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Statistical downscaling of multi-decadal climate change projections: Bridging the gap between climate models and the end-user

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Abstract

Multi-decadal regional climate projections are assimilated into a statistical model in order to produce an ensemble of mid-summer maximum temperature for southern Africa. The statistical model uses atmospheric thickness fields (geopotential height differences between the 500 and 850 hPa levels) from high-resolution reanalysis data as predictors in a perfect prognosis approach in order to develop linear equations which represent the relationship between atmospheric thickness fields and gridded maximum temperatures across the region. The statistical model is found to be able to replicate the increasing maximum temperature trends of the driving regional climate model. Since dry-land crops are not explicitly produced by climate models but are sensitive to temperature extremes, the effect of these projected maximum temperature trends is assessed on dry-land crops over multiple decades by employing a statistical approach similar to the one introduced for maximum temperatures.

Key words: Southern Africa, perfect prognosis, regional climate projections, maximum temperatures, dry-land crops

Introduction

Global climate change has been confirmed and recently such changes have also been manifested across southern Africa (IPCC 2007). Modelling efforts to simulate these and future changes have subsequently increased and international programmes have been established in order to produce, among other outcomes, reliable high-resolution regional projections over multiple decades. These modelling efforts are being focused on both regional climate models and on statistical downscaling methods (e.g. Maraun et al 2010). At the Council for Scientific and Industrial Research the regional modelling capability established there has been developed around the conformal-cubic atmospheric model (CCAM; McGregor 2005) and extensively reported on (e.g. Malherbe et al 2013a). This paper introduces a unique statistical downscaling method that assimilates an ensemble of high-resolution CCAM output over multiple decades and is applied to maximum temperatures and dry-land crop yield.

Data and Method

The CCAM has been configured for a number of applications, including weather and seasonal climate prediction, multi-decadal projections and high-resolution reanalysis (Engelbrecht et al 2011). Recently a 30-year period of 0.5° resolution 6-hourly data from 1979 to 2008 were produced by providing the CCAM at 6-hourly intervals with NCEP reanalysis data. Seasonal (3-month) averages of this CCAM-based reanalysis data set were subsequently calculated and used here as predictors for perfect prognosis statistical downscaling (Maraun et al 2010). Specifically, the predictors are the CCAM reanalysis DJF thickness fields as represented by the geopotential height differences between the 850 and 500 hPa levels. The predictand in the perfect prognosis equations are gridded UEA CRU TS3.1 (Mitchell and Jones 2005) DJF maximum temperatures. The perfect prognosis equations are created by the canonical correlation analysis (CCA) option of the Climate Predictability Tool (CPT). The predictor domain is the area between the equator and 45°S, and between 15°W and 60°E; the predictand domain is between 12°S and 35°S, and 11°E to 41°E. CCAM multi-decadal simulations of regional climate for the period 1961 to 2100 at the same horizontal resolution as the CCAM-reanalysis set were performed by forcing the CCAM with the bias-corrected sea-surface temperature (SST) and sea-ice output of a number of different coupled global climate models used in AR4 of the IPCC (CSIRO, GFDL20, GFDL21, MIROC, MPI and UKMO). All six of these projections were for the A2 SRES emission scenario.

The developed statistical relationships between the thickness fields and predictands are assumed to remain valid under future climate conditions and also that the large-scale structure, variability and trends of the fields are well characterized by the CCAM. The CCA perfect prognosis equations are subsequently used to simulate the DJF maximum temperature fields over 139 years from 1961/62 to 2099/00 and for each of the six CCAM-AR4 projections in order to produce an ensemble of statistically post-processed projections. The statistically projected DJF maximum temperature data averaged over the 30-year period from 1961/62 to 1990/91 are compared with averaged CRU maximum temperatures over the same period in order to calculate an estimate of the bias of each of the six projections. Bias adjustment is subsequently applied over the entire 139-year period and for each simulation.

Fig. 1 shows the area-averaged ensemble mean of both the raw CCAM-AR4 and perfect prognosis maximum temperature bias-adjusted projections. A second-order polynomial is applied to both time series. A close resemblance between the two projections is evident which provides evidence that the perfect prognosis statistical model is a skillful representation of raw model output. This result is particularly encouraging since atmospheric thickness fields and not the CCAM's maximum temperature projections are used as predictors in the perfect prognosis equations.

