A framework for the simulation of regional decadal variability for agricultural and other applications

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Abstract

Climate prediction on decadal time scales is currently an active area of research. Although there are indications that predictions from dynamical models may have skill in some regions, assessment of this skill is still underway, and reliable model-based predictions of regional "near-term" climate change, particularly for terrestrial regions, have not yet been demonstrated.

Given the absence of such forecasts, synthetic data sequences that capture the statistical properties of observed near-term climate variability have potential value. Incorporation of a climate change component in such sequences can aid in estimating likelihoods for a range of climatic stresses, perhaps lying outside the range of past experience. Such simulations can be used to drive agricultural, hydrological or other application models, enabling resilience testing of adaptation or decision systems. The use of statistically-based methods enables the efficient generation of a large ensemble of synthetic sequences as well as the creation of well-defined probabilistic risk estimates.

In this report we discuss procedures for the generation of synthetic climate sequences that incorporate both the statistics of observed variability and expectations regarding future regional climate change. Model fitting and simulation are conditioned by requirements particular to the decadal climate problem. A method for downscaling annualized simulations to the daily time step while preserving both spatial and temporal subannual statistical properties is presented and other possible methods discussed. A "case-study" realization of the proposed framework is described.

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1 Introduction

Climatic shifts that might be expected over the next few decades, sometimes referred to collectively as "near-term climate change," have received increasing attention in recent years. This owes in part to the perceived difficulty of initiating adaptive responses based on the projections discussed in assessment reports of the Intergovernmental Panel on Climate Change (IPCC), which takes a century-long perspective. Rising interest within the adaptation community in the evolution of climate in the near term finds a parallel in current analyses and experiments aimed at elucidating the potential for numerical models to forecast climate variations on decadal time scales; a suite of such experiments will be described in the forthcoming IPCC assessment (expected 2013.)

Some studies of potential decadal predictability [e.g., *Boer and Lambert*, 2008] suggest that skill in terrestrial regions is likely to be low. Other research [e.g., *Teng and Branstator*, 2010] has tended to focus on oceanic variables, perhaps based on the expectation that results are likely to be more promising than those obtained for land regions. In any event, reliable near-term climate forecasts for terrestrial regions, particularly at local to regional scales, have not been demonstrated. Alternative methods for assessing near-term climate-related risks may thus have value.

One technique that can be useful in this regard involves stochastic simulation: the creation of synthetic climate sequences having statistical properties representative of a region or locality of interest. Such sequences, while not forecasts *per se,* can nonetheless help to quantify ranges of uncertainty associated with near-term climate variability. Simulations may be structured so as to incorporate estimates of long-term trends associated with anthropogenically-forced climate change (including the uncertainty in these trends). The projected climate change signal then provides a slowly-changing background state on which decadal and higher-frequency fluctuations are superimposed. Together these influences provide a better description of the expected range of near-term climate variations, and their potential impacts on statistics of interest for agriculture or other applications, than either alone. It is the generation of such sequences that constitutes the focus of the present report.

The discussion presented here constitutes an exploration of some of the practical considerations involved in generating such simulations. The general plan consists in decomposing regional climate variability into three components: A "trend-like" component that may be associated with anthropogenically-induced climate change, an annual-to-decadal component, comprising variability on those time scales, and a subannual component, including the seasonal cycle and daily variability. As will be seen, this is a tidy description of what may turn out in practice to be a less-than-tidy procedure, but it can usefully serve as a template for simulation model development.

The remainder of this presentation is organized as follows: In Section 2 we provide some theoretical background and describe the conceptual decomposition by time scale that underlies the proposed simulation methodology. Section 3 considers issues encountered in model design and specification. Section 4 presents a detailed framework for the construction of a simulation model, in light of the information presented in earlier sections. In Section 5 elements of a case study that illustrate one possible realization of the simulation methodology is considered. A discussion and summary follow in Sections 6 and 7, respectively.

2 Decomposition by time scale

Climate variability is often parsed according to time scale, the various canonical scales corresponding *approximately* to different classes of climate process. There are at least two reasons for the qualifier: First, changes in climate behavior on different time scales may not be strictly independent: there is a possibility of cross-scale influence. Second, and particularly with regard to anthropogenic "trends," the separation of such trends from low-frequency variability that may not be anthropogenic in nature is not always straightforward *Solomon et al.* [2011].

The above caveats notwithstanding, the simulation strategy to be discussed utilizes such a decomposition. The three time scales are treated quasi-independently, but without ignoring the possibility of climatic influence on annual and subannual variability. The treatment of such interaction, as well as the so-called "separation problem," are discussed in the relevant sections of the report.

2.1 Climate change

On the longest time scales to be considered are the secular climate shifts referred to as "climate change," which play out over the course of a century or longer. These time scales involve, to first order, anthropogenic forcing of the climate through changes in the radiative properties of the Earth's atmosphere. One well-known result of this forcing is the rise in Earth's surface temperature owing to the increasing atmospheric burden of carbon dioxide (CO_2) and other greenhouse gases. Because this forcing has an incremental character [see, e.g., Fig. 2.3a in *Solomon et al.*, 2007], we identify a "climate change" time scale, and associate with it slow, trend-like components in the signals analyzed.

2.2 Subannual variations

At the opposite end of the spectrum we find subannual variability, including the seasonal cycle and daily weather fluctuations. Because the chaotic nature of the atmosphere limits weather prediction to a time horizon of a week or two, daily variability is often simulated for application purposes using stochastic daily weather generators [*Wilks and Wilby*, 1999; *Wilks*, 1999]. This strategy is analogous to what we propose here for the annual-to-decadal scale, where predictability is also likely to be limited to time horizons shorter than those for which future information is desired. A brief consideration of weather generation schemes that might be utilized in conjunction with the decadal simulations is presented in Section 4.7.2.

2.3 The annual-to-decadal scale: "Near-term" climate change

The annual-to-decadal time scale occupies a nominal middle ground between the climate change and subannual (weather to seasonal) scales, and is of course central to the theme of this report. Natural climate variability on this broad range of time scales arises from a range of processes, including the El Niño-Southern Oscillation (ENSO) phenomenon, large-scale decadal "modes," filtering of "weather noise" via the large thermal inertia of the oceans, volcanic eruptions and solar variability. Anthropogenic factors such as land use/land cover changes and emissions of aerosols and certain other trace gases may also produce decadal-scale climatic responses. These processes are effective to differing degrees in different ocean basins, latitude bands and regions, resulting in a rich and complex mosaic of regionally-differentiated variability on annual and longer time scales.

For the purposes of simulation it is the net effect of all of these processes, as expressed in the region of interest, with which we will be concerned. To the extent that it is possible to attribute specific components of variability to particular climate processes, such information may be useful in informing the generation of stochastic sequences. (This applies as well to trend or trend-like behavior.) Conversely, to the extent that attribution is unclear, ambiguities may remain, that the simulation process will need to take into account.

2.4 Cross-scale dependency

A modeling issue of potential importance concerns the dependence of variability at one time scale to shifts or changes on other scales. Such dependencies are often framed in terms of the effects of slow anthropogenic climate change on the more rapidly-evolving interannual or subannual scales. One example of such a dependency is the widely-expected increase in interannual precipitation variability as climate warms, owing to the rapid increase in water saturation vapor pressure with temperature. Shifts in daily rainfall statistics, such as wet- and dry-spell lengths or precipitation extremes, that might come about as a consequence of global warming are another possibility.

In general, the dependency of decadal variations on climatic shifts is more difficult to evaluate, since longer records are required to characterize such dependencies with a comparable degree of uncertainty. There is no simple solution to this problem, but useful information may possibly be obtained from paleorecords or climate models.

3 Modeling contingencies

Issues that arise in the course of simulation design include the availability of suitable data to which to fit the statistical model, characteristics of the regional climate and the requirements of follow-on applications models. These are discussed in turn.

3.1 Data

3.1.1 Observations

If the simulations are to have realistic properties, sufficient data, of reasonably good quality and of sufficient temporal and spatial extent, must be available to fit the statistical model. The primary source of such data over land regions is weather station records, derived from measurements made *in situ*. This means that regions in which station measurements are sparse may present greater modeling challenges than those for which extensive records exist.

Satellite data are widely available but these commence only around 1979, thus are rather short for the confident characterization of decadal signals. The Atlantic Multidecadal Oscillation (AMO), for example, the primary large-scale mode of sea-surface temperature (SST) variability in the north Atlantic, exhibits what appears to be oscillatory behavior (Fig. 1), but the period of these "oscillations," 65-70 yr, is so long compared to the length of the observational record (here 139 yr) that periodicity cannot be confidently diagnosed. (Thus the more general designation, Atlantic Multidecadal *Variability,* that is sometimes applied.) From the satellite perspective, i.e., beginning in 1979, the series has the appearance of an upward trend, with little suggestion of oscillatory behavior.

