Deriving Regional Precipitation Scenarios from General Circulation Models

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Report to the Water Research Commission
by the
Department of Environmental and Geographical Science
University of Cape Town

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Report to the Water Research Commission on the Project

"Analysis of regional precipitation and water resource impacts from GCM derived regional climate change scenarios"

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DERIVING REGIONAL CLIMATE CHANGE SCENARIOS FROM GENERAL CIRCULATION MODELS

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EXECUTIVE SUMMARY

Background

South Africa is characterised by a relatively dry climate with a high degree of inter-annual and intra-seasonal variability. Coupled with the growing demand on natural resources, and the utilisation of marginal land, the potential vulnerability to future climate change impacts is high. At present there is a high probability that anthropogenically induced global climate change will have significant impacts on the regional climate dynamics, perhaps most noticeably through the impact on water resources. This is a perspective largely accepted by the scientific community and supported by the high degree of consensus.

Regional climate change thus poses an important threat, and current scenarios of potential change are severely limited due to problems in obtaining accurate regional climate information from the General Circulation Models (GCMs), especially with regard to precipitation. As GCMs are the only really viable means of generating future climate scenarios there is a critical need to use the capabilities of GCMs to their best advantage in developing viable scenarios in order to plan for the future. Downscaling, whereby one uses the larger scale circulation dynamics to infer local climate, is one widely recognized methodological approach for dealing with GCM inadequacies in developing regional scale climate change scenarios, and is considered the most viable for the South African context.

Multiple approaches to downscaling are available, although some have significant infrastructural constraints or problematic assumptions which underly their procedures. The methodological option of direct downscaling, in which direct quantitative transfer functions between atmospheric forcing and local climate response are used, offers perhaps the most viable approach for South Africa. Early developments in this regard were undertaken in an earlier Water Research Commission study, and made significant advances. An evaluation of the initial methodology against three other downscaling approaches has shown that the downscaling approach adopted is able to capture important aspects of regional climates not managed by other techniques. However, problems were also identified in the comparative study, and this project seeks to address these, and provide a more stable and extensible methodological procedure.

Project Objectives

The initial objectives of the project were:

- Application of methodologies to multiple GCMs.
- Analysis of scenarios in terms of temporal characteristics.
- Transfer of scenarios for use in hydrological applications.
- Disaggregation of regional scenarios of catchment basin and station scales.

These objectives have been addressed, although the application of the methodologies to multiple GCMs was, in the second year, suspended in favour of focusing further on the methodology and temporal characteristics with one GCM.

Downscaling

Of all empirical downscaling techniques, the direct transfer function approach is arguably the method with the least problematic assumptions, and provides a tractable procedure for developing regional scenarios from long term GCM simulations, and for use with multiple GCM data sets. In this approach transfer functions are derived using observed atmospheric and local climate data. After validation, the functions are applied to atmospheric data from GCM simulations of future climates, and used to derive the local climate response, and hence climate change scenarios. The means adopted for deriving the functions is that of Artificial Neural Nets (ANNs), a non-linear procedure analogous to multiple regression.

In determining the local climate response three primary sources of forcing need to be accounted for:

1. Atmospheric circulation dynamics. This determines the transport characteristics of the air mass, and the dynamics determining vertical motion, and hence condensation, cloud formation, and the precipitation processes.

2. Atmospheric water vapour content. This attribute, neglected by many other studies, is of critical importance in the context of global warming. The water vapour content determines the precipitable water from the atmosphere, and under global warming it is probable that atmospheric water vapour will increase due to increase evapotranspiration from land and ocean surfaces.

3. Local sources. These refer to variance from features such as the particular trajectory taken by a precipitating convective cell. This source of variance is important if analysis of future climates is to be done with daily resolution data from the GCM, as opposed to seasonal means. As this source of variance is relatively insensitive to the climate change signal, it can be treated mathematically as a stochastic process.

The three sources of forcing on the local climate are incorporated into a downscaling methodology based on ANN empirical transfer functions using observational data. Validation of the ANN techniques has shown the procedure to be viable and effective in capturing the primary forcing over a wide range of climate regimes and seasonal variation. Using geopotential height fields representing circulation dynamics, and atmospheric humidity as an indicator of precipitable water, the ANN procedure is able to effectively capture the spatial and seasonal attributes of precipitation over South Africa.

The role of atmospheric humidity is evaluated in two downscaling experiments, and is shown to be a critical variable in terms of the local climate response to global change. The precipitation parameterization in GCMs is largely based on values of relative humidity, and with increases in temperature under future climate is potentially misleading with regard to the total moisture availability for precipitation events. Thus the inclusion or exclusion of specific humidity (a measure of total water vapour content) in the procedure can influence the results to such an extent that over certain regions the sign of the climate change may change, let alone the magnitude. Consequently downscaling without cognizance of the role of atmospheric humidity leads to scenarios that only represent climate response to circulation dynamics, which, while informative, may be substantially different from actual climate response.