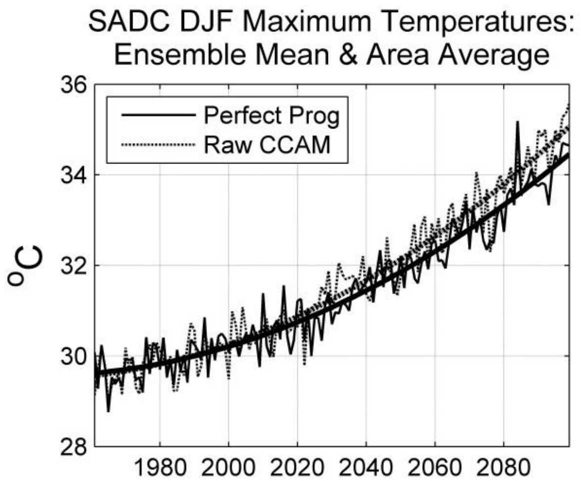

Fig. 1. Area-averaged ensemble mean (from six bias corrected projections) of both the raw CCAM-AR4 output and perfect prognosis DJF maximum temperatures. Simulations for each year and for fitted polynomials are presented.

Since one of the assumptions in a perfect prognosis approach is that the model(s) providing the predictor data is (are) perfect, the statistical downscaling presented here does not necessarily improve on raw model output, nor does it present higher resolution projections here since both the CRU grid and the raw output are at the same resolution. Take note that our reason for developing statistical post-processing procedures that may be able to replicate the output from a regional climate model serves the main purpose of developing the capability of producing multiple decade projections of variables not explicitly simulated by models but whose variation may be strongly linked to climate variations. For this purpose insight into the spatial description of the extent to which the statistical post-processing is replicating the raw model output may be useful. Further insight into the ability of the perfect prognosis approach to replicate the raw model output is presented in Fig. 2.

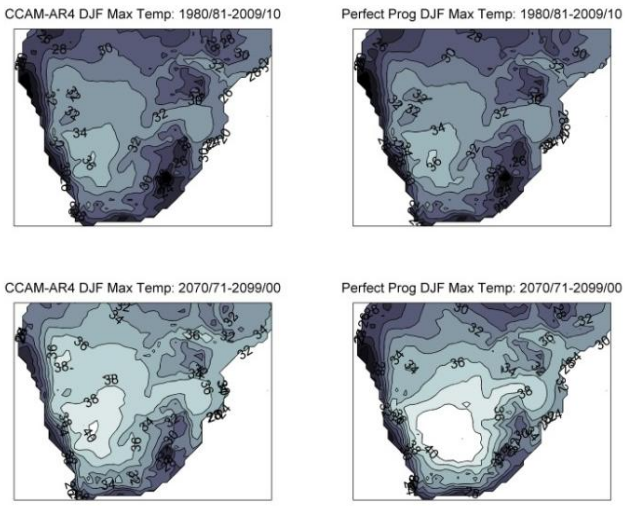

Fig. 2. Ensemble mean 30-year climates of the raw CCAM (left panels) and of the perfect prognosis (right panels) DJF maximum temperatures.

The present-day climates of both systems (top panels of Fig. 2) are in strong agreement. However, differences are evident over the 2070/71 to 2099/00 period (bottom panels of Fig. 2), especially over the western-central and over the far northern parts where the statistical method respectively simulates DJF maximum temperature climates too warm and too cold relative to the raw CCAM data. Strong agreement is found for the eastern Highveld of South Africa where the maize production districts of Witbank are located. The perfect prognosis post-processing presented here is subsequently applied to Witbank dry-land maize yields. Maximum temperatures may be considered as a proxy for dry-land maize production since droughts are most often associated with summer seasons of intense heat. Higher than normal temperatures and more sunshine hours are both factors that will increase yield stress and will consequently result in lower yield figures. This notion is demonstrated in Fig.3 that shows the 5-year-out cross-validation results obtained by using DJF 850-500 hPa thickness fields of the CCAM reanalysis as a predictor of Witbank's detrended maize yield in a principal component regression (PCR) model (Malherbe et al 2013b). The Spearman's rank correlation between the 29-year simulated and observed yields is 0.39 ($p<0.02$). The PCR model is subsequently applied to dry-land crops by using the DJF 850-500 hPa thickness simulations of the six CCAM-AR4 projections as predictors over 139 years. Bias adjustment on the simulated yields is performed similar to the adjustment procedure explained above for maximum temperatures but with a maize yield present-day climate period of 1981 to 2009. Fig. 4 shows the bias-adjusted dry-land maize yields at Witbank together with one standard deviation error bars and fitted second-order polynomial.