3.1.2 Paleodata

Given the limited length of many observational records, one can imagine a role for paleoclimate data, which may extend hundreds of years or more into the past. Tree-ring reconstructions were used, e.g., by *Prairie et al.* [2008], for stochastic simulations of Colorado river streamflow. The paleorecord in that case shows evidence of "megadroughts" — dry epochs whose lengths greatly exceed those in the historical record. Beyond the obvious requirement that suitable paleorecords, applicable to the

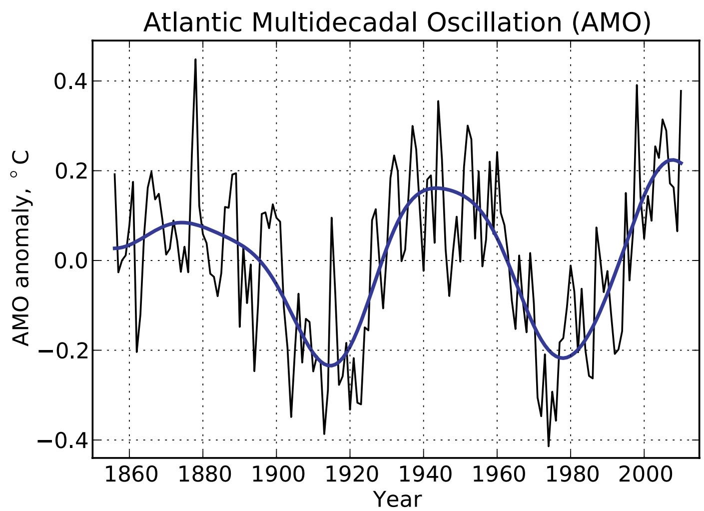

Figure 1: Atlantic Multidecadal Oscillation (linearly detrended) as computed using the Hadley Center HADISST v 1.1 SST data, and a lowpass-filtered version, generated with a filter having a half-power point at period of 30 yr.

region under study, must be available, the introduction of such data raises calibration and other technical issues. If these can be resolved in a satisfactory manner, appropriate paleodata may prove of value in the characterization of decadal variability. (Tree-ring evidence was considered for the case study discussed in Section 5, but coverage in that case was deemed insufficient.)

3.1.3 Spatial coverage and domain size

Training data for the statistical model should be representative of the locality or region for which simulations are to be generated. However, these data also serve to characterize regional low-frequency variability. If the "region" under consideration is too small, any low-frequency component that is present may be masked by the relatively larger local variability in the record. Decadal-scale processes tend to have relatively large-scale footprints. Modeled regions should be of sufficient spatial extent to capture such fluctuations, while also remaining representative of the study area for which simulations are to be generated.

If the region of interest is climatically coherent it may be reasonable to model its spatially-averaged variables directly. (This procedure is followed in the case study.) However if sufficiently extended it may be preferable to prefilter the data in terms of empirical orthogonal functions (EOFs), modeling instead a subset of the expansion coefficient time series. This would permit the statistical model to capture behavior having more complex spatial signatures while also increasing the signal-to-noise ratio in the modeled data. In the more detailed discussions that follow we offer a conceptual description of such a strategy.

3.2 Regional climate characteristics

We review here the three time scales referenced in Section 2, from a general modeling-based perspective.

3.2.1 Trends and trend-like behavior

Trends represent nonstationarity in the mean: a local average, changing with time, around which decadal and higher-frequency signals fluctuate. Even if the character of these fluctuations changes little, a persistent trend will eventually bring about the occurrence of climate anomalies lying outside the range of the observational past. An agriculturally-significant maximum temperature threshold may be crossed more and more often as climate warms, for example or a critical number of consecutive frost days may be exceeded less and less frequently. The inclusion of trends in simulated sequences is thus essential from the estimation-of-risk perspective.

Observed trends may tell us something about regional sensitivity to anthropogenic forcing, particularly with regard to temperature. However the warming observed during the 20^{th}century has not been large, compared with that expected for the future. In addition, certain anthropogenic inputs, such as aerosol or ozone forcing, may change in the future in ways that are not reflected in the 20^{th}-century record. For these reasons it may be useful to also consider what climate models may have to tell us regarding future temperature and precipitation trends.

A possible third source of information is the body of theoretical work that has developed in regard to future climate expectations. The expectation that global warming will bring about in a poleward shift of the dry subtropical zones and midlatitude storm tracks, for example, preconditions the discussion and may tilt the balance in favor of accepting, or at least entertaining, a projection that is consistent with such an outcome.

3.2.2 Systematic vs. random variations

We model annual-to-decadal variability as a combination of what can loosely be termed "systematic" and "random" variations. In practice this means that we adopt, as a random climatic background, the first-order autoregressive, or AR(1) process. Because the model may comprise more than a single variable this background may be multivariate. Signal components that demonstrably do not conform to the AR(1) model are then defined as "systematic."

Given the wide range of random process types from which one might choose, there would appear to be a degree of arbitrariness in the way this distinction is drawn. The AR(1) structure seems appropriate, however, because it is the simplest such process having "memory," and because it requires few assumptions about underlying physical mechanisms. As noted earlier, the AR(1) response can arise simply as a result of random high-frequency "weather noise," forcing a sluggish, high-inertia ocean, this in fact being the paradigm for the generation of low-frequency stochastic variability in middle and high latitudes. It is not accidental that AR(1) noise is often taken as the classical "null hypothesis" for oceanic variability in these regions [*Deser et al.*, 2010].

It is important to note that in some situations climatic variations may follow "regime-like" behavior. Such behavior is characterized by states having residence times that are "long," compared with the time required for state-to-state transitions. Such behavior might occur on the subannual scale, for example, in connection with transitions among a set of "weather states," or regimes, and state-based models have been utilized to good effect for the purposes of downscaling [*Greene et al.*, 2008, 2011]. It may be difficult to distinguish between "regime-like" and "wave-like" systems: there is not a sharp break but rather an infinite range of gradiations between the two types of behavior [*Rudnick and Davis*, 2003; *Overland et al.*, 2006]. Ultimately, if it is clear that the system to be modeled is in fact regime-like on the annual-to-decadal scale, a state-based model may prove more appropriate than one based on the systematic/random dichotomy described above. This sort of model is exemplified in the streamflow simulations of *Prairie et al.* [2008].

Aside from the low-order physical justification, use of the AR(1) process clarifies the modeling framework, by providing a baseline statistical structure with which climate records that are candidates for simulation may be compared. Rejection of the AR(1) null hypothesis is then taken as evidence for the existence of a "systematic" signal. Such a signal would require either a reconsideration of the basic structure of the data, or possibly an independent submodel, in the same way that seasonality requires its own submodel when analyzing data containing seasonal effects: The seasonal cycle is not AR(1). A modeling framework consistent with the systematic/random paradigm, wavelet autoregressive modeling (WARM) is described by *Kwon et al.* [2007, 2009].

3.2.3 Subannual variability

Seasonality is a significant factor in many, if not most, regions. In the simulation context it may useful to model only the rainy season, since this is likely also the growing season and outside this window little significant precipitation may occur. A variety of daily weather statistics, including distribution shape, extremes and spell lengths, for both temperature and precipitation, may be at issue, and the daily component of a complete simulation scheme should attempt to account for these.

Since the simulation context is malleable and dependent on setting, it may prove desirable in some cases to produce simulations that are not daily-resolved. Agricultural models typically do require daily values of climate parameters, but there may already be an extant daily simulator (weather generator), for example, tuned to the localities of interest and designed to accept monthly mean values as inputs. In such a situation the simulation model can be modified so as to generate monthly sequences, for subsequent use driving the weather generator.

3.3 Follow-on modeling requirements

Ultimately, it is the application model that determines whether simulations need extend to the daily time step, and which data are to be simulated. If required variables have not been recorded, empirical rules, perhaps based on data from similar sites, may have to be devised in order to obtain useful values. An example would be the creation of two insolation distributions, for wet and dry days, in the case that adequate primary data are not available. Insolation values would then be sampled from these distributions conditional on the occurrence of rain, as generated by the core simulation model.

In some cases, such as the Colorado River streamflow mentioned earlier, univariate simulations suffice: The single parameter encodes sufficient information for inference concerning relevant "downstream" impacts. In others, such as the case study to be described, multivariate simulations are required; intervariable correlation on annual and longer time scales then becomes an important simulation target. Follow-on models will also play a role in determining simulation statistics of interest, and thus the generation of simulation ensembles.

3.4 A note on modeling philosophy

As with many statistical models, the machinery of simulation provides many "knobs" that the experimenter can turn at will, generating in the process a potentially very wide range of outcomes. We believe that it is most sensible, given such a choice, to focus on climatic shifts that external evidence informs us are likely to occur, or whose occurrence are supported by theoretical arguments. Otherwise the risk exists of generating scenarios that have little probability of actually occurring. In effect this is simply a recommendation for the principle of parsimony.

4 The simulation model

4.1 Overview

Model development is keyed to the decomposition by time scale (or more or less equivalently, process class) discussed in Sec. 2, as conditioned by the contingencies discussed in Section 3. These include the availability of observational training data, requirements of agricultural or other follow-on models and the characteristics of regional climate variability. We note here the ways in which these contingencies affect the development of a suitable model.

