REVIEW OF DOWNSCALING METHODOLOGIES FOR AFRICA CLIMATE APPLICATIONS

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EXECUTIVE SUMMARY

Downscaling is the term used to describe the various methods used to translate the climate projections from coarse resolution GCMs to finer resolutions deemed more useful for assessing impacts. Projections of future climate are produced using complex, coupled atmosphere-ocean models (GCMs). The GCMs are most reliable at the continental scale. Due to the inherent uncertainty of the climate system and the inevitable existence of model errors, multi-model ensembling is the recommended approach for characterizing expected climate changes. As downscaling is dependent on the ability of GCMs to successfully project the climate change signal, it is limited to where that signal is clear. Assessments of climate change in Africa indicate some consensus of reduced winter rainfall in southern Africa, increased annual rainfall in east Africa and uncertainty for the rest of Africa. Selection of GCMs that "do better" over Africa, or any region, is difficult and probably not warranted, given the general parity in model skill and the difficulty in identifying which models are more skillful. Ensemble means or medians offer the highest level of projection accuracy. Downscaling approaches are generally categorized as dynamical, using regional climate models, and statistical, using empirical relationships. However, dynamical downscaling often includes statistical modeling in the form of "bias correction." Dynamical downscaling is useful for incorporating topographic features, such as strong orography, and land use and vegetation. It is recommended where those features play a significant role in regional climate. However, computational time and the uncertainties that accompany complex models outweigh the benefits of dynamical downscaling where these features are not significant. The spatial resolution that can be achieved is on the order of tens of kilometers. Statistical downscaling is simpler and more efficient than dynamical downscaling. It is preferred where estimates of specific variables, especially at point locations, are sought for input to sector models (e.g., hydrologic models) or decision making. However, statistical modeling can mask a true understanding of regional climate dynamics and estimates may be overconfident. In summary, downscaling is best understood as an attempt to increase the understanding of climate change influences at the regional scale. In that context, a variety of methodologies should be explored, using all tools possible to increase that understanding. A set of "Best Practices" is recommended for pursuing this effort.

OUTLINE SUMMARY

1. Climate Forecasting Basics

- Climate projections are presently produced with the aid of complex, coupled atmosphere-ocean general circulation models (AOGCMs).
- The most comprehensive assessment of ongoing climate modeling efforts is carried out by the Intergovernmental Panel on Climate Change (IPCC).
- A range of climate simulations was surveyed in the recent IPCC Fourth Assessment Report (AR4).
- Three marker scenarios were emphasized, designated A2, A1B and B1, ordered here from greatest to least greenhouse gas concentrations, and consequently, degree of warming.
- Most, if not all, of the AOGCMs discussed in the AR4 incorporate interactive land-surface schemes.

2. What can we learn from GCMs?

- GCMs generally are more skillful in simulating temperature than simulating precipitation
- GCMs are more skillful at predicting means (averages) of precipitation or temperature than any higher order statistics (i.e., variability).
- The skill of GCM projections of temperature and precipitation generally decrease along with the spatial and temporal scales under consideration. That is, the models have more skill over larger spatial areas (continental or regional scale) and larger time scales (long term mean versus monthly values)
- Currently, there is a lack of ability to predict near term climate change, i.e., climate variations on decadal time scales.
- Interannual climate variability, in some cases related to ENSO (El Niño/Southern Oscillation) is likely to dominate precipitation variability relative to changes due to secular trends for the near term (next 10 to 20 years)

3. What is the thinking on Africa?

- Uncertainty reigns for much of the tropics
- Wet get wetter; dry get dryer
- Winter rainfall in southern Africa is likely to decrease
- Annual mean rainfall is likely to increase in east Africa

4. Selection of GCMs

- Current GCM runs have not been designed for assessing historical skill in the variables that are useful (i.e., only long term summary statistics can be compared for precipitation)
- A wide variety of metrics can be considered for evaluating climate models, but there are no models that perform uniformly well across a large suite of such measures.
- Correlation with 20th century observations does not necessarily imply skillful projections of the 21st century

- Multi-model ensembling remains the recommended approach for assessing climate changes. This helps reduce the effects of model errors in one particular model and natural variability (randomness) in any particular run
- Screening of GCM may be possible to remove models that do not demonstrate any skill for a region. All others could then be included in the multi-model ensemble.

5. Introduction to Downscaling

- Downscaling is the term for using models (statistical or dynamic) to increase the resolution of GCM output for a particular location.
- It may be performed to increase the temporal resolution (e.g., from monthly to daily values of P and T) or the spatial resolution (e.g., from a GCM grid cell size down to the weather station scale)
- Since downscaling is a transformation of GCM outputs, it cannot add skill that is not present in the GCM output.
- It is most appropriate where the GCM output has some basis for being skillful (e.g., demonstrated consistency between GCM and observed climate).

6. Dynamical Downscaling

- Dynamical downscaling uses regional climate models (RCMs) that transform outputs from GCMs into finer spatial and temporal resolution outputs.
- Their primary contribution is through the inclusion of more realistic topography and land use/vegetation.
- Due to systematic errors that inevitably occur, RCMs require statistical corrections to provide realistic output.

7. Statistical Downscaling

- Statistical downscaling utilizes relationships between GCM output and historical data to produce finer spatial and temporal resolution climate data at the regional level.
- Methods are typically as effective and less expensive than dynamical downscaling.
- Especially useful for temporal downscaling (from monthly to daily values)

8. Hydrologic Modeling from Downscaled GCM projections

- Hydrologic models add little uncertainty relative to the uncertainty associated with climate models
- The choice of hydrologic model should be determined in accordance with the ability to estimate the desired variable
- Hydrologic model choice affects the downscaling method selection

9. Downscaling applications in Africa

- Many downscaling studies have been performed for diagnosis of regional climate features (e.g., Sahelian drought).
- Fewer downscaling studies for hydrologic applications have been completed.
- Emphasis is on providing better understanding of regional climate and responses to climate change, over specific projections of change.

10. Downscaling "Best Practices"

- Climate change projections should be based on multi-GCM ensembles

- Downscaling is appropriate where there is consensus on the direction of change in the GCMs
- Downscaling must be based on an understanding of how regional climate is expected to respond to large scale climate forcings and relative to the dominant modes of climate variability (interannual, decadal) at a particular location.
- In any specific case, the selection of downscaling methodology should be based on the particular application in terms of the variables of interest, time frame and spatial resolution required, the existence of previous studies and the availability of historical observation data.
- Statistical downscaling tends to be a better value than dynamical downscaling for hydrologic applications, being as effective and less expensive
- Dynamical downscaling is valuable where local topography and land use or vegetation have significant influence on regional climate.
- Temporal precipitation downscaling to resolutions of daily scale is an active research area, with statistical approaches showing the most promise.
- Results of climate change projections and downscaled regional results should be understood within the context of climate variability at interannual and decadal timescales, as well as socioeconomic changes.

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The most comprehensive assessment of the ongoing climate modeling efforts being carried out throughout the world is performed by the Intergovernmental Panel on Climate Change (IPCC). The IPCC has recently released its Fourth Assessment Report (AR4, Solomon et al., 2007). This comprehensive document reports research findings based on simulations from 25 climate models.

A range of climate simulations was surveyed in the recent IPCC Fourth Assessment Report (AR4). The modeling centers that participated in the AR4 were asked to perform a variety of simulations. These included the "20th Century Climate in Coupled Models" (20C3M) experiment, for which each center made a "best attempt" to simulate the climate of the 20th century, and several "marker" scenarios for the future, based on the IPCC Special Report on Emissions Scenarios (Nakicenovic et al., 2000).

Three marker scenarios were emphasized, designated A2, A1B and B1, ordered here from greatest to least greenhouse gas concentrations, and consequently, degree of warming. The marker scenarios span a range of possible trajectories for the evolution of human society during the coming century, including regional populations, energy sources, land use and other significant climatic influences. When "processed" by the IPCC climate models, a corresponding range of climate responses results. The marker scenarios utilized are designated A2, A1B and B1, ordered from greatest to least greenhouse gas concentrations, and consequently, degree of warming. The "middle," A1B scenario is often used illustratively, although there is some evidence that the actual global trajectory has been closer to A2. Thus, the B1 scenario would probably be least likely to represent the climate of tomorrow, given recent observations.

