AgMIP simulations for West Africa

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1 General

The files in this collection were created as part of the AgMIP project (`www.agmip.org`), for the purpose of delineating climate uncertainty over during the next few decades in terms of agricultural yields. The basic method of their creation, using the software suite *simgen,* is detailed in Greene et al. (2015).

2 Domain and season

The West Africa domain for these simulations is delimited by latitude 10°–20°N, longitude 20°W–20°E, as will be seen by display of the data in map form.

Similarly to the procedure followed in Greene et al. (2015), the year is divided into two large-scale seasons, a growing season and an off-season (those months that are not part of the growing season). Here the growing season is taken as June through September, or JJAS. This is a common partition for West African (or more generally, Sahelian) domains, and corresponds to the season of the West African summer monsoon.

The growing season is the primary modeled season, i.e., the statistical model is fit to that season, and it is JJAS values that are simulated by the model and temporally downscaled. Other months are filled with the off-season climatological pattern, superimposed on trends paralleling those inferred for the growing season. This procedure is used in order to (a) increase signal-to-noise in the modeled season and (b) insure that there is not a growing discontinuity between modeled and off-season climates, particularly in the case of trending temperature, but also for precipitation.

3 Data reduction

Fitting of a simulation model involves a two-step detrending process applied to the observational dataset employed, here the UEA CRU TS3.21 product (Harris et al., 2013), followed by application of a first-order vector autoregressive (VAR) model (see, e.g., Holden, 1995). Three variables are modeled jointly – precipitation and daily maximum and minimum temperatures. After detrending, the training data are expressed in terms of principal components, and it is to these PCs that the VAR model is applied. The number of retained modes depends in part on the need to reproduce within-region covariances in the simulated data. Twenty PCs are utilized for the simulations in this dataset. Because each EOF encodes variation over the entire domain there is no need for spatial downscaling (although there is a temporal disaggregation step).

4 Detrending and natural decadal variability

Decadal variability in the Sahel during the 20th century has been notable, compared with other regions, and the detrended regional-mean signals, particularly precipitation, do retain considerable decadal variance. An unknown fraction of this variability may derive from natural causes, such as variations in the Atlantic Meridional Overturning Circulation (AMOC). To address this uncertainty we first lowpass the residual signals using a Butterworth filter with 30-year cutoff. A parameter is then assigned to designate the naturally-forced fraction of the lowpassed signal, and the complementary fraction of the lowpassed signal is removed from the data passed to the VAR model. This fraction is set here at 0.5 to reflect our lack of certainty. The intended result is that the model will be applied to only the natural component of variability, which will in turn be replicated, in the statistical sense, for the simulations going forward. In other words, is *not* assumed that the anthropogenically-forced decadal variability observed during the past century will also characterize future decadal statistics.

5 Future trends

Trends for the future cannot, of course, be inferred from the observational record. Rather, a *distribution* of future trends is obtained from an ensemble of Coupled Model Intercomparison Project, phase 5 (CMIP5) models (Taylor et al., 2011). Future precipitation is expressed as a regional sensitivity — percent regional precipitation change per degree global warming — while future temperature trends are normalized by the global mean temperature. Then all that is required to project local precipitation and temperature trends into the future is a global mean temperature record. For this purpose a multimodel mean signal is utilized, based on the same CMIP5 models.

6 Downscaling

As noted above, the full spatial domain is represented in the PCA-based modeling procedure and no spatial downscaling is required or performed. However the simulations produced by the VAR model are only annually resolved, representing mean JJAS values (for each of the three variables). Again as described in Greene et al. (2015), a k-NN resampling step (Rajagopalan and Lall, 1999) is utilized to recover monthly values over the domain for the modeled season. Infilling of the off-season months was described above.

For daily data k-NN is also deployed. However the target dataset is now AgMERRA (Ruane et al., 2015), which also comprises a number of subsidiary variables of agricultural interest. These are (with their data library identifiers) dew point (dewp), relative humidity (hur), incoming solar radiation (rsds), vapor pressure (vp) and wind speed (wind). The primary variables, precipitation (pre) and maximum and minimum daily temperatures (tmx, and tmn, respectively) are also included.

7 Simulation IDs

In each case (monthly or daily) the nine archived simulation files constitute a "basic set," combining three precipitation trends with each of three decadal fluctuations. A typical file name might be "simall_JJAS_05_02649_WA_003." Here, "JJAS" refers to the modeled season, while the two digits following ("05") identify the trend percentile (fifth). The following five-digit identifier encodes the percentile of the 10-year precipitation fluctuation, which occurs in each case during 2031-2040. Table 1 shows the fluctuation percentile associated with each of these codes. "WA" identifies the West Africa domain. The final numerical identifier is an internal ID, maintained for possible future reference.

Code	Fluctuation percentile
02649	5th
07053	50th
00747	95th

Table 1: Decadal fluctuation percentiles associated with each of the five-digit file name codes.

8 Further information

The user is encouraged to consult Greene et al. (2012, 2015) and the references cited therein for additional information on the methodology employed to generate these simulations.

References

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