Model requirements may be expected to differ from setting to setting, and design must adjust accordingly. What is common is the separate treatment of trend, annual-to-decadal and subannual variability (considering possible cross-scale interactions), the introduction of climate information beyond that embodied solely in the datasets employed, and the use of an AR(1) model as random background on the annual-to-decadal time scale, against which systematic variations play out.

4.2 Treatment of trend

First, we require a *detrending* procedure, to remove the estimated forced response from the observational data on which the decadal component of the simulation model is to be trained. Second, in the simulation step we require an estimate of how mean process levels will evolve in the future. Past and future trends need not be the same.

There are many options available for fitting both linear and nonlinear trends to time series, the simplest perhaps being the straight line fit. Such a line can be extrapolated, providing a trend for the future. However, past and future trends may differ, rendering such an approach questionable. The use of nonlinear trends, using exponential or other parametric forms, does not address this problem. Further, trends computed as a function of time alone have no *physical* underpinning, being essentially numerical in nature.

We propose instead to parameterize trend in terms of *regional climate response* to global temperature change: Since we associate anthropogenic trend with warming of the planet (so-called "greenhouse warming"), we model local trends in terms of a linear association with global temperature change: In the absence of anthropogenic forcing the globe does not warm and future trends are null. We utilize a model representation of the global mean temperature, solving both past and future trend problems at once: 20^{th}-century model values are used for detrending and 21^{st}-century values for projection, harmonizing the response across centuries. The planet is not expected to warm uniformly; modeling local trends as dependent on the global mean temperature takes such spatial variation into account.

For local *temperature* we model both past and future trends based on the assumption that it is the spatial pattern of temperature dependence, rather than the local rate of warming, that is stationary. Thus, regional or local temperature trends are regressed on a global mean temperature signal, according to

$$T_r = \beta_0 + \beta_1 T_g, \tag{1}$$

where T_r is the regional or local temperature record, T_g is a multimodel-mean, global mean temperature signal, β_0 is an intercept term and and β_1 represents the regional response to global temperature change. The fitted values $\hat{T}_r$ are used to detrend the observed temperature record, while the β_0 and β_1 are used to project local temperature forward, based on the future global mean temperature signal. The multimodel-mean global mean signal used as regressand is derived from an ensemble of GCMs participating in a recent IPCC Assessment Report.

The assumption of a consistent relationship between both past and future local temperatures and the global mean temperature can be verified in the GCM domain. If the climate models do not confirm such consistency the modeler will have to consider the available information and make a reasoned choice about how to proceed. In the case study, temperature, but not precipitation trends were found to behave consistently across centuries. The manner in which this inconsistency was resolved is illustrative, but not comprehensive, since many types of behavior may be possible.

The global temperature signal used as regressand is shown in Fig. 2. To obtain this series the global mean temperature records for the 20$^{\text{th}}$ and 21$^{\text{st}}$ centuries from an ensemble of 14 GCMs from the Coupled Model Intercomparison Project (CMIP5) were first concatenated into records spanning the years 1901-2095. Each GCM's record was then smoothed, using a Butterworth filter [*Smith*, 2003] of order five, having a half-power point, or "cutoff," at a period of 10 yr. (Results are not sensitive to the particular method of filtering.) The plot shows the average of the 14 smoothed series thus obtained.

Internal variability is intrinsic to each of the GCMs but is largely incoherent among them. Averaging thus acts to suppress this variability, while enhancing that part of the signal that the GCMs have in common — that of climate change. Thus, model averaging enhances the climate change signal while attenuating "internal variability noise." The filtering further smooths this signal, suppressing residual high-frequency variability and short-lived transients such as the effects of volcanic eruptions (although the latter are still discernible in Fig. 2, and may be reflected to a modest degree in inferred 20$^{\text{th}}$-century trends). Volcanos are treated here as unpredictable external forcing, unrelated to climate; no attempt is made to simulate their future effects. The simulations thus produced may be considered as representing a volcano-free perspective on the next few decades.

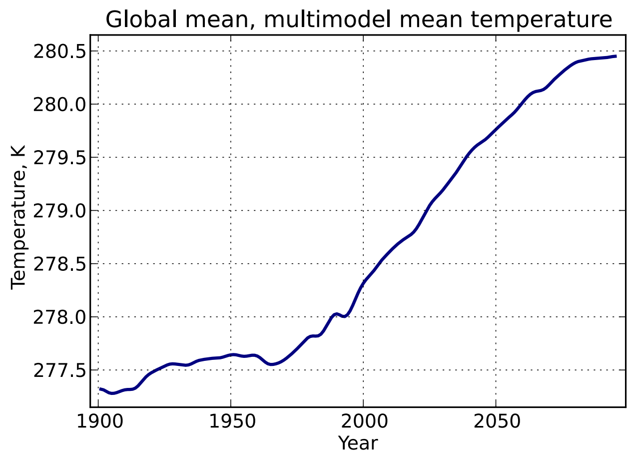

Figure 2: The smoothed global mean, multimodel mean temperature time series used as regressand in the detrending of observations and for the projection of future trends.

When local or regional signals are regressed on the series of Fig. 2, the fitted values, now representing the local or regional climate change trend, appear as a scaled and shifted version of that series. This process and its result are shown in Fig. 3, where we have taken as an example the AMO signal described earlier. The original signal is shown in panel (a), along with the fitted trend, which appears as a scaled and shifted version of the the curve shown in Fig. 2. Note that this trend, although linearly dependent on the global mean temperature signal, is not linear in *time.* In particular, because the globe has warmed (in GCMs, but also in reality) more rapidly toward the end of the century, the trend accelerates during this period. The effect is that a greater portion of the AMO signal is assigned to anthropogenic causes than would be the case if the AMO were linearly detrended. The ability to follow changes in the planetary response to anthropogenic forcing is what gives this detrending method its appeal.

Residuals from the regression fit of the AMO to global mean temperature are plotted against time in Fig. 3b. The curve exhibits large interdecadal swings, of peak-to-peak amplitude $\sim$0.4°C. This slow "oscillation" identifies the AMO signal as one of the principal large-scale modes of *decadal* climate variability. It can also be seen that fluctuations are not limited to the multidecadal band, but comprise considerable year-to-year variation as well. Thus, the "annual-to-decadal" component in this case includes variability on multiple time scales.

The response of precipitation to changes in global mean temperature has an important indirect component, in that it depends not just on shifts in temperature but also, an possibly in a significant way, on changes in atmospheric circulation. Thus,

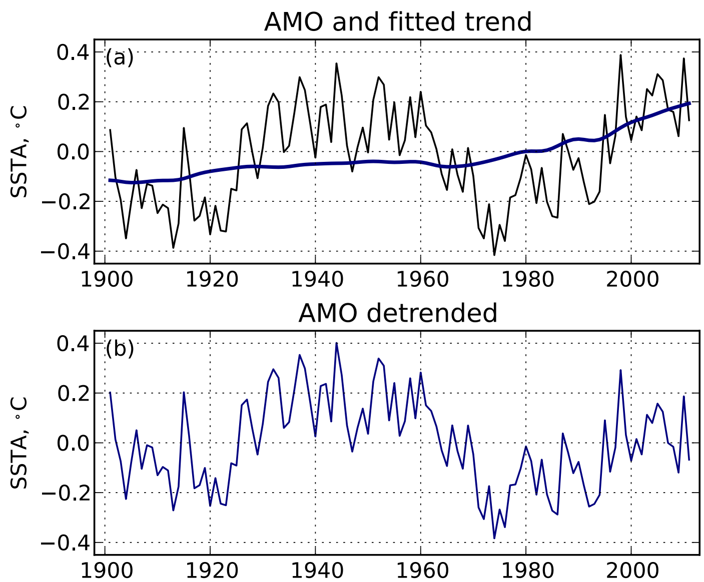

Figure 3: (a) The raw AMO time series (Kaplan SST data) and a fitted trend computed by regression on the global mean temperature signal shown in Fig. 2. (b) Residuals from this regression, representing the "natural" component of variability.

projecting forward the results of a 20$^{\text{th}}$-century regression is a less certain enterprise than is the case with temperature. Additional evidence, in the form of GCM simulations, attribution studies or detailed model experiments may be helpful in informing the modeler's judgment in this case. *Shin et al.* [2010] present an attribution study along these lines. Ultimately it may be prudent to provide explicit uncertainty bounds when projecting trend.

4.3 Treatment of "systematic" components

The objective now is to fit a statistical model to time series that correspond to what is shown in Fig. 3b for the AMO — detrended sequences comprising a possibly wide spectrum of variability on periods of one year and longer. If the data is determined to be regime-like, a hidden Markov model or some elaboration thereof might be considered [e.g., *Norris*, 1997]. Such models are based on the idea that the underlying process is governed by transitions between well-defined "hidden states," that can be inferred via the observations. The strategy followed here is not state-based, but follows instead the systematic/random signal decomposition described in Section 3.2.2, by testing the candidate series against a red-noise null hypothesis.