Most, if not all, of the AOGCMs discussed in the AR4 incorporate interactive land-surface schemes. The land-surface schemes are interactive in the sense that fluxes from the land surface are "felt" by the modeled atmospheres. Such schemes can be quite sophisticated, taking into account different vegetation types, interaction between solar radiation and canopy cover, transpiration, the effects of soil moisture and so on. However, carbon-cycle feedbacks are not generally modeled, and possible *changes* in vegetation cover are not presently taken into account in climate change simulations.

2. What can we learn from GCMs about future climate?

- GCMs generally are more skillful in simulating temperature than simulating precipitation
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- Currently, there is a lack of ability to predict near term climate change, i.e., climate variations on decadal time scales.
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GCMs generally are more skillful in simulating temperature than simulating precipitation. From the IPCC Fourth Assessment Report (AR4) Ch. 8, "Climate models and their evaluation" (Solomon et al., 2007):

There is considerable confidence that Atmosphere-Ocean General Circulation Models (AOGCMs) provide credible quantitative estimates of future climate change, particularly at continental and larger scales. Confidence in these estimates is higher for some climate variables (e.g., temperature) than for others (e.g., precipitation).

Thus, both the variable and the spatial scale should be considered when deciding how much confidence to place in model-simulated climate changes. For a given spatial scale, temperature is generally simulated with greater fidelity than precipitation. Although a hydrologic variable such as streamflow represents an aggregation of rainfall (over a basin-scale area), effects of evaporation (which depends in part on winds), soil, vegetation… interacting with topography, may introduce biases.

GCMs are more skillful at predicting means (averages) of precipitation or temperature than any higher order statistics (i.e., variability). Both temperature and precipitation (the two surface variables of primary importance for life at the Earth's surface) can be characterized in a variety of ways. In addition to annual means, each exhibits a more-or-less characteristic seasonal cycle. For many applications, maximum and minimum temperatures are as important as mean values, while with respect to precipitation such "higher-order" features as frequency of heavy rainfall events, or length of dry spells, may have significant sectoral impacts. Such attributes may be poorly simulated by models even though mean annual precipitation is reasonably well-represented. Thus a statement about which variables are well- or poorly-simulated should be qualified with respect to those attributes that are most important for the application at hand.

Dai (2006), in an assessment of precipitation in the AR4 suite of climate models, found systematic biases in the statistics of daily rainfall, particularly in the tropics, where models tend to produce too much drizzle and too few heavy rainfall events. These effects tend to cancel, so that mean precipitation amounts may be reasonable, despite the distributional bias. There were also other systematic biases, including a tendency for too large a fraction of rainfall to be generated by convective, as opposed to stratiform, processes, and biases in the diurnal cycle of rainfall. The latter may be particularly important for climate simulations, since phasing of the diurnal cycle of clouds has a large impact on the surface radiation budget.

The skill of GCM projections of temperature and precipitation generally decrease along with the spatial and temporal scales under consideration. That is, the models have more skill over larger spatial areas (continental or regional scale) and larger time scales (long term mean versus monthly values). Resolution in the AR4 models is typically on the order of 2-3° (latitude and longitude). However, the models cannot be considered reliable on the scale of individual grid boxes. In general, IPCC authors consider the present generation of models to be relatively reliable only on continental or subcontinental scales, so much of the detailed discussion on regional climate projections (IPCC Ch. 11) is organized with respect to regions of this scale (e.g., Africa is divided into four regions, South America into just two). In comparisons of differing time periods, the use of 20-year means is also typical in the AR4, although this may be less a matter of "reliability" than simply obtaining statistical estimates of reasonably small variance.

Currently, there is a lack of ability to predict near term climate change, i.e., climate variations on decadal time scales. There has been a recent interest on climate changes that might occur over some period that is *intermediate* between the 6-9 month lead times characteristic of seasonal-interannual (SI) forecasts and the 100-year time horizons considered in assessment reports of the IPCC. Thus, emphasis has been placed on changes that might occur within the span of a few decades, such a time frame having more utility in practical, "actionable" terms than century-length periods. Consideration of climate change on such "near-term" time scales poses special problems, however, owing to the nature of climate variability, and the processes responsible for it.

On the SI time scale, there is a single dominant source of climate variability: The El Niño-Southern Oscillation, or ENSO. ENSO is a more-or-less deterministic process that is relatively well-understood, has been successfully represented in climate models and for which there exists demonstrated (although not perfect) predictive skill. Climate variations that may occur over the coming few decades, on the other hand, are *not* known to be governed by a comparable, dominant mechanistic process. Not only are there several processes operating in the climate system on such time scales, whose effects may be mutually reinforcing or opposing, but it is quite likely that a good deal of variability on these "decadal" scales is not deterministic but *random,* i.e., arising from essentially unpredictable atmosphere-ocean interactions. Although expressions of decadal variability (such as the Pacific Decadal Oscillation, or Atlantic Multidecadal

Variability) have been identified, and studied for some time, the underlying mechanisms are themselves poorly understood at present, and there exists essentially no demonstrated predictive skill for these processes at the present time.

Since true decadal predictability, particularly in the regional sense, has not yet been demonstrated, the most sensible course of action, with respect to user needs, may be to try to at least *characterize* regional decadal variability, so that a range of climatic uncertainty for the next few decades can be estimated. This may be accomplished by various means, the most promising involving the use of both instrumental records and paleodata (such as tree ring chronologies). In general, for the characterization of variability on long time scales, long records are required, which is why the use of paleodata assumes increasing importance in considering “near term” climate change.

Climate variability related to ENSO (El Nino/Southern Oscillation) is likely to dominate precipitation variability relative to changes due to secular trends for the near term (next 10 to 20 years). In many regions (including most tropical locations), the portion of climate variability ascribable to decadal “modes” is relatively small, while that attributable to ENSO is significant. In addition, secular trends in precipitation tend to be small. Thus, it is likely that over the coming few decades, year-to-year variations will dominate climate changes due to the more slowly evolving decadal processes. However, to the degree that the latter in effect define the climatic “background,” the dominant year-to-year variations will be occurring against a slowly shifting mean state; even over the course of a few decades such shifts may produce significant impacts, for example in the form of more frequent exceedances of critical thresholds for agriculture or human health.

3. What is the current thinking on Africa?

- Uncertainty reigns for much of the tropics
- Wet get wetter; dry get dryer
- Winter rainfall in southern Africa is likely to decrease
- Annual mean rainfall is likely to increase in east Africa

Current understanding of climate change in Africa mirrors that for the tropics in general: theoretical understanding of the dynamics of climate is weaker than for mid- to high-latitudes, and is exemplified in the lack of consensus among models in their projections of climate change, especially precipitation. In mid to high latitudes, warming and a reduced equator-to-pole temperature gradient are expected to be accompanied by a poleward shift in precipitation, which would make the subtropical latitudes drier, and higher latitudes wetter. The drying projected for the southern African Cape and Mediterranean coast of North Africa is a manifestation of the former. In addition, projections of change in the intensity and frequency of ENSO, the dominant mode of seasonal to interannual climate variability, whose impact is most strongly felt throughout the tropics, are uncertain.

That is not to say that there are no hypotheses about how tropical climate change may come about. The increase in precipitation that is projected with some confidence in eastern equatorial Africa is consistent with the idea that "the rich will get richer" – that is to say, that regions where climatological rainfall is abundant, the regions at the core of monsoons, will get wetter, and conversely, that regions at the margins, like the Caribbean basin and Central America (the Sahel?), may get drier (Neelin et al 2003). This is because a warmer atmosphere is also moister, hence at the core of monsoon regions, where there is no lack of moisture, warmer may imply wetter. In contrast, a reduction in moisture supply at the margins, where moist and dry air meet, could limit the increase in precipitation that one would expect thermodynamically, from the increase in atmospheric temperature. Uncertainty in tropical climate change is compounded by the fact that the monsoon systems are dynamically interconnected. While it is reasonable to expect that a strengthening of the South Asian monsoon, or an increase in precipitation over the Maritime continent/Western Pacific warm pool, may have global impacts, just like ENSO does, exactly how that may come about is not fully understood.

According to the IPCC (AR4), winter rainfall in southern Africa is likely to decrease, annual mean rainfall is likely to increase in east Africa while other areas remain uncertain.
From IPCC Chapter 11, "Regional climate projections":

Re simulations of *present* climate:

There are biases in the simulations of African climate that are systematic across the MMD [i.e., IPCC] models, with 90% of models overestimating precipitation in southern Africa, by more than 20% on average (and in some cases by as much as 80%) over a wide area often extending into equatorial Africa.

