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Assessing the suitability of statistical downscaling approaches for seasonal forecasting in Senegal

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Abstract

This work tests the suitability of statistical downscaling (SD) approaches to generate local seasonal forecasts of daily maximum temperature and precipitation for a set of selected stations in Senegal for the July–August–September season during the period 1979–2000. Two-month lead raw daily maximum temperature and precipitation from the five models included in the ENSEMBLES seasonal hindcast are compared against the corresponding downscaled predictions, which are obtained by applying the analog technique based on two different types of predictors: the direct surface variables and a combination of appropriate upper-air variables. Beyond correcting the large biases of the low-resolution raw model outputs, SD is found to add noteworthy value in terms of forecast association (as measured by interannual correlation), providing thus suitable (i.e. calibrated) predictions at the local-scale needed for practical applications, which means a clear advantage for the end-users of seasonal forecasts over the area of study. Moreover, a recommendation on the adequacy of surface (large-scale) predictors for SD of maximum temperature (precipitation) is also given.

Keywords: **statistical downscaling; seasonal forecasting; Senegal**

1. Introduction

Given their low spatial resolution, the global seasonal forecasts provided by the current climate models need to be satisfactorily translated to the local-scale required for most practical applications (see, e.g. Hanssen-Bauer *et al.*, 2005). One option for this is statistical downscaling (SD), which is based on empirical/statistical relationships linking the global model simulations (predictors) with the local observations of the target predictand variable (e.g. daily maximum temperature and precipitation in this work). However, though SD has been widely used in climate change studies, only a few works have applied it for seasonal forecasting (see, e.g. Gutiérrez *et al.*, 2004; Landman *et al.*, 2009; Frías *et al.*, 2010; Min *et al.*, 2011; Wu *et al.*, 2012; Shao and Li, 2013; Manzanas *et al.*, 2017). Moreover, SD methods have been mostly implemented for extra-tropical regions since several problems still hinder their successful application in the tropics (Paeth *et al.*, 2011). First, since the local climate is largely driven by meso-scale processes, the statistical relationships between the local- and the large-scale are weaker than in the extra-tropics. Second, reliable observational networks for the local predictand data are often not available. As a result of these factors, most of the downscaling studies undertaken to-date for West Africa have relied on dynamical approaches, that is, regional climate models (van den Hurk and van Meijgaard, 2010; Giorgi *et al.*, 2012; Sylla *et al.*, 2012), even though the skill of global seasonal forecasts these models are nested to is limited there (see, e.g. Manzanas *et al.*, 2014). Therefore, assessing the suitability of SD approaches for seasonal forecasting over West Africa, where the capacity to invest in regional climate models is limited and the strong interannual climate variations are crucial for various socio-economic sectors (Ndiaye, 2010), is of large interest.

With these considerations in mind, this work focuses on seasonal forecasts of average daily maximum temperature and precipitation for Senegal, a region for which high-quality observations were available. In particular, the potential added value of SD is assessed by comparing the downscaled results with the raw model predictions in terms of forecast association and accuracy. Moreover, this study also tests the suitability of two different types of predictors which may be used for SD: the model counterpart of the variable being predicted (i.e. low-resolution surface maximum temperature/precipitation for predicting local maximum temperature/precipitation) and a combination of appropriate upper-air variables which best describe the synoptic phenomena determining the interannual variability of the local predictands.

The paper is organized as follows: the data used are described in Section 2. Section 3 details the methodology applied. Results are presented and discussed through Section 4 and a summary of the main conclusions obtained is given in Section 5.