4.3.1 Wavelets

Wavelet analysis [see, e.g., *Mallat*, 1999] provides a way of examining variability in both the time and frequency domains simultaneously. The wavelet decomposition, or spectrum, as applied to a time series, is represented by a two-dimensional plot showing time along the x-axis and period (as in the period of an oscillation) on the y-axis. Examination of the spectrum reveals intervals or times when the signal variance was high in particular frequency bands, while a time-averaged summary, the "global" wavelet spectrum indicates whether frequency-specific behavior differs significantly from AR(1) noise, the criterion we utilize for differentiating systematic from random variability. An example will illustrate the principle.

Figure 4 shows a wavelet decomposition of the NINO3 SST index [*Trenberth*, 1976], with Figs. 4a, 4b and 4c showing the NINO3 time series, the wavelet spectrum and the global wavelet spectrum, respectively. In the last of these three plots, the dotted line indicates the 10% red noise significance level. Spectral power exceeds this level in the ENSO band, corresponding to periods of roughly 2-8 yr, meaning that the probability is less than 10% that ENSO-band signal variance represents the expression of an AR(1) process. A red-noise model would therefore not suffice for the generation of NINO3 simulations. By our definition, a systematic component has been detected in the data.

Figure 4 also shows that activity in the ENSO band has not been constant over time, with a period of relative quiescence between about 1920 and 1960. Assuming that systematic NINO3 variability can be modeled with a higher-order stochastic model of some sort, the modeler is now faced with a question: On which period should the NINO3 model be trained? Such a model might be based on the "active" periods in the record, resulting in a relatively vigorous simulated ENSO. Alternatively, the "quiet" period could be modeled, resulting in simulations having relatively weak ENSO variability. A second-order model might also be utilized, in which ENSO activity is amplitude-modulated on multidecadal time scales. In the latter case a decision would be required regarding the modeling of transitions between strong and weak ENSO phases: Should a regime-like model be used, or one in which transitions are more gradual? More generally, does the data permit differentiating between these alternatives?

Because future climate behavior is at issue, a role is suggested for GCM-based information, that might help inform the modeler's decision. GCMs exhibiting realistic ENSO variability tell us only that anthropogenic influence on ENSO in the coming century is likely to be weak [*Coelho and Goddard*, 2009]; the best alternative might thus be to include both strong and weak variability, in a model in which transition characteristics are to be determined.

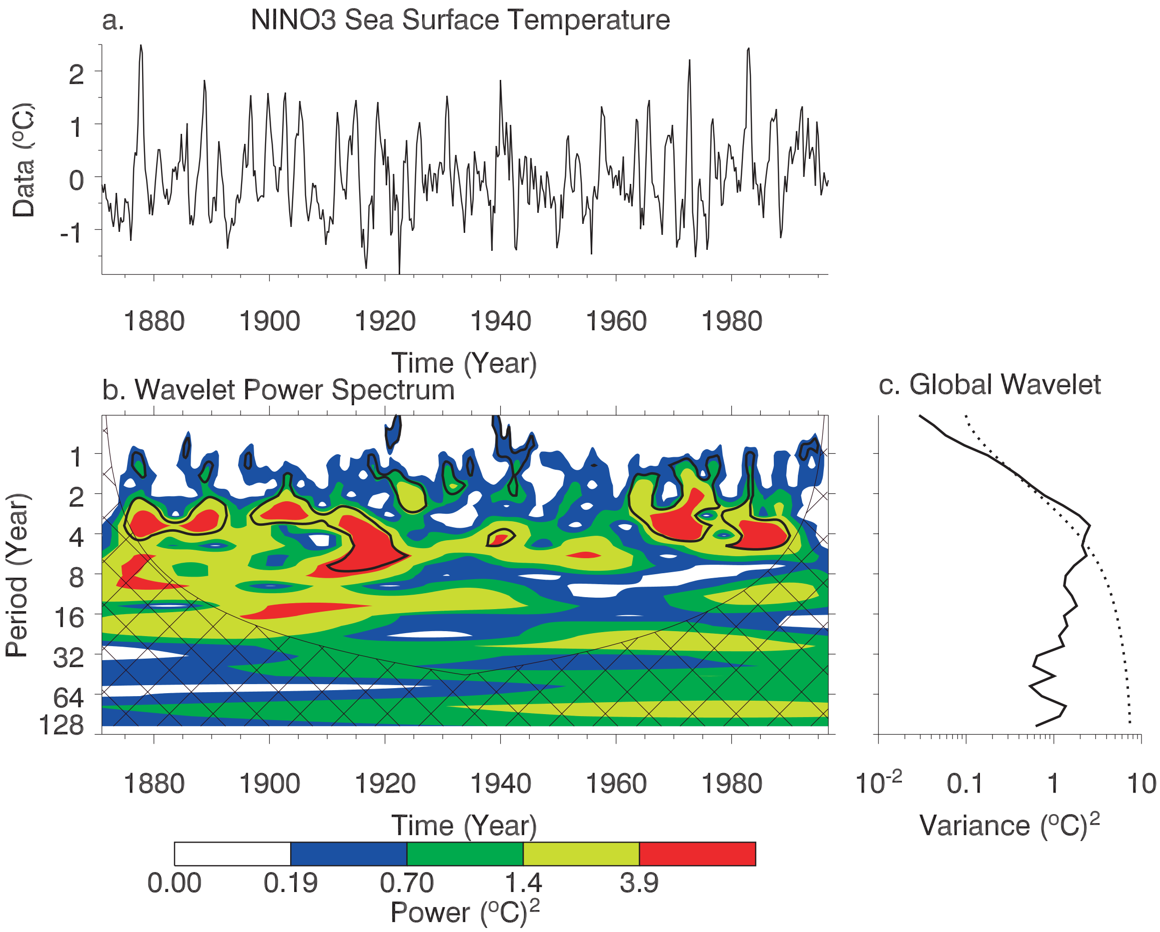

Figure 4: Time series plot of the NINO3 index (a), wavelet spectrum (b) and global wavelet spectrum (c), showing the 10% significance level for a red noise process. This is a spectral decomposition of the signal as a function of time, which appears on the abscissa. Period appears on the ordinate and spectral power is indicated by colors (i.e., levels) on the plot. The 10% significance level is indicated in (b) by black contours and in (c), which averages the spectrum over time, as a dotted line. ENSO variability in the 2-8 year band, as defined by this metric, differs from red noise at the 10% significance level. Analysis courtesy of http://paos.colorado.edu/research/wavelets.

4.3.2 Representation of systematic components

An objective method for decomposing signals using wavelets, identifying components that differ significantly from a red noise background, modeling those components individually as low-order autoregressive processes and combining results in order to generate simulations is known as wavelet autoregressive modeling (WARM) [*Kwon et al.*, 2007, 2009]. Such a method is inherently consistent with our systematic/random decomposition. *Kwon et al.* discuss only univariate series, but extension to the multivariate case should not pose a significant obstacle to implementation. Thus, the combination of WARM with the other elements described herein could constitute a complete "toolkit" for the generation of stochastic decadal simulations.

Another option, also utilizing a sophisticated red-noise significance test, is Monte Carlo singular spectrum analysis (MCSSA) [*Allen and Smith*, 1996]. The resulting spectral decomposition also resolves the target signal into systematic and random (red noise) components; the former can be projected forward using a technique called linear predictive coding [*Press et al.*, 1986-1992], while the multichannel variant of SSA (MSSA) offers an extension to the multivariate case. These methods are perhaps more appropriate when it is believed that the systematic component is at least quasi-periodic.

As suggested in Section 4.3.1 a systematic component such as that represented by the 2-8-year band in the NINO3 series might possibly be represented by a stochastic model of higher order than AR(1). *Kwon et al.* claim that the WARM decomposition performed better than a single model fit to those time series with which they have experimented, but for a given series this is a testable hypothesis, and in some cases a single model might provide a parsimonious alternative to WARM, in which every frequency component exceeding the global significance level is assigned its own model.

4.3.3 Oceanic variability and predictability

Since the source of much low-frequency variability is believed to reside in the oceans, predictability studies have tended to focus on oceanic variables, typically SST or upper ocean heat content [*Knight et al.*, 2005; *Newman*, 2007; *Teng and Branstator*, 2010]. Although such studies may be informative, for the purpose of simulating terrestrial variations it is ultimately necessary to deconstruct and model them directly. The degree to which oceanic signals are effectively communicated, via atmospheric teleconnections, lies beyond the scope of the present report, but in general it appears that such signals are diluted in transmission, rendering terrestrial decadal predictability weaker than that for the oceans. *Teng and Branstator* [2010] report extratropical Pacific SST predictability of just a few years. Given dilution of the predictable signal in transit, the potential for introducing a true predictive element into the stochastic simulations may be limited. The decadal hindcast experiments that are being performed in conjunction with the next IPCC report, part of the Coupled Model Intercomparison Project (CMIP5), will shed light on the skill with which current-generation GCMs are able to predict terrestrial decadal variations [*Goddard et al.*, 2012].

