Meteorologische Zeitschrift, PrePub DOI 10.1127/metz/2017/0811

Decadal and multi-year predictability of the West African monsoon and the role of dynamical downscaling

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(Manuscript received June 2, 2016; in revised form January 24, 2017; accepted January 25, 2017)

Abstract

West African summer monsoon precipitation is characterized by distinct decadal variability. Due to its well-documented link to oceanic boundary conditions in various ocean basins it represents a paradigm for decadal predictability. In this study, we reappraise this hypothesis for several sub-regions of sub-Saharan West Africa using the new German contribution to the coupled model intercomparison project phase 5 (CMIP5) near-term prediction system.

In addition, we assume that dynamical downscaling of the global decadal predictions leads to an enhanced predictive skill because enhanced resolution improves the atmospheric response to oceanic forcing and land-surface feedbacks. Based on three regional climate models, a heterogeneous picture is drawn: none of the regional climate models outperforms the global decadal predictions or all other regional climate models in every region nor decade. However, for every test case at least one regional climate model was identified which outperforms the global predictions. The highest predictive skill is found in the western and central Sahel Zone with correlation coefficients and mean-square skill scores exceeding 0.9 and 0.8, respectively.

Keywords: decadal predictability, West Africa, monsoon rainfall, dynamical downscaling

1 Introduction

In recent years, increasing scientific attention has been drawn to the decadal predictability of climate (Murphy et al., 2010). Decadal climate predictions are between seasonal forecasts which are operational by now, and longer-term climate change projections, e.g. for the end of the 21st century (Boer, 2011). They are of particular relevance to decision making in public and economic planning (Meehl et al., 2009). Decadal predictability is expected to arise from a combination of predictable boundary conditions, especially scenarios of greenhouse gas and aerosol concentrations (Booth et al., 2012; Mehta et al., 2013), and an accurate initialization of slowly varying components of the climate system, most notably the three-dimensional state of the oceans (Smith et al., 2007; Branstator and Teng, 2012; Matei et al., 2012b; van Oldenborgh et al., 2012; Hazeleger et al., 2013).

Previous studies in this context have revealed some decadal prediction skill in the North Atlantic region (Matei et al., 2012a; Gastineau et al., 2013; Garcia-Serrano et al., 2015), associated with the Atlantic Multidecadal Oscillation (AMO) and in various tropical ocean basins (Keenlyside et al., 2008; Kim et al., 2012; van Oldenborgh et al., 2012), whereas the North Pacific appears to be less predictable at the decadal time scale (Guemas et al., 2012). However, Knight et al. (2014) have recently demonstrated that in their modeling approach the correct simulation of climate variability in the tropical Pacific is a key to decadal predictability in a global sense. There is also some predictive skill in temperature over maritime land masses (Jia and DelSole, 2012). In addition, some prominent features of 20th and early 21st century climate variability could be reproduced by adequately initialized decadal simulations with global climate models. This includes the relatively warm 1970s (Müller et al., 2014), the climate shift in the mid-1970s and the so-called hiatus of the mid 2000s (Meehl and Teng, 2014). At present, the first real-time decadal predictions for the upcoming 10 to 20 years are available (Smith et al., 2013; Meehl and Teng, 2014).

Here, we investigate the decadal and multi-year predictability of the West African summer monsoon (WAM) rainfall which is a key factor for livelihood and food se-

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curity in one of the poorest regions on Earth (Benson and Clay, 1998). By means of initialized climate model simulations, predictability is assessed for different time scales and aspects of rainfall variability: (1) interannual variations over 3 to 10 years within decades, and (2) variations of 3-year to 10-year means over decades. In this study, summer relates to the June-September period because this represents the time of the year when all considered regions of sub-Saharan West Africa experience a rainfall peak (Nicholson, 2001). Previous studies have shown that the Guinea Coast (~ 5–10° N) and Sahel (~ 10–20° N) exhibit different characteristics in terms of interannual to decadal rainfall variability and of teleconnections to remote oceanic boundary conditions (e.g. Ward, 1998; Moron, 1997; Camberlin et al., 2001; Paeth and Stuck, 2003). The Guinea Coast shows much larger year-to-year rainfall fluctuations, whereas in the Sahel decadal-scale wet and dry periods alternated between 1921 and 2010 (Sanogo et al., accepted). From their study it is also evident that rainfall anomalies on decadal scales co-vary between the two regions with the well-known drought conditions in the 1970s and 1980s being much more pronounced in the Sahel. Nonetheless, there is also a distinct decadal component in rainfall variability along the Guinean Coast region as revealed by AMIP (atmospheric model intercomparison project) type simulations (Paeth and Friederichs, 2004; Paeth and Hense, 2004). Rainfall at the Guinea Coast is strongly correlated to sea-surface temperature (SST) anomalies in the adjacent eastern equatorial Atlantic (Paeth and Hense, 2004) with the relation being robust and prominent on interannual time scales in the last century (Diatta and Fink, 2014). The latter authors used SSTs in the Atlantic 3 region (ATL3, 0–20° W, 3° S–3° N) that reflect Atlantic Benguela Niño events to show that in a multilinear regression model the ATL3 index outperforms all other predictors used for the Guinea Coast rainfall that relate to the Mediterranean Sea, Indian and Pacific oceans. The correlation between ATL3 and Sahel rainfall was found to be non-stationary with mostly non-significant correlations since about the 1970s. Losada et al. (2012) argue that the ATL3 SST impact on WAM rainfall changed from a zonal dipole to a monopole response over West Africa due to a prevalent anticorrelation between Atlantic and Pacific Niño events since the 1970s. In other words, cold ATL3 SSTs years having favored more rainfall in the Sahel before the 1970s are in recent decades overcompensated by the rainfall inhibiting influence of Pacific El Niño events.

Rainfall in the Sahel is also known to be related to the AMO on decadal time scales. Diatta and Fink (2014) found this correlation to be significantly non-stationary over time with recent decades experiencing an enhanced correlation. The latter is consistent with the conclusion of Mohino et al. (2011) that the AMO is largely responsible for the current upturn in Sahel rainfall. Since tropical Atlantic SSTs have some forecast potential at the multi-year time scale (Dunstone et al., 2011; van Oldenborgh et al., 2012) it is thus not surprising that Corti et al. (2012) identified Africa as one among various continental regions with noticeable predictive skill at multi-year time scales. However, climate models in the coupled model intercomparison project phase 5 (CMIP5) decadal prediction system differ considerably in terms of their decadal predictability of Sahelian precipitation (Gaetani and Mohino, 2013; Bellucci et al., 2014; Martin and Thorncroft, 2014). These authors concluded that the accuracy of SST hindcasts in each model is the crucial factor, as well as the models' ability to reproduce the observed response of Sahelian rainfall to the Atlantic meridional SST dipole.

There are also contributions to decadal variability of WAM rainfall from other ocean basins than the tropical Atlantic. Paeth and Friederichs (2004) have systematically analyzed the time scales of these teleconnections and revealed coherence at multi-year and decadal scales between WAM rainfall and the Indian Ocean SST dipole, the North Atlantic basin SSTs as well as the inter-decadal Pacific Oscillation pattern (cf. Paeth and Stuck, 2003; Mohino et al., 2011; Gaetani and Mohino, 2013; Martin and Thorncroft, 2014).

