The Multidecadal Atlantic SST—Sahel Rainfall Teleconnection in CMIP5 Simulations

ELINOR R. MARTIN and CHRIS THORNCROFT

Department of Atmospheric and Environmental Sciences, University at Albany, State University of New York, Albany, New York

BEN B. B. BOOTH

Met Office Hadley Centre, Exeter, United Kingdom

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ABSTRACT

This study uses models from phase 5 of the Coupled Model Intercomparison Project (CMIP5) to evaluate and investigate Sahel rainfall multidecadal variability and teleconnections with global sea surface temperatures (SSTs). Multidecadal variability is lower than observed in all historical simulations evaluated. Focus is on teleconnections with North Atlantic SST [Atlantic multidecadal variability (AMV)] as it is more successfully simulated than the Indian Ocean teleconnection. To investigate why some models successfully simulated this teleconnection and others did not, despite having similarly large AMV, two groups of models were selected. Models with large AMV were highlighted as good (or poor) by their ability to simulate relatively high (low) Sahel multidecadal variability and have significant (not significant) correlation between multidecadal Sahel rainfall and an AMV index. Poor models fail to capture the teleconnection between the AMV and Sahel rainfall because the spatial distribution of SST multidecadal variability across the North Atlantic is incorrect. A lack of SST signal in the tropical North Atlantic and Mediterranean reduces the interhemispheric SST gradient and, through circulation changes, the rainfall variability in the Sahel. This pattern was also evident in the control simulations, where SST and Sahel rainfall variability were significantly weaker than historical simulations. Errors in SST variability were suggested to result from a combination of weak wind–evaporation–SST feedbacks, poorly simulated cloud amounts and feedbacks in the stratocumulus regions of the eastern Atlantic, dust–SST–rainfall feedbacks, and sulfate aerosol interactions with clouds. By understanding the deficits and successes of CMIP5 historical simulations, future projections and decadal hindcasts can be examined with additional confidence.

1. Introduction

Precipitation in the Sahel region of Africa has undergone large multidecadal variability over the past century (Fig. 1), with wet conditions in the 1940s and 1950s, a switch to dry conditions in the 1960s, and a recovery to near-average conditions since 2000. With decadal-scale variability (as measured by variance and shown in Fig. 1) accounting for almost half the total variability, understanding and simulating these observed decadal variations is a vital step in making decadal and longer-term predictions for the Sahel in order to prepare and adapt to changes in water availability in the future.

The role of sea surface temperature (SST) is frequently highlighted as the driver for decadal variability of rainfall in West Africa (e.g., Lamb 1978a,b; Hastenrath 1990; Folland et al. 1986). Atmospheric general circulation models (AGCMs) forced with observed SSTs over the past century are able to reproduce variability in Sahel rainfall, although the magnitude varies between models, reinforcing the driving of decadal Sahel rainfall variability by SSTs (Folland et al. 1986; Giannini et al. 2003; Lu and Delworth 2005; Hoerling et al. 2006; Scaife et al. 2009) and highlighting the need for coupled model simulations to correctly capture the SST structure and atmospheric response to SSTs.

Several regions have been promoted as being a driver for the decadal-scale drought and wet periods in the Sahel. Atlantic multidecadal variability (AMV) has been the focus of much attention, particularly the interhemispheric pattern of SST and the Atlantic multidecadal oscillation (AMO) (Lamb 1978a,b; Folland et al.
The AMO is characterized by large-scale SST changes in the North Atlantic with a period of approximately 50–70 yr (Kerr 2000) that is associated with warming over much of the North Atlantic (including the tropical North Atlantic and Mediterranean) during a positive AMV period, as was observed during the 1940s, 1950s and 2000s. The warming of the North Atlantic and Mediterranean associated with the AMV coincides with wet periods in the Sahel and is attributed to a northward movement of the ITCZ, a stronger Saharan heat low, and increased African easterly wave activity (Lamb 1978a,b; Hastenrath 1990; Folland et al. 1986; Rowell et al. 1995; Martin and Thorncroft 2013). The changes in SST, African easterly wave activity, and vertical wind shear in the Atlantic that occur in conjunction with increased Sahel rainfall are likely causes of the decadal variability observed in tropical cyclones in the region (Goldenberg et al. 2001; Aiyyer and Thorncroft 2011; Martin and Thorncroft 2013).

The tropical interhemispheric SST gradient that occurs during a positive AMO event shows many similarities to the Atlantic meridional mode (AMM), which is characterized by changes in SST and winds north and south of the ITCZ causing meridional movement of the ITCZ and consequently possibly impacting Sahel rainfall (Servain 1991; Carton et al. 1996; Chiang and Vimont 2004). The similarities between the structure of the AMO and AMM in the tropical Atlantic has led some authors to view the variability as one phenomenon (e.g., Xie and Tanimoto 1998) and others to view them as two distinct but related features (e.g., Vimont and Kossin 2007). Vimont and Kossin (2007) suggest that on decadal time scales, the AMO can excite the AMM.

Sulfate aerosols and dust have been shown to project onto a similar spatial and temporal pattern of AMV in the North Atlantic (Rotstayn and Lohmann 2002; Chang et al. 2011; Booth et al. 2012). In the case of sulfate aerosols, this acts as an external forcing of AMV in addition to natural ocean circulation–driven changes associated with the AMO (Delworth and Mann 2000; Knight et al. 2005), although the relative magnitudes of natural and forced variability is an open question (Zhang et al. 2013). In this regard, we use AMV as an overarching term encompassing contributions to SST variability from the AMO, AMM, and potential external forcing.

In addition to the Atlantic and Mediterranean, the Indian and Pacific Oceans impact decadal variability of Sahel rainfall. Indian Ocean warming has been linked to drying over the Sahel by Bader and Latif (2003), Giannini et al. (2003), and Lu (2009) through increased subsidence and stability over West Africa. However, it has been suggested by Mohino et al. (2011) that the Indian Ocean signal is a superposition of the Atlantic and Pacific signals. The dominant mode of decadal variability in the Pacific is the interdecadal Pacific oscillation (IPO) (Zhang et al. 1997), which has been shown to be related to Sahel rainfall (Mohino et al. 2011) although the mechanisms are not yet fully understood.

Multimodel comparisons of the teleconnections between Sahel rainfall and global SSTs, using the suite of models from phase 3 of the Coupled Model Intercomparison Project (CMIP3), have shown some success in the Atlantic at interannual and multidecadal time scales (Lau et al. 2006; Joly et al. 2007; Biasutti et al. 2008). The correlation between Sahel precipitation and the Atlantic interhemispheric SST gradient at low frequencies was weaker than observed but still evident in the control and historical (forced with twentieth-century observed atmospheric composition changes) simulations, suggesting that the multidecadal teleconnection is internal to the climate system (Joly et al. 2007). The correlation with Indian Ocean SST, however, was weak or nonexistent in the model simulations at a range of time scales (Joly et al. 2007; Biasutti et al. 2008). In the recent generation of models from phase 5 of the Coupled Model Intercomparison Project (CMIP5), Ault et al. (2012) shows that the decadal variability of precipitation in historical simulations is too weak in North Africa and across the globe, highlighting an important problem in the current generation of numerical models.
if we expect them to make skillful predictions of the future.