Re simulations of *future* climate:

Rainfall in southern Africa is *likely* to decrease in much of the winter rainfall region and western margins. There is *likely* to be an increase in annual mean rainfall in East Africa. It is unclear how rainfall in the Sahel, the Guinean Coast and the southern Sahara will evolve.

In this case it appears that *changes* in model-simulated rainfall are trusted to some extent, even though the models may not simulate present-day rainfall very well. On the other hand, the last of these statements ("It is unclear…") reflects a *lack of consensus* among the IPCC models, with respect to Sahel rainfall.

One additional caveat regarding simulations of African climate: None of the IPCC models predict vegetation changes, i.e., in all simulations vegetation is *prescribed.* This means that potentially important precipitation feedbacks involving the land surface are not represented in these models.

4. Selection of GCMs

- Current GCM runs have not been designed for assessing historical skill in the variables that are useful (i.e., only long term summary statistics can be compared for precipitation)
- A wide variety of metrics can be considered for evaluating climate models, but there are no models that perform uniformly well across a large suite of such measures.
- Correlation with 20th century observations does not necessarily imply skillful projections of the 21st century
- Multi-model ensembling remains the recommended approach for assessing climate changes. This helps reduce the effects of model errors in one particular model and natural variability (randomness) in any particular run
- Screening of GCM may be possible to remove models that do not demonstrate any skill for a region. All others could then be included in the multi-model ensemble.

Comparing GCMs for suitability for a particular region or in terms of a particular output (e.g., precipitation) is an area of active research. A number of concerns accompany such efforts. The idea of *testing* the various models and choosing one (or a small subset) that performs well for a region naturally arises. Cook and Vizy (2006) have done just this, with a focus on the west African monsoon. From their findings, we have:

Based on the quality of their twentieth-century simulations over West Africa in summer, three GCMs are chosen for analysis [from an initial set of 18]. Each of these models behaves differently in the twenty-first-century simulations.

The authors used a detailed analysis of models to determine which were best at simulating the historical observations over West Africa. They chose three from among 18, and yet those three models disagreed on their projections of climate change. This is another indication that present-day simulation skill, although it is sometimes regarded as a prerequisite, may not be *sufficient* as an indicator of skill in simulating future climates. Of the three models selected in the initial round, (GFDL-CM2.0, MRI-CGCM2.3.2 and MIROC3.2 medres), Cook and Vizy identified the MRI model as producing the most plausible future simulations, given the known dynamics of the west African monsoon system.

While the rationale for their procedure is understandable, the selection of a single model with which to predict future climate implies a belief that the outcomes predicted by this model have probability = 1, while those from even the other two “finalists” have probability = 0, i.e., there is absolutely no uncertainty in the projection that is attributable to imperfect knowledge about the representation of climate in numerical models. Even on the basis of well-reasoned arguments, this seems an overly radical position.

It is also important to note that this study focused on a very specific and well-studied region, whose climate dynamics could therefore be evaluated in detail in climate models. Without an analysis of similar depth, it is not possible to say that the MRI model would perform similarly well for South Africa, or other African regions.

Multi-model ensembling remains the recommended approach for assessing climate changes. This helps reduce the effects of model errors in one particular model and natural variability (randomness) in any particular run**.** The study of Cook and Vizy leads us to another important idea, one that is in evidence throughout the IPCC AR4. This is the use of a *multimodel ensemble,* meaning a group of climate models, for estimating not only potential changes in climate but also the *uncertainties* associated with those changes. A single model, if run multiple times with differing initial conditions, can provide an estimate of the uncertainty due to natural variability. But there are also uncertainties associated with model physics and parameterizations, as well as with structural aspects of the models themselves. No individual model can span the range of these uncertainties. If, as is sometimes reported in the pages of the AR4, there is a broad “consensus” among models for some aspect of climate change, then we can at least say that such a change is *robust* with respect to model formulation and physics, while at the same time the spread among models provides an estimate of the uncertainty in the projected climate outcome owing to uncertainties in the modeling framework. This information is valuable, because it helps determine the level of trust we can place in the projected climate changes.

What then, about models that fail to reproduce even the most basic aspects of the climate of a particular region? Must these also be included in a multimodel ensemble? The IPCC often reports multimodel means (or medians), while using the spread among models to quantify uncertainty. This is typically done without the elimination or suppression of individual models. Paradoxically, the work of Cook and Vizy illustrates the value of this approach, in that it demonstrates how much detailed analysis must be applied in the case of just a single climate regime (the west African monsoon), in order to stratify models by performance. Use of the whole ensemble can therefore be seen as an expedient, given that such detailed studies are lacking for many localized climate systems.

Screening of GCM may be possible to remove models that do not demonstrate any skill for a region. All others could then be included in the multi-model ensemble.   It is nevertheless possible that some sort of *screening* might profitably be employed, whereby those models deemed grossly unrepresentative of the regional climate in question might be eliminated from the ensemble, leaving a “core” group that has at least passed some minimal qualification check. The issue of model metrics, i.e., the “scoring” of models in some way with respect to their simulation fidelity, is a complex one (Gleckler et al., 2007). Assuming a screening could be applied, this would represent a middle path between attempting to choose the single “best” model for a particular region and uncritically accepting all models, and would retain some advantages of the discrimination process while also providing uncertainty estimates for climate change projections.

The figure below, from Gleckler et al., (2007) is illustrative of two important points. The figure depicts model errors in the major GCMs. First, the two results with the lowest errors (far left on x-axis) are the multimodel mean and median. These values clearly outperform the results of every individual model. Second, the individual models vary in their ability to skillfully reproduce various climate variables (listed in the box on the right) but none standout as skillful in comparison to the multimodel mean or median. There are, however, three models at the right of the x-axis that appear to exhibit more errors than the rest and may be candidates for screening.

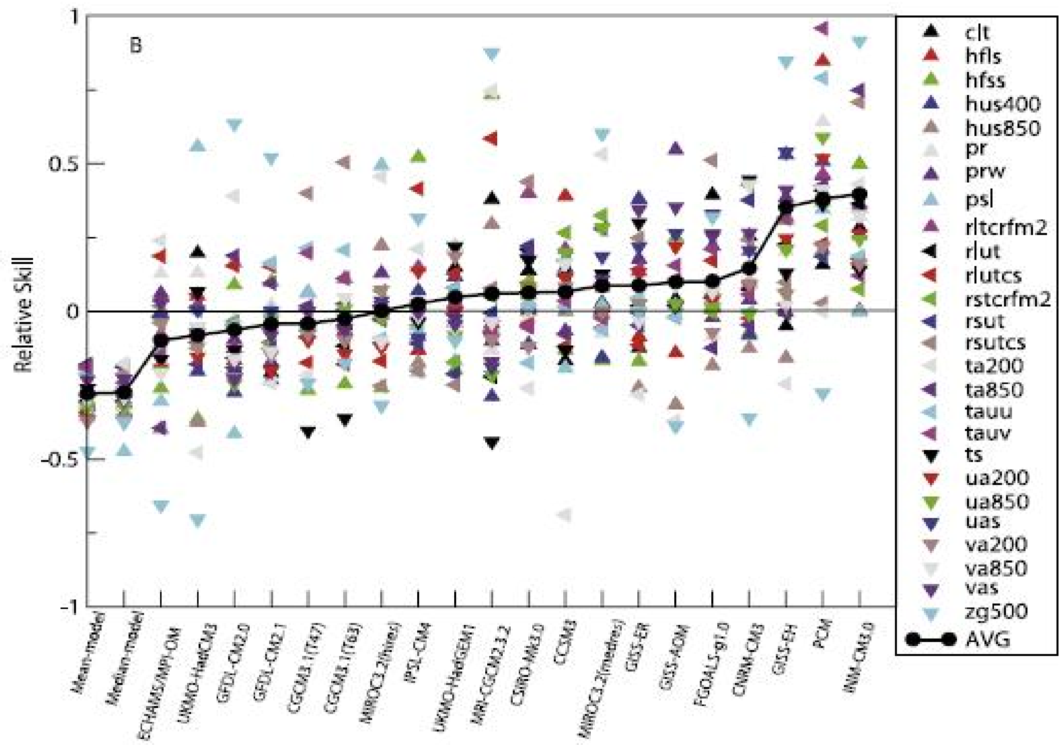


Figure 7. Relative errors, with models ordered by the "Model Climate Performance Index," for (a) NHEX (20N–90N) taken from Figure 3d, and (b) Tropics (20S–20N) taken from Figure 3e. The indices are connected by the solid line, and the colored symbols indicate the relative error for each of the variables that contribute to the index.