4.3.4 Range of possible models

Evidently, systematic behavior can assume many forms, this being one reason that a definitive formula for decadal simulation cannot be specified *a priori.* If, however, as suggested by WARM modeling, most systematic elements can be represented, for the purposes of simulation, as the sum of low-order autoregressive components, the minimally-sufficient model class would be limited to a reasonably small set. Application in a variety of simulation settings will help to delimit this class. We note in passing that the reports of *Kwon et al.* focused on the simulation of nonlinear elements, without specifically addressing regime-like behavior.

4.4 Treatment of random components

By construction, that part of the target signal not identified as systematic does not differ significantly from AR(1) noise. An AR(1) model is thus taken here as a basis for the random simulation component. Since this process has *memory*, it can generate "slow" fluctuations, including potentially long spells above or below the mean (if the autoregressive parameter is large enough). However, although such processes may meander up and down, they are not periodic: The AR(1) spectrum has no peaks.

Because agricultural or other applications models typically require multivariate input, we consider a natural generalization of the AR(1) model, the first-order vector autoregressive, or VAR(1) model:

$$\mathbf{y}_t = \mathbf{A}\mathbf{y}_{t-1} + \mathbf{u}_t, \tag{2}$$

where $\mathbf{y}_t$ is the process vector at time t, $\mathbf{A}$ is a matrix of coefficients and $\mathbf{u}_t$ is a stationary white noise process with expectation $\mathbf{0}$ and covariance matrix $\Sigma_u = E(\mathrm{u}^\mathrm{T}\mathrm{u})$. Note that this is completely analogous to the univariate AR(1) model, the difference being that scalars have been replaced with vectors (or in the case of $\mathbf{A}$, by a matrix). The process represented by (2) represents not only serial autocorrelation but also first-order lag correlations across variables.

4.5 A nonparametric alternative

Nonparametric resampling techniques such as the k-nearest-neighbor (k-NN) method [*Lall and Sharma*, 1996; *Rajagopalan and Lall*, 1999] offer a possible alternative to (parametric) stochastic models for the annual-to-decadal component. The k-NN method can in theory account for serial correlation in the data, and because it "blindly" mimics the target series without parametric constraints it is capable of generating simulations with distributional properties that might be difficult to reproduce with parametric methods. Using such a scheme it might even be possible to dispense with the disaggregation into systematic and random components, regenerating the statistics of the complete annual-to-decadal signal via resampling alone. Depending on the complexity of the target series, the method may require a large training set for reasonably precise replication of desired statistical properties. Experimenting with such methods may prove worthwhile, however.

4.6 Reassembly

In generating the simulated sequences the decomposition process is reversed: The trend and annual-to-decadal components are simulated individually and the results then combined. In Section 3.1.3 we mentioned two possibilities: Treatment of the primary climate variables averaged over the simulation domain and prefiltering in terms of EOFs. Details will depend on which of these alternatives is adopted.

If domain-averaged variables are utilized there will exist both a trend model and a stochastic simulation model for the annual-to-decadal component, both applicable to the domain as a whole, Both the projected trends and the simulated variability will presumably be multivariate; they are combined variable by variable, resulting in a regional-scale simulation that is temporally complete down to the annual level. This simulation will then be propagated to locations within the domain, effecting a spatial downscaling on the annual-to-decadal level.

Prefiltering in terms of EOFs implies a domain of sufficient extent so that climate variability is better described in terms of patterns, as opposed to simple regional averages. Subject to experiment, detrending may be performed either at the local level prior to computing EOFs or on those of the principal component (PC) time series having significant trends. In either situation the relevant signals are regressed on the global mean temperature record, as with regionally-averaged variables. Operating on the PCs implies a stationarity assumption on intervariable trend covariance, establishing an internal control on future projections, but also may be viewed as entangling temperature and precipitation trends, thus enforcing a relationship that may or may not be appropriate for the coming century.

As in the case of regionally-averaged variables, there will exist a model, or models, for annual-to-decadal variations, now applicable not to the regional climate variables but to those PCs that are retained as being statistically significant. Systematic, then random components would then be simulated and combined as before, again resulting in a simulation that is temporally complete down to the annual scale. However the simulations in this case would already be spatially disaggregated down to the local scale (i.e., the spatial scale of the data on which the EOFs are computed).

4.7 Downscaling

The resultant of the "reaggregation" procedure described in Section 4.6 is a simulation resolved at the annual level. If domain-averaged climate variables have been utilized the simulation will apply to the region as a whole; if prefiltering by EOFs, the simulation will be expressed at individual locations, being already downscaled at the annual time step. In the latter case it is presumed that only a small number of EOFs/PCs are retained, according to some test of statistical significance (typically a "stopping rule" in the case of PC analysis). Variance at individual locations will then have to be increased if it is to match that of the local signal being simulated. Since the "discarded" PCs are assumed to represent noise, the missing variance can be consistently supplied by adding uncorrelated noise at each location.

In the case that domain-averaged climate variables are modeled there will be a single (multivariate) simulation for the entire domain. This may be propagated to individual locations via linear regression, again adding uncorrelated noise to bring simulation variance into agreement with what is observed at the location.

For either of the above strategies the result at this stage will be a fully spatially-resolved simulation that incorporates both expected climatic trends and variability down to the annual level. Assuming that daily values will be required in the final simulation product, what remains is to disaggregate the annually-resolved signal to the daily time step. In doing so several data characteristics must be respected: First, the annual values generated by the simulation procedure up to this point must be reproduced. Second, spatial covariability at the daily level must be preserved. Note that this is in addition to the spatial coherence imposed at the annual-to-decadal level. Third, to the extent possible, future behavior with respect to significant characteristics of daily variability, such as spell lengths and extremes, should be anticipated.

4.7.1 Resampling

Use of a nonparametric scheme, with specific reference to k-NN, was mentioned as a means of simulating annual-to-decadal variability. Use of such a method is also feasible for the simulation of daily variability. Spatial coherence may be preserved by resampling the entire domain at once. However literal resampling of the observational data will result in discrepancies in annual values, since the available set of observational records is finite and will not in general comprise exact matches with the imposed simulation values. An additional shortcoming arises in the case where climate change measurably shifts the range of simulated values with respect to the range of the observational data. In this case there may not exist, in the observational record, values that are representative of the simulation. Resampled observations may be rescaled to match the imposed simulation, but this may have the undesirable effect of distorting daily distributions (of precipitation, for example). Moreover, rescaling does not account for potential changes in spell lengths. In spite of these shortcomings resampling methods may be acceptable in some circumstances. A k-NN scheme is utilized in the case study.

4.7.2 Weather generators

Stochastic weather models offer an alternative means of generating daily weather sequences that are consistent with stochastic decadal simulations of interannual variability. The input parameters of a stochastic weather generator can be manipulated to reproduce synthetic weather having the statistical properties of interest. This approach is often used to provide daily weather inputs for agricultural or hydrological models for climate change impact studies, based on GCM or RCM simulations of future climate.

Changing individual parameters can have unintended consequences on the statistical properties of simulated weather sequences because of the dependencies in time and among meteorological variables. For a class of relatively simple, parametric stochastic weather models, work by *Wilks* [1992]; *Katz* [1996] and *Mearns et al.* [1997] are illustrative, and provide useful guidance on how to adjust parameters to approximate (with sufficient replication) target statistics.

Adapting this approach to stochastic decadal simulations would be more complex than adjusting parameters to capture the statistics of a future climate: First, to capture trends and multi-decadal variability, the parameters would need to be adjusted for every year of each realization of the stochastic decadal simulation. Second, because stochastic weather models have their own interannual variability (although most tend to under-represent it), superimposing generated daily weather sequences on stochastic decadal simulations without correction would inflate the variability (in time and among realizations) of annual statistics and the uncertainty of the modeled agricultural impact.

A more promising approach is to constrain the generated daily sequences to match target monthly or seasonal values. Generated temperature data can be rescaled to match a target mean through a simple additive shift. To avoid unrealistic combinations of rainfall frequency and intensity, rainfall can be constrained to a target value by iteratively sampling and testing generated sequences for a target period (e.g., month or season) until the total is acceptably close to a target value, then rescaling to exactly match the target [*Hansen and Indeje*, 2004; *Kittel et al.*, 2004; *Hansen and Ines*, 2005]. Advantages of this approach are: (a) it is easier to implement since it doesn't require complex parameter adjustments or a large number of replicates each year, (b) it would not inflate the variability of the stochastic decadal simulations, and (c) variation in rainfall frequency and mean intensity would be more realistic. *Hansen and Ines* [2005] describe an implementation built on the stochastic weather generator distributed with the DDSAT crop modeling suite.

4.8 Additional considerations

Although the simulation model can be fit to annual mean values, this is not necessarily optimal. The rainy season, for example, may cross the calendar boundary from one year to the next, so it might be more sensible to define a hydrological year that differs from the calendar year. Modeling annual values for a specified season less than 12 months in length may also constitute a useful strategy, perhaps utilizing climatology for the portion of the year not simulated explicitly. In general simulation design will be constrained by follow-on modeling requirements.