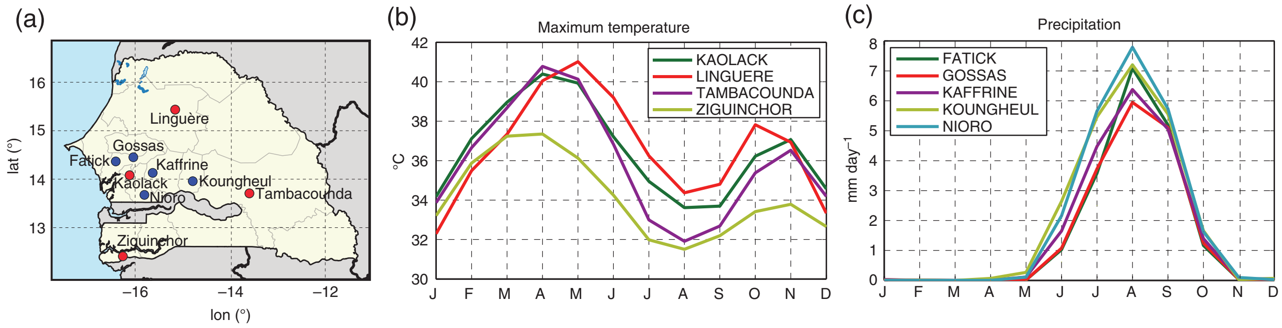

Figure 1. (a) Stations considered for maximum temperature (in red) and precipitation (in blue). (b) Annual cycles of maximum temperature for the period 1979–2000. (c): As (b), but for precipitation.

2. Data

2.1. Predictands

Daily observed maximum temperature (precipitation) from the Agence Nationale de la Météorologie du Sénégal for a set of 4 (5) stations was available for this work for the period 1979–2000 (panel (a) in Figure 1). These stations were quality-controlled by applying tests for detection of outliers and temporal inhomogeneities, and they presented less than a 2% of missing data for the period of study.

Panels (b) and (c) in Figure 1 show the observed annual cycle in these stations for maximum temperature and precipitation, respectively. Whereas maximum temperature presents a bimodal distribution with the first (second) peak around April–May (October–November) and the lowest values in July–August–September (JAS hereafter), precipitation is mainly conditioned by the seasonal migration of the inter-tropical convergence zone (Sultan and Janicot, 2003) and all the stations exhibit a unique rainfall peak in JAS. As the interannual variations of JAS precipitation are key for local agriculture (see, e.g. Wade *et al.*, 2015), only this season was considered in this work.

2.2. Predictors

Daily predictors from the ERA-Interim reanalysis (Dee *et al.*, 2011) were used as catalog for the search of analogs (see Section 3). Seasonal forecasts were obtained from the five models contributing to the ENSEMBLES seasonal hindcast (see Table 1). Note that, although the ENSEMBLES models are several years older than state-of-the-art seasonal forecasting systems, they form the most homogeneous and comprehensive multimodel ensemble publicly available to-date. Each of these models ran an ensemble of nine members which were produced by perturbing the observed state of the atmosphere and the ocean four times a year (the first of February, May, August and November), providing daily data for 7 month-long retrospective runs (see Weisheimer *et al.*, 2009, for further details about the experiment). Therefore, for JAS, only 2-month lead predictions were available.

Table 1. Main components of the five atmosphere–ocean coupled models contributing to the ENSEMBLES multimodel seasonal hindcast.

Centre	Atmospheric model and resolution	Ocean model and resolution
ECMWF	IFS CY31R1 (T159/L62)	HOPE (0.3–1.4°/L29)
UKMO	HadGEM2-A (N96/L38)	HadGEM2-O (0.33–1.0°/L20)
IFM-GEOMAR	ECHAM5 (T63/L31)	MPI-OM1 (1.5°/L40)
CMCC-INGV	ECHAM5 (T63/L19)	OPA8.2 (2.0°/L31)
MF	ARPEGE4.6 (T63)	OPA8.2 (2.0°/L31)

Table 2. Potential predictors considered for this work.

Code	Name	Level	Units
T	Temperature	850, 500, 200, 50 hPa	K
Z	Geopotential	850, 500, 200, 50 hPa	$m^2\,s^{-2}$
U	Zonal wind	850, 500, 200, 50 hPa	$m\,s^{-1}$
V	Meridional wind	850, 500, 200, 50 hPa	$m\,s^{-1}$
Q	Specific humidity	850, 500, 200, 50 hPa	$g\,kg^{-1}$

Only predictor variables which were available for both ERA-Interim and the ENSEMBLES models were considered (see Table 2). All of them were re-gridded onto the same 2° regular grid covering the domain encompassed by (20–10°W) and (10–18°N).