Given the low decadal variability of precipitation in North Africa in CMIP5 models (Ault et al. 2012), it is likely that the models are not correctly representing the decadal and multidecadal teleconnections between Sahel rainfall and global SSTs. This study aims to evaluate the simulation of these teleconnections in the CMIP5 suite of models and investigate the mechanisms involved in the teleconnections in the models to assess why some models are more successful than others. We focus predominantly on the Atlantic because of the better simulation of this teleconnection in the models (see section 3), which is highlighted at interannual time scales in CMIP5 models by Rowell (2013).

A description of the observations, reanalysis products, and model output analyzed is contained in section 2. An overview of the multidecadal teleconnections between Sahel rainfall and global SSTs is contained in section 3 before an explanation of which model simulations will be further investigated (section 4). The simulation of the mean summer conditions is shown in section 5, and a detailed examination of the mechanisms of the Atlantic–Sahel teleconnection is shown in section 6. This is followed by a discussion and conclusions in sections 7 and 8.

2. Data and methodology

a. Observations

Observations of precipitation from two different sources are used. First, the Climate Research Unit (CRU), version 3.10.01, gridded (0.5° × 0.5°) land-only monthly precipitation for the period 1901–2009 (Mitchell and Jones 2005) is used. This long dataset makes the investigation of decadal variability over the Sahel possible. However, as the CRU data covers land only, supplemental monthly global precipitation data (1979–2009) from the Global Precipitation Climatology Project (GPCP), version 2.2, at 2.5° resolution (Huffman et al. 2001) are used for model comparisons.

Monthly SST data from the Hadley Centre Sea Ice and Sea Surface Temperature (HadISST) dataset, version 1.1, at 1° resolution (Rayner et al. 2003) are used for the same period as the CRU data. Additional monthly data including winds and sea level pressure (SLP) are obtained from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis product at 2.5° resolution (Kalnay et al. 1996). Although this is not the most modern reanalysis, it is available from 1948 onward and as such includes the wet period over the Sahel (Fig. 1) that would be missed if using the modern reanalyses that begin in 1979. The total cloud amount (fractional areal coverage of all clouds for the given month) data from the International Satellite Cloud Climatology Project (ISCCP) (Schiffer and Rossow 1983; Rossow and Schiffer 1999) are used and are available from July 1983 to the end of 2009.

The Sahel is defined as lying between 10° and 20°N, 20°W and 10°E throughout this study (see Fig. 2, region Sa for reference). Additional regions of interest are also included in Fig. 2. For all variables, we focus on July–September (JAS) when the Sahel receives the majority of its rainfall during the West African monsoon (e.g., Thornicroft et al. 2011). Trends estimated from simple linear regression are removed to highlight variability. Decadal and multidecadal time scales are selected using a low-pass filter with a 10-yr cutoff for all analysis except for the comparison of mean conditions. Anomalies are calculated as anomalies from the annual cycle prior to detrending and filtering.
b. CMIP5 model output

Monthly-mean output from 20 coupled GCMs from the CMIP5 experiment is used. The models chosen were based upon availability when originally downloading data from the Earth System Grid (ESG). Further details about CMIP5 and the experimental design are described by the Program for Climate Model Diagnosis and Intercomparison (available online at http://cmip-pcmdi.llnl.gov/cmip5/) and in Taylor et al. (2012).

The majority of this study will focus on the historical simulations covering approximately the same period as the observations (1900–2005). The historical simulations are forced with observed changes in anthropogenic and natural forcing, such as greenhouse gases, aerosols, and volcanoes. Each historical simulation is initialized with conditions from a free-running control simulation with fixed external forcing, and therefore it is not expected that the timing of, for example, drought periods in the Sahel would exactly match observations unless these drought periods are completely forced externally. The control simulations, which give insight into the internal variability of the models, will also be examined.

A list of the models used in this study and associated pertinent information (including all model abbreviations) is shown in Table 1. In total, 72 ensemble members from 20 models were available for the historical experiments. Variables matching those from observations and reanalyses were obtained for each ensemble member. In addition, the total cloud fraction from the models is used, which is the amount of cloud in the whole atmospheric column, as seen from the surface or the top of the atmosphere, and it includes both large-scale and convective clouds that are analogous to the total cloud amount from the ISCCP data.

All model output is linearly interpolated to a 2° × 2° horizontal resolution to allow for comparison between simulations with differing resolutions. All model data are treated the same as the observations described in section 2a. Multimodel means are calculated using a one vote per model approach, averaging all ensemble members from a model before averaging across models.

3. Historical simulations of global teleconnections

Figure 2 shows the observed correlations between filtered Sahel rainfall and filtered global SSTs for JAS. This figure is similar to Fig. 2 in Lu and Delworth (2005) and Fig. 9 in Lu (2009) that were calculated using a different filtering technique and data but show consistent results. As discussed in section 1, significant correlations are observed with the North Atlantic, Mediterranean, and Indian Ocean on decadal time scales. In the Pacific, large positive correlations are seen in the northern midlatitudes with a pattern similar to that of the IPO (Zhang et al. 1997). As shown by Mohino et al. (2011) in a modeling experiment, the Sahel rainfall is forced by the tropical component of the IPO, and as such our focus is on the Indian Ocean rather than the large correlations in the North Pacific.

We streamline the analysis by focusing on four key regions that explain a large fraction of the Sahel rainfall decadal variability [North Atlantic (At), tropical North Atlantic (TAt), Mediterranean (Me), and Indian Ocean (In)] and calculate correlations between filtered SSTs area averaged in each region (as shown in Fig. 2) and filtered Sahel rainfall. The significance of correlation values is assessed using a one-tailed Student’s t test, with an effective sample size equal to the number of years (typically 105) divided by 10 to account for the decadal filtering. In observations, the correlation values for the North Atlantic, tropical North Atlantic, and Mediterranean are all positive and significant at 90% or more (0.58, 0.51, and 0.57, respectively). For the Indian Ocean, the correlation is significant and negative with a magnitude similar to that of the correlation with the North Atlantic (−0.60).

Figure 3 shows the significance level of the correlation between filtered Sahel rainfall and regional-filtered SSTs from each model ensemble member in each region. Each subfigure presents values from an ocean region and each square within the subfigures show significance levels from correlations for all 72 ensemble members. Green corresponds to correlation values that are significant at 90%, yellow shows values significant between 70% and 90%, orange shows weak correlation values between 50% and 70%, and red values indicate correlation values with the opposite sign to observations. As the correlations for all SST regions are significant at 90% in observations, the more green that is present in each large box the more successfully simulated the multidecadal teleconnection between Sahel rainfall and SSTs in that region.

The most distinct region is the Indian Ocean (Fig. 3a). The majority of ensemble members simulate positive correlations between Indian Ocean SST and Sahel rainfall, which is opposite to observations. The multimodel mean for the correlation with Indian Ocean SSTs is 0.10 with a range from −0.51 to 0.51. The poor simulation of this Indian Ocean teleconnection was also seen in simulations from the CMIP3 models (Joly et al. 2007), and these results suggest little to no improvement. It is possible that the poor simulation of the Indian Ocean teleconnection may contaminate the results from other regions; however, the nature of the Indian Ocean teleconnection and the poor simulation will not be...
TABLE 1. List of Intergovernmental Panel on Climate Change (IPCC) CMIP5 models that were used in this study along with model abbreviations, horizontal resolution, and number of ensemble members in the historical simulations. Group indicates if an ensemble member from that model was identified as either good (G) or poor (P) (see text for details). Further model details, including references, can be found at the PCMDI website (http://www-pcmdi.llnl.gov).