We have assumed that simulations will be downscaled to daily time resolution, but this may not always be required. Some hydrological applications, such as reservoir management, may function as well using monthly values. The strategies outlined above should be amenable to generating monthly outputs, if these are desired.

A resampling method, used for downscaling to the daily level, may implicitly encode some dependence between climate change (i.e., trend) and subannual scales, via the the selection of "neighbors" from which the resampled statistics are ultimately drawn. Weather generators may include such linkages explicitly. However we have not described a mechanism for linking changes in climate to variability on the annual-to-decadal scale. An example of such a link would be an increase in interannual precipitation variance as global temperature increases. Such dependencies can be investigated with the aid of GCMs and, if deemed significant, incorporated explicitly in the simulation model.

4.9 End product

The end result of the above steps is a set of daily-resolved simulations that are spatially resolved at the station or gridbox level (depending on the nature of the training data). These simulations will include trends that may vary over the domain and that have been informed by observational data and/or GCM simulations of future climate, and possibly theoretical expectations regarding future climatic tendencies. Variability on both the annual-to-decadal and daily time scales, including spatial coherence over the domain, should approximate that represented by the observations, again as informed by information from GCMs and theory (insofar as the modeler has chosen to incorporate particular inferences in the simulation code).

It will evidently be worthwhile for the modeler to validate the simulations, to verify that statistical properties are as expected. This can be accomplished through the usual statistical comparisons, in particular using simulations of the observational period. Assessments of simulation-model adequacy must take into account the degree to which any deficiencies identified are actually material with respect to eventual application.

Finally, sequences can be generated that explore a range of plausible climatic futures for the region of interest. Since all of the variability is model-generated it becomes possible to quantify the likelihood of particular outcomes, either by direct computation or by the analysis of simulations, in the case that the model incorporates nonparametric elements. When translated, for example, into crop yields, through the agency of an agricultural model, results should prove useful for purposes of planning or adaptation. This is the motivation for the methodology described in this report.

5 Elements of a case study: The Berg and Breede Water Management Areas, Western Cape, South Africa

The ideas and methods presented herein represent an attempt to generalize some lessons learned from both the implementation described in *Greene et al.* [2012] and ongoing work in implementing the method in other regions, including southeastern South America and parts of monsoonal Asia. We abstract here certain elements of the first of these implementations, to show how the framework described in the foregoing sections might be realized in a specific regional setting and application-model context. The treatment here is abbreviated; the reader is referred to *Greene et al.* for additional information. The code used to generate the subject simulations, along with a user guide, is available for download; see Acknowledgments for details.

5.1 Setting

The study region (Fig. 5), located in the Western Cape province of South Africa, comprises the Berg Water Management Area (WMA) and parts of the Breede WMA and covers ~19000 km^2. The Berg and Breede rivers drain into the Atlantic and

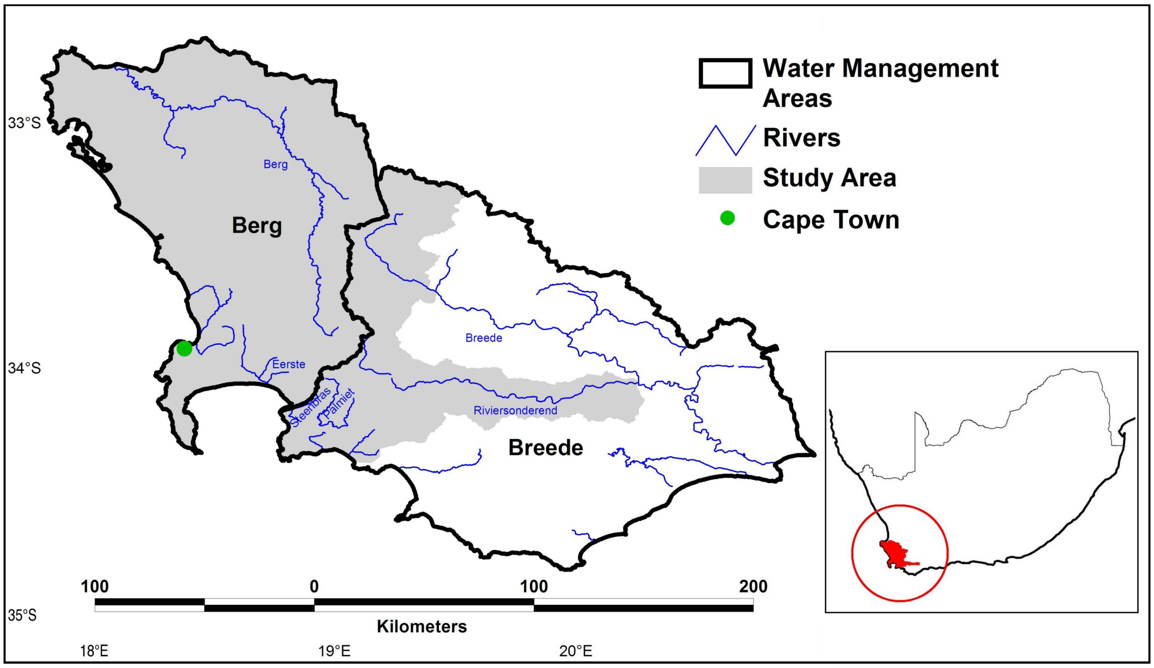

Figure 5: The study area. Inset map shows location within South Africa. Reproduced from *Greene et al.* [2012].

Indian oceans, respectively, but there are interbasin transfers and the two WMAs are managed as an integrated system.

In addition to economically-significant agriculture, the WMAs provide water for industrial use and constitute the principal source of supply for the city of Cape Town (Fig. 5). Urban water demand has steadily increased over the last three decades, tripling since the late 1970s, while there is a moderately strong consensus among the IPCC models [see, e.g., Ch. 11 in *Solomon et al.*, 2007] that the region will dry in coming decades, with rising global temperatures. The combination of economic importance (in large part attributable to the production of high-value crops), rising urban demand and potentially decreasing supply has motivated intensive study and modeling of the region's water resources. *Greene et al.* [2012] constitutes a part of this effort.

An agrohydrology model developed at the University of KwaZulu-Natal (Pietermaritzburg, South Africa), denoted ACRU [*Schulze*, 1995; *Smithers and Schulze*, 2004] has been used to model the WMAs. The simulations to be described were designed to drive this model, the considerations ranging the use of input data keyed to subcatchments within the WMAs and the simulation of a minimally-required suite of input variables, to the detailed file formatting requirements of ACRU. As the designation suggests, ACRU represents not only basic hydrological responses such as runoff and soil moisture, but also includes some crop modeling capabilities. Further along in the chain, a general equilibrium economic model, developed at the UNEP Risø Centre on Energy, Climate and Sustainable Development (Roskilde, Denmark), is being used to assess potential economic impacts of the modeled climate fluctuations. It is worth noting that the existence of a comprehensive follow-on modeling framework is synergistic with the production of simulated climate sequences: It energizes and guides the generation of the simulations while also benefiting from them, in the context of an integrated approach to impact assessment.

5.2 Data

5.2.1 Observations

The WMAs have been mapped into 171 quinary-level catchments, for which a daily dataset spanning the years 1950-1999, including precipitation and maximum and minimum daily temperatures (pr, Tmax, Tmin), was available. These three variables represent the minimal set required for driving ACRU. The annual-to-decadal simulation model is based on a multivariate "regional" signal consisting of the catchment-averaged variables, reduced to annual time resolution (Fig. 6). Trend lines shown in the figure are based not on time, but on the regional response to global mean temperature change, as discussed in Section 4.2. It can be seen that upward tendencies for both Tmax and Tmin begin around 1970; the global signal also exhibits this behavior, providing a better fit to data than does a linear trend. (In the case of precipitation the trend is essentially null, and the shape of the regressand makes little difference.)

5.2.2 Information from GCMs

Simulations of temperature and precipitation for both the 20^{th} and 21^{st} centuries (the "historical" and "RCP4.5" experiments, respectively) were obtained from the most recent archive of the Coupled Model Intercomparison Project (CMIP5). These were utilized, at the regional scale, for inference regarding past and future trends. In addition, temperature was utilized at the global scale for detrending and projection, as described in Section 4.2.