3. Methodology

The popular non-parametric analog technique (Lorenz, 1963, 1969) assumes that similar (or analog) atmospheric configurations (e.g. a set of predictors defined over the aforementioned domain) lead to similar meteorological outcomes (local maximum temperature/precipitation in this work). Here, a deterministic version of the technique which considers only the closest analog (Zorita *et al.*, 1995; Cubasch *et al.*, 1996) is applied. Therefore, for each daily atmospheric configuration simulated by the ENSEMBLES models, the corresponding local downscaled forecast is given as the observations corresponding to the most similar atmospheric configuration found in ERA-Interim. Similarity between atmospheric configurations is measured in terms of the Euclidean norm, which has been shown to perform satisfactorily in most cases (Matulla *et al.*, 2008). The same method has been already used for SD of seasonal forecasts in previous studies (see, e.g. Frías *et al.*, 2010; Manzanas *et al.*, 2017).

To avoid over-fitting, a k-fold cross-validation approach (Gutiérrez *et al.*, 2013) was followed, with $k=4$ non-overlapping test periods, covering the full period of study 1979–2000. Finally, note that SD is performed on a daily basis, thus providing 2-month lead daily downscaled time-series.

Two types of different model predictors were used: the direct surface (SF) variables to be downscaled and a combination of upper-air (UA) variables accounting for the most relevant synoptic phenomena determining the local climate. Whereas the latter approach is the most common for SD in perfect prognosis (see, e.g. Wilby *et al.*, 2004), the utility of the former, which may be highly beneficial since no predictor screening is required, has been rarely tested to-date (see, e.g. Turco *et al.*, 2011).

For the UA case, a step-wise-like algorithm was used to find the optimum combination of predictor variables for each target predictand. Starting from a single predictor taken at random, in each iteration the algorithm performed the SD for all combinations resulting from including/excluding one extra variable (among those shown in Table 2), the downscaled results were validated against observations and the best combination was retained for the next iteration only if a relative improvement of a 1% was reached. Such an improvement was measured in terms of interannual correlation with observations, which is the basis of skill in seasonal forecasting. The optimum UA–predictor combination obtained from this automatic screening for maximum temperature (precipitation) was Z500-T850 (T500-Q850-U850), which account for thermodynamic- and circulation-related processes. For these UA predictor combinations, the leading principal components (PCs, see Preisendorfer, 1988) explaining the 95% of the entire predictor variance were considered (5 for the case of maximum temperature and 18 for precipitation). PCs were obtained, both for the reanalysis and for the seasonal forecasts, by projecting the corresponding standardized fields onto the empirical orthogonal functions obtained from the reanalysis, which were computed simultaneously on all predictor variables.

For each ENSEMBLES model, SD was independently applied to each of the nine available members, obtaining nine daily downscaled time-series. The multi-model ensemble mean (MM henceforth) was calculated by averaging the 45 (5 models $\times$ 9 members) available members, thus giving equal weights to all models and members.

4. Results and discussion

The 2-month lead daily downscaled predictions obtained for JAS for the period 1979–2000 were yearly aggregated and validated against the corresponding observations in terms of interannual correlation and mean absolute error (MAE), which account for different aspects of forecast quality: association and accuracy, respectively.

Panels (a) and (b) ((c) and (d)) of Figure 2 show the results obtained for maximum temperature (precipitation). For brevity, only the MM is shown since it was found to outperform the individual models in most of cases, which is in agreement with previous studies (see, e.g. Batté and Déqué, 2011; Landman and Beraki, 2012; Manzanas *et al.*, 2014). For each station, the gray bar corresponds to the MM raw outputs (shown for benchmarking purposes), whereas the blue (green) bar displays the results from SD when considering SF- (UA-) predictors from the MM. This figure allows to assess both the potential added value of SD – by comparing the blue and green bars with the gray one – and the relative performance of SF- and UA-predictors – by comparing blue and green bars.