The research hypotheses underlying this study and its experimental design follow the conceptual model illustrated in Fig. 1 which presents the main drivers of rainfall variability in sub-Saharan West Africa according to our current process understanding. The spatio-temporal pattern of rainfall in the Sahel zone and along the Guinean Coast region emanates from a complex interplay of oceanic forcing from various ocean basins (e.g. Giannini et al., 2003; Paeth and Hense, 2004), interactions with the land surface – in particular, vegetation cover and soil moisture (e.g. Nicholson, 2001; Paeth et al., 2009) – and radiative forcing by greenhouse gases (GHGs) and aerosols (e.g. Paeth and Feichter, 2006). Oceanic forcing governs larger-scale wind patterns, evaporation and moisture advection. Land surface processes mainly impact on the local energy budget and hydrological cycle. Radiative forcing affects all these processes in the climate system. African rainfall responds to changes in SSTs, aerosol and GHG concentrations, land cover characteristics and initial soil moisture conditions. Thus, the predictability of African rainfall should be proportional to the extent these processes and boundary conditions are reliably represented in climate model. We assume that this is more likely to be the case in high-resolution regional climate models rather than in state-of-the-art global climate models and, hence, put high effort in downscaling global decadal predictions.

We assess as a first hypothesis that decadal predictability exists for various rainfall regions of sub-Saharan West Africa using the current version of the German decadal prediction system. Pohlmann et al. (2013) have revealed that this global system exhibits a very promising forecast skill in the form that observed changes of near-surface air temperature and sea surface temperature are well reproduced over several years after initialization, especially in those oceanic regions

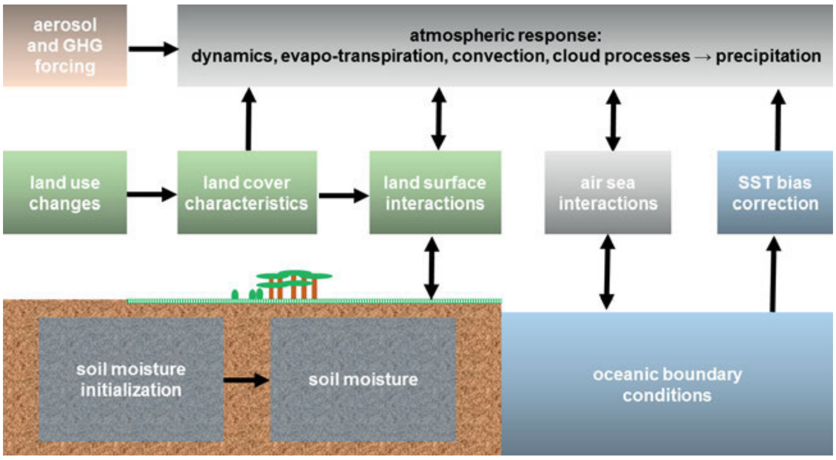

Figure 1: Determinants of precipitation and its spatiotemporal variability in sub-Saharan West Africa, at the same time processes and boundary conditions considered in this study to assess and enhance multi-year to decadal predictability of precipitation.

which are closely tied to precipitation in sub-Saharan West Africa (cf. Paeth and Friederichs, 2004). Furthermore, over the WAM region decadal-scale rainfall variability and trends seem to be amplified or extended in time by interactions with the land surface and vegetation (Nicholson, 2001; Giannini et al., 2003; Paeth et al., 2009). Therefore, we test as a second hypothesis that dynamical downscaling leads to an improved representation of decadal climate variability in the WAM region, compared with the driving global climate model. In a recent study, we have shown that dynamical downscaling leads to an improved representation of West African climate (Paxian et al., 2016) and assess now whether this added value is transferred to enhanced predictability over several years up to one decade. Various ensembles of global and regional climate model experiments are presented with three-dimensional initialization of the ocean and atmosphere, according to the new CMIP5 decadal predictions (Taylor et al., 2012). While only one global prediction system is considered, the dynamical downscaling is performed by three regional climate models (RCMs), namely REMO, COSMO-CLM (CCLM) and WRF, one of them (REMO) with different parameterizations and with ocean coupling, in order to account for model differences and peculiarities. This leads to a large set of individual simulations and an unprecedented insight into the potential added value of RCMs in decadal climate predictions.

In the following section, the experimental design and the statistical methods are described. Section 3 is dedicated to the results which are further discussed in Section 4. Conclusions are drawn in Section 5.

2 Experimental design and methods

We have set up two types of model experiments, spanning various decades within the 1960–2010 period: (1) regional climate models are driven by reanalysis data including observed SSTs, (2) regional climate models are driven by initialized coupled global climate model simulations from the German decadal prediction system.

Table 1: Number of available ensemble members of the considered global and regional climate model simulations for each model period. For model nomenclature see Section 2.

Model	Model period			
	1966–1975	1981–1990	1991–2000	2001–2010
MPI-ESM	10	10	10	10
REMO-ERA	1	1	1	1
REMO-W	3	3	3	3
REMO-H	3	3	3	3
REMO-O1	3	3	3	3
REMO-O2	3	3	3	3
WRF	2	2	2	2
CCLM-ERA	1	1	1	1
CCLM	3	3	3	3

First, RCM experiments have been realized which are nested in reanalysis data in order to assess the models' ability to reproduce interannual to decadal climate variability under more or less realistic lateral and oceanic boundary conditions. One set of experiments is carried out with REMO version 2009 (Jacob, 2001, REMO-ERA in Table 1) and one with the non-hydrostatic RCM COSMO-CLM (Rockel et al., 2008; CCLM-ERA in Table 1) which has been applied and evaluated in CORDEX-Africa configuration (Panitz et al., 2014). The reanalyses are taken from ERA40 (Uppala et al., 2005) before 1990 and from ERA-Interim (Dee et al., 2011) after this year. Each RCM simulation starts with steady-state soil characteristics from ERA40/ERA-Interim driven spin-up experiments covering a six-year period prior to the hindcasts. The aim is to avoid cold start problems in the lower soil layers. We are aware that our results will also depend on the choice of the driving reanalysis data. ERA40 and ERA-Interim have been used in the described way in order to be consistent with the atmospheric initialization of

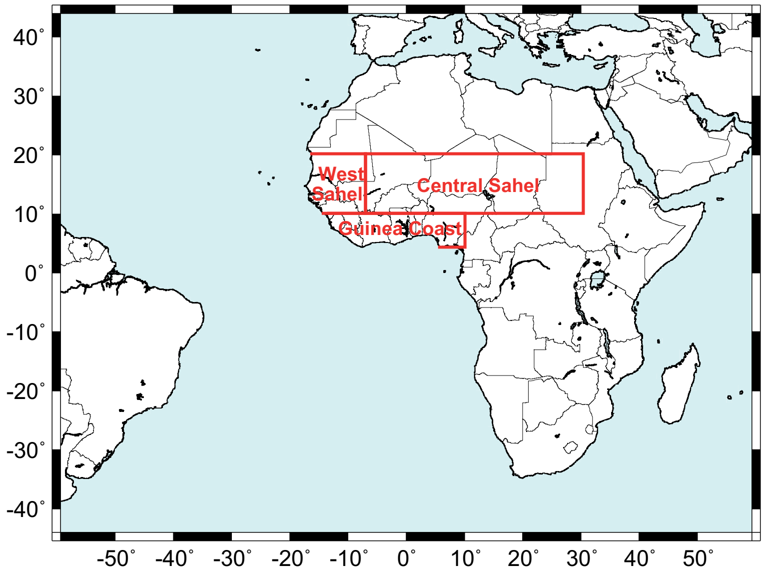

Figure 2: Domain for regional climate downscaling of MPI-ESM decadal predictions with REMO, CCLM and WRF. The framed regions denote the Guinea Coast, West Sahel and Central Sahel as areas of spatial averaging.

the global MPI-ESM prediction system (cf. Pohlmann et al., 2013).