<table>
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<tr>
<th>Center, country</th>
<th>Identification name</th>
<th>Model expansion</th>
<th>Horizontal resolution (lon x lat)</th>
<th>Historical ensemble members</th>
<th>Group</th>
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<td>Beijing Climate Center, Climate System Model, version 1.1</td>
<td>T42 (~2.8°)</td>
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<td>Second Generation Canadian Earth System Model</td>
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<td>CNRM-CM5</td>
<td>Centre National de Recherches Météorologiques Coupled Global Climate Model, version 5</td>
<td>T127 (~1.4°)</td>
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<td>CSIRO Mk3.6.0</td>
<td>Commonwealth Scientific and Industrial Research Organisation Mark, version 3.6.0</td>
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<td>Hadley Centre Global Environment Model, version 2, Carbon Cycle</td>
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addressed further, but it is an essential avenue for further research if we wish to predict (both in the long and near term) Sahel rainfall.

The remainder of this study will focus on the connections between SST in the Atlantic and Sahel rainfall. Beginning with the entire North Atlantic basin (Fig. 3b), it is clear that the simulations are more successful than in the Indian Ocean, with the majority of simulations showing positive correlations and almost 70% having positive correlations with significance levels of at least 70% (yellow and green in Fig. 3). The multimodel mean correlation is 0.31 compared with 0.58 in observations. When looking at only the tropical North Atlantic (Fig. 3d), which has been shown to be the main driver in tropical climate variability in the Atlantic (Sutton and Hodson 2007), similar results are seen (multimodel mean of 0.30 compared to 0.51 in observations), which may not be surprising considering the domain of the North Atlantic contains the domain for the tropical North Atlantic (Fig. 2).

In the Mediterranean, which is an important region for Sahel rainfall variability on multiple time scales (Rowell 2003; Gaetani et al. 2010; Fontaine et al. 2010; Martin and Thorncroft 2013), the model simulations (Fig. 3c) show similar numbers of green ensemble members to the north and tropical North Atlantic (Figs. 3b,d), but more orange and red, suggesting less overall agreement with observations. This is also clear when comparing the multimodel mean correlation of 0.25 to the observed value of 0.57. It is evident from Figs. 3b and 3c that a model ensemble member can have a significant correlation between North Atlantic SSTs and Sahel rainfall but simulate no correlation between Mediterranean SSTs and Sahel rainfall on decadal time scales, despite observed SSTs in these regions varying coherently at decadal time scales (Marullo et al. 2011).

4. Model selection

To investigate the mechanisms involved in the decadal variability of Sahel rainfall and the connections with AMV, we begin by assessing the decadal variability simulated by CMIP5 historical simulations in both regions. The decadal variance fractions are calculated using the variance of the JAS SST (or rainfall) time series and the variance of the low-pass filtered JAS SST (or rainfall) time series to establish how much variability is contained within the decadal and longer time period. These statistics, in addition to the correlation between filtered Sahel rainfall and an index of AMV, for the observations and the CMIP5 multimodel historical mean are shown in Table 2. The AMV index is calculated following Enfield et al. (2001); monthly SST anomalies area averaged over 0°–70°N and 10°–75°W (Fig. 2) and then detrended.

In observations, the fraction of decadal variance of the AMV index is larger than that of the Sahel rainfall, but both are high at 66% and 44%, respectively. In the CMIP5 multimodel mean, the decadal variance in both North Atlantic SSTs and Sahel rainfall are lower than observed. For the AMV index, the multimodel mean is two-thirds of the observed value, and this disparity is even larger for the Sahel rainfall (the multimodel mean is approximately one-third of the observed). The precipitation decadal fraction values are a similar magnitude to Ault et al. (2012), despite different methods for identifying decadal variability, adding confidence to the suggestion that models only capture weak variance of Sahel rainfall.

To examine the decadal teleconnection between North Atlantic SSTs and Sahel rainfall in the CMIP5 historical simulations, two groups of models are selected for detailed analysis. Selection of the two model groups “good” and “poor” is based on the following criteria

FIG. 3. Correlation coefficients from CMIP5 historical simulations between detrended JAS-filtered Sahel precipitation anomalies and filtered SST anomalies in the (a) Indian Ocean, (b) North Atlantic, (c) Mediterranean, and (d) tropical North Atlantic (see Fig. 2 for area locations). Each small square within each box represents one simulation. Colors indicate significance level of correlation coefficient with a significance level less than 50% (wrong sign) in red, between 50% and 70% in orange, between 70% and 90% in yellow, and significance level above 90% in green. Letters G and P indicate the ensemble members selected for the good and poor groups, respectively (see text for details on model selection).
with thresholds for selection determined by the CMIP5 historical multimodel mean as shown in Table 2:

(i) Fraction of decadal variance in North Atlantic SSTs (AMV index) above 44% for both good and poor groups;
(ii) Fraction of decadal variance in Sahel-averaged precipitation above 16% for good group (and below 16% for poor group); and
(iii) The correlation between filtered Sahel rainfall and North Atlantic SSTs (AMV index) is significant at 90% for the good group (and not for poor group).

The selection criteria allow for a distinction between model ensemble members that have large (or relatively large when compared to the mean) AMV but have distinctly different abilities to simulate decadal variability in the Sahel. The selection criteria identify 8 good and 16 poor ensemble members (of the 72 total). From this select group, six are placed in the good category and six are placed in the poor category by selecting only one ensemble member per model (as some models had multiple ensembles members in a group; however, the results are not sensitive to the member chosen). The models that had ensemble members selected in either the good or poor group are indicated in Table 1. It should be noted that models classified as poor in this study will not necessarily poorly simulate other important climate phenomena.

The mean values in the good and poor model groups for each criterion are shown in Table 2. Because of the selection method, the mean fraction of decadal variance of the AMV for both groups of models is large, but not as high as observed. The good model mean AMV decadal variance fraction (60%) is slightly larger than the poor model mean (51.6%), but this difference is much less than the values for the decadal fraction of Sahel rainfall. Considering Sahel rainfall decadal variance, both the good and poor model means are less than 50% of the observed Sahel rainfall decadal variance fraction making the good and poor distinction a relative one. However, the good model mean of Sahel decadal variance fraction is almost twice as large as the poor model mean. This low variance could be related to the simulation of mean conditions, as discussed in section 5.

5. Simulation of summer-mean conditions

We begin by assessing the simulation of mean conditions in each group of models to establish their ability to simulate the main features of the West African monsoon. From the annual cycle of Sahel rainfall, shown in Fig. 4a, it is evident that the models capture the summertime peak in Sahel rainfall, but the magnitude is underestimated in the majority of models. This was also present in the CMIP3 simulations (Biasutti et al. 2008). The good and poor model means are also shown in Fig. 4a. The mean annual cycles between the two groups of models are very similar, with the good model mean having a slightly larger August maximum compared to the poor models (4.0 versus 3.7 mm day$^{-1}$).