5. Introduction to Downscaling

- Downscaling is the term for using models (statistical or dynamic) to increase the resolution of GCM output for a particular location.
- It may be performed to increase the temporal resolution (e.g., from monthly to daily values of P and T) or the spatial resolution (e.g., from a GCM grid cell size down to the weather station scale)
- Since downscaling is a transformation of GCM outputs, it cannot add skill that is not present in the GCM output.
- It is most appropriate where the GCM output has some basis for being skillful (e.g., demonstrated consistency between GCM and observed climate).
- Downscaling is best practiced as an attempt to increase the understanding of climate change influences on regional climate

Global climate models (GCMs) are typically run at relatively coarse spatial resolutions, generally greater than 2.0° latitudinally and longitudinally. The result is a spatial scale mismatch between available climate change projections and the scale of interest to most water resources users (e.g. subcatchment or gridded watershed) (Varis et al 2004). To overcome this, statistical models or dynamical regional climate models (RCMs), with higher spatial resolution, are constructed for downscaling to smaller areas. These high resolution models utilize small-scale features, e.g., vegetation and topography in the case of dynamical model, or empirical relationships in statistical models, that are otherwise poorly represented in the low resolution GCMs.

In essence, the models "translate" the larger scale climate dynamics to local effects on precipitation, temperature and other surface variables. As a result, for the local results to be meaningful, the larger scale dynamics provided by the GCM must be skillful and the downscaling approach must also be skillful. Thus, a prerequisite for attempting downscaling is some confidence in the climate signal that is intended to be downscaled.

If downscaling is deemed appropriate, there is a choice among dynamical or statistical approaches. Dynamical downscaling is accomplished with regional climate models that use the results of GCMs as their boundary conditions. For the case of dynamical downscaling, the question of model skill is prominent. Regional models are highly complex and as such, accompanied by questions of uncertainty in model results. The lack of the ability to validate the models' responses to climate changes means that the uncertainty remains difficult to characterize. In the case of statistical downscaling, the major question is the validity of the stationarity assumption that inevitably underpins such formulations. That is, statistical downscaling is based on empirical relationships found in past climate observations and thus, may or may not hold in the possible future climates.

In view of the limitation of GCMs and dynamical and statistical downscaling approaches, the recommended approach to downscaling is to view it as an attempt to improve the understanding of regional climate and climate change influences on it. All sources of information should be exploited, including dynamical and statistical downscaling, and analysis of historical variability. In most regions in Africa, interannual variability such as related to ENSO (east and southern Africa) and decadal scale variability (west Africa) have major influences on regional climate. Since the effect of climate change on these phenomenon are not well understood, consideration of these sources of variability must be prominent when planning for future climate.

6. Dynamical Downscaling

- Dynamical downscaling uses regional climate models (RCMs) that transform outputs from GCMs into finer spatial and temporal resolution outputs.
- Their primary contribution is through the inclusion of more realistic topography and land use/vegetation.
- Due to systematic errors that inevitably occur, RCMs require statistical corrections to provide realistic output.

General Theory

Dynamical downscaling seeks to couple large scale climate dynamics and local climate and hydrological features. It does so by utilizing higher resolution regional climate models (RCMs) that respond to the output of GCMs. The GCM output is provided as boundary conditions, which are the values at the edges of the spatial domain of the RCM. RCMs are used for downscaling seasonal climate forecasts and for diagnostic studies of regional climate in addition to their use with climate change projections. In diagnostic studies, the RCMs are often run with observations of the actual climate as the boundary conditions. This approach has been used extensively for investigations of the Sahel drought of the late 20th century (see Jenkins et al., 2002). Since such runs are based on historical climate, in theory they could serve as a basis for comparisons between RCMs. In practice however, the spatial domain, years and seasons analyzed are often not matched, precluding simple comparisons (Pal et al., 2007).

Principles within RCMs are very similar to GCMs (fluid dynamics of atmospheric physics, etc.), only concentrated over a finer spatial resolution and therefore able to incorporate additional local features (i.e. topography, land cover) (Xu et al 2005). Initial and boundary conditions, consisting of atmospheric/meteorological and surface conditions, are generated from the GCM (or a historical database [NCEP, ECWMF] for calibration) (Cocke and LaRow 2000; von Storch et al 2000). RCMs are often nested within GCMs to save on processing time and costs, in lieu of running the two models in successive fashion. However, the nested structure is still based on mono-directionality – from the GCM to the RCM only. That means the boundary conditions provided by the GCM do not respond to the evolution of climate conditions within the RCM.

Horizontal resolution for most RCMs is on the order of tens of kilometers, which begins to be effective for distributed hydrological and land surface model processing, but may still be too large for effective impact studies (Schulze 1997). Research shows that a resolution jump of approximately 10 represents the upper limit for RCMs to be able to regenerate the high-resolution information of the GCM large domain (Leung et al 2003).

In terms of temporal resolution, RCMs are usually most skillful at monthly or coarser timescales. Distributed hydrological and land surface models often require daily inputs (Guo et al 2002; Wilby et al 1998). This is often achieved via stochastic "weather generators" which are statistical models that randomly generate daily weather that is consistent with the seasonal or monthly statistics provided by the RCM or GCM. In general RCMs are much more useful for spatial downscaling rather than temporal downscaling.

Some degree of forecast uncertainty estimates are accomplished by using forecast ensembles, which are a series of runs that are initialized with slightly different initial conditions. This accounts for natural variability (in theory) but does not account for the uncertainty associated with model errors. For this reason, as with the case of GCMs, multi-model ensembling is recommended to account for model uncertainty.

In dynamical downscaling, an RCM must be given realistic boundary conditions if one expects it to produce realistic downscaled simulations. If this condition is met, RCMs add significant orographic and physical geography details to the simulations that is absent in GCM runs. However, where such orography is not important, the uncertainties associated with RCMs may outweigh any benefit of higher resolution (Jung and Kuntsmann, 2007)

Assumptions and Concerns

While the advancement of RCMs has been significant in the recent past, concerns and obstacles remain. One of the largest sources of model error is the parameterization of convective precipitation (Pal et al., 2007). This is naturally a significant concern in the tropics where convection is the major source of moisture transport. Another major sticking point is the inherited systematic biases from GCMs (Hay et al 2002; Vari et al 2004). For example, RCMs tend to underestimate extreme precipitation (Jorgensen et al 2004) just as GCMs do.

There exists a need to reduce biases in present simulations and improve representation of climate change feedbacks (i.e. clouds) (Murphy 2000). Bias is a systematic difference or error between the model output and observations. Bias typically increased with resolution, and so RCMs may have more bias. Graham (2007) finds that the choice of GCM boundary conditions for an RCM is more influential on assessment of hydrological change than the choice of emissions scenario. Thus, the need for a multi-model approach to using GCMs is again warranted.

Currently, systematic biases for present and future climates are often assumed to be the same (Graham 2007). This assumption is the basis for “bias corrections,” which are statistical models applied to model output statistics to better match observations. Bias correction is typically required to shift the climatology, i.e., long term averages, to a reasonable range. However, the validity of the assumption that these relationships will not change can be questioned. In fact, it is identical to the question underpinning statistical downscaling. The fact that dynamical downscaling often requires statistical bias correction calls into question the value it adds over purely statistical approaches.

Another concern is the lateral boundary interface. RCMs use fixed lateral fluxes into and out of their domain according to the large-scale conditions provided by the GCM (Leung et al 2003). The evolution of climate within the RCM does not effect the output provided by the GCM, which is not true in reality. For monthly mean atmospheric states, biases in lateral boundary conditions generally contribute more to the overall uncertainty than biases in the initial conditions. (Wu et al 2005). The lack of feedback or bi-directionality between RCMs and GCMs contributes to this deficiency.

The fact that RCMs are computationally demanding is also a drawback; typical prediction/analysis periods are restricted (often to 10 years) due to processing limitations, and are still not meeting needs of spatially explicit models (Xu et al 2005; Kunstmann and Jung 2005; Wilby and Wigley 1997).

Temporal resolution remains an issue; as time increments decrease, uncertainties generally increase, since chaotic atmospheric dynamics dominate at short timescales (Leung et al 2003; Roberts 2006, personal communication). The reliability in GCMs, carried through to RCMs for temporal resolution less than monthly, is uncertain, specifically pertaining to hydrologic variables of interest (Wilby et al 1998).