For maximum temperature, SD outperforms in all cases the correlation of the MM raw outputs (see panel (a)) when considering SF-predictors (especially in Ziguinchor), whereas no substantial improvements are obtained for UA-predictors. Moreover, as expected by construction (SD methods are calibrated towards the observed climate), SD allows to reduce the MAE of the MM raw outputs (see panel (b)), either when considering SF- or UA-predictors (similar results are obtained in both cases).

For precipitation, whereas SF-predictors do not yield any added value in terms of correlation, the use of UA-predictors allows for clearly improving the forecast association of the MM raw outputs (see panel (c)). In particular, whereas the MM exhibits nearly zero correlations in all stations, SD yields significant (at a 95% confidence level) values in all of them (this effect is especially notable in Fatick, where an improvement of about 0.6 correlation units is reached). An explanation for this might be in relation to the results found by Manzanas *et al.* (2017), who proved that the use of UA-predictors can provide an opportunity to improve model precipitation in those cases for which the large-scale is well simulated by the model. Note that, whilst providing a good representation of the large-scale, models can still forecast erroneous precipitation since this variable is strongly affected by local forcing such as small-scale processes and/or orography, which usually are not properly represented in the models. Furthermore, as for the case of maximum temperature, SD outperforms the MM raw outputs in terms of MAE in all stations (see panel (d)), with SF- and UA-predictors yielding similar results.

For completeness, Table 3 shows the results obtained for the five individual ENSEMBLES models in two illustrative stations; Ziguinchor and Fatick, respectively. For providing the best correlation improvements (see Figure 2), SF- (UA-predictors) are considered in the former (latter). It is clear from Figure 2 and Table 3 that, beyond correcting the distinct biases found for