Also seen in Fig. 4 is the meridional propagation of rainfall in West Africa ($20^\circ$W–$10^\circ$E) from the Gulf of Guinea in spring to the Sahel in summer. This northward propagation is shown by GPCP data (Fig. 4b) and agrees well over land with CRU data (Fig. 4c). The meridional propagation of the peak in precipitation during the year from the good and poor multimodel means is shown in Figs. 4d and 4e, respectively. Neither of the model groups propagates the rainfall far enough northward. The peak rainfall is $2^\circ$–$4^\circ$ (at least one grid box) farther south than observed and is consistent with the drier Sahel in the CMIP5 models. Both model groups have excessive precipitation over the Gulf of Guinea throughout the year but particularly during spring. This excessive rainfall over the Gulf is the largest difference between the good and poor model groups. This southward displacement of the ITCZ and monsoon over West Africa and enhanced rainfall over the Gulf of Guinea is evident in CMIP3 (Cook and Vizy 2006; Richter and Xie 2008) and other CMIP5 models (Richter et al. 2012), and is attributed in part to the warm SSTs simulated by the models in the Gulf of Guinea.

Summertime (JAS) mean SST, SLP, 925-hPa zonal wind, and vertical wind shear across the Atlantic are shown in Fig. 5 for observations or reanalysis and the
good and poor multimodel means. In general, both model groups simulate the location of large-scale climate features, but there are noticeable biases in magnitude. Both model groups have SSTs that are colder than observed in the Atlantic warm pool region and warmer than observed in the Atlantic cold tongue region (Figs. 5a–c), features that were evident in CMIP3 models (Richter and Xie 2008; Misra et al. 2009) and other CMIP5 models (Richter et al. 2012). However, the good multimodel mean (Fig. 5b) has cooler SSTs (closer to observations) than the poor model mean (Fig. 5c) in the Gulf of Guinea, consistent with enhanced Gulf of Guinea rainfall in the poor models (Fig. 4).

Regarding SLP (Figs. 5d–f), the location of the North and South Atlantic subtropical highs in the models are consistent with reanalysis, although the good model mean has slightly stronger subtropical highs and higher SLP over the Sahara. However, low-level (925 hPa) zonal wind (Figs. 5g–i) in both good and poor model means agrees well with the reanalysis product except in

FIG. 4. (a) Annual cycle of Sahel (10°–20°N, 20°W–10°E) rainfall from observations (CRU) and historical simulations. Annual cycle of Sahel (20°W–10°E) zonal rainfall progression (from 10°S to 25°N) for (b) GPCP and (c) CRU observations, (d) good model mean, and (e) poor model mean. Solid black contours in (b)–(e) show 1 and 6 mm day\(^{-1}\) GPCP contours for reference. Dashed black line in (b)–(e) shows the location of the Guinea Coast.
the region of the Caribbean Sea where the Caribbean low-level jet is too strong [consistent with CMIP3 models as shown in Martin and Schumacher (2011)]. Onshore westerly winds have similar position and magnitude to the reanalysis over West Africa (Fig. 5h).

Vertical wind shear (VWS) is calculated as the magnitude of the vector difference of the 200- and 850-hPa horizontal winds from the NCEP–NCAR reanalysis following Aiyer and Thorncroft (2006). Vertical wind shear is an important large-scale environmental variable for tropical cyclones, which have also been shown to undergo multidecadal variability linked to the AMO (Goldenberg et al. 2001; Zhang and Delworth 2006). Multidecadal variability in VWS has been shown by Aiyer and Thorncroft (2011) and linked to variability in Sahel precipitation.

Fig. 5. JAS mean conditions from (left) observations and reanalysis, the (center) good group model mean, and the (right) poor group model mean: (a)–(c) SST (HadISST, °C), (d)–(f) SLP (NCEP–NCAR reanalysis, hPa), (g)–(i) 925-hPa zonal wind (NCEP–NCAR reanalysis, m s⁻¹), and (j)–(l) vertical wind shear between 200 and 850 hPa (NCEP–NCAR reanalysis, m s⁻¹).
The JAS mean VWS from NCEP–NCAR reanalysis (Fig. 5j) is consistent with Aiyyer and Thorncroft (2006) who use a different reanalysis product. Two regions of the VWS maximum are evident: one extending from the Caribbean to northwestern Africa and a second peak along the Guinea coast. Both good (Fig. 5k) and poor (Fig. 5l) model means show the two regions of maximum VWS but the magnitudes vary substantially. The southern peak along the Guinea coast is too weak by at least 5 m s\(^{-1}\), and the northern peak is too strong off the coast of northwest Africa (by at least 2 m s\(^{-1}\)) in both model groups.

Figure 5 shows that while the large-scale climate features tend to have the correct location in the good and poor groups, large biases exist in magnitude. Most notably, and perhaps most relevant for Sahel rainfall, is the warm and wet bias in the Gulf of Guinea in the poor models (Fig. 4). While the SST in the Gulf of Guinea was shown by Martin and Thorncroft (2013) not to be a key feature in the AMO–Sahel relationship (also evident in Fig. 2), the bias must still be considered when assessing the teleconnections in the models.

6. Atlantic–Sahel teleconnection

Empirical orthogonal functions (EOFs) are used to identify the dominant mode of multidecadal variability in North Atlantic SST. The first principal component time series represents an AMV index and is almost identical to the AMV index used for model selection. Variables are regressed onto the first principal component (or AMV index) to determine how they vary with the observed and simulated AMV. This method allows the structure and response to the AMV to be compared between observations and models. The EOF and regression analysis is performed on each individual ensemble member and then averaged together to create a multimodel mean for the good and poor groups.

a. Sea surface temperatures

The AMV pattern (or dominant mode of multidecadal variability) in observations and the two multimodel group means is shown in Fig. 6. The first principal component in observations (Fig. 6a) explains 57.7% of the multidecadal variance. In observations, the pattern of SSTs is well correlated with the pattern of the AMO from previous studies (e.g., Enfield et al. 2001; Sutton and Hodson 2005; Knight et al. 2005). Large and significant SST variability is seen across most of the North Atlantic and Mediterranean with smaller SST signals across the rest of the globe. Within the North Atlantic, a horseshoe pattern in SST variability is evident with maxima south of Greenland and in the tropical North Atlantic. This southern branch of the horseshoe and small signals in the South Atlantic lead to a strong interhemispheric SST gradient, similar to the AMM pattern (e.g., Chiang and Vimont 2004) that is known to impact Sahel precipitation (e.g., Folland et al. 1986; Hastenrath 1990).

In both the good (Fig. 6b) and poor (Fig. 6c) model simulations, the leading mode of multidecadal variability in the North Atlantic explains a large amount of the variance (45.1% and 35.3%, respectively), although less than the observations. The leading mode of multidecadal variability in each group shows large SST variability in the North Atlantic. The level of consistency across the good and poor ensemble members is measured by the ratio between the multimodel ensemble
mean and the intermodel standard deviation, with a value greater than one indicating high consistency (Meehl et al. 2007). For the SST patterns, both the good and poor groups show high consistency in the North Atlantic but with differing spatial patterns. The good multimodel mean (Fig. 6b) has a structure that is consistent with observations in both spatial patterns and magnitude, with the SST horseshoe pattern well defined. The SST variability across the South Atlantic and the rest of the globe is small, leading to a large interhemispheric SST gradient in the Atlantic, consistent with observations. The large and consistent SST values in the Mediterranean are in agreement with observations and other work showing the covariability between AMV (the AMO in particular) and Mediterranean SSTs (Marullo et al. 2011; Mariotti and Dell’Aquila 2012). However, the magnitude of the SST variability in the Mediterranean is less than observed (0.3°C versus 0.2°C per standard deviation).