Models risk smoothing variability in an unnatural manner. Also, hydrologic models are calibrated based on existing conditions (Bergstrom et al 2001). In one study (Booji 2004) uncertainty under climate change projections for river flooding (40%) proved significantly greater than uncertainty under current climate conditions (10%.)

Questions regarding the value of dynamical downscaling exist, given their complexity. Their response under future conditions may be different than in the past, rendering the bias correction through some statistical or empirical method inapplicable. Although these models arguably account for atmospheric and physical changes in the environment, they have not been shown to lead to large improvement in hydrological simulation after bias correction and spatial disaggregation (Wood et al. 2004). Their value is strongest where orographic effects and other localized surface conditions are significant climate influences. In addition, they play an important role in diagnostic studies of regional climate and have an additional role where observations are limited.

7. Statistical Downscaling

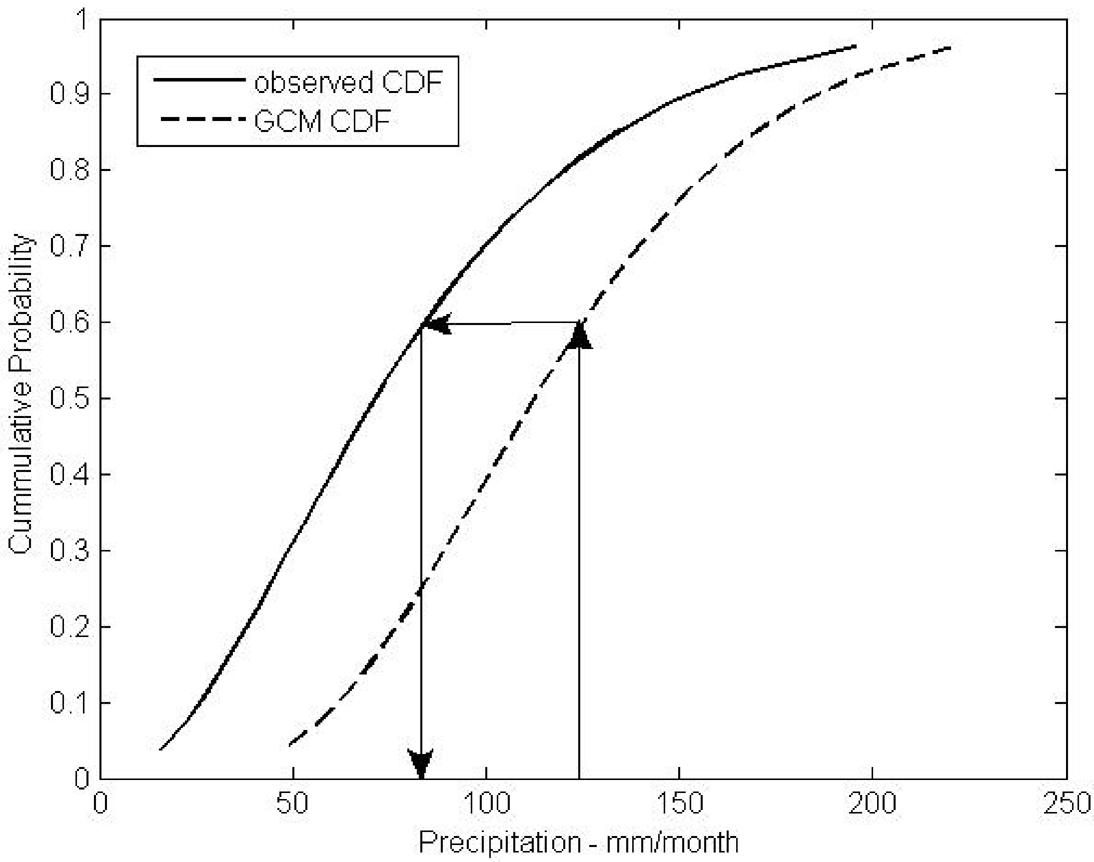
- Statistical downscaling utilizes relationships between GCM output and historical data to produce finer spatial and temporal resolution climate data at the regional level.
- Methods are typically as effective and less expensive than dynamical downscaling.
- Especially useful for temporal downscaling (from monthly to daily values)

General Theory

Statistical downscaling consists of modeling the relationship between GCM output and observations to produce results that are useful as inputs to sector models (e.g., crop or hydrologic models) or for direct use in decision making. The general principle is to form empirical relationships between predictors and historically observed values, then apply the empirical relationship to future projections. Statistical models are simpler in nature, significantly easier to construct and manage, and require much less computational time than dynamical downscaling. The usual approach is to use a statistical model to downscale a GCM output, (e.g. precipitation) to a resolution that is used as input to a sector model (e.g., hydrological model). This is where statistical models are particularly useful: they can be designed to produce the quantity that is of interest for a particular application.

Spatial downscaling using statistical methods is possible through a variety of methods. Straight linear interpolation may be the simplest statistical technique for downscaling large-scale GCM projections to finer grids or points, representative of a hydrological modeling scale (Mimikou et al 2000; Arnell 2002). Variations of this include adding anomalies from GCM projections to an observed baseline record (Maurer and Duffy 2005; Maurer 2007) or using inverse square interpolation (Tripathi et al 2006). To add spatial variability to the above GCM interpolations, gridded anomaly fields created by aggregation and interpolation of climatological information may be added (Wood et al 2004). A second approach utilizes large-scale atmospheric or surface patterns or indices as predictors to downscale a hydroclimatic variable. Uncertainty estimates are achievable by applying Monte Carlo or stochastic methodologies to generate forecast ensembles.

Bias correction is often a component of statistical (and as noted earlier dynamical) downscaling. The basis for bias correction is to shift GCM output to a reasonable range, based on observed conditions. Typically this involves matching monthly or seasonal average GCM output with observed averages. Common methods include quantile, histogram, or probability mapping of GCM projections (precipitation, temperature, etc) to baseline observations using probability density functions or cumulative distribution functions (Maurer and Duffy 2005; Woods et al 2004; Maurer 2007; Vanrheenen et al 2004; Christensen et al 2004; Hayhoe et al 2004; Payne et al 2004). The following figure (IRI working paper) provides a visualization of this process.



The figure demonstrates probability mapping of monthly GCM precipitation data based on two cumulative distribution functions (CDF): i) the historical observed data and ii) GCM produced historically simulated data (ensembles if available.) Each CDF is fit with a gamma distribution, with equal shape and scale parameters. The relationship between the CDFs is used to shift the GCM output to match the observed range of precipitation values.

Linear or multivariate regression is frequently employed for downscaling using synoptic patterns that are well simulated by GCMs and local variables instrumental in hydrological modeling (Wilby et al 1998; Xu 1999b). One deviation includes regression of a cumulative distribution function based on GCM output and local precipitation statistics (e.g. daily rainfall amounts or probabilities of wet/dry days) (Nawaz et al 2007). Another uses regression for matching observed and projected probability density functions of daily time series (Dettinger et al 2004). A third alternative, the expanded downscaling method (Burger 1996), utilizes the relationship between local climate anomalies and global circulation anomalies, and purports to better model extreme precipitation in comparison to traditional regression (Menzel et al 2006).

Additional statistical or empirical methods utilized for climate change downscaling in the context of hydrological modeling also exist, including weather generators and artificial neural network transfer functions (Wilby et al 1998), circulation-based analogues (Xu, 1999b), hybrids between a stochastic weather generator and a regression method (Wilby and Harris 2006; Wilby et al 2006), and support vector machine approaches (Tripathi et al 2006).

Statistical techniques for temporal downscaling are also available, most commonly used to produce realistic series of daily rainfall. Although GCMs simulate at sub-daily timescales, they are typically unreliable for aggregation less than months or seasons. The simplest method for downscaling temporally (say monthly to daily) is to divide the sum evenly among days, although this may be no more informative than using straight GCM output. A common approach involves selecting a month from the observed record and scaling (precipitation) or shifting (temperature) daily values using GCM projected anomaly fields means (Maurer and Duffy 2005; Woods et al 2004; Maurer 2007; Hayhoe et al 2004; Salathe 2005). A variation uses "change factors" (Wilby and Harris 2006), which use the changes in monthly means of variables from GCM projections to adjust a daily baseline period to reflect these changes. Consequently, the baseline and scaled projections differ only by means, not variability or range. Other techniques incorporate an additive shift (temperature) or multiplicative scaling (precipitation) approach between baseline observations and GCM projections (Wood et al 2002; Salathe 2005). For example, to temporally downscale precipitation, the following equation or similar may be used:

$$P_{fd} = P_{od} * \left(\frac{P_{fm}}{P_{om}} \right)$$

where *P* is precipitation, *f* is future, *o* is observed, *d* is daily, and *m* is monthly. Monthly values are based on means or medians of observed or future months. None of these methods account for potential changes in number of rainy days or shifting of seasons, etc. Stochastic "weather generators" are also frequently employed (Wilby et al 1998), as are first-order Markov chain models. These statistical models produce daily values in a random manner that is consistent with the statistics provided by the GCM output.