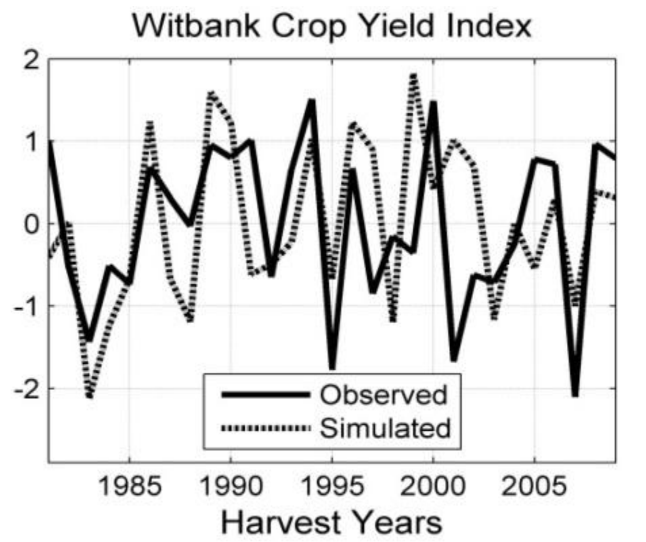

Fig. 3. Observed vs. simulated dry-land maize yield index obtained by using CCAM reanalysis DJF 850-500 hPa thickness fields as predictors in a PCR model.

The statistical procedure presented here is simulating a reduction in dry-land maize yield over the Witbank area of about two standard deviations by the end of this century – a substantial reduction in crop yield associated with the projected increase of mid-summer maximum temperatures. Such a reduction in crop yield seems realistic since the dry-land maize may need more water to keep up with increased evapotranspiration associated with increased maximum temperatures.

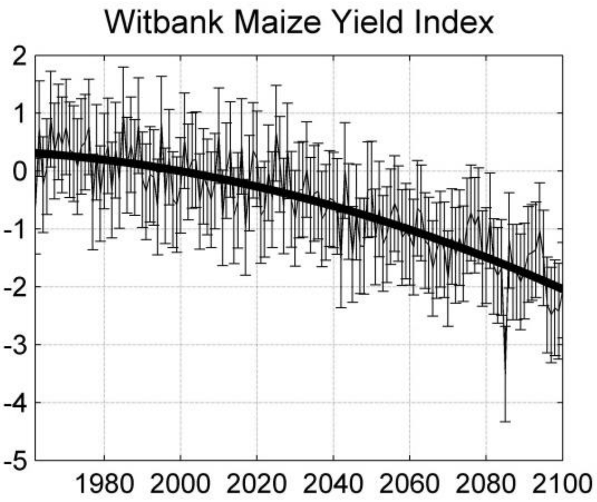

Fig. 4. Perfect prognosis projected ensemble mean of Witbank dry-land maize yields. Simulations for each year and for a fitted polynomial are presented, as well as 1-standard deviation error bars.

Conclusion

The notion of developing statistical procedures to objectively simulate commodities such as dry-land crops over multiple decades was investigated in this paper. First it was shown that perfect prognosis applied to regional climate model outputs is able to capture the models' upward trends in maximum temperatures over southern Africa during mid-summer. The simulation of crop yields over the eastern Highveld was subsequently performed and it was found that yields may be reduced by as much as two standard deviations by the end of this century. This result is of course based on the assumption that the maize cultivars are not genetically enhanced. Notwithstanding, the procedure may at least be able to provide guidance to policy makers responsible for action plans to mitigate and adapt to the impacts of increasing temperatures on dry-land maize yield.

References

Engelbrecht FA, Landman WA, Engelbrecht CJ, Landman S, Bopape MM, Roux B, McGregor JL, Thatcher M, 2011. Multi-scale climate modelling over southern Africa using a variable-resolution global model. WaterSA, 37. 647-658.

Engelbrecht FA, McGregor JL, Engelbrecht CJ, 2009. Dynamics of the conformal-cubic atmospheric model projected climate-change signal over southern Africa. International Journal of Climatology, 29. 1013-1033.

Climate Change, 2007. Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, Pachauri, R.K and Reisinger, A. (eds.)]. IPCC, Geneva, Switzerland, 104 pp.

Malherbe J, Engelbrecht FA, Landman WA, 2013a. Projected changes in tropical cyclone climatology and landfall in the southwest Indian Ocean region under enhanced anthropogenic forcing. Climate Dynamics, 40. 2867-2886. DOI 10.1007/s00382-012-1635-2.

Malherbe J, Landman WA, Olivier C, Sakuma H, Luo J-J, 2013b. Seasonal forecasts of the SINTEX-F coupled model applied to maize yield and streamflow estimates over north-eastern South Africa. Meteorological Applications, DOI: 10.1002/met.1402.

Maraun D, and 16 co-authors, 2010. Precipitation downscaling under climate change. Recent developments to bridge the gap between dynamical models and the end user. Reviews of Geophysics, 48. RG3003, doi:10.1029/2009RG000314.

McGregor JL, 2005. C-CAM: Geometric aspects and dynamical formulation. CSIRO Atmospheric Research Technical Paper, No 70, 41.

Mitchell T D, Jones PD, 2005. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. International Journal of Climatology, 25.