The poor multimodel mean SST regression onto the first principal component of multidecadal North Atlantic SSTs (Fig. 6c) has a different structure to the observations and good multimodel mean. In the far North Atlantic, SST variability is strong but the peak is shifted north of Iceland in the poor multimodel mean. There is evidence of the horseshoe pattern in the eastern and tropical North Atlantic, but it is weaker than the observations and the good multimodel mean by approximately 0.1° and 0.15°C per standard deviation, respectively. This weaker southern and eastern portion of the SST horseshoe pattern is consistent across the poor model ensemble members. The weak SST variability in the tropical North Atlantic leads to a weaker interhemispheric SST gradient than in observations and the good group. As in the good models, the covariability of SST between the North Atlantic and Mediterranean is evident, but the Mediterranean signal is weaker and not consistent across the ensemble members, with values less than 0.1°C per standard deviation.

The correlation between the regional SST and Sahel rainfall in the Mediterranean and tropical North Atlantic are shown in Figs. 3c and 3d. As indicated by the letters G and P in each regional box, it is clear that the good models are more successfully simulating the multidecadal teleconnection between the tropical North Atlantic and Mediterranean SSTs and Sahel rainfall. The Mediterranean correlations show that five out of six good models are significant at 90%, while only one of the six poor models is. In the tropical North Atlantic, correlations significant at 90% are found in four of the six good models, but in none of the poor models. These results, along with Fig. 6, suggest that the strongly differing spatial patterns of SST multidecadal variability in the North Atlantic between the good and poor models may be a key factor in their ability to simulate a connection with Sahel rainfall.

b. Precipitation

As expected, when precipitation is regressed onto the leading multidecadal mode of North Atlantic SST variability, large precipitation variability is seen in the Sahel (Zhang and Delworth 2006; Martin and Thornicroft 2013). In observations (Fig. 7a), when the North Atlantic is warm, precipitation in the Sahel increases significantly. Decreases in precipitation are seen in South America, the central United States, and the Guinea Coast, and rainfall increases are seen in the Caribbean, Florida, and parts of northern South America and India. Results from the CRU data (Fig. 7a) are consistent with the shorter time series GPCP data over land and show an increase in rainfall in the Atlantic stretching between the Sahel and Caribbean (not shown).
Consistent with the SST pattern (Fig. 6b), the good multimodel mean in precipitation (Fig. 7b) has many similarities to observations. When the North Atlantic is warm, a band of precipitation increase extends from the Caribbean to the Sahel, with a reduction in rainfall to the south. This is a consistent pattern among all six good models, especially in the rainfall increase across the Sahel. This is despite the band of increased precipitation variability being located 2°–3° farther south over Africa in the good multimodel mean than in the observations, consistent with the southerly location of the mean ITCZ (section 5).

Over West Africa, the rainfall variability is approximately half the magnitude of the rainfall variability over the ocean in the multimodel mean, with a sharp boundary in precipitation variability at the coast. The variability in the eastern Sahel is not evident in the model simulations, with only one simulation out of six showing significant rainfall variability east of 20°E in the Sahel. These rainfall changes in the Atlantic and Sahel are consistent with increased variability in the interhemispheric SST gradient and Mediterranean SSTs shown in Fig. 6b.

The response of rainfall to the multidecadal variability of North Atlantic SSTs in the poor multimodel mean (Fig. 7c) is quite different from observations and consistent with the lack of variability in the interhemispheric SST gradient and Mediterranean SSTs. Little rainfall variability is seen in the multimodel mean across the whole domain due to the lack of consistency in sign and location of any rainfall variability. In the individual model simulations, one model has a band of increased rainfall across the Sahel, but another has reduced rainfall, while the remaining four have close to zero change with varying North Atlantic SST.

c. Other variables

It is clear from Fig. 7 that in the poor models, precipitation over the Sahel is not varying with the model representation of AMV the same way as in the observations. This may be because of the discrepancies in SST pattern, differing response of the atmosphere to the SSTs, or an error in the precipitation response to atmospheric anomalies. The large errors in SST in the poor models have been shown (Fig. 6), and Scaife et al. (2009) show that even with observed SSTs, the Sahel rainfall response is underestimated. Thus it is necessary to assess the ability of the good and poor models to simulate the atmospheric component of the teleconnection by investigating changes in circulation with the multidecadal SSTs.

During the warm phase of AMV, SLP decreases over much of the Northern Hemisphere (Fig. 8a), which has

![Figure 8](image-url)
also been shown to be a signature of the AMM (Vimont and Kossin 2007) and the AMO (Grossfeld et al. 2008). Three main SLP centers of action are seen over the southeast United States, Europe, and the Sahara. In the Southern Hemisphere, the SLP variability is low apart from an increase in SLP in the region of the South Atlantic subtropical high. The differing Northern and Southern Hemisphere SLP response leads to a strong interhemispheric SLP gradient, as for SST.

The role of the Sahara low in driving decadal rainfall variability in the Sahel was suggested by Biasutti et al. (2009). Martin and Thorncroft (2013) demonstrated from observations and reanalysis that increases in the strength of the Sahara heat low during warm AMO periods leads to a stronger monsoon and Sahel rainfall through increases in the shallow meridional circulation (e.g., Zhang et al. 2008; Thorncroft et al. 2011). It is suggested that the models must simulate both the large-scale interhemispheric SLP gradient and regional Sahara SLP variability if they are to capture the correct Sahel rainfall variability.

Large differences are evident between the good (Fig. 8b) and poor (Fig. 8c) multimodel means, as expected from the SST variability patterns in Fig. 6. As in observations, the good multimodel mean has an interhemispheric SLP gradient consistent across the ensemble members, including SLP variability over the Sahara. Differences are evident, however, including the orientation of the SLP pattern across the Atlantic, and the SLP response is approximately half of that in the reanalysis. This SLP signal is much less evident in the poor model mean, especially over the Sahara, likely resulting from the reduced SST variability in the Mediterranean (Rowell 2003; Martin and Thorncroft 2013). The SLP is also weak in the North Atlantic and Europe so there is no interhemispheric SLP gradient, which is hypothesized to be as a result of the lack of SST variability in the tropical North Atlantic.

The increase in SST and SLP interhemispheric gradient leads to an increase in low-level cross-equatorial winds and westerly winds into the Sahel, providing additional moisture for convection. This is evident in the variability of 925-hPa zonal wind with the leading mode of multidecadal variability in North Atlantic SSTs shown in Fig. 9a. As the North Atlantic warms, westerly winds across the tropical Atlantic and Sahel increase, consistent with a reduction in the strength of the subtropical high and associated trade winds. This reduction in the trade wind reinforces the warm SST conditions through the wind–evaporation–SST (WES) feedback (Xie 1999) that can help maintain warm (or cold) SSTS in the tropical North Atlantic for decadal periods.