Assumptions and Concerns

Statistical downscaling approaches are favorable for being based on standard, accepted principles, computationally inexpensive, flexible, and their explicit use of observed records (von Storch et al 2000); however, they also assume no future change in predictor/predictand relationship, require long calibration records, and demonstrate skill dependent on climatic region and season (Goodess et al 2001; Wetterhall et al 2005a,b; Xu 1999).

The assumed relationship of stationarity between predictors (large-scale atmospheric or surface patterns) and the predictand (typically local precipitation) with statistical downscaling techniques is called into question under a changing climate (Charles et al 2004). If the assumption is to hold, the predictors chosen must be robust and fully represent the climate change signal (Tripathi et al 2006; Kavvas et al; Xu 1999b). If not, it is conceivable that the choice of predictors may even change the signs of the downscaled climate change signals. Recent experiments with predictor–predictand relationships, however, suggest that the stationarity assumption is not invalidated under future climate forcing provided the choice of predictors is judicious (Leung et al 2003; Murphy 2000). Wilby et al (1998) recommend including sufficient predictors, yet still strive for parsimony.

Another potential drawback is the lack of a universal, best-performing method for all locations (Wetterhall et al 2005a,b). While certain methods have proven less effective for hydrological modeling purposes (linear interpolation, Wood et al 2004), different models stand out, depending on spatial resolution and domain and the choice of downscaled variable.

Statistical downscaling models may also suffer from short observational records, specifically in reference to calibration. These short time series may produce relationships or probability distributions not representative of historical conditions. Quantifying sampling bias, however, may be achievable through a Monte Carlo type framework (Wood et al 2004.)

An advantage of statistical models is the ability to characterize and incorporate the uncertainty of the downscaled results. This is particularly important in hydrologic modeling applications, where uncertainties in climate change scenarios and downscaling has been found to outweigh uncertainties in hydrological model parameters (Wilby and Harris 2006; Menzel et al 2006). Statistical models provide the ability to fully explore the implications of the uncertainty that accompanies downscaling. One common approach to quantifying total model uncertainty is through stochastic analysis utilizing multiple models (GCMs, emission scenarios, downscaling techniques, hydrological models and hydrological parameters) to perform Monte Carlo simulations (Nawaz et al 2007; Wilby and Harris 2006). Another approach involves moving toward a probabilistic framework by assigning weights or using conditional probabilities (Wilby et al 2006).

8. Hydrologic Modeling from Downscaled GCMs

- Hydrologic models add little uncertainty relative to the uncertainty associated with climate models
- The choice of hydrologic model should be determined in accordance with the ability to estimate the desired variable
- Hydrologic model choice affects the downscaling method selection

A variety of approaches exist for generating hydrologic variables, such as streamflow, from GCM output. Hydrologic models transform climate variables such as precipitation and temperature into these hydrologic variables. In general, the hydrologic modeling component of downscaling is a source of much less error and uncertainty than the climate model components. There are a variety of validated hydrologic models that will serve effectively, including statistical models, lumped parameter models and distributed models. Distributed models produce spatially distributed results and require large input datasets. Uncertainty increases as a result of the many parameters and the difficulty in calibration. Lumped parameter models and statistical models allow explicit representation of uncertainty, are easily calibrated and have reduced parameter uncertainty, but may require long timeseries data. In general, the choice of hydrologic model will be contingent on the particular application of interest.

Fully distributed, physically-based models, such as water balance models or land surface models, require a large set of input climate data. For this reason, a dynamic downscaling model (RCM) is typically used since it generates this data automatically. Lumped parameter models, rainfall runoff models and statistical models require less input data. Statistical downscaling is then favored, since it can be designed to produce the input variables actually required relatively efficiently.

Fully distributed hydrological models exist at a variety of scales. Global water-balance models (e.g. Vorosmarty et al 2000) calculate a water balance for each grid (0.5°x0.5°) globally and route water to oceans or inland sinks in a very simple manner, given limited available data. Global routing models use gridded runoff to compute lateral water flow only; these models typically include a dynamic vegetation component for evapotranspiration and carbon fluxes (Gerten et al 2004). Finally, macro-scale water-balance models use GCM or RCM output for continental scale hydrologic simulations, focusing on large river basins; models are transferable from one continent to another (Xu et al 2005). An example is the Variable Infiltration Capacity (VIC) model, a semi-distributed, grid based hydrologic model, which has been widely applied (Liang et al., 1999). In all cases, these models are limited by the large number of parameters and limited observations that are available to calibrate those parameters.

9. Downscaling Applications in Africa

- Many downscaling studies have been performed for diagnosis of regional climate features (e.g., Sahelian drought).
- Fewer downscaling studies for hydrologic applications have been completed.
- Emphasis is on providing better understanding of regional climate and responses to climate change, over specific projections of change.

In general, downscaling efforts for regional climate in Africa have focused on diagnostic analyses of climate dynamics. The primary example is the use of regional climate models in various experimental designs to investigate Sahelian drought in West Africa (e.g., Jenkins et al., 2002; Jenkins et al., 2005; Giannini et al., 2003; Herceg et al., 2007). There are several efforts to downscale climate change projections to Africa regions, and fewer studies of downscaling for hydrologic applications. The most commonly utilized regional models are the RegCM3 of ICTP, the MM5 of Penn State University/NCAR (Grell et al., 1994), and the PRECIS model (Providing REgional Climates for Impacts Studies; Jones et al., 2004) of the Hadley Centre, UK. Given the uncertainty that reigns for much of Africa climate projections (see section 3), these studies place emphasis on characterizing the responses of regional climate features to climate change dynamics. The focus is on establishing a better understanding of general responses of regional climate over specific predictions of local impacts. This is also our recommended approach for any downscaling activities in Africa.

Two illustrative examples of dynamical downscaling of climate change projections for hydrological modeling are identified here. The first addressed hydropower potential over southern Africa using downscaled precipitation and temperature for 2070-2079 (Mukheibir 2007). The study used two RCMs to produce early and late summer (seasonal) total precipitation and average temperature (Tadross et al 2005). The MM5 and PRECIS regional climate models were used for downscaling. Both RCMs were nested within 10 years of control and future integrations of the GCM projections HadAM3P, which are forced by SSTs from HadCM3 and the A2 emissions scenario (Jones et al., 2004). Results are primarily non-quantitative, and focus on the limited information available regarding potential impacts at the hydroelectric sites. The authors encourage further study at the basin level to determine the effects of climate change before altering energy strategies.

The second study dealt with water availability in the Volta basin, West Africa, for 2030-2039 (Kunstmann and Jung 2005). Projections from the ECHAM4 (Roeckner et al 1996) GCM were downscaled using the MM5 RCM at three spatial scales: 81x81 km^2, 27x27 km^2, and 9x9 km^2. Additionally, the RCM was linked with a land surface model to account for feedbacks between soil moisture, temperature, vegetation, soil properties, and atmospheric conditions on monthly timescales. The IS92a-scenario, which assumes a 1% annual increase in CO_2 starting in 1990 was simulated. The results indicated a small number of positive trends in historical river discharge during the wet season, and predicted increases of 18% in mean annual surface runoff, compared with 1991-2000, for the smallest spatial scale.

Research studies employing statistical downscaling over Africa are more numerous than dynamical downscaling. Downscaling climate change projections over Africa in general is still not very common. One study assessed a water balance model's sensitivity to various climate change scenarios on White Nile streamflow using the HadCM1 and CM2 GCMs and used spatial interpolation for downscaling (Sene et al 2001). The authors found that some idiosyncratic features of the White Nile favored a network simulation approach.