Similarly, the role of the local forcing is evaluated by downscaling both with and without the local forcing component included. The addition of this source of variance is shown to substantially improve the daily characteristics of the downscaled climates and allows scenarios to be constructed in terms of the daily behavior of the downscaled climate.

In the context of a GCM's skill in simulating the larger scale atmospheric dynamics, and given the limitations of alternative regional scenario schemes, the downscaled procedure represents a viable, justifiable, and pragmatic solution for meeting the immediate and near future climate change impact research needs.

Assessment of Products and Applications

The primary product has been the development of a sophisticated methodology and stable software package. This has been applied to GCM data to generate climate projections for South Africa. In addition the project has involved two MSc. post-graduate students and one PhD student. These have all graduated, and two are continuing with a climatology career. A number of journal papers have appeared which utilize the results developed in this project, and further journal papers are in preparation or under review. In light of the above, the project has addressed the initially stated objectives, although not applied to multiple GCM data sets.

The WRC project has also resulted in a number of ongoing research thrusts. Most importantly, the methodologies have been adopted by the South African national climate change assessment team to provide climate projections. Furthermore, the same methodology has been used in projects in the USA to investigate climate change over the USA, Mexico, and Bulgaria. The methodologies are now forming a basis of the new USA national climate change assessment. Finally, the software now forms a basic tool in ongoing research at UCT, and has been adopted by three research groups internationally.

Future directions and recommendations

While this project does produce a preliminary set of climate change scenarios, the primary focus is the suite of software tools for ANN-based downscaling. The software has been packaged into a (relatively) user-friendly package and is already in use by other researchers. The software package will be made available to relevant researchers on request, with collaboration encouraged.

However, within the South African context the primary need is to apply the procedure to as wide a range of recent generation GCM experiments as possible. In the light of the variable nature of the South African climate system, and the high degree of vulnerability to climate change, a clear view of possible future impacts is needed, with rational interpretation and associated levels of confidence in the climate projections. The only tractable means of developing such a broad base of scenarios within the next few years is through analysis of ensembles of current-generation long-term (100 year+) regional climate-change projections derived from GCMs with empirical downscaling. In ensemble simulations the GCM is repeatedly run using nominally different starting conditions, resulting in time series that generate a range of possible climate projections. Such ensembles are becoming available, and through the application of downscaling it is possible to generate a suite of regional climate projections that span the possible range of outcomes.

Thus, follow-on work focused on accessing suitable GCM simulation data sets and using these for downscaling, is highly encouraged. In addition, such work should take place in close collaboration with scientists in other disciplines to ensure valid interpretation of the potential climate change impacts within South Africa. Furthermore, given the trans-national nature of the climate system, such work should also take cognizance of the southern African nations to the north of South Africa. This should be not only in terms of benefiting their understanding of climate change impacts, but also in terms of interactions of the climate system over the broader region.

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1. Introduction

South Africa is characterised by a relatively dry climate, a high degree of inter-annual and intra-seasonal variability, and consequently a high degree of vulnerability to changes in the climate system. At present there a high probability that anthropogenically induced global climate change will impact in a significant manner on society – a perspective largely accepted by the scientific communities and readily apparent from the extensive investment by nations into climate change research. It is also generally accepted that climate change, if not already detectable above the ambient variance of the climate system, is nonetheless probably already occurring. In addition there is a high degree of consensus among the scientific community that current research points emphatically to global climate change being probable, and that this is a problem of global importance (see IPCC, 1995a,b,c).

In order to respond effectively to possible impacts on society, it is imperative that scientists within South Africa investigate the regional consequences of global change in terms of the sensitivities of the physical system, the vulnerabilities on a regional basis, and the possible adaptations that can be made. Across disciplines this has already begun to take place in individual projects, and has recently received valuable support after South Africa's ratification of the Framework Convention on Climate Change (FCCC) treaty in 1997. Subsequent to this a broad spectrum of work has been funded on relevant aspects of climate change in both the social and physical sciences.

However, fundamental to any such work is the requirement for plausible and justifiable scenarios of potential change within the climate system *on the regional scale.* Without such scenarios any impacts work becomes little more than educated thought experiments. As a result there has been a growing demand, magnified by the FCCC work, for climate change scenarios at the regional scale to be used in a range of disciplinary studies. It was in response to such needs that the work presented here was initiated (see Hewitson, 1997), and was a similar incentive for a number of other research projects around the world. The aims of this project were thus set out as:

- The application of downscaling methodologies to multiple GCMs.