**FIG. 9.** As in Fig. 6, but for JAS 925-hPa zonal wind regressed onto the leading principal component of the North Atlantic low-pass filtered SST (m s$^{-1}$ per standard deviation). NCEP–NCAR reanalysis is shown in (a).
As expected from the reduced amplitude of SLP (Fig. 8), the low-level wind response to varying SSTs is weaker than observed in both model groups. Both have evidence of increased westerlies with a warmer North Atlantic, with consistent variability in the good multimodel mean (Fig. 9b) confined to a band between 10° and 20°N, extending across the entire Atlantic and Africa. However, the magnitude of the variability is less than half what is observed. The low-level wind signal in the poor multimodel mean (Fig. 9c) is more diffuse with less consistency between ensemble members because of the differing locations of the signal in the individual models. Four of the six poor models have a band of increased westerly winds across the Atlantic, but they range in location from 0° to 25°N and are weaker than observed. This large reduction in magnitude and spatial extent of the low-level wind response to AMV in the poor models is a factor in the reduced SST variability in the tropical North Atlantic, as the WES feedback will be reduced in comparison to the good models and observations. However, the WES feedback is not the only possible mechanism for reduced SST variability in this region and will be discussed further in section 7.

The multidecadal variability of tropical cyclones in the Atlantic, and the relation with AMV (and thus Sahel rainfall) was highlighted by Goldenberg et al. (2001). By examining the variability of the VWS with the leading mode of North Atlantic SSTs, the ability of the models to simulate changes in large-scale environmental variables that are known to impact tropical cyclones can be examined. Figure 10a shows that as North Atlantic SSTs warm and Sahel rainfall increases, VWS is reduced in a band across the Atlantic from the Caribbean to northwest Africa as a response to circulation changes due to the variability in Sahel rainfall (Aiyyer and Thorncroft 2011). This reduction in VWS in conjunction with increased SSTs favors enhanced tropical cyclone activity.

The good multimodel mean (Fig. 10b) produces a band of negative values across the Atlantic (reduced westerly shear) and positive values along the Guinea Coast (increased easterly shear), consistent with increased upper-level easterlies and low-level westerlies associated with a wet Sahel, as in observations. However, the magnitude is half that of the reanalysis over the Caribbean, and it weakens further as the signal extends toward Africa. In the poor multimodel mean (Fig. 10c), the variability of VWS in the Atlantic has the same southwest–northeast tilt, but the magnitude is less than a quarter of that in the reanalysis, and the region of positive values along the Guinea Coast is not evident. This has implications for simulations of variability of tropical cyclones (or tropical cyclone–like features) in CMIP5 models, as the environment is not varying with North Atlantic SSTs as much or in the same way as in observations. In the poor models specifically, neither the SST variability in the tropical North Atlantic (Fig. 6c) nor the VWS (Fig. 10c) are as strong as observed, suggesting much less multidecadal variability in tropical cyclones in these simulations.

These results show that the simulation of the teleconnection between Sahel rain and North Atlantic SSTs is sensitive to the spatial pattern of multidecadal SST variability. The poor model simulations have large multidecadal variability in area-averaged North Atlantic SSTs as much or in the same way as in observations.
but have large differences in the spatial pattern and thus have circulation and rainfall patterns that vary greatly from what is observed. In the good models, however, a multidecadal SST pattern similar to the observations is simulated leading to similar patterns of SLP, circulation, and rainfall. However, despite the well-simulated spatial patterns, the variability of the atmospheric response in the models is weaker than observed.

7. Discussion

The analysis in section 6 indicates that the ability of the selected group of CMIP5 models to simulate the relationship between North Atlantic SSTs and Sahel rainfall on multidecadal time scales is strongly dependent on the spatial SST pattern of AMV. The key SST regions are the tropical North Atlantic (0°–30°N) and Mediterranean, with large differences between the SST variability patterns in the good and poor models (Fig. 6). The identification of the tropical North Atlantic as a key region agrees with Sutton and Hodson (2007), who use model experiments to show that the tropical climate response to multidecadal SST fluctuations in the North Atlantic is primarily forced by tropical SST anomalies. The Mediterranean SST variability has also been highlighted as important to Sahel decadal rainfall variability (Rowell 2003; Mohino et al. 2011; Martin and Thorncroft 2013).

Results shown here highlight the importance of correctly simulating the tropical and Mediterranean components of AMV in coupled CMIP5 GCMs. The role of the WES feedback in enhancing or suppressing this SST variability has been discussed in section 6c, and this section will present a selection of additional mechanisms that may be leading to the incorrect simulation of the tropical and Mediterranean contribution to AMV. We focus on the tropical North Atlantic because of the recent debate in the literature on the role of aerosols in the region (Booth et al. 2012; Zhang et al. 2013). The feedbacks discussed here, along with the WES feedback, would be expected to enhance warming (or cooling) independent of whether the SST change is driven naturally through changes in ocean dynamics or because of aerosols.

a. Control simulations

The simulation of AMV, and its connection with Sahel rainfall, has been investigated using CMIP5 control simulations. The control runs are long, free-running simulations with fixed preindustrial greenhouse gas concentrations and can give insight into the natural variability of the model without influence from anthropogenic forcing. At least 240 yr of control simulations from models in the good and poor group were available. The same EOF analysis used in section 6 was applied to the control simulations.

The SST and precipitation regressed onto the leading mode of North Atlantic SST multidecadal variability for the multimodel good and poor means are shown in Fig. 11 and can be compared to observations and historical simulations in Figs. 6 and 7. The similarities between the control and historical simulations in each model group are striking, particularly for the precipitation variability. The SST variability pattern in the North Atlantic is a horseshoe with a strong tropical signal in the good mean (Fig. 11a) and a weak tropical signal and interhemispheric SST gradient in the poor mean (Fig. 11). North Atlantic SST variability in good models is consistently stronger than the poor models in both the historical (forced) and control (unforced) simulations.

The precipitation response to the SST variability in the control simulations is stronger in the good models (Fig. 11c) than in the poor models (Fig. 11d). In the good models, the Sahel rainfall response in the control is approximately half the response in the historical simulations, as illustrated in Table 3, which shows the Sahel precipitation response to the North Atlantic low-frequency SST variability calculated from Figs. 7 and 11. The Sahel rainfall response to AMV is significantly larger (at 95%) in the historical simulations than the control in both the good models and the full CMIP5 multimodel mean. This suggests that there are fundamental differences in how Sahel rainfall responds to AMV in the good and poor models, even in the unforced control simulations.

In the absence of historical forcing, AMV in good models is reduced, particularly in the Mediterranean. This reduction is suggested to be a cause of the reduced rainfall response over the Sahel in the control simulations (Fig. 11) as a warmer Mediterranean enhances Sahel rainfall through changes in the Sahara heat low (Rowell 2003; Martin and Thorncroft 2013). However, the strong tropical SST signal (not evident in poor models) is still apparent. Poor models fail to capture this cross-equatorial SST gradient and Mediterranean SST variability and hence fail to capture the shift in the position of the seasonal rainfall.