A second study addressed Blue Nile streamflow sensitivity to climate change and associated uncertainties for three periods in the 21st century (Nawaz et al 2007). Downscaling techniques included regression based on cumulative distribution functions of CGCM2, ECHAM4, and HADCM3 GCM output and local precipitation statistics, in addition to a multidimensional stochastic rainfall generator. Streamflow projections initiated by two of the three GCMs forecasted reductions in future mean flow.

A third study considered impacts on Nile basin discharge in 2025 from the Blue Nile and Lake Victoria sub-basins (Conway and Hulme 1996). Three GCMs were chosen, a dry (Geophysical Fluid Dynamics Laboratory [GFDL; Weatherald & Manabe, 1986]), a wet (Goddard Insti tute for Space Studies [GISS; Hanson et al., 1984]) and a composite (weighted mean of seven GCMs) based on precipitation changes; precipitation and temperature are interpolated by the eight adjacent grid boxes using a Gaussian space-filtering method. Results indicate a small surplus in Egyptian flows no matter the state, given current demand projections.

Another study of Nile basin streamflow (Yates and Strzepek 1998), used spatially averaged temperature and precipitation for 12 sub-basins using interpolation through GIS by 6 GCMs (GFDL, GFDLT, GISS, UKMO, MPI, CCC). Most GCMs predicted significantly larger flows in Equatorial Africa and expansion of Sudd swamps. A wide range of flows was predicted for the Ethiopian highlands.

A final study evaluated potential changes in surface water supply across continental Africa under projected climate changes. Scenarios were based on results from a group of six GCMs, assembled by the Climate System Analysis Group in Cape Town, South Africa, with downscaled precipitation obtained through empirical methods (self-organizing maps.) This precipitation series resulted in a projected decrease in perennial drainage area, with implications surface water access across 25% of Africa by the end of this century (Wit and Stankiewicz 2006).

10. Summary Recommendations

Due to the limitations of regional climate models and GCMs, and the general chaotic nature of climate, any downscaling effort is fraught with uncertainty. For this reason, downscaling is best understood as an attempt to characterize regional climate and its response to climate change. No single model, group of models or specific methodology has emerged as definitive for downscaling. In fact, selecting “better” GCMs is difficult; using multi-model ensemble means is the recommended approach to dealing with model errors and the natural uncertainty of the climate system. Downscaling efforts should exploit all available information, including output from multiple GCMs, regional dynamic models and statistical models that utilize empirical relationships. Where GCMs do not agree, statistical modeling approaches may be used to reduce the uncertainty of future climate by characterizing the major modes of variability and trends based on historical observations. Where GCMs do agree, downscaling models can increase the temporal resolution and spatial resolution of the GCM signals. Dynamical downscaling is preferred where topography and local scale features, such as land use patterns and vegetation have large effects on regional climate. They may also be more useful in land management applications. All dynamical downscaling approaches typically utilize a form of “bias correction” which is a statistical model applied to the dynamical model out puts. Statistical downscaling is effective for temporal downscaling, for example, providing realistic daily rainfall values from monthly (or daily) GCM output. Statistical models are also recommended where particular hydrologic variables are of interest, as they can be “tailored” to provide estimates of desired quantities. The choice of hydrologic model to provide streamflow estimates should be determined by the specific hydrologic variables required. The hydrologic models, especially statistical or lumped parameter models, add very little uncertainty in comparison to the climate models.

Downscaling “Best Practices”

- Climate change projections should be based on multi-GCM ensembles
- Downscaling is appropriate where there is consensus on the direction of change in the GCMs
- Downscaling must be based on an understanding of how regional climate is expected to respond to large scale climate forcings and relative to the dominant modes of climate variability (interannual, decadal) at a particular location.
- In any specific case, the selection of downscaling methodology should be based on the particular application in terms of the variables of interest, time frame and spatial resolution required, the existence of previous studies and the availability of historical observation data.
- Statistical downscaling tends to be a better value than dynamical downscaling for hydrologic applications, being as effective and less expensive
- Dynamical downscaling is valuable where local topography and land use or vegetation have significant influence on regional climate.
- Temporal precipitation downscaling to resolutions of daily scale is an active research area, with statistical approaches showing the most promise.

- Results of climate change projections and downscaled regional results should be understood within the context of climate variability at interannual and decadal timescales, as well as socioeconomic changes.

References:

Akhtar, Ahmad, Booij, 2008. The impact of climate change on the water resources of Hindukush-Karakorum-Himalaya region under different glacier coverage, *Working Paper, UK Met office*. http://precis.metoffice.com/docs/Akhtar_water_resources.doc

Arnell, N.W. 2002. Relative effects of multi-decadal climatic variability and changes in the mean and variability of climate due to global warming: future streamflow in Britain, *J Hydrol* 270, 195-213.

Bergstrom, S., B. Carlsson, M. Gardelin, G. Lindstrom, A. Pettersson, M. Rummukainen 2001. Climate change impact on runoff in Sweden – assessments by global climate models, dynamical downscaling and hydrological modeling, *Clim Res* 16, 101-112.

Booij, M.J. 2005. Impact of climate change on river flooding assessed with different spatial model resolutions, *J Hydrol* 303, 176-198.

Burger, G. 1996. Expanded downscaling for generating local weather scenarios, *Climate Res* 7, 111–128.

Cook, K and E. Vizy, Coupled Model Simulations of the West African Monsoon System: Twentieth- and Twenty-First-Century Simulations, *J. Clim.*, (19) 3681-3703, 2006.

Charles, S., B. Bates, I. Smith, J. Hughes 2004. Statistical downscaling of daily precipitation from observed and modelled atmospheric fields, *Hydrol Process* 18, 1373–1394.

Christensen, N.S., A.W. Wood, N. Voisin, D.P. Lettenmaier, R.N. Palmer 2004. The effects of climate change on the hydrology and water resources of the Colorado River basin, *Clim Change* 62, 337-363.

Cocke, S. D. and T. E. LaRow 2000. Seasonal prediction using a regional spectral model embedded within a coupled ocean-atmosphere model, *Mon Wea Rev* 128, 689–708.

Conway, D. and M. Hulme 1996. The impacts of climate variability and future climate change in the Nile basin on water resources in Egypt, *Water Res Dev* 12(3), 277-296.

Dai, Aiguo, Precipitation Characteristics in Eighteen Coupled Climate Models, *J. Clim.* (19), 4605-4630.

de Wit, M., and J. Stankiewicz 2006. Changes in surface water supply across Africa with predicted climate change, *Science* 311,1917-1921.

Dettinger, M.D., D.R. Cayan, M.K. Meyer, A.E. Jeton 2004. Simulated hydrologic responses to climate variations and change in the Merced, Carson, and American river basins, Sierra Nevada, California, 1900-2099, *Clim Change* 62, 283-317.

Gerten, D., S. Schaphoff, U. Haberlandt, W. Lucht, S. Sitch 2004. Terrestrial vegetation and water balance—Hydrological evaluation of a dynamic global vegetation model, *J Hydrol* 286, 249–270.

Giorgi, F. and R. Francisco 2000. Evaluating uncertainties in the prediction of regional climate change, *Geo Res Letters* 27, 1295–1298.

Gleckler, P.J., K.E. Taylor, and C. Doutriaux, "Performance metrics for climate models," *J. Geophys. Res*., in press, 2007.

Goodess, C., M. Hulme, T. Osborn 2001. The Identification and Evaluation of Suitable Scenario Development Methods for the Estimation of Future Probabilities of Extreme Weather Events, *Working Paper 6, Tyndall Centre for Climate Change Research*, Norwich, UK, 44pp.

Graham, L.P., J. Andreasson, B. Carlsson 2007. Assessing climate change impacts on hydrology from an ensemble of regional climate models, model scales and linking methods – a case study on the Lule river basin, *Clim Change* 81, 293-307.

Grell, G., J. Dudhia, D. Stauffer 1994. A description of the fifth-generation Penn State/NCAR Mesoscale Model (MM5), *NCAR Technical Note NCAR/TN-398+STR,* 117 pp., Natl. Cent. for Environ. Res., Boulder, Colo.

Guo, S., J. Wang, L. Xiong, A. Ying, D. Li 2002. A macro-scale and semi-distributed monthly water balance model to predict climate change impacts in China, *J Hydrol* 268, 1-15.

Hansen, J., A. Lacis, D. Rind, L. Russell, P. Stone, I. Fung, R. Ruedy, J. Lerner 1984. Climate sensitivity analysis of feedback mechanisms, in: J. Hansen & T. Takahashi (Eds) *Climate Processes and Climate Sensitivity*, Geophysical Monograph No. 29 (Washington, DC, American Geophysical Union), pp. 130± 163.