Second, the coupled general circulation model (GCM) decadal predictions for the second type of RCM experiments are carried out with the new version of the Max-Planck Institute for Meteorology Earth System Model (MPI-ESM in Table 1) based on the coupled global climate model ECHAM6/MPI-OM in T63 resolution (~ 1.9°) with 47 vertical levels in the atmosphere and ~ 1.5° with 40 levels in the ocean (Stevens et al., 2013; Pohlmann et al., 2013). These simulations represent the multi-year forecast potential arising from the long-term memory of the ocean. In contrast to former versions of the German decadal prediction system (Matei et al., 2012b; Müller et al., 2012), the oceanic component of the coupled MPI-ESM system is initialized with salinity and temperature anomalies from the ORAS4 ocean reanalysis (Balmaseda et al., 2013) and the atmosphere is initialized with ERA40 before 1990 and ERA-Interim after 1990 (Pohlmann et al., 2013). Once initialized each MPI-ESM simulation is run over 10 years. The first 10-year hindcast period starts in 1961, the last one in 2012. Four of these hindcast periods are used for downscaling (see below). For every hindcast period 10 ensemble members are realized using oceanic and atmospheric initial conditions with a 1-day lag around 1st of January in each starting year. After initialization these coupled experiments are evolving without any nudging, according to a real-time decadal forecast system, yet natural (volcanic aerosols) and anthropogenic (greenhouse gases and aerosols) forcings are prescribed.

The dynamical downscaling of the MPI-ESM runs is conducted with a multi-model ensemble of three RCMs. All RCM simulations are based on a 0.44° resolution and cover the domain from 59.4° W to 59.4° E and from 44° S to 44° N (see Fig. 2). We use the same CCLM version as for the ERA experiment mentioned above (CCLM in Table 1), the non-hydrostatic weather research and forecasting model (WRF, Skamarock et al., 2008), and four different versions of REMO: the standard version REMO-W, REMO-H with improved parameterizations for tropical climate including cloud processes, gravity-waves and soil properties. REMO-O1 and REMO-O2 use the setting of REMO-H and are fully coupled to the Max Planck Institute Ocean Model (MPI-OM) over the entire RCM domain. The MPI-OM configuration was different from the one used in the standard MPI-ESM setup, having much higher resolution (20–30 km) in the Tropical Atlantic. A detailed description of the coupling procedure can be found in Sein et al. (2015). We assume that heat fluxes, wind stress and precipitation from a higher-resolution RCM improve the representation of the oceanic mixed layer and, hence, the oceanic boundary conditions which, in turn, are a key to multi-year to decadal predictability. Both versions only differ with respect to how the 50-year spin-up period has been implemented, using a more sophisticated approach for REMO-01 than for REMO-02. REMO has been widely used for climatological applications in Africa and was found to simulate the main characteristics of the WAM system in a reliable way when nested into reanalyses and global GCMs (Paeth et al., 2005, 2009, 2011).

For reasons of limited computing resources, we have restricted the RCM decadal predictions to four decades and mostly 3 ensemble members for each RCM (see Table 1). Nonetheless, this has led to a total of 720 model years performed by our RCMs. To choose three out of ten available MPI-ESM ensemble members for each decade we rely on the following procedure: (1) based on observed precipitation from CRU (Climatic Research

Unit, Mitchell and Jones, 2005) and SSTs from GISST (Rayner et al., 1996) the most relevant oceanic regions for the West African summer monsoon rainfall are identified at a monthly scale (cf. Paeth and Friederichs, 2004). (2) In each of the ten MPI-ESM ensemble members the skill of the SST reproduction in these ocean basins is assessed via correlation analysis (cf. Gaetani and Mohino, 2013). On this basis a weighted mean skill score for each MPI-ESM ensemble member is determined in order to achieve a rating into better and worse hindcasts of observed SST variability. (3) The three-member ensemble for the dynamical downscaling comprises the best, the worst and an intermediate MPI-ESM decadal hindcast experiment for each decade. For WRF, only the best and worst simulations are selected.

For the validation of simulated WAM rainfall and the assessment of its decadal forecast potential three commonly used gridded observational data sets are considered, CRU (Mitchell and Jones, 2005, updated), GPCC (Rudolf, 1995, updated) and WMMA (Willmott and Matsuura, 2001, updated). All three data sets are available at 0.5° resolution and cover the full range of considered simulation periods. When comparing regional mean time series of precipitation, all observational data sets and the MPI-ESM have been interpolated to the common resolution of the RCMs.

The skill of the decadal predictions with MPI-ESM and various RCMs is evaluated by means of two standard skill scores: the Pearson correlation coefficient (Wilks, 2006) and the mean squared skill score (MSSS, Goddard et al., 2013). While the former only measures the phase relationship between time series, the MSSS also depends on the ability of the prediction system to reproduce the observed variance. While Hawkins et al. (2014) argue that biases in decadal predictions should experience more scientific attention in order to improve the prediction systems, we put more stress upon the correlation coefficient because it has been demonstrated that the bias of decadal predictions can reasonably be reduced via statistical post-processing (Kharin et al., 2012). This is particularly true for West African rainfall: sophisticated model output statistics applied to the RCM REMO has led to fairly realistic precipitation characteristics in terms of mean and variance (Paeth, 2011). Note that when the simulated and observed variance are identical, the MSSS is a linear function of the Pearson correlation coefficient r_{xy} according to $MSSS = 2 \cdot r_{xy} - 1$.

3 Results

This section is subdivided into the results from the multi-year predictability within decades as derived from the initialized MPI-ESM and RCM simulations and the predictability between decades from the same model runs.

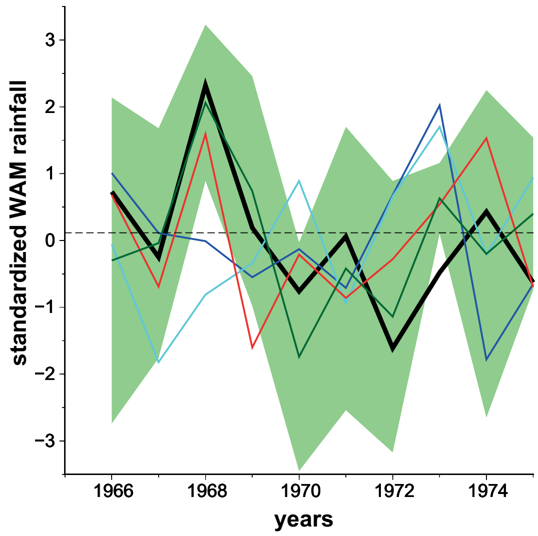

Figure 3: Time series of standardized WAM summer rainfall during the 1966–1975 period in the Guinea Coast region from WMMA observations (black) and the ensemble means from the MPI-ESM (blue), REMO-W (green, with 95 % confidence interval) and REMO-ERA (red, one member) decadal simulations. In addition, the uninitialized MPI-ESM ensemble mean from the 20th-century experiments according to IPCC (2013) is plotted (cyan).

3.1 Multi-year predictability within decades

In this subsection, the predictability of interannual variations within a decade is investigated based on RCM experiments nested into the initialized MPI-ESM 10-year hindcasts. This is the most ambitious and most practice-oriented goal of decadal predictions because it offers a year-by-year adaptation to near-time climate variability. A prominent example for an ensemble-mean decadal prediction from the MPI-ESM prediction system and two types of dynamical downscaling with REMO-W, one nested in MPI-ESM and one driven by ERA40, is displayed in Fig. 3 for the Guinea Coast region in the domain 13.6° W to 10.1° E and 4.4° N to 10.1° N (cf. Fig. 2). For this region the SST impact is expected to be highest on West African precipitation (cf. Giannini et al., 2003, Paeth and Stuck, 2003; Paeth and Hense, 2004). The period 1966–1975 has been chosen since it was characterized by a substantial decrease of summer monsoon rainfall in sub-Saharan West Africa (e.g. Nicholson, 2001). All time series have been standardized in order to remove systematic biases in the mean and variability and to highlight the phase relationship between observed and predicted rainfall (cf. Section 2). The bias in terms of precipitation totals in our experimental setting has been addressed by Paxian et al. (2016): all RCMs and the driving global climate model exhibit a systematic wet bias in most parts of sub-Saharan West Africa, arising from a warm bias in the tropical Atlantic SSTs. Concerning the bias in variability, Table 2 indicates that RCM simulations driven by reanalyses overestimate the observed interannual rainfall variability. The observations indicate a change from plus 2 to minus 2 standard deviations from the late 1960s

Table 2: Time series characteristics of simulated and observed WAM summer rainfall in the Guinea Coast region during the 1966–1975 period: correlation coefficient r_{xy} and MSSS between decadal predictions from various models and the RCM multi-model ensemble mean (RCM-MM) and WMMA; standard deviation s_m in mm of model runs and ensemble means, respectively, to be compared to the standard deviation s_0 = 83.26 from WMMA. For model nomenclature see Section 2.

