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A climate generator for agricultural planning in southeastern South America

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ABSTRACT

A method is described for the generation of climate scenarios in a form suitable for driving agricultural models. The scenarios are tailored to the region in southeastern South America bounded by 25–40° S, 45–65° W, denoted here as SESA. SESA has been characterized by increasing summer precipitation, particularly during the late 20th century, which, in the context of favorable market conditions, has enabled increases in agricultural production. Since about year 2000, however, the upward tendency appears to have slowed or possibly stopped, raising questions about future climate inputs to regional agricultural yields.

The method is not predictive in the deterministic sense, but rather attempts to characterize uncertainty in near-term future climate, taking into account both forced trends and unforced, natural climate fluctuations. It differs from typical downscaling methods in that GCM information is utilized only at the regional scale, subregional variability being modeled based on the observational record. Output, generated on the monthly time scale, is disaggregated to daily values with a weather generator and used to drive soybean yields in the crop model DSSAT-CSM, for which preliminary results are discussed. The simulations produced permit assessment of the interplay between long-range trends and near-term climate variability in terms of agricultural production.

1. Introduction

During the 20th century, particularly its latter half, southeastern South America (SESA) experienced an upward trend in summer rainfall (Gonzalez et al., 2013; Liebmann et al., 2004). Together with favorable market conditions, and in the context of technological advances, this upward tendency has enabled increases in agricultural yields (Magrin et al., 2005; Viglizzo and Frank, 2006). Since about year 2000, however, the upward tendency in rainfall has slowed, or possibly reversed. Neither the steady upward trend nor its recent slowing is well-simulated by global climate models (Gonzalez et al., 2014), leaving its cause and future evolution in question. The recent decadal hindcast experiments conducted as part of the Coupled Model Intercomparison Project, phase 5 (CMIP5) do not indicate significant decadal prediction skill for SESA for either temperature or precipitation, based on initializing the models with the observed ocean state (Goddard et al., 2013). This leaves an unfilled need for useful climate information for the next few decades, in particular for the purposes of assessing the climatic contribution to potential fluctuations in agricultural yields.

We present here a methodology, not for predicting the future of SESA hydroclimate in a deterministic sense, but rather, for the characterization of future regional climate uncertainty over the next few decades. The method represents an extension of that described in earlier work in the Western Cape Province of South Africa (Greene et al., 2012, hereinafter referred to as G12), and accounts for uncertainties in both the response to anthropogenic forcing and in natural, unforced climate variability. A key question in the forcing of SESA hydroclimate concerns the influence of stratospheric ozone (e.g., Gonzalez et al., 2014); a simple method for representing the associated uncertainty is implemented. Possible cross-scale interaction is incorporated into the simulation framework as necessary. The final output is downscaled using a modification of the k-nearest-neighbor (k-NN) resampling method, applied to observational data that may have either monthly or daily time resolution. The core statistical model represents spatial covariability as well as serial autocorrelation in individual variables.

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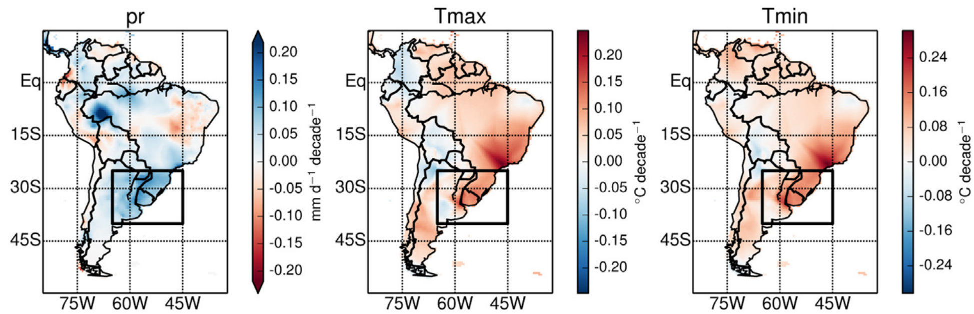

Fig. 1. Trends for precipitation and maximum and minimum daily temperatures for 1901–2011, aggregated to the seasonal (SONDJF) level. Note the reversal of colors between the precipitation and temperature scales.