Hay, L.E., M P. Clark, R.L. Wilby, W.J. Gutowski, G.H. Leavesley, Z. Pan, R.W. Arritt, E.S. Takle 2002. Use of regional climate model output for hydrologic simulations, *J Hydrometeorology* 3(5), 571–590.

Hayhoe, K. and coauthors 2004. Emissions pathways, climate change, and impacts on California, *Proc Natl Acad Scien* 101(34), 12422-12427.

Jones, R.G., M. Noguer, D.C. Hassell, D. Hudson, S.S. Wilson, G.J. Jenkins, J.F.B. Mitchell 2004. Generating high resolution climate change scenarios using PRECIS, *report, Met Off. Hadley Cent*., Exeter, UK, 40 pp.

Jørgensen, A.T., R.M. Johansen, M. Grum, J.J. Linde, O.B. Christensen, J.H. Christensen, Extreme precipitation on a sub-daily scale simulated with an RCM: Present day and future climate, *Geo Res Abstracts*, 6, 05303.

Kavvas, M.L., Z.Q. Chen, N. Ohara, A.J. Bin Shaaban, M.Z.M. Amin 2007. Impact of climate change on the hydrology and water resources of peninsular Malaysia, *Intl Cong on Riv Bas Man.* http://www.dsi.gov.tr/english/congress2007/chapter_2/42.pdf

Kunstmann, H. and G. Jung 2005. Impact of regional climate change on water availability in the Volta basin of West Africa, *Reg Hydrol Impacts of Clim Var and Change (Proceedings seventh IAHS scientific assembly),* IAHS Publ. 295.

Leung, L. R., L.O. Mearns, F. Giorgi, R.L. Wilby 2003. Regional Climate Research, *Bull Amer Meteorol Soc* 84, 89–95.

Maurer, E.P. and P.B. Duffy 2005. Uncertainty in projections of streamflow changes due to climate change in California, *Geo Res Ltrs* 32, L03704.

Maurer, E.P. 2007. Uncertainty in hydrologic impacts of climate change in the Sierra Nevada, California, under two emissions scenarios, *Clim Change* 82, 309-325.

Menzel, L., A.H. Thieken, D. Schwandt, G. Burger 2006. Impact of climate change on the regional hydrology – scenario-based modeling studies in the German Rhine catchment, *Natr Haz* 38, 45-61.

Mimikou, M.A., E. Baltras, E. Varanou, K. Patazis 2000. Regional impacts of climate change on water resources quantity and quality indicators, *J Hydrol* 234, 95-109.

Mukheibir, P. 2007. Possible climate change impacts on large hydroelectricity schemes in Southern Africa, *J Energy in Southern Africa* 18(1), 4-9.

Murphy, J. 2000. Predictions of climate change over Europe using statistical and dynamical downscaling techniques, *Int J Climatol* 20(5), 489–501.

Nakicenovic, Nebojsa and Swart, Rob (eds.), Special Report on Emissions Scenarios, Cambridge University Press, Cambridge, U.K., 612 pp., 2000.

Nawaz, R., T. Bellerby, M. Elshamy 2007. Quantifying uncertainties in the assessment of blue Nile flow sensitivity to climate change, *Hydro Scien (in review)*.

Payne, J.T., A.W. Wood, A.F. Hamlet, R.N. Palmer, D.P. Lettenmaier 2004. Mitigating the effects of climate change on the water resources of the Columbia river basin, *Clim Change* 62, 233-256.

Roeckner, E., K. Arpe, L. Bengtsson, M. Christoph, M. Claussen, L. Dümenil, M. Esch, M. Giorgetta, U. Schlese, U. Schultz-Weida 1996. The atmospheric general circulation model ECHAM4: model description and simulation of the present-day climate, *Report 218, MPI f. Meteorology*, Hamburg, Germany.

Rowell, DP. 2006. A demonstration of the uncertainty in projections of UK climate change resulting from regional model formulation. *Climatic Change* **79**: 243-257.

Salathe Jr., E.P. 2005. Downscaling simulations of future global climate with application to hydrologic modelling, *Int. J.Clim.* 25, 419-436.

Schulze, R.E. 1997. Impacts of global climate change in a hydrologically vulnerable region: challenges to South African hydrologists, *Progress in Physical Geography* 21, 113–36.

Sene, K.J., E.L. Tate, F.A.K. Farquharson 2001. Sensitivity studies of the impacts of climate change on White Nile flow, *Clim Change* 50, 177-208.

Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (editors), Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 996 pp., 2007.

Tadross, M., C. Jack, B. Hewitson 2005. On RCM-based projections of change in Southern African summer climate, *Geophysical Res Letters* 32, L23713.

Tripathi, S., V.V. Srinivas, R.S. Nanjundiah 2006. Downscaling of precipitation for climate change scenarios: A support vector machine approach, *J Hydrol* 330, 621-640.

Vanrheenen, N.T., A.W. Wood, R.N. Palmer, D.P. Lettermaier 2004. Potential implications of PCM climate change scenarios for Sacaramento-San Joaquin river basin hydrology and water resources, *Clim Change* 62, 257-281.

Varis, O., T. Kajander, R. Lemmela 2004. Climate and water: From climate models to water resources management and vice versa, *Clim Change* 66, 321–344.

von Storch, H., H. Langenberg, F. Feser 2000. A spectral nudging technique for dynamical downscaling purposes, *Mon Wea Rev* 128, 3664–3673.

Vorosmarty, C. J., P. Green, J. Salisbury, R.B. Lammers 2000. Global water resources: Vulnerability from climate change and population growth, *Science* 289, 284–288.

Weatherald, R.T. and S. Manabe 1986. An investigation of cloud cover change in response to thermal forcing, *Clim Change* 8, 5-23.

Wetterhall, F., S. Halldin, C.-Y. Xu 2005. Statistical precipitation downscaling in central Sweden with the Analogue Method, *J Hydrol* 306, 174–190.

Wetterhall, F., S. Halldin, C.-Y. Xu, 2007. Seasonality properties of four statistical-downscaling methods in central Sweden, *Theor Applied Climatol* 87, 123-137.

Wilby, R.L. and T.M.L. Wigley 1997. Downscaling general circulation model output: a review of methods and limitations, *Progress in Physical Geography* 21, 530-548.

Wilby, R.L., T.M.L. Wigley, D. Conway, P.D. Jones, B.C. Hewitson, J. Main, D.S. Wilks 1998. Statistical downscaling of general circulation model output: a comparison of methods, *Water Resour Res* 34(11), 2995-3008.

Wilby, R.L. and I. Harris 2006. A framework for assessing uncertainties in climate change impacts: low-flow scenarios for the River Thames, UK, *Water Resour Res* 42, W02419.

Wilby, R.L., P.G. Whitehead, A.J. Wade, D. Butterfield, R.J. Davis, G. Watts 2006. Integrated modeling of climate change impacts on water resources and quality in a lowland catchment: River Kennet, UK, *J Hydrol* 330, 204-220.

Wood, A. W., E. P. Maurer, A. Kumar, D.P. Lettenmaier 2002. Long-range experimental hydrologic forecasting for the eastern United States, *J Geophys Res* 107(D20), 4429, doi:10.1029/2001JD000659.

Wood, A.W., L.R. Leung, V. Sridhar, D.P. Lettenmaier 2004. Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs, *Clim Change* 62, 189-216.

Wu, W., A.H. Lynch, A. Rivers 2005. Estimating the Uncertainty in a Regional Climate Model Related to Initial and Lateral Boundary Conditions, *J Climate*18, 917–933.

Xu, C. 1999a. From GCMs to river flow: a review of downscaling methods and hydrologic modeling approaches, *Prog in Phys Geog* 23(2), 229-249.

Xu, C. 1999b. Climate change and hydrologic models: a review of existing gaps and recent research developments, *Water Res Man* 13, 369-382.

Xu, C., E. Wilden, S. Halldin 2005. Modelling hydrological consequences of climate change – progress and challenges, *Adv Atmos Scien* 22(6), 789-797.

Yates, D.N. and K.M. Strzepek 1998. Modeling the Nile basin under climatic change, *J Hydrol Eng* 3(2), 98-108.

Zierl, B. and H. Bugmann 2005. Global change impacts on hydrological processes in Alpine catchments, *Water Resour Res* 41, W02028.