Model	r_{xy}	MSSS	s_m
MPI-ESM	−0.18	−0.14	19.67
REMO-ERA	0.55	−0.08	96.67
REMO-W	0.72	0.37	27.43
REMO-H	0.01	−0.26	43.30
REMO-O1	0.05	−0.15	36.83
REMO-O2	0.59	0.31	33.01
CCLM-ERA	0.73	0.01	120.31
CCLM	−0.05	−0.47	53.14
WRF	−0.12	−1.35	87.11
RCM-MM	0.25	0.06	22.51

to the early 1970s, leading to the first severe drought in the Sahel and Guinea Coast regions (Nicholson, 2001). The ensemble mean from the MPI-ESM global prediction system is closer to the observed anomaly in the first and second year than the uninitialized MPI-ESM simulations taken from the 20th-century experiments of CMIP5 which are emanating from stochastic initial conditions in the year 1850 (IPCC, 2013). This can be interpreted as an improvement by ocean-atmosphere initialization in the global model. However, the initialized MPI-ESM runs are uncorrelated with the observations for the subsequent years of the decade. In contrast, the REMO-W ensemble nested in MPI-ESM is well in line with the observed year-to-year variations. Under the given conditions, the decadal prediction from REMO-W would have predicted the first drought of the 1970s with several years lead-time. Note that this statement only holds for this particular global and regional climate model ensemble, decade and region, and may simply occur by chance. Therefore, a more systematic assessment is presented below. The ERA40-driven REMO run is also close to the observations but uses information which would not be available for a real-time decadal forecast. Comparing the REMO-W simulations driven by the initialized MPI-ESM and by ERA40 with each other allows for the assessment of errors in the RCM that are inherited from the global model, assuming that ERA40 is characterized by substantially less biases than MPI-ESM. In this particular case however, the RCM run nested in the global model is closer to the observed rainfall changes during the 1966–1975 period than the one driven by reanalyses (r = 0.72 versus r = 0.55, see Table 2). It will be shown later that this is not a consistent result for all regions and decades. Therefore, we interpret this finding as a compensation of structural errors from the GCM and RCM, just by chance.

In order to understand the different performances of MPI-ESM and REMO-W under the same oceanic forcing during the 1966–1975 decade, we compare linear trends over 10 years from both models, addressing various atmospheric variables that are relevant to the generation of rainfall in West Africa (Fig. 4). Given the same SSTs, the atmospheric response in REMO consists of a noticeably stronger reduction of sea level pressure in the tropical North Atlantic compared with MPI-ESM, which is indicative of a northeastern shift of the North Atlantic subtropical anticyclone (shading in top panels). This leads to enhanced westerlies over the ocean at the southern margin of the low pressure system and a stronger cyclonic circulation over the tropical North Atlantic (wind vectors in top panels). Within this larger-scale circulation pattern, a stronger offshore wind component occurs west of Guinea and, hence, advection of humid air masses over most of continental sub-Saharan West Africa is reduced, notably to a larger extent in the RCM than in the GCM. Decreasing moisture advection implies decreasing vertically integrated liquid water content over the western Guinea Coast region and the Sahel Zone. This effect is more pronounced and spatially more extended in REMO-W than in MPI-ESM during this decade (bottom panels). It is difficult to deduce what causes the stronger response of sea level pressure in the RCM to the same SST forcing as implemented in MPI-ESM. The two models differ in terms of their radiation schemes, horizontal resolution and various aspects of model physics such that every interpretation is highly speculative. It is also conceivable that the specific domain for downscaling, which cuts off the northwestern part of the North Atlantic subtropical high, is responsible for these different behaviors. Additional effects may arise from the different land surface schemes in REMO-W and MPI-ESM: soil hydrology in REMO-W is based on the improved Arno scheme (Hagemann and Dümenil Gates, 2003) which was found to substantially improve the simulation of sub-Saharan precipitation (Paeth et al., 2009). Note that a comparison of these simulated trend patterns with observations is difficult because wind and liquid water content can only be derived from low-resolution reanalyses and, especially, the latter is partly subject to uncertain parameterizations of convection and cloud processes in the model the reanalysis is based on.

To assess whether predictability is systematically larger in RCMs compared with the global model, Table 2 lists the correlation coefficients and MSSS for all considered RCM ensembles during the 1966–1975 period. It is obvious that the models differ substantially in terms of their predictive skill during this prominent drought period in the Guinea Coast region. The best results are found for the ERA40-driven experiments, as to be expected, for REMO-W, for one of the coupled atmosphere-ocean REMO versions, and, to some extent, for the RCM ensemble mean (without ERA40-driven runs). Yet, not all RCMs exhibit an added value compared with the MPI-ESM decadal prediction system. The MSSS is mostly positive when the correlation coefficient is high, but with some prominent exceptions

