations are found with season average temperature in JJA. The implication is that the success of crops is more dependent on adequate rainfall earlier in the season, when plants are earlier in development and have less drought resilience. Later in the season, crops show a greater sensitivity to temperature variations as leaves develop and evapo-transpiration increases. The results suggest that consideration of different periods is important, especially in any work to extend the application of seasonal forecasts to provide impact information for crop production.

One key limitation of this work is that the meteorological parameters are averaged over the whole country, and crops are not grown uniformly but rather concentrated in specific regions (Figure 1). Future work may seek to focus on the specific regions where crops are grown, since crop-sparse areas are likely to influence the correlations found. However, focusing on sub-national scales would introduce additional challenges. For example, research would require up-to-date and accurate crop yield data for the regions where crops are grown. Furthermore, since our aim is to understand potential applications for seasonal forecasts, at finer spatial scales the reliability and accuracy of seasonal forecasts reduces, meaning that even if clear relationships exist we would not be able to provide meaningful seasonal forecast information with current capabilities. Nevertheless, considering the spatial distribution of crops, or temporal distribution throughout the season, and relating this to seasonal climate in greater detail is a potential topic for future work. However, it should be noted that the links between forecast weather and crop yield are expected to be weaker than the links between observed weather and crop yield (Palin et al., 2016). It is necessary to establish whether there is skill in the forecast of the chosen weather parameter, which is the subject of Pirret et al. (2019, in preparation).

Ideally, longer timeseries of data would be used, as complex relationships and teleconnections can be inadequately sampled by shorter time periods. We have used the longest time period available using consistent meteorological observations that rely on satellite data. Another limitation is the impact of climate change. In a non-stationary climate, the nature of the relationships between crops and climate may change, so past data may not be appropriate to infer such relationships in the future. Also, climate change will affect seasonal weather patterns, which has already had an adverse effect on global production of several major crops (Lobell and Field, 2007). While increasing  $CO_2$  directly increases

yields, the secondary effects on temperature and precipitation impact negatively on yields. Climate change is expected to increase temperatures, but effects on total precipitation in West Africa are less clear (Christensen et al., 2013, Section 14.2.4). Despite this uncertainty, African cereal crop productivity is expected to reduce (IPCC, 2014, Section 22.3.4.1). In West Africa, increasing temperatures mean increasing potential evapo-transpiration and a negative impact on yield, which is not balanced by the positive effects of increasing  $CO_2$  or by changes in precipitation (Roudier et al., 2011; Sultan and Gaetani, 2016). The expected increase in interannual rainfall variability (Christensen et al., 2013, Section 14.2.4) is likely to have an adverse impact on crop yields (Thornton et al., 2014), particularly in a region where food security is relatively low and where climate and non-climate factors can interact to exacerbate the threat (IPCC, 2014, Section 22.3.4.5).

#### 5 Conclusions

This work examines the relationships between seasonal climate parameters (total precipitation and average temperature) and crop yields over Senegal during the main rainy season (July to September). Using observations covering 1981-2013, we assess the strength of these relationships for the four main food crops in Senegal: maize, millet, sorghum and rice.

There are significant correlations between season total precipitation and yields of maize, millet and sorghum, but not for rice. Significant correlations were also identified between seasonal average temperatures and yields of the same three crops. The lack of significant correlations for rice may be due in part to its growth in paddy fields, giving it reduced sensitivity to interannual sensitivity in precipitation and temperature. The correlations are shown to remain broadly significant using the standard June to August period as well as using different observational data sets, different historical periods, and other crop parameters (total production and area harvested).

The links between ENSO and seasonal total precipitation or seasonal average temperature are unclear in Senegal, and this is reflected in the lack of clear relationships between ENSO and crop yields. This is consistent with the findings of Joly and Voldoire (2009), where rainfall variability in the western Sahel is less closely related to ENSO compared to eastern regions of the Sahel. This can be seen by our work following Davie et al. (2019), identifying regions where crop yields correlate with DJF SSTs; here, we do not find correlation with the SSTs in the ENSO region across all crops, but do find correlation with Equatorial South Pacific SSTs in sorghum and millet and more local influences in the Atlantic near West Africa.

We also build on work by Kent et al. (2017), linking seasonal total precipitation and seasonal average temperature to crop yields, identifying that drier and warmer years tend to result in negative yield anomalies. However, the relationships are less clear than in the findings of Kent et al., indicating that factors other than simple seasonal climate means are driving the variability in crops yields. Preliminary results using combined thresholds of seasonal total precipitation and seasonal average temperature to forecast yield 'shocks' show promising results for maize, sorghum and millet, but not for rice.

Overall, the significant correlations between crop yield and seasonal total precipitation and seasonal average temperature provide a basis for undertaking further work to assess the potential of using seasonal forecasts to provide crop-relevant information in Senegal, that could inform planning on the necessary timescales for agriculture (Sultan et al., 2005). A key next step is to integrate the findings here with assessments of the quality of seasonal forecasts for the metrics evaluated in this study.