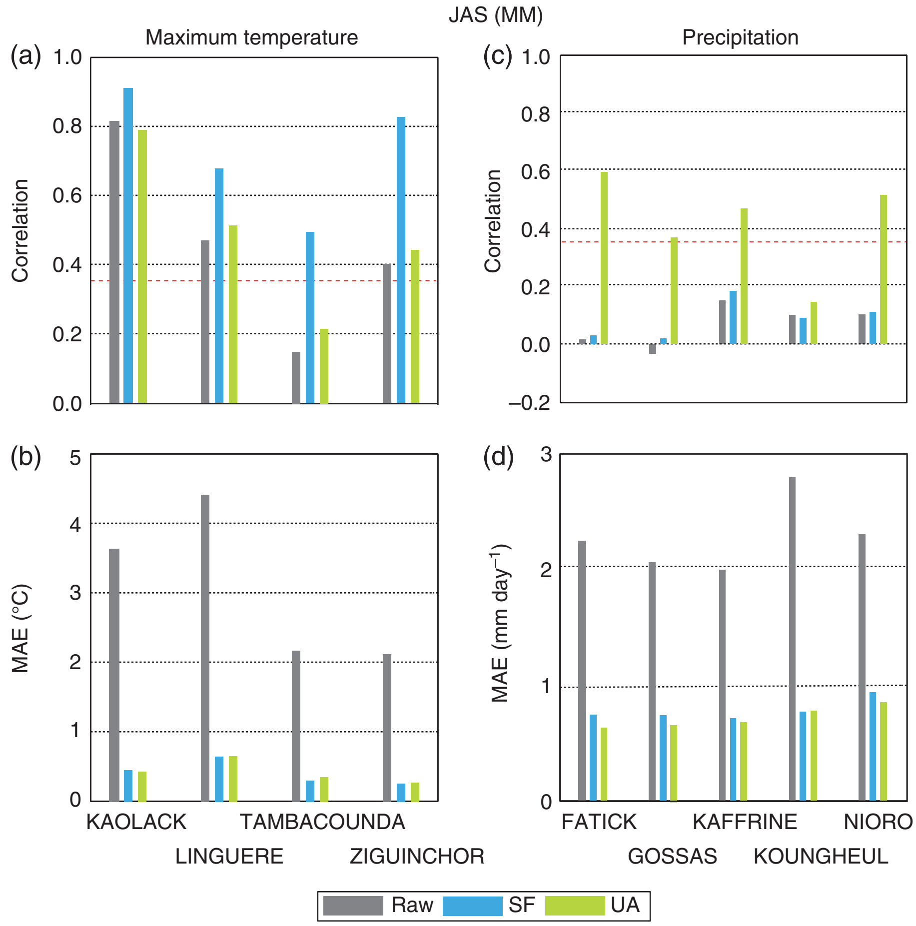

Figure 2. Results obtained for maximum temperature and precipitation in terms of interannual correlation (panels a and c) and MAE (panels b and d). For each station, the gray bar corresponds to the MM raw outputs (shown for benchmarking purposes), whereas the blue (green) bar shows the results from SD when considering SF- (UA-) predictor variables. Correlations above the red horizontal lines are statistically significant at a 95% confidence level, according to a Student's *t*-test.

the different models, SD can considerably improve the correlation attained by their raw outputs when using adequate predictors, providing thus more realistic local-scale climate information, which is needed for real user applications. At this point is important to highlight that simpler bias correction methods allow also to reduce the biases from the different models; however, differently to the SD method presented here, they can deteriorate forecast association (see, e.g. Manzanas *et al.*, 2014).

Although the results from this work mean a clear advantage for the end-users of seasonal climate forecasts in Senegal, it is important to note that they may be not extensible to other regions and/or seasons of interest, and further investigation is still needed to provide a more conclusive overview on the potential merits of SD in the context of seasonal forecasting. For instance, SD might be a beneficial option to compute climate impact indicators, which are sensitive to model biases (particularly those based on absolute thresholds, such as the number of heating or cooling degree days) and typically require working with properly calibrated daily data (Casanueva *et al.*, 2014). This kind of analysis is out of the scope of this paper, but might be matter of study in a future work.

5. Conclusions

This work assesses the suitability of different statistical downscaling (SD) approaches – which, as compared to dynamical downscaling, are computationally cheaper and do not require *a posteriori* correction since they directly incorporate observations into the method – to generate local seasonal forecasts of average daily maximum temperature and precipitation for a set of selected stations in Senegal for the July–August–September season during the period 1979–2000. To this, a nearest analog method is applied to surface (SF) and upper-air (UA) predictors from a number of global seasonal forecasting models (2-month lead predictions are considered). The daily downscaled predictions are yearly-aggregated and validated in terms of correlation and mean absolute error, which account for different aspects of forecast quality. The results obtained indicate that, beyond correcting the large biases of the different global forecasting models, SD adds noteworthy value to the low-resolution raw model outputs in terms of correlation. This clear advantage indicates that SD might be used by end-users in Senegal to obtain suitable (i.e. calibrated) forecasts at the local-scale needed some months ahead of the target season. Moreover,

Table 3. Results obtained for the five individual ENSEMBLES models for maximum temperature (precipitation) in Ziguinchor (Fatick), in terms of interannual correlation and MAE. For providing the best correlations improvements (see Figure 2), SF-(UA-predictors) were chosen.

		ECMWF		UKMO		IFM-GEOMAR		CMCC-INGV		MF	
		Raw	Downscaled	Raw	Downscaled	Raw	Downscaled	Raw	Downscaled	Raw	Downscaled
Ziguinchor	Correlation	−0.05	0.41	0.33	0.79	0.31	0.62	0.59	0.74	0.42	0.66
	MAE (°C)	3.14	0.30	3.47	0.23	3.33	0.35	5.09	0.26	3.68	0.31
Fatick	Correlation	−0.06	0.38	0.09	0.56	−0.17	0.52	−0.23	0.49	−0.24	0.53
	MAE (mm/day)	2.72	1.06	1.59	0.91	2.26	0.13	1.70	0.84	3.93	0.98

whereas UA variables are found to provide better results for SD of precipitation, simpler configurations relying exclusively on SF variables do perform better for maximum temperature. Note the convenience of the latter approach since no predictor screening is required, being thus a cost-effective and pragmatic choice.

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