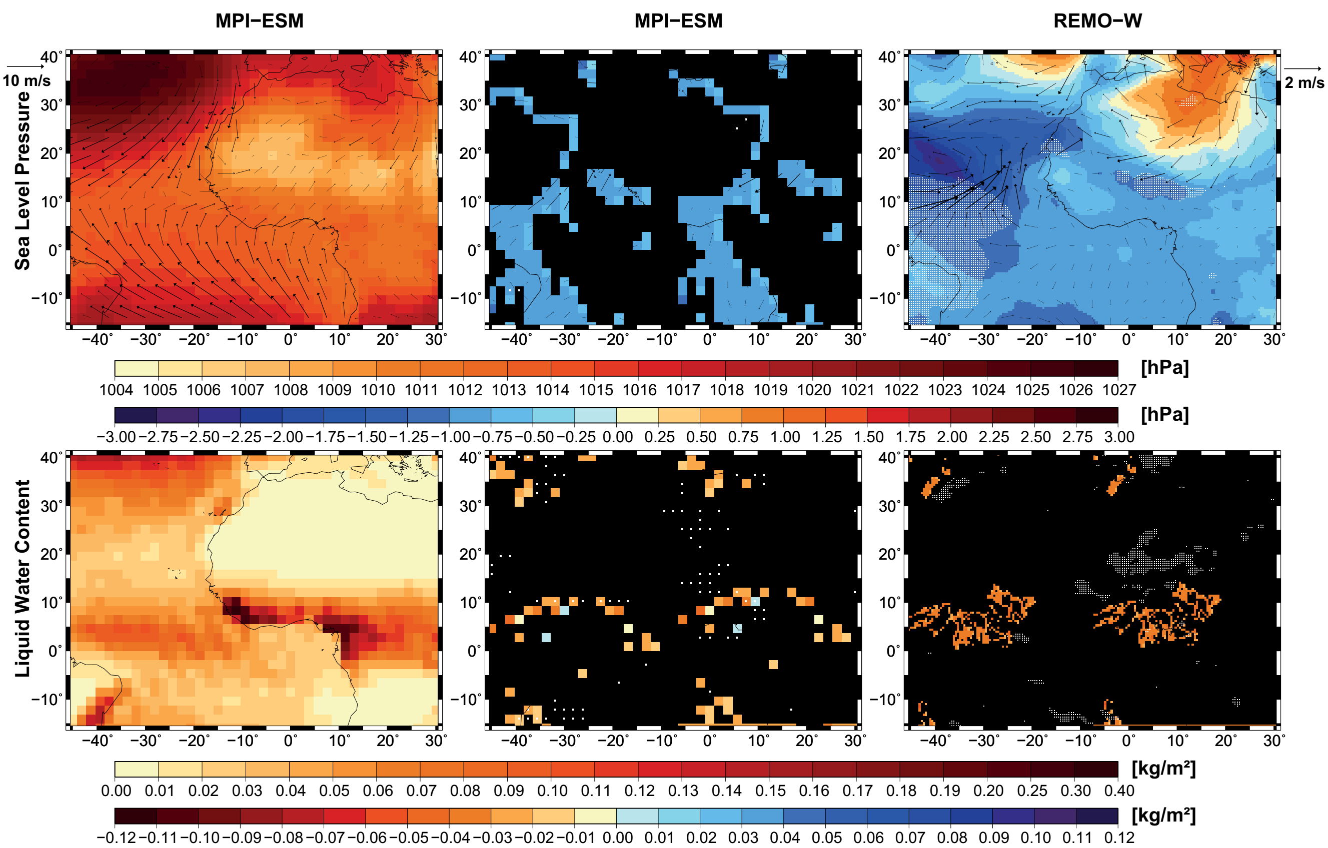

Figure 4: Means (left panels) and linear trends (middle and right panels) of summer sea level pressure (top), near-surface wind vectors (top) and vertically integrated liquid water content (bottom) during the 1966–1975 period from the MPI-ESM and REMO-W initialized decadal predictions, both using the same oceanic forcing. White dots mark trends significant at the 5 % level.

(see Table 2): REMO-ERA has a negative MSSS despite $r_{xy} = 0.55$ because it slightly overestimates the observed standard deviation. In contrast, REMO-W exhibits a much lower standard deviation due to ensemble averaging, but has the highest MSSS. Given this asymmetry of the MSSS (cf. Goddard et al., 2013) and the assumption that systematic model biases with regard to the observed variance can be accounted for by statistical post-processing (e.g. Paeth, 2011), we prefer to use the correlation coefficient as a measure of decadal predictive skill which is standardized and easy to interpret.

Fig. 5 depicts the correlation coefficients between observed and predicted summer monsoon for all considered model ensembles, decades and three different sub-regions. These three regions have been adapted to those sectors in sub-Saharan West Africa that, according to Nicholson and Palao (1993), show homogeneous rainfall variability. In addition to the Guinean Coast region which has been defined above, the West Sahel is marked by the following borders: 17.6° W – 7.0° W and 10.1° N – 20.2° N. The Central Sahel extends from 7.0° W to 30.4° E and from 10.1° N to 20.2° N (Fig. 2). At first sight, a rather incoherent picture is drawn: there is no RCM which outperforms all other models over all regions and decades. In most cases, the MPI-ESM meets at least one initialized RCM which performs better. The RCM simulations with forcing by reanalyses mostly reproduce the observed year-to-year variations within the analyzed decades, especially in the Guinea Coast region. However, the skill is generally low and mostly not significant, except for the Guinea Coast and the decade 1966–1975 where a strong trend over 10 years has occurred. Nonetheless, we could not identify any relationship between the predictive skill of a model and the given strength of a climate anomaly within a certain decade or the accuracy of SSTs reproduced by MPI-ESM, nor highlight one single RCM which could serve as a reliable decadal prediction system over all decades or regions. Thus, it must be concluded that the observed year-to-year variations over a whole decade cannot be reproduced reasonably, neither by MPI-ESM nor by the RCMs. On the basis of individual ensemble members, a rather systematic finding for most regions and decades is that the added value by downscaling is larger for the worst than for the best MPI-ESM ensemble members (not shown). Thus, a good performance in the global model can only slightly be enhanced (or sometimes reduced) by RCMs, while distinct deficiencies in MPI-ESM ensemble members can be more clearly and systematically overcome by dynamical downscaling.

The predictive skill of climate models as given by Fig. 5 may also be a function of the considered observational data set. Indeed, Paeth et al. (2010) and Ring et al. (2015) have revealed substantial discrepancies be-

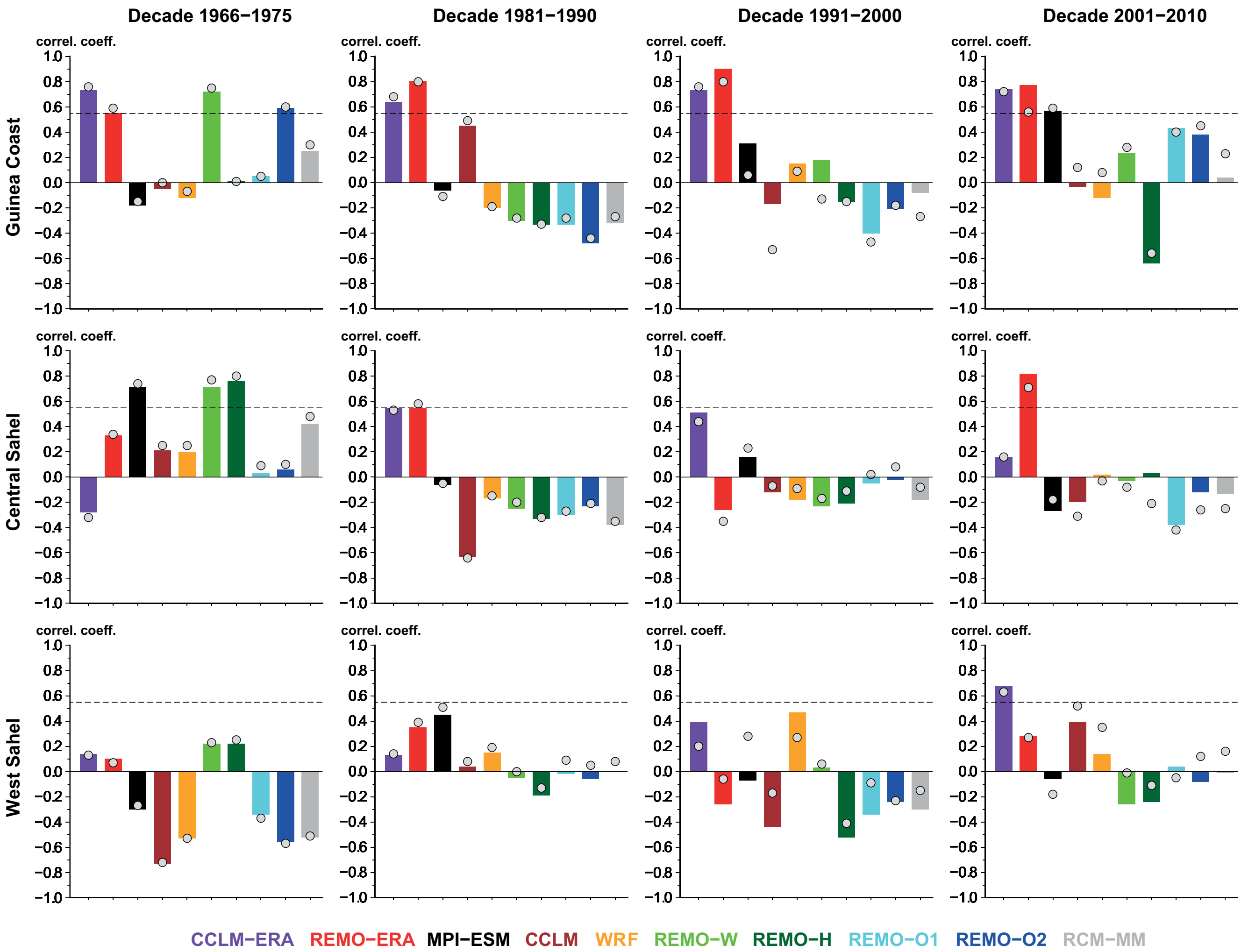

Figure 5: Correlation coefficients between observed (WMMA) and simulated WAM summer rainfall from various GCM and RCM decadal predictions in three different regions and during four different decades. Each bar refers to the ensemble members indicated in Table 1. The dashed line denotes the 5 % significance level for a one-sided test. The black circles mark the same result for every model, region and decade but using CRU instead of WMMA as observations.

tween well-established data sets of observed precipitation in Africa, especially at the seasonal scale. Therefore, we have repeated the analysis with the CRU data set, another commonly used source of rainfall information that covers all considered decades. The grey dots in Fig. 5 clearly demonstrate that the results for the Guinea Coast region based on CRU hardly differ from the ones achieved on the basis of WMMA (colored bars in Fig. 5). In detail, correlation coefficients are virtually identical during the first two decades, whereas some very minor differences occur after 1990 when WMMA and CRU slightly diverge. The following analyses rely on WMMA, according to the recommendation by Parker et al. (2011).