#### Acknowledgements

This work was completed as part of the ASPIRE project (Met Office, 2018), funded by DFID as part of the WISER initiative. Thank you to Jemma Davie for use of her code to produce Figure 11, associated support and useful discussions. We acknowledge useful discussions with Andrew Colman, Issa Lélé and Chris Kent. We are grateful to Ed Pope and Richard Graham for reviewing this report.

#### References

- Becker, A., P. Finger, A. Meyer-Christoffer, B. Rudolf, K. Schamm, U. Schneider, and M. Ziese, 2013: A description of the global land-surface precipitation data products of the Global Precipitation Climatol-ogy Centre with sample applications including centennial (trend) analysis from 1901-present. *Earth System Science Data*, **5** (1), 71–99, URL https://www.earth-syst-sci-data.net/5/71/2013/.
- Cash, D. W., W. C. Clark, F. Alcock, N. M. Dickson, N. Eckley, D. H. Guston, J. Jäger, and R. B. Mitchell, 2003: Knowledge systems for sustainable development. *Proceedings of the National Academy of Sciences*, **100 (14)**, 8086–8091, doi:10.1073/pnas.1231332100.
- Christensen, J., and Coauthors, 2013: Climate phenomena and their relevance for future regional climate change. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, T. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. Midgley, Eds., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, URL Availableathttp://www.climatechange2013.org/, accessed 2018-03-08.
- Davie, J., E. Pope, and C. Kent, 2019: D2.1: Relationships between large-scale modes of natural climate variability and crop yield variations. *CSSP-China: WP5.2b Food Security*, Met Office Hadley Centre, Exeter, UK.
- Dee, D. P., and Coauthors, 2011: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, **137 (656)**, 553–597, doi:10.1002/qj.828.
- Food and Agriculture Organisation of the United Nations, 2017: FAOSTAT. URL http://www.fao.org/faostat/en/#data/QC, online; accessed 2018-12-10.

- Food and Agriculture Organisation of the United Nations, 2019: GIEWS Country Brief Senegal. URL http://www.fao.org/giews/countrybrief/country.jsp?code=SEN, online; accessed 2019-05-31.
- Frieler, K., and Coauthors, 2017: Understanding the weather signal in national cropyield variability. *Earth's Future*, **5**, 605–616, doi:10.1002/2016EF000525.
- Funk, C., and Coauthors, 2015: The climate hazards infrared precipitation with stations a new environmental record for monitoring extremes. *Scientific Data*, 1–21, doi:10.1038/sdata.2015.66, URL http://chg.geog.ucsb.edu/data/chirps/.
- Hansen, J. W., S. J. Mason, L. Sun, and A. Tall, 2011: Review of seasonal climate forecasting for agriculture in sub-Saharan Africa. *Experimental Agriculture*, **47 (2)**, 205–240, doi:https://doi.org/10. 1017/S0014479710000876.
- Harris, I., P. Jones, T. Osborn, and D. Lister, 2014: Updated highresolution grids of monthly climatic observations the CRU TS3.10 dataset. *International Journal of Climatology*, **34**, 623–642, doi:10. 1002/joc.3711.
- Hatfield, J. L., K. J. Boote, B. A. Kimball, L. H. Ziska, R. C. Izaurralde, D. Ort, A. M. Thomson, and D. Wolfe, 2011: Climate Impacts on Agriculture: Implications for Crop Production. *Agronomy Journal*, 103, 351–370, doi:https://doi.org/10.1017/S0014479710000876.
- IPCC, 2014: Climate change 2014: Impacts, adaptation, and vulnerability. Part B: Regional aspects. *Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, V. Barros, C. Field, D. Dokken, M. Mastrandrea, K. Mach, T. Bilir, M. Chatterjee, K. Ebi, Y. Estrada, R. Genova, B. Girma, E. Kissel, A. Levy, S. MacCracken, and a. L. W. P.R. Mastrandrea, Eds., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 688.
- Joly, M., and A. Voldoire, 2009: Influence of ENSO on the West African Monsoon: Temporal Aspects and Atmospheric Processes. *Journal of Climate*, **22**, 3193–3210, doi:https://doi.org/10.1175/2008JCLI2450.1.
- Kent, C., E. Pope, V., Thompson, K. Lewis, A. A. Scaife, and N. Dunstone, 2017: Using climate model simulations to assess the current climate risk to maize production. *Environmental Research Letters*, 12, 054 012, doi:https://doi.org/10.1088/1748-9326/aa6cb9.
- Lobell, D. B., and C. B. Field, 2007: Global scale climate-crop yield relationships and the impacts of recent warming. *Environmental Research Letters*, 2, 014 002, URL https://doi.org/10.1088/1748-9326/ 2/1/014002.
- Lobell, D. B., W. Schlenker, and J. Costa-Roberts, 2011: Climate trends and global crop production since 1980. *Science*, **333 (6042)**, 616–620, doi:10.1126/science.1204531.