The larger SST and rainfall responses in the good models in the historical simulations (Figs. 7 and 11) hint at the role of externally forced changes in amplifying AMV (in the tropical North Atlantic and Mediterranean) and the associated Sahel rainfall response. Additional investigation is needed to establish whether the increased Sahel rainfall variability in the historical runs is due to either the larger magnitude of SST variability or the enhancement of the SST-Sahel teleconnection,
but such investigation is outside the scope of this paper. The simulation of natural and external influences on SST simulations including clouds, dust, and sulfate aerosols will be examined further in this discussion.

b. Clouds

One of the factors that can influence model response in the Atlantic region is the simulation of clouds, particularly low-level stratocumulus (Wood 2012). It is therefore useful to look into the intermodel differences in cloud amount and cloud response to AMV within the two model groups. Clouds and cloud feedbacks are a well-known problem for climate models, with low clouds being particularly challenging (e.g., Bony and Dufresne 2005; Zhang et al. 2005; Soden and Vecchi 2011). As described in section 2b, mean cloud amounts are investigated using total cloud fraction from the historical CMIP5 simulations. As results from the control and shorter atmosphere-only simulations show similar outcomes, the focus here will be on historical simulations of clouds. The summertime mean total cloud fractions are shown in Fig. 12 from the two model groups and from the ISCCP data.

Evident in Fig. 12 are the larger cloud amounts in the ISCCP data compared to historical CMIP5 multimodel means. The largest differences in the CMIP5 simulations are in the ITCZ and the subtropical stratocumulus regions off the coast of Africa in the North and South Atlantic. While a more defined ITCZ is seen in the poor model mean (Fig. 12c), cloud amounts north and south of the ITCZ in the eastern Atlantic are reduced in the poor models. The improved simulation of clouds in the eastern Atlantic basin in the good models (compared to the poor models) may be in part as a result of the more realistic SSTs in these regions (Fig. 5), or the better cloud simulation could be causing the improved SSTs. However, as similar cloud patterns are seen in the atmosphere-only simulations (not shown), this suggests that cloud parameterizations are also important.

The reduced cloud amounts in the eastern North Atlantic in the poor models is hypothesized to be a leading factor in the reduced SST variability of the tropical

| TABLE 3. Comparison of Sahel precipitation response to North Atlantic low-frequency SST variability (AMV) in the historical and control simulations in units of millimeters per day per standard deviation of North Atlantic low-frequency SST variability (AMV index). See text or Fig. 2 for location of regions. |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
| Observations                    | CMIP5 mean      | Good mean       | Poor mean       |
| Historical                      | 0.29            | 0.15            | 0.03            |
| Control                         | —               | 0.07            | 0.07            |
|                                 |                 | 0.01            | 0.02            |

Fig. 11. JAS (a),(b) SST (°C per standard deviation) and (c),(d) precipitation (mm day$^{-1}$ per standard deviation) regressed onto the leading principal component of North Atlantic low-pass filtered SST from control runs of the CMIP5 simulations. Results are multimodel means from the (left) good and (right) poor model groups. Stippling indicates regions where the multimodel ensemble-mean regression value is larger than the intermodel standard deviation of the regression values (Meehl et al. 2007).
North Atlantic in the historical simulations through differences in the cloud–SST feedbacks. This is illustrated in Fig. 13, which shows total cloud fraction regressed onto the leading principal component of multidecadal SST variability in the North Atlantic from the historical simulations. When the North Atlantic warms in the good model group (Fig. 13a), the total cloud fraction consistently increases over the Sahel in conjunction with increased rainfall but consistently reduces over the North Atlantic, especially in the eastern subtropical North Atlantic. This region is dominated by stratocumulus, a bright low-level cloud that reduces in response to SST warming, acting as a feedback on SST [as discussed by Wood (2012) and references therein]. This positive feedback in low cloud allows SSTs to warm further and sustain anomalies for longer periods of time. In the poor models (Fig. 13b), cloud variability is lacking with varying North Atlantic SSTs. As SSTs in the North Atlantic increase, cloud amounts cannot reduce substantially in the poor models as they have less cloud in the mean (Fig. 12c), leading to a reduced feedback on SSTs.

It is seen that SST variability is larger in models with more realistic (larger) total cloud amounts in the eastern North Atlantic. This may also explain why models in the good group show enhanced SST variability in the equatorial region (associated with ITCZ shifts) as low cloud loss enhances warming in this region. There is a strong need to examine this relationship further, as well as further investigation of cloud height. As the positive feedback is observed for low clouds and we only examine total cloud amount in the simulations, the model simulation of cloud height could have a large influence on the SST variability. These results suggest that the deficiencies in the mean cloud amount in the poor models may be playing a role in the reduced SST variability in the tropical Atlantic that leads to reduced precipitation variability in the Sahel.

c. Sulfate aerosols

Tropical Atlantic SSTs, and the interhemispheric gradient of SSTs, have been shown to be impacted by anthropogenic aerosols (Rotstayn and Lohmann 2002). Sulfate aerosols, which are emitted mainly in the Northern Hemisphere, have recently been the focus of much attention for their potential role in AMV as highlighted by Ackerley et al. (2011), Booth et al. (2012), and Zhang et al. (2013). Sulfate aerosols impact SSTs through direct (absorption and scattering of radiation) and indirect (changing cloud properties) effects (Rotstayn and Lohmann 2002; Chang et al. 2011; Booth et al. 2012). Historical periods where aerosol emissions have increased more rapidly than the underlying warming trends are linked to periods of colder North Atlantic SSTs that contrast with warmer conditions linked to periods of weaker increases or reductions in aerosol emissions (Chang et al. 2011; Booth et al. 2012). Hence, the relationship between sulfates and cloud (via indirect effects) could be important in accurately simulating the role of sulfates on SST. As discussed in section 7b, the presence of low clouds can act as an important feedback on SST, enhancing the southern and eastern North Atlantic SST variability. In addition, model discrepancies in the total amount of cloud simulated may well be linked to differences between good and poor model groups. Low cloud representation is also important for mechanisms that link sulfate aerosol changes with SST variability (Chang et al. 2011; Booth et al. 2012) as it may determine the spatial pattern of the SST response to aerosols.
The atmospheric mass content (load) of sulfate aerosols was obtained from the CMIP5 models. However, while both sulfate aerosols (and dust as discussed in section 7d) were available for all six good model simulations, only two poor model simulations were available. Two important factors in model representation can play a role in explaining differences between good and poor simulations. The first is whether models include aerosol–cloud interactions (indirect effects). Five of the six good models and only one of the six poor models (which is one of the two with available aerosol loads) have aerosol models that do so. We would thus expect any aerosol driver of SST variability to be stronger in the good models, simply because a larger fraction of these models include this process. The second factor is how well the models simulate low clouds in this region. As seen in section 7b (and Fig. 12), models in the poor group tend to underestimate the total cloud in the stratocumulus region (and by inference therefore underestimate low clouds in this region). The implication is that even if the models in the poor group did represent the cloud–aerosol interactions (an interactive indirect effect), the deficiency in the cloud amount would be expected to limit the extent that aerosol changes could drive the magnitude and pattern of SST variability in the poor group.