Complementary to the consideration of the full 10-year hindcast period, we also assess the predictability of shorter sub-periods within a decade. This is motivated by two hypotheses: (1) models may have a higher skill for the first than for the last years of a 10-year prediction, and (2) the skill may increase after some initial shock in the first year(s) caused by the imposed initial conditions in the atmosphere and ocean (cf. Müller et al., 2012; Pohlmann et al., 2013). All possible sub-periods of at least three years length are accounted for by varying the first and the last year of the sub-period between the first and the 10^{th} year of a decade, respectively. In Fig. 6, the first year of these sub-periods, for which the predictive skill is assessed, is indicated by the x-axis and the last year by the y-axis. Correlation coefficients are assessed over all decades for each region and model. The 95 % quantiles extend from 0.50 to 0.26 for the shortest and longest sub-periods, respectively. There is at least one RCM, often REMO-W or REMO-H, which outperforms the MPI-ESM global prediction system: REMO-W displays the highest added value of all RCMs in the Guinean Coast region, reaching significance during the middle years of a decade. In the Central Sahel, WRF shows higher and significant correlations than MPI-ESM during the first years, but no RCM is able to enhance the high skill of the global

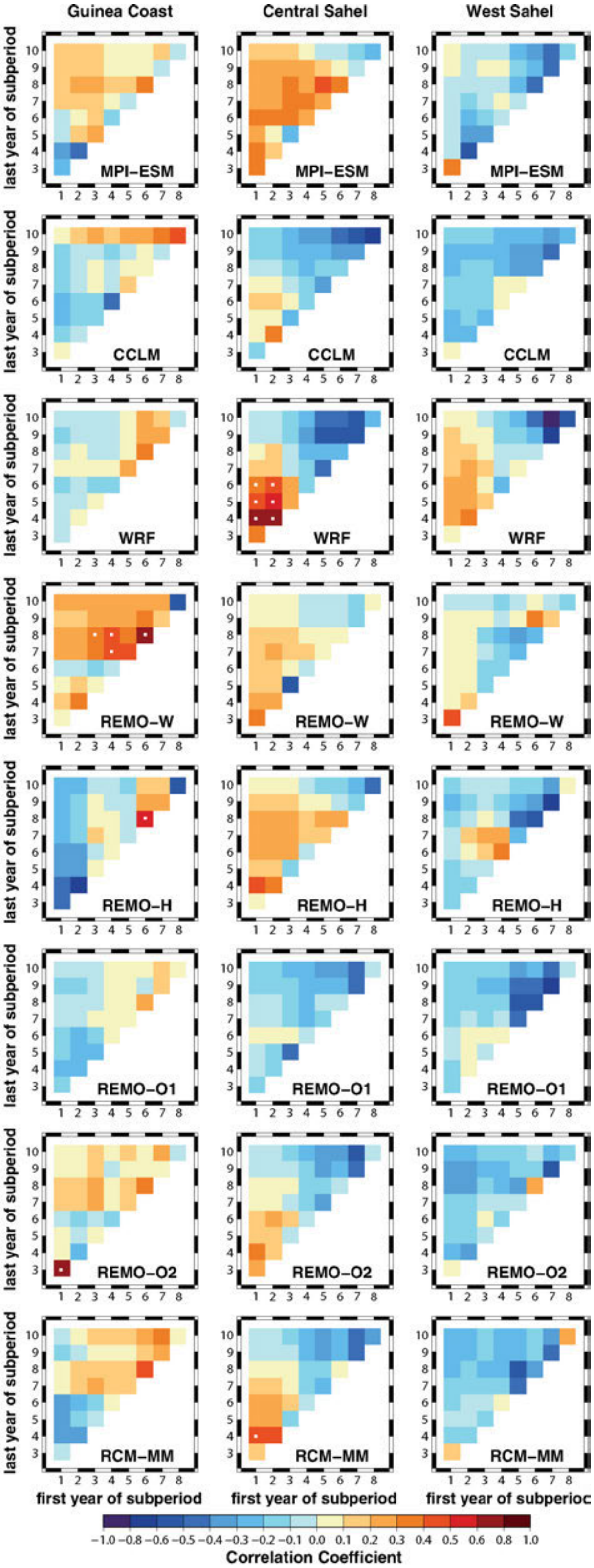

Figure 6: Correlation coefficients between observed and simulated WAM summer rainfall for all considered regions (columns) and GCM/RCM decadal predictions, including the RCM multi-model ensemble mean (rows), assessing the correlation coefficients over all four decades. The x-axis (y-axis) denotes the first (last) year within a decade considered for correlation. Each coefficient refers to the ensemble members indicated in Table 1. White dots indicate correlations statistically significant at the 5 % level for a one-sided test.

model during the middle years and the whole decade. The West Sahel is marked by a low skill in all considered models and subperiods, but WRF outperforms MPI-ESM during the first years and the whole decade, yet not reaching statistical significance. The first three years of the prediction are not necessarily characterized by the strongest in-phase relationship with the observations, reflecting some initial shock (cf. Müller et al., 2012; Pohlmann et al., 2013). In summary, none of the considered prediction systems reaches a very high and systematic forecast potential for year-to-year variations of West African precipitation.

3.2 Predictability of climatological means between decades

In the next step, we follow another approach of decadal predictability, i.e. various sub-periods within a decade are averaged and the correlation with observations is built over different decades. According to Garcia-Serrano and Doblas Reyes (2012), the underlying assumption is that the correlation between time series increases with the averaging period because the external oceanic forcing stands out from the unpredictable internal variability. Fig. 7 displays the correlation coefficients for different averaging periods, regions and models. The MPI-ESM has hardly any predictive skill in the Guinea Coast region with mostly negative correlation coefficients, except for the last years, but performs well in both Sahelian regions with significant r_{xy} larger than 0.8, except for the last years of the decadal prediction. In the Guinea Coast region, CCLM exhibits the highest skill, partly significant at the 5 % level ($r_{xy} > 0.9$). Especially, the decadal means have been captured in a realistic way. Compared with MPI-ESM this represents a striking added value in terms of a decadal prediction system with potentially practical relevance: correlation increases from about −0.6 in MPI-ESM to about 0.9 in CCLM. Note that this tremendous increase in predictability is based on four decades and, hence, should not be over-interpreted. In fact, the other RCMs and the RCM ensemble mean do not perform as well as CCLM. This is totally different for the Central Sahel: all models exhibit a distinct predictive skill with respect to the decadal means and to shorter sub-periods including the first years of the prediction, except for WRF. Dynamical downscaling still improves the prediction, especially when using REMO-H. In addition, the first year of the decades is much better reproduced by RCMs compared with MPI-ESM. Thus, the initial shock in the Central Sahel region appears to be overcome by dynamical downscaling which, however, is not the only reason for the added value by RCMs since later sub-periods also perform better in several RCMs compared with MPI-ESM. In terms of the West Sahel, the added value of RCMs mainly refers to the last years of a decade, especially for REMO-H, whereas MPI-ESM performs quite well for the first years and the decadal mean. Again, none of the