- Meinke, H., R. Nelson, P. Kokic, R. Stone, R. Selvaraju, and W. Baethgen, 2006: Actionable climate knowledge: from analysis to synthesis. *Climate Research*, **33**, 101–110, doi:10.3354/cr033101.
- Met Office, 2016: ENSO Impacts. URL https://www.metoffice.gov.uk/research/climate/ seasonal-to-decadal/gpc-outlooks/el-nino-la-nina/enso-impacts, online; accessed 2018-12-19.
- Met Office, 2018: Adaptive Social Protection Information for Enhanced REsilience (ASPIRE). URL https://www.metoffice.gov.uk/about-us/what/working-with-other-organisations/international/ projects/wiser/aspire, online; accessed 2019-06-28.
- Monfreda, C., N. Ramankutty, and J. A. Foley, 2008: Farming the planet: 2. geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles*, **22**, GB1022, doi:10.1029/2007GB002947.
- NWS Climate Prediction Center, 2018: ENSO Impacts. URL http://origin.cpc.ncep.noaa.gov/products/ analysis\_monitoring/ensostuff/ONI\_v5.php, online; accessed 2019-01-07.
- Palin, E., A. Scaife, E. Wallace, E. Pope, A. Arribas, and A. Brookshaw, 2016: Skillful seasonal forecasts of winter disruption to the UK transport system. *J. Appl. Meteor. Climatol.*, 55, 325–344, URL https: //doi.org/10.1175/JAMC-D-15-0102.1.
- Pope, E., C. Buontempo, and T. Economou, 2017: Quantifying how user-interaction can modify the perception of the value of climate information: A Bayesian approach. *Climate Services*, 6, 41–47, URL https://doi.org/10.1016/j.cliser.2017.06.006.
- Pope, E., C. Kent, C. Bradshaw, and J. Davie, 2019: Uk food security in a changing climate annual report. Tech. rep., Met Office Hadley Centre, Exeter, UK. In print.
- Rees, D., 2001: Essential Statistics. Fourth edition ed., Chapman & Hall / CRC.
- Rodríguez-Fonseca, B., and Coauthors, 2011: Interannual and decadal SST-forced responses of the West African monsoon. *Atmospheric Science Letters*, **12**, 67–74, doi:10.1002/asl.308.
- Roudier, P., B.Sultan, P. Quirion, and A. Berg, 2011: The impact of future climate change on West African crop yields: What does the recent literature say? *Global Environmental Change*, **21 (3)**, 1073–1083, URL https://doi.org/10.1016/j.gloenvcha.2011.04.007.
- Rowell, D. P., 2011: Simulating SST teleconnections to Africa: what is the state of the art? *Journal of Climate*, **26**, 5397–5418, URL https://doi.org/10.1175/JCLI-D-12-00761.1.
- Schroeer, K., and G. Kirchengast, 2018: Sensitivity of extreme precipitation to temperature: the variability of scaling factors from a regional to local perspective. *Climate Dynamics*, **50**, 3981–3994, URL https://doi.org/10.1007/s00382-017-3857-9.
- Smith, M. R., and S. S. Myers, 2018: Impact of antropogenic CO2 emissions on global human nutrition. *Nature Climate Science*, **8**, 834–839, doi:10.1038/s41558-018-0253-3ID.

- Sultan, B., C. Baron, M. Dingkuhn, B. Sarr, and S. Janicot, 2005: Agricultural impacts of large-scale variability of the West African monsoon. *Agricultural and Forest Meteorology*, **128 (1–2)**, 93–110, doi:https://doi.org/10.1016/j.agrformet.2004.08.005.
- Sultan, B., and M. Gaetani, 2016: Agriculture in West africa in the Twenty-First Century: Climate change and impacts scenarios, and potential for adaptation. *Frontiers in Plant Science*, **7**, 1262, doi:10.3389/fpls.2016.01262.
- Taylor, C., and Coauthors, 2017: Frequency of extreme sahelian storms tripled since 1982 in satellite observations. *Nature*, **544**, 475–478, URL https://www.nature.com/articles/nature22069.
- Thompson, V., N. J. Dunstone, A. A. Scaife, D. M. Smith, J. M. Slingo, S. Brown, and S. E. Belcher, 2017: High risk of unprecedented uk rainfall in the current climate. *Nature Communications*, **8**, 107, doi:10.1038/s41467-017-00275-3.
- Thornton, P. K., P. Ericksen, M. Herrero, and A. J. Challinor, 2014: Climate variability and vulnerability to climate change: a review. *Global Change Biology*, **20**, 3313–3328, doi:10.1111/gcb.12581.
- Weedon, G. P., G. Balsamo, N. Bellouin, S. Gomes, M. J. Best, and P. Viterbo, 2014: The WFDEI meteorological forcing data set: WATCH Forcing Data methodology applied to ERA-Interim reanalysis data. *Water Resources Research*, **50**, 7505–7514, doi:10.1002/2014WR015638, URL http://www.eu-watch.org/data\_availability.

Met Office FitzRoy Road Exeter Devon EX1 3PB United Kingdom