5.3 Implementation

5.3.1 Preliminaries

Use of catchment-averaged variables represents the approach whereby the entire region is modeled as a unit, rather than that in which the spatially-differentiated data is

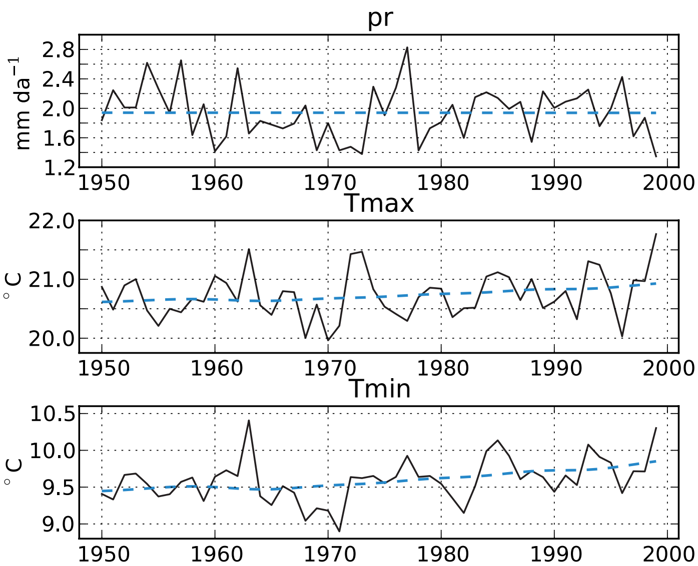

Figure 6: Regional trivariate observational record for the Berg catchment, reduced to annual time resolution. Dashed lines show fitted trends.

prefiltered in terms of EOFs. We believe the regionally-averaged approach is justified because the study area – the combined WMAs – behaves coherently on the annual-to-decadal level. In propagating both trend and annual-to-decadal fluctuations to the catchment level, mechanisms are included that permit a degree of intercatchment dispersion, mimicking that in the observational record.

To detrend the regional series, each component was regressed on the global temperature signal shown in Fig. 2. The fitted values are overplotted on the regional series in Fig. 6. The fitted trends are subtracted from the series to obtain the residual "natural" component of variability. Like the regional series, this natural residual, which becomes the target for the annual-to-decadal simulation model, has annual time resolution.

The wavelet spectrum of each of the three detrended variables (pr, Tmin, Tmax) was computed; these spectra gave no indication that the component series differed from red noise. In other words, systematic variability, as previously defined, was not detected in the regional record. Because of this, a modeling step accounting for such variability would have been superfluous. A significant degree of serial autocorrelation was identified in both of the temperature series; the red-noise model is thus not only sufficient for representing the statistics of these series, but also necessary. The regional precipitation signal was indistinguishable from white noise.

The absence of a systematic element in the target records, by removing a degree of "modeling freedom," renders the method perhaps less interesting than might have

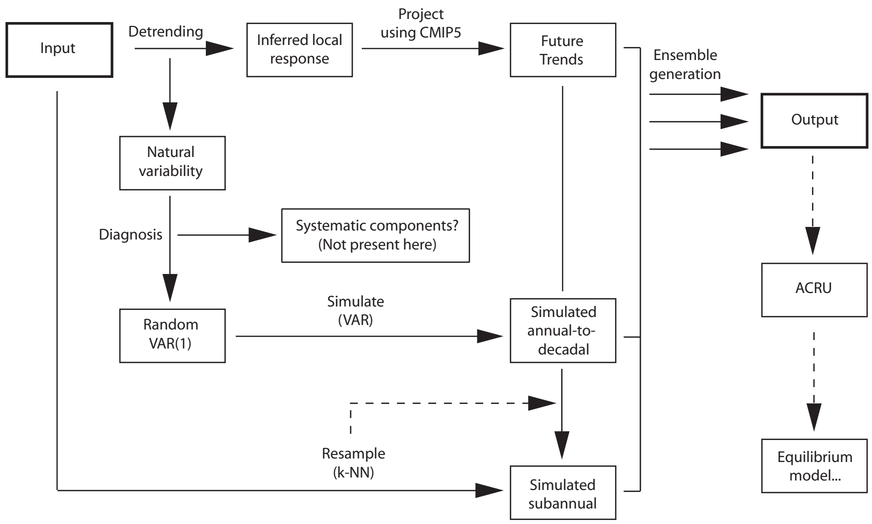

Figure 7: A schematic representation of the case study simulation process. Downward arrow from "Future Trends" signifies the linkage between climate change and both classes of variability; dashed line indicated by "Resample" indicates information from the observational record used, along with climate change expectations, to condition subannual variability. Figure reproduced from *Greene et al.* [2012].

been the case in other regions. A survey of annual and seasonal precipitation around the globe (not shown) suggests, however, that regions where significant deviations from a red noise (or even white noise) background occur tend to be the exception, rather than the rule. Reduction of the annual-to-decadal model to a VAR(1) structure may thus represent a widely applicable situation.

A schematic of the case study simulation is provided as Fig. 7. This is a simplified picture, in which some of the symbols have multiple levels of meaning. For example, the method of projection differs for temperature and precipitation trends, but only a single path is shown. Details are elucidated in the text, and in *Greene et al.* [2012].

5.3.2 Treatment of the annual-to-decadal component

A first-order VAR model was thus fit to the detrended regional series. A single, very long simulation (500 kyr) was then generated, using the inferred parameter values. This is equivalent to an ensemble of 10000 50-yr simulations, many more than would be required for driving ACRU. However the abundance of simulation data is useful in that it provides a large "library" from which shorter sequences having desired statistical properties can be extracted. Statistics computed on the simulated sequence indicate that it reproduces well the observed intervariable correlations as well as serial autocorrelation (thus persistence, or low-frequency variability in the AR(1) sense) in the individual variables.

For purposes of illustration we focus on deviations from the long-term trend of 10-year mean precipitation, modeling the 5^{th} and 95^{th} percentiles (for 10-year means). The simulated decadal deviations are situated in the 2041-2050 decade; by this time the modeled trend has resulted in a reduction in regional mean annual precipitation of about 10%.

The very long simulation sequence permits fairly precise screening, enabling the identification of 10-year sequences for which the mean precipitation falls very near the specified percentiles, while corresponding means of Tmin and Tmax lie reasonably close (plus or minus about half a standard deviation) to their conditional means, given the specified value of pr. This second condition is imposed so that hydrology driven by the simulations will not be accidentally biased by atypical, if nevertheless possible, temperature values. In addition it was required that the decadal pr anomaly during the preceding decade (i.e., 2031-2040) not be large, so as to avoid accidental bias owing to hydrologic memory.

5.3.3 Treatment of trend

Analysis of the CMIP5 ensemble indicated that for temperature, 20^{th}- and 21^{st}-century regional trends behaved consistently with respect to the global mean trend, while precipitation trends diverged, the 20^{th}-century trend being essentially null while the 21^{st}-century trend was significantly negative. Because of this divergence the two variables were treated differently with respect to future trends.

For the temperature components (Tmax, Tmin), each catchment's record was regressed on the 20^{th}-century global-mean multimodel-mean temperature (Fig. 2); the derived coefficients were then used, in conjunction with the 21^{st}-century global mean temperature to project temperature trends forward, enforcing a consistent behavior across centuries.

For precipitation the 21^{st}-century trend was computed using the GCM ensemble without reference to the observations. There is significant dispersion among the model trends, the multimodel ensemble mean and standard deviation amounting to -6.7% and 6.6% change in regional precipitation per degree global warming, respectively. Of the 14 models in the ensemble, three exhibit wetting tendencies for the Western Cape region, suggesting a distinct, if relatively small, probability of such an outcome. It is worth noting that a drying trend is consistent with theoretical expectations regarding expansion of the dry subtropics with global warming, with a particularly robust response occurring toward the poleward margins of the subtropical dry zones. Southwestern South Africa lies in just such a zone [See Fig. 11.2 in *Solomon et al.*, 2007]. The temporal pattern of drying expressed by the overall model ensemble seems consistent with the poleward advance of a dry subtropical regime that reaches, and eventually overrides, the region of the Western Cape. Owing to the dispersion in ensemble precipitation response, it is left to the modeler to select a quantile for simulation from the multimodel distribution. This choice is made at runtime, as the simulations are generated.

5.3.4 Downscaling

Modeling of the trend and annual-to-decadal components, as described above, produces an intermediate simulation product, applicable to the regional as a whole and resolved on the annual time step. Downscaling involves the propagation of these sequences to the individual catchments, as well as the generation of subannual variability.

1. Subannual values will be generated by resampling the observations in one-year blocks over the entire domain, then scaling observed values to agree, in the regional annual mean, with those of the imposed simulation, including both trend and annual-to-decadal variations. As a preliminary to this procedure the sequence of observed years corresponding to the simulated sequence is selected, using a modified k-NN scheme.

2. Temperature trends are propagated to the catchment level as described above, through linear regression on the 20$^{\text{th}}$-century global mean, then projection using the 21$^{\text{st}}$-century global mean. Because modeled regional values represent catchment averages the average of future catchment trends will approximate the imposed regional trend.

3. The regional precipitation trend, as selected by the modeler, is imposed, but it would be unrealistic to simulate identical trends at all catchments. Thus the 20$^{\text{th}}$-century precipitation trends are used to induce some scatter around the imposed trend value. Again, the average over catchments produces an overall trend closely approximating the imposed value (since the average 20$^{\text{th}}$-century trend is near zero).

4. Separately, imposed annual-to-decadal variations are propagated to the catchments via linear regression, uncorrelated noise (at the annual level) being added in order to replace variance lost to regression.