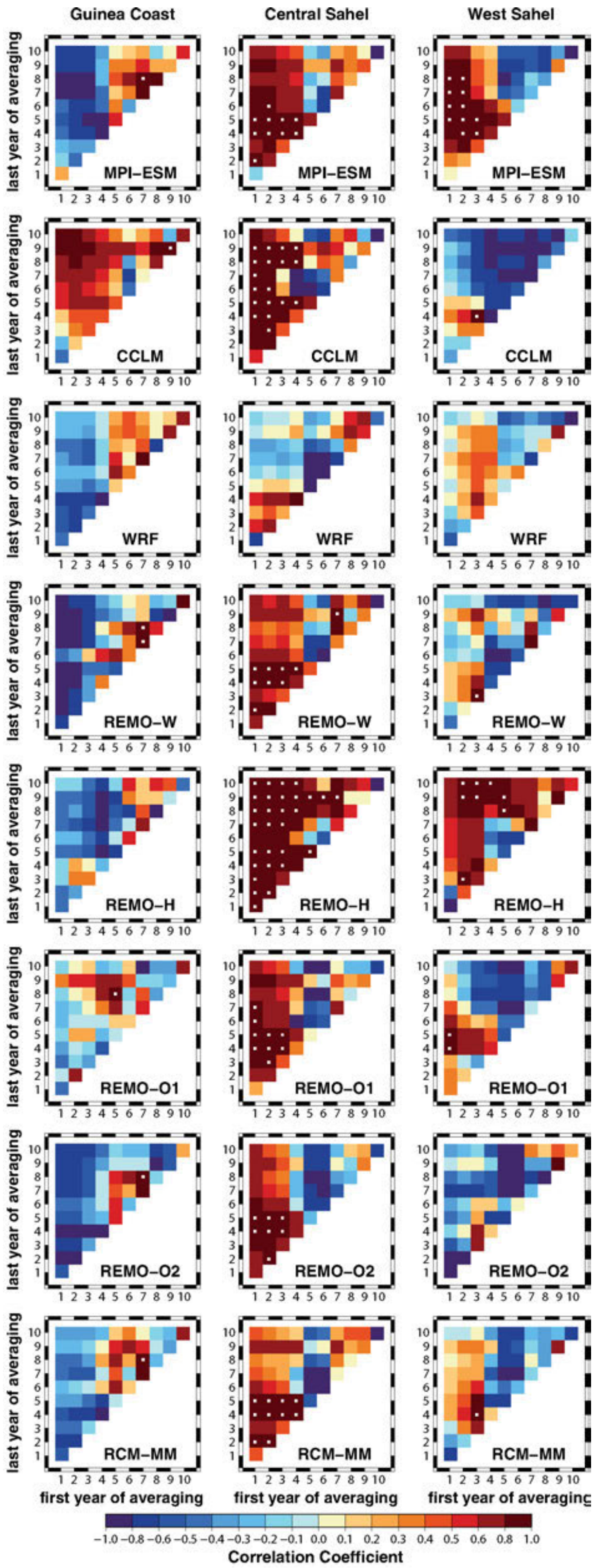

Figure 7: Same as Fig. 6 but now the x-axis (y-axis) denotes the first (last) year of averaging when computing the correlation coefficients for averaged sub-periods over all decades.

RCMs outmatches all others in all regions, making it difficult to rely on a one-model decadal prediction system. However, the RCM multi-model ensemble mean does not outperform the added value of individual RCMs.

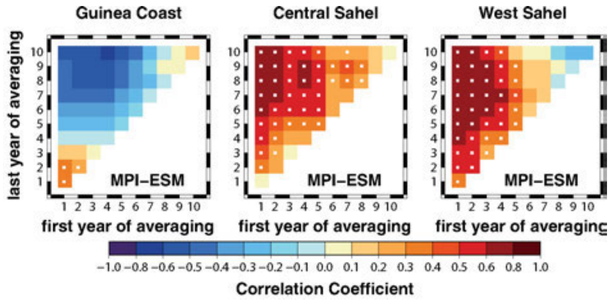

Figure 8: Same as Fig. 7 but for all available 41 decades (1961–1970, 1962–1971, …, 2001–2010) and 10 ensemble members of the MPI-ESM decadal prediction system.

Due to the RCM multi-model ensemble approach and limited computing resources, the number of realized decades and ensemble members is still quite small. Thus, the question arises whether our results are representative for other decades and ensemble members. This issue still cannot be addressed on the basis of RCMs but on the MPI-ESM for which 41 decadal predictions are available, each one year apart with the first starting year in 1961 and the last in 2001 (cf. Pohlmann et al., 2013). The correlation coefficients in Fig. 8 are based on these 41 decades and, in addition, 10 instead of three ensemble members. They represent a much larger sample size and, hence, the critical value for statistical significance is lower ($r_{xy} > 0.26$). It is obvious that the patterns are rather similar to the ones in the top row of Fig. 7. There is hardly any predictive skill in the Guinea Coast region but an excellent in-phase relationship with observed rainfall in the West and Central Sahel reaching correlation coefficients of up to 0.8 over all 41 decades and 10 ensemble members, except for the last years of a decade. The highest correlation of almost 0.8 is found for the decadal means. Thus, we can conclude that the findings from the selected four decades and three ensemble members are more or less representative for the overall decadal predictive skill of MPI-ESM. With respect to the added value of RCMs, this conclusion cannot be drawn with certainty yet.

4 Discussion

This study was dedicated to the decadal predictability of the West African summer monsoon rainfall in various regions of sub-Saharan Africa and to the role of dynamical downscaling in terms of the predictive skill. For this purpose, we have set up two types of RCM experiments – driven by reanalyses and driven by initialized global coupled GCM simulations. Moreover, we have assessed two time scales of predictability – year-to-year variations within decades and changes of time averages between decades. RCM simulations driven by reanalyses, i.e. realistic oceanic and lateral atmospheric boundary conditions, mainly reproduce the observed interannual variability in the Guinea Coast region. This is a promising result (cf. Paeth et al., 2005) but for the targeted real-time decadal predictions such observed boundary conditions are not available.

The second type of experiments consisted of a multi-model ensemble of three RCMs nested in the new German decadal prediction system MPI-ESM (Pohlmann et al., 2013). Concerning the year-to-year variations within the whole decade, the MPI-ESM and most RCMs failed in reproducing the observed rainfall dynamics. An exception is given by REMO for the Guinea Coast region during the 1966–1975 period when a substantial decadal-scale decrease of rainfall occurred in sub-Saharan West Africa (cf. Nicholson, 2001; Paeth et al., 2005). However, this promising result could not be confirmed for all considered decades and regions. The predictive skill and the added value of RCMs are more apparent when the analysis is based on sub-periods within a decade. However, the highest predictive skill is not reached by the same RCM in all regions and decades, and the RCM multi-model ensemble mean does not systematically enhance the added value and skill of individual RCMs.

By far the best results are found when sub-periods within decades are time averaged and compared between decades. In this case, the decadal predictive skill for Central Sahel rainfall is very high and statistically significant in most models, including the MPI-ESM. In the West and Central Sahel the good performance of MPI-ESM is still outmatched by at least one RCM (e.g. REMO-H), in the Guinea Coast region MPI-ESM fails but CCLM provides a useful prediction. Although we have realized more than 700 model years with our RCMs, these promising findings are derived from a relatively low number of decades and ensemble members – a drawback which is still due to limited computing resources. At least for MPI-ESM, we can conclude that our results are representative for the decadal predictive skill of WAM rainfall during the second half of the 20$^{\text{th}}$ century.