The data utilized are described in Section 2 and the method in Section 3. Validation of various climate diagnostics is covered in Section 4. The downscaling component is described in Section 5 and preliminary application using an agricultural model in Section 6. A discussion and conclusions are presented in Sections 7 and 8, respectively.

2. Data

We employ both observational data and climate model simulations. When downscaling directly to the daily time step, a hybrid product based on in situ observations, satellite data and reanalysis is employed. These data types are described in turn.

2.1. Observations

The basic observational dataset employed is the TS3.21 product of the Climatic Research Unit, University of East Anglia (Harris et al., 2013), which is gridded at 0.5° and has monthly time resolution. The dataset is complete, but includes values that may have been filled, either by interpolation from nearby stations or with climatological values. The northerly extent of the study domain was limited by the presence of filled values between 20° S and 25° S. The TS3.21 data extend from 1901 through the end of 2012; since we model here a growing season (SONDJF) that crosses the year boundary, we limit the nominal range to 1901–2011, permitting the use of 111 full six-month seasons in modeling and resampling.

The study domain appears as a box in each panel of Fig. 1, which shows 1901–2011 linear trend coefficients for SONDJF for the three variables modeled: precipitation and maximum and minimum daily temperatures (Tmax and Tmin, respectively). The increasing tendency of precipitation in the SESA box can clearly be seen, as can the general increase in both of the temperature variables. The Tmax plot shows an area in the southwest of the SESA box with weakly negative coefficients, even as the rest of the box has warmed. Post-1971, however, a period of increasing global temperatures, Tmax has increased more uniformly within the box. It is of interest that Tmin increases more rapidly with time, even for trends beginning in 1901, implying a decrease in the diurnal temperature range. Future trends are modeled separately for the two temperature variables.

For precipitation, comparison was made with version 6 of the Global Precipitation Climatology Center (GPCC Schneider et al., 2011). The regional SONDJF means (3.41 mm d^{-1} and 3.58 mm d^{-1}) and standard deviations (1.34 mm d^{-1} and 1.47 mm d^{-1} for CRU and GPCC, respectively) agree fairly well, as do the regional mean 20th-century trends (0.085 and 0.086 mm d^{-1} decade^{-1}, respectively). Trend patterns within the SESA are also reasonably well-correlated (r = 0.67). Since the CRU dataset comprises similarly computed and gridded values for Tmax and Tmin, and since these variables are modeled jointly with precipitation, it was decided to utilize CRU for the work presented herein.

2.2. Climate model simulations

In G12, future regional precipitation trajectories were selected by quantile from a distribution over a set of CMIP5 climate models. For reasons to be discussed we do not utilize this procedure here. However a CMIP5 ensemble is utilized to estimate the global and regional responses to external forcing, to investigate covariation between future regional trends in precipitation and temperature and for comparison with projected temperature trends. The models utilized are listed in Table 1.

Questions have arisen regarding model interdependence (Knutti et al., 2013). Only minor differences were noted here when distributions were computed after first averaging over models within a family. The full multimodel set (one ensemble member per model) was therefore utilized.

2.3. Satellite data and reanalyses

In the present report we describe downscaling to the monthly time step; the possibility also exists of generating daily output, by resampling from a dataset such as AgMERRA, a product based on the MERRA reanalysis (Rienecker et al., 2011) developed for crop modeling as part of the international AgMIP project (http://agmip.org). This is discussed in Section 5.

2.4. Stratospheric ozone

Because stratospheric ozone may affect SESA precipitation we model a partial dependence. Both past and projected concentration data, as compiled by the Stratosphere–troposphere Processes And their Role in Climate (SPARC) activity of the World Climate Research Program (Cionni et al., 2011), are utilized. This dataset serves as a boundary forcing for the majority of CMIP5 models, which do not compute stratospheric ozone interactively.

3. Method

The procedure developed herein advances the work described in G12, in part by adding refinements but also though the representation of within-region variability in terms of principal components. This enables the consideration of larger, more climatically complex regions than could easily be accommodated using the earlier method. In common with G12, climate variability is decomposed into long-range trend, annual-to-decadal variability and subannual variations. The first two of these are modeled independently and the results combined, producing annually-resolved seasonal simulations over the entire gridded domain. These simulations are then downscaled in time, using a k-NN variant. In South Africa the