Bringing these two factors together, we have good reason to expect the impact of sulfate aerosol changes on SST variability to be underestimated in the poor multi-model mean. Similar to the discussion of low clouds as a positive feedback on SST change, the spatial pattern of clouds can also be important in influencing the tropical North Atlantic enhancement of SST variability through aerosol impacts. The poor models simulate climatologically less extensive stratocumulus cloud decks in the southern and eastern North Atlantic than the poor models, and thus there is a smaller cloud area on which aerosol can impact. This is illustrated in Fig. 14, showing considerably less overlap between mean sulfate aerosol loads and clouds in the southern and eastern North Atlantic in the poor models. Further examination of the impacts and feedbacks involved in the aerosol–SST relationship is required when more models make aerosol information available.

d. Dust feedbacks

An additional feature of natural variability that may be impacting North Atlantic tropical SSTs is dust. Dust represents one of the key feedback processes in the Atlantic SST–Sahel teleconnection. Covariability between tropical North Atlantic SST, Sahel rainfall, and dust has been shown by Prospero and Lamb (2003), Evan et al. (2012), and Wang et al. (2012) on decadal time scales. Dry Sahel conditions, linked to cool North Atlantic SSTs, are historically associated with periods of increased dust amounts, the transport of which over the Atlantic acts to further cool SSTs (e.g., Mahowald et al. 2012; Wang et al. 2012). This positive feedback between SSTs and Sahel rainfall (through dust changes) is important for models to capture. Inclusion of interactive dust source terms with some CMIP5 models means that we can potentially capture this; however, we have yet to see the validation of CMIP5 model dust–SST feedbacks appear in the literature.

The dust load regressed onto the leading principal component of North Atlantic multidecadal variability for the good and poor models is shown in Fig. 15.
relationship between warm SST and reduced dust (and increased Sahel rainfall as seen in Fig. 7) is evident in the good multimodel mean, with negative values extending across much of West Africa and the Atlantic, despite differences in how dust is modeled between the good models. The signal shows less consistency between the good model ensemble members than other variables because of the differing location of the dust response, which is likely a function of wind responses and dust source terms in the models. In the poor models, this reduction in dust as the North Atlantic warms is not seen in the two available models and is consistent with the small rainfall response to SST variability (Fig. 7b).

While these results show correlation between SST, dust, and rainfall, they do not indicate causation. The lack of a dust relationship with SST in the poor model group potentially points to a process deficiency (dust output from all six models would be useful to establish this). However, factors other than process representation may be at play here. As has already been shown (Fig. 7), poor models underestimate the SST–Sahel rainfall response so the weakness in dust response (Fig. 15b) could equally be due to the lack of the rainfall driver response to changes in the dust source. It is encouraging, however, that some models are able to capture the correct relationship at multidecadal time scales between dust, SST, and Sahel rainfall.

8. Conclusions

The Sahel region of Africa has been highlighted as an area with large decadal variability attributed to changes in North Atlantic SST, the Atlantic interhemispheric SST gradient, Mediterranean SST, and Indian Ocean SST. It has been shown by Ault et al. (2012) and in this study that despite the observed high decadal variance of rainfall in the Sahel, CMIP5 models greatly underestimate this variability. Using model output from the CMIP5 historical simulations we have investigated the simulation of teleconnections between Sahel rainfall and global SSTs on multidecadal time scales in order to understand why models underestimate decadal to multidecadal rainfall variability in the Sahel.

In historical simulations, models are most successful in simulating the correlation between Sahel rainfall and AMV and least successful with Indian Ocean SSTs. The multidecadal variance in North Atlantic SSTs and Sahel rainfall was used along with the correlation between North Atlantic SSTs and Sahel rainfall on multidecadal time scales to select two groups of models for further investigation. The first group of models, the good group, consisted of six simulations with large AMV, relatively large Sahel rainfall multidecadal variability (above the CMIP5 historical mean), and a significant correlation between the AMV and Sahel rainfall. In contrast, the poor group of models also had large AMV but weak
Sahel multidecadal variability and weak correlations between the AMV and Sahel rainfall. By selecting these two groups we were able to highlight key processes and mechanisms involved in the successful simulation of the AMV–Sahel connection. The successful simulation of the teleconnection does not appear directly related to successful simulation of the climatological rainfall in the models, which was also observed by Rowell (2013) on shorter time scales.

The teleconnection mechanisms were investigated by regressing onto the first principal component of North Atlantic multidecadal SSTs, which in observations is consistent with the AMO. In observations and the good models, a horseshoe-shaped SST pattern with a strong interhemispheric gradient was evident. This SST pattern was consistent with reduced SLP across the North Atlantic and Sahara, increased westerly flow into the Sahel, and enhanced rainfall across the Sahel and the Atlantic. Despite the poor models also having large AMV (by selection), the SST variability was not distributed correctly across the Atlantic. In the poor models the Mediterranean and tropical North Atlantic SST variability was small, causing a smaller interhemispheric SST gradient, smaller SLP changes, weaker westerly onshore winds, and little to no change in Sahel rainfall.

Several explanations for the reduced multidecadal variability in the tropical North Atlantic SST were explored, including a reduction in low-level winds reducing the WES feedback in poor models. We find similar spatial patterns of SST in unforced control simulations for both the good and poor model groups. However, the magnitude of the Sahel rainfall response was much larger in historical simulations, suggesting that external forcing via tropical and Mediterranean SSTs could play an important role in amplifying the signal. In addition, cloud patterns were different between the two model groups, especially in the stratocumulus regions of the eastern Atlantic.

As SST warms, cloud fractions reduce, but in the poor models (that already have low cloud amount) this reduction is limited and hence will have less impact on the underlying SSTs than the good models that have stronger cloud variability. In addition to incorrect simulation of cloud amounts, the poor models also fail to capture the relationship between SST, rainfall, and dust and the collocation of sulfate aerosols and clouds; both additional mechanisms for reduced tropical North Atlantic SST variability in the poor models.

Both the natural cloud feedback and dust feedbacks would be expected to influence the tropical North Atlantic SST variability and hence the interhemispheric SST pattern in the control simulations. The sulfate aerosol mechanism would be expected to influence SSTs only during the historical period and is the external forcing factor most likely to explain the amplification of the SST variability signal between the control and historical simulations. This suggests that both the natural processes (cloud and dust feedbacks) and the aerosol forced process have important roles to play in the better Sahel teleconnections in the good model group. While it is not possible in this study to quantify the role of each mechanism, it does highlight consistencies between the two groups of models. In all likelihood, it is a combination of wind, clouds, dust, and sulfates that leads to the reduced tropical North Atlantic SST variability in the poor models that ultimately impacts Sahel rainfall variability. Ocean dynamics, including subsurface temperatures and meridional overturning are key in simulating naturally driven AMV. Relevant to the focus of this paper,
a recent study by Wang and Zhang (2013) does not find any consistent differences in these features between the good and poor models used in this study, suggesting perhaps that model ocean differences play a smaller role in explaining poor and good Atlantic–Sahel teleconnections than the atmospheric feedback and forced processes. Sensitivity studies performed with multiple models would help in establishing the leading mechanisms in each model, as there is no guarantee that the contribution of each mechanism would be the same in each model.

It is necessary to investigate the simulation of Sahel rainfall multidecadal variability in the historical CMIP5 simulations and understand the deficiencies of the models if we wish to put future projections of decadal variability into perspective. Sahel rainfall multidecadal variability is underestimated in the CMIP5 models, but some successes are seen in the teleconnection with AMV. An accurate simulation of the teleconnection between AMV and Sahel rainfall requires the correct interhemispheric pattern of Atlantic and Mediterranean SST variability to be developed by the model. Errors in the multidecadal variability of tropical North Atlantic SST have been highlighted here, potentially caused by a combination of errors in winds, clouds, dust, and sulfate aerosols. Decadal rainfall variability has large economic and social impacts in Africa, and by furthering our understanding of the capabilities of CMIP5 models to simulate decadal variability, twenty-first-century projections and the new decadal projections can be interpreted more completely.

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