In summary, there are unambiguous indications that summer monsoon rainfall in sub-Saharan West Africa exhibits a valuable prediction potential at multi-year and, particularly, decadal time scales. This was already suggested by other studies (e.g. Paeth and Stuck, 2003; Paeth and Hense, 2004; Knight et al., 2006; Dunstone et al., 2011; Mohino et al., 2011; Rodríguez-Fonseca et al., 2011; Corti et al., 2012; van Oldenborgh et al., 2012; Gaetani and Mohino, 2013; Martin and Thorncroft, 2014). The novel aspect of our study pertains to the specific role of RCMs in the reproduction of multi-year and decadal rainfall fluctuations in the WAM region. Indeed, some added value could be identified in almost all analyzed regions and decades. However, there is no single RCM that consistently improved the GCM decadal hindcasts. The highest predictive skill, as indicated by correlation coefficients between 0.6 and 0.9, was often given by REMO-W and WRF for multi-year variations and by REMO-H and CCLM for the decadal time scale. As a consequence, we cannot suggest a reliable decadal prediction system based on one given RCM. The multi-model ensemble mean over all RCM predictions neither was expedient in all decades and regions.

The crucial question is why different regional climate models and the driving global model vary in terms of their skill in reproducing the observed year-to-year and decadal variations of rainfall in the considered sub-regions of sub-Saharan Africa. In fact, the investigated climate models differ in so many respects and the various model components and parameterizations cannot be exchanged among each other ad libitum, that it is hardly possible to identify those properties in the model physics which favor a good performance of one model in one specific region. The most relevant differences between the models pertain to the used radiation schemes, convection and cloud parameterizations, land-surface processes and interactions and, with respect to the global model, horizontal resolution. Indeed, Li et al. (2014) have demonstrated how sensitive WAM rainfall and dynamics are to the radiation physics in their RCM. The results of our process study (see Fig. 4) indicate that the added value imposed by REMO compared with MPI-ESM is not a simple outcome of a higher resolution of convection and rainfall processes but rather involves all elements of thermodynamics, including atmospheric circulation and the distribution of mass and cloud water. Although the question which characteristics of model physics are superior is of utmost importance to the development of improved climate models, analyses based on multi-model ensembles typically have difficulties to derive robust relationships between model performance and model characteristics. This is also true for the model uncertainties presented and discussed in the IPCC reports (e.g. IPCC, 2013). Recently, Ring et al. (2015) have analyzed the ability of CMIP3 and CMIP5 climate models to reproduce observed precipitation characteristics worldwide and could not systematically relate this ability to rather intuitive model properties such as horizontal or vertical resolution. Paeth and Pollinger (2010) reported the same problem concerning extratropical modes of atmospheric circulation. As a consequence, our multi-model study may provide a reasonable assessment of model uncertainty in multi-year and decadal predictability of West African monsoon rainfall, but we could neither identify a superior RCM nor an ideal combination of model properties that may serve for an ad hoc, ready-to-use operational forecast system. In terms of the regional aspect, however, it can be concluded that multi-year predictability appears to be higher in the Sahel, especially the central Sahel, than along the Guinean Coast region. The fact that the predictive skill of each individual climate model also varies from decade to decade is a clear indication that internal variability still plays a substantial role.

At first sight, the fact that the multi-model ensemble mean does not perform a higher multi-year or decadal predictability than the best individual RCM is against expectation. Paeth et al. (2011) have shown that the multi-model ensemble mean over nine RCMs is closer to the observed rainfall characteristics than each individual climate model. Krishnamurti et al. (1999) and Paeth (2015) achieved the best seasonal and longer-term predictions for the multi-model ensemble mean when the ensemble members were weighted by their ability to reproduce observed climate features in the past. In the present case, there is no such weighting and, hence, averaging over RCM simulations, which are partly positively and partly negatively correlated with the observed rainfall time series, leads to a worse overall result. Thus, an operational forecast system, which relies on multi-model information, would benefit from an appropriate weighting metric, e.g. based on a Bayesian approach (Paeth, 2015).

5 Conclusions

There are two important conclusions to be drawn from this study: (1) There is a promising forecast potential of WAM rainfall at the multi-year to decadal time scale arising from oceanic forcing. (2) Dynamical downscaling tends to enhance the predictive skill. Yet this finding is still subject to uncertainty because only a low number of decades and ensemble members could be realized and the picture is quite incoherent across different decades and sub-regions in West Africa. The most likely explanation for the added value of RCMs refers to the better resolved atmospheric and land-surface processes and to a more realistic response of the atmosphere to interannual and decadal SST changes, especially in the tropical Atlantic. While the added value of RCMs in the presentation of rainfall climatologies in West Africa has been reported before (e.g. Paeth et al., 2011, Nikulin et al., 2012), we now have identified some first indications that dynamical downscaling also enhances the predictability of multi-year to decadal climate variations (cf. Racherla et al., 2012). Note that a thorough analysis of the WAM rainfall bias from the MPI-ESM driven RCM simulations presented here has been addressed in another paper (Paxian et al., 2016). Comparing the findings from Paxian et al. (2016) with the results presented here, it must be reasoned that there is no systematic relationship between rainfall bias and predictive skill of the considered RCM simulations.

There remains a number of aspects to be further developed and addressed in future investigations. Besides the relatively small samples, another source of uncertainty is the selection of one global decadal prediction system, i.e. MPI-ESM. Previous studies in the context of the CMIP5 decadal predictions have revealed inconsistent results in terms of the predictive skill in various ocean basins (e.g. Keenlyside et al., 2008; Guemas et al., 2012, Kim et al., 2012; van Oldenborgh et al., 2012; Gaetani and Mohino, 2013; Martin and Thorncroft, 2014). In fact, the MPI-ESM decadal climate predictions seem to exhibit a stronger initialization bias within the first years than other CMIP5 models (Müller et al., 2012). It was shown in this study that this also affects the first predicted year of WAM rainfall, but is often overcome by dynamical downscaling. It is likely that when addressing a larger set of global decadal predictions from several GCMs, the highest predictive skill would sometimes be assigned to one of the GCMs rather than the RCMs. As limited computer power still does not allow for a larger experimental setting with several GCMs and RCMs, a good option is certainly to improve the initialization of the ocean (cf. Meehl et al., 2009; Murphy et al., 2010). Dunstone et al. (2011) have shown that predictability in the tropical Atlantic is related to the correct representation of the North Atlantic which may be a key player in decadal prediction and, hence, a benchmark for a more regionally improved ocean initialization.

Another option beyond the initialization problem is the implementation of additional boundary conditions which have some predictability over ten years, and improved model components and processes which lead to a generally better performance of climate models. Forcing by realistic AODs and man-made land cover changes represent promising candidates for enhanced predictive skill in the WAM region (cf. Paeth and Feichter, 2006; Paeth et al., 2009; Mehta et al., 2013).

Acknowledgements

We thank the Max-Planck Institute for Meteorology, the ECMWF, the IIASA, the Joint Research Centre, the FAO, OpenStreetMaps, the University of Delaware, the NASA-GSFC, the Climatic Research Unit and the ESA for providing the MPI-ESM decadal predictions, the ERA40, ERA-Interim and ORAS4 reanalyses, the WATCH-WFDEI data set, the GLC2000 land use data set, the FAO statistical data sets, the street data set, the Willmott-Matsuura data set, the GPCP data sets, the CRU data set and the ESA CCI soil moisture data set, respectively. This work was carried out in the framework of the German MiKlip project and supported by the German Minister of Education and Research (BMBF) under grants No. 01LP1129A-F. We thank three anonymous reviewers for their valuable comments which helped to improve the quality and readability of the paper.

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