5. To generate subannual variability, resampled values at each catchment are rescaled — in one-year blocks — so as to match the simulated trend plus annual-to-decadal variations, as propagated to the catchment level. In effect subannual *patterns* of variability are preserved, but annual-mean *amounts* are

imposed, the intrinsic observational mean values being stripped out. Because the resampling is performed over the domain as a whole, spatial coherence is preserved at subannual scales.

5.3.5 Model validation

On the annual-to-decadal scale, both intervariable correlation and serial autocorrelation in individual variables were found to be quite well-simulated, justifying *ex post facto* the use of the VAR(1) model.

Comparison of simulations for 1950-1999 with the observational record indicated that the k-NN scheme captured well the observed dependencies of daily precipitation statistics on annual mean precipitation, both for the study area as a whole and with respect to individual catchments. Statistics examined were wet- and dry-spell counts and lengths, wet-spell mean amounts and three-day extreme precipitation. Resampling was able to account for ∼90% of the variability in annual mean precipitation, meaning that little rescaling was necessary in order to bring resampled values into agreement with the imposed simulation. These results suggest that, given the relatively modest warming expected during the next few decades (∼1°C), the simulation scheme should be able to capture reasonably well shifts in daily rainfall statistics that may come about as a result of global temperature increases.

5.3.6 Example simulations

Two simulated sequences, for the same quinary catchment, are shown in Fig. 8. For the sake of comparison with the simulations, values for 1950-1999 consist of the original catchment observations. The precipitation trend was specified at the 50^{th} quantile; combining this with with small negative 20^{th}-century catchment trend resulted in a net sensitivity of -7.2% per degree global warming, slightly more negative than the multimodel median.

Decadal fluctuations representing the 5^{th} and 95^{th} percentiles for 10-year mean precipitation (left and right panels, respectively) are imposed during the 2041-2050 decade, demarcated on the plot by red vertical lines. The values of trend and decadal fluctuations are such that for the 5^{th} percentile the long-term drying tendency is approximately doubled, while for the 95^{th} percentile it is approximately canceled. Temperature fluctuations during 2041-2050, as well as 10-year mean precipitation during 2031-2040, are constrained as indicated in Section 5.3.2. In general, the balance between trend and decadal fluctuations will vary by catchment, in part because the imposed trend is expressed as a percent change per degree warming, and will depend, in the absolute sense, on the individual catchment's mean annual precipitation, while the imposed decadal fluctuation has a dependence on the degree to which

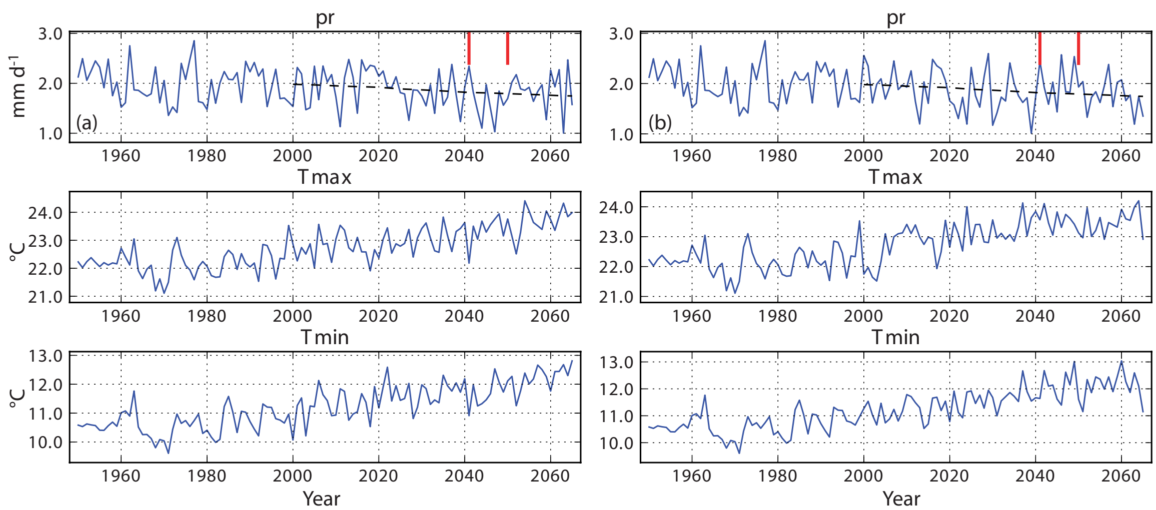

Figure 8: Two simulated sequences for the same quinary-level catchment,, reduced here to annual time resolution. Decadal precipitation fluctuations for 2041-2050 lie at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles in the left and right panels, respectively. Figure reproduced from *Greene et al.* [2012].

the catchment "subscribes" to the regional mean signal and the individual catchment variance. These variations superimpose a degree of randomness on intercatchment variability, increasing simulation realism.

Figure 8 shows that both decadal and anthropogenic signals play out against a background of strong year-to-year variability. Planning for climatic stresses on interannual time scales thus remains an important consideration in the overall risk assessment profile.

6 Discussion

The methodologies we have discussed above comprise at least two levels of generality: The simulation framework itself is broadly sketched out, while realization at the level of the case study is considerably more particularized. Starting from a broad-brush outline, then, simulation details must be elaborated according to the available evidence and particularities of the setting under consideration. Evidence to be considered includes the observational record, information from GCMs, theoretical expectations and possibly paleorecords, if the latter are available. These sources must be weighed with respect to both content and reliability and a coherent narrative woven from the various evidentiary threads that they present. Constructing this narrative may not be a simple task.

The simulation methodology described, like many statistical models, is computationally inexpensive compared with both global and regional dynamical models. It is also informed, as we have discussed, by a multiplicity of sources. It is both a strength and a weakness that the modeler can combine these sources according to their perceived degrees of reliability, arriving at a final structure that reflects a differential, and perhaps personal, view of climate information. Of course the metrics involved in information assessment are at least semi-objective, and every statistical model begins with some intuitive, if initially inchoate, sense of the relationships between covariates and predictand. In the end, the advantages of such models must be weighed against their inability to anticipate shifts or changes owing to processes or interactions that have not been accounted for in some way. This justifies reliance on a broad informational background during model design.

An illustration of such reliance can be provided for the case of temporal precipitation variability. As a result of anthropogenic warming it is widely believed that this variability will increase, owing to the rapid increase of water saturation vapor pressure with temperature: A warmer atmosphere can transport more water vapor. Because of this it can rain more but also become drier, atmospheric demand can also increase. There is no mechanism in the statistical model we have described that would act to bring such an increase about. Precipitation variability in southwestern South Africa in both the CMIP3 and CMIP5 simulations was analyzed, however, and found not to increase (or decrease) significantly during first half of the 21st century. Thus no basis was found for including a cross-scale mechanism linking precipitation variability in the subject region to global temperature change.

The initialized decadal hindcast experiments being performed as part of CMIP5 were mentioned in Section 4.3.3. At present, predictive skill for SST appears limited to less than one decade in most oceanic regions, so the degree to which such simulations might help to constrain future trends in terrestrial regions is not clear. However, ocean initialization has been limited by a lack of subsurface observations, a situation which is being remedied, and models are constantly being improved. There also may be particular regions where predictive skill is significant. While these outcomes remain to be determined, the potential for such initialized forecasts to guide the evolution of modeled trend and low-frequency simulation components remains.

7 Summary

We have described a framework for the generation of stochastic simulations, with the end in mind of driving agricultural or other applications models that require detailed climate information that includes a realistic representation of decadal variability. The incorporation of such variability into impacts studies represents an advance over the simple comparison of mean states that has typically been performed in climate change impact studies.

The approach presented is based loosely on classical time series analysis, in that an observational record, which is taken to represent regional climate variability, is decomposed into trend, systematic and random components, each of these being treated independently. An association is made between trend — a secular shift in the mean — and anthropogenic forcing. Accordingly, this component of variability is modeled by regression on a global mean temperature signal, meaning that it is modeled as a response to global temperature change, rather than simply as a time-dependent level. Detrending, as refracted through this procedural prism, then amounts to separating climatic changes due to anthropogenic effects, and natural variability intrinsic to the climate system itself. Possible problems that arise in attempting to effect such a separation using short time series were discussed.

Trend having been removed, the residual variability is examined for evidence of systematic processes, in the sense that the residual variations differ significantly from AR(1) noise. If such processes are identified, they would be modeled as separate independent components, with the *residual* from this step modeled as an AR(1) stochastic process. This component of the analysis offers perhaps the widest latitude in the simulation scheme, depending as it does on the available climate records, which may exhibit widely varying characteristics. It was noted that the presence of regime-like behavior, although sometimes difficult to verify, may require state-based or other alternate model forms.

It is hoped that the methodology outlined here will prove useful in delineating uncertainties owing to natural internal variability, in the context of a background climatic state undergoing secular, forced shifts. Indeed, this is the situation in which we are likely to find ourselves in coming decades. The investigation and characterization of such uncertainties can play an important role in anticipating potential climate risks in the near term; the more confidently such risks can be defined, the better prepared we will be to deal with them in coming years and decades.

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directory located at http://iri.columbia.edu/ amg/CCAFS/simgen.

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