- The analysis of downscaled climate projections in terms of temporal characteristics.

- To transfer of scenarios for use in hydrological applications.

- The disaggregation of regional scenarios of catchment basin and station scales.

In general the only viable approach to evaluating future climate conditions is through the use of General Circulation Models (GCMs), and GCMs thus initially formed the basis of information for developing regional scenarios (e.g. Schulze et. al., 1993). However, it was quickly recognised that while GCMs are able to simulate the synoptic scale atmospherics dynamics over South Africa quite well (e.g. Hudson, 1997, Hudson and Hewitson, 1997), they are particularly poor at representing regional climate, and are especially problematic when representing precipitation. In this respect the GCMs are at odds with end-user needs; while the skill of the GCM increases with greater spatial/temporal aggregation, the needs of the impacts researcher are conversely greatest at high spatial and temporal resolutions.

The difficulty in the development of regional scenarios directly from GCMs has thus lead to the development of a range of alternative techniques for deriving regional and sub-grid-scale climate information (e.g. Hewitson, 1996; Crane and Hewitson, 1997), and is an accepted area of research methodology now commonly termed downscaling.

The pragmatic demands on downscaling are, however, more than simply the derivation of sub-grid-scale information from GCMs, and additionally include the need for a range of climate change scenarios from multiple GCM simulations. This is required in order to evaluate consensus among GCMs as a means of attaching confidence levels to the scenarios, and in order to span a reasonable range of future climate possibilities. Thus any downscaling methodology should, from the perspective of impacts research, focus on the spatial and temporal needs of the end-user, and present a tractable means for handling multiple scenarios from different GCM sources.

2. Downscaling Options

In all cases the basis for downscaling is the implicit assumption that local climates are dominantly a response to larger scale atmospheric forcing – an assumption that, as will be shown, is largely true but has a number of important caveats. Downscaling uses those atmospheric variables indicative of (primarily) the synoptic scale circulation and dynamics in order to determine the local climate response, and then uses these variables from the GCM to derive the local climate change scenarios. The premise in this case is that GCMs are able to simulate adequately the larger scale dynamics of the climate system, in contrast to the poor "skill level" (von Storch et. al., 1992) at the regional scale.

Figure 1 outlines the two downscaling approaches available to the researcher. The one approach is nested modeling of the regional scale dynamics using physics-based models, and an alternative, empirical downscaling. A third option is to combine both options, but this will not be discussed here as this is still in the early stages of development.

The nested modelling approach typically drives a limited area dynamics-based model with boundary fields derived from the GCM in order to resolve a regional climate solution consistent with the given set of boundary conditions. In the long term this approach is likely to provide the most stable and interpretable means for deriving regional scenarios. However, at present, and for the near future (the next 5 years or more), the nested model approach is unlikely to form the primary methodology for South African research activities, or for analyses based on multiple GCMs. This is mostly due to the computationally intensive nature of nested modelling, where the computational requirements are as great as those needed for running a GCM. In addition, the process of coupling a regional and global model in some respects remains problematic, and this should be viewed as a methodology under development. The above constraints with nested modelling means that for long term GCM simulations (100 years or more), and for using multiple GCMs, it is computationally impractical to use nested modelling in an African context for developing a broad base of climate change scenarios. South Africa is not alone in this situation, and many of the leading research organisations in the world still sit with the same computational constraint, albeit to a lesser degree.

Empirical downscaling, on the other hand, is computationally efficient, and can easily be applied to multiple GCM simulations over multiple regions. The empirical approach is founded on the premise that the local climate is dominantly a response to the larger scale atmospheric forcing. This is largely true, as the results bear out, and may be seen even on a simple qualitative level, whereby the local climate is seen as a response to synoptic systems (e.g. cold fronts), air mass characteristics (e.g. humidity), and air mass trajectory and source regions. Even convective activity or orographic rainfall, nominally local scale features, are nonetheless dependent on the larger scale synoptic conditions.

However, while the above premise may be accepted, the synoptic controls are never the complete determinant of the local climate, and two important alternative aspects needs to be recognised. Firstly, and of critical importance in the context of global warming, is the atmospheric water vapour content, and secondly, the role of local forcing. Nonetheless, while these two factors are important, they are largely secondary to the role played by the synoptic forcing, and will thus be discussed later as refinements of the downscaling.

The primary principle in empirical downscaling is to use observational data (training data) in order to derive a relationship between variables representative of the larger scale circulation and the local climate response of interest, for example, precipitation. The derived relationship is then applied to the same atmospheric variables from the GCM simulations in order to derive the sub-grid-scale response and develop climate change scenarios.

As discussed earlier the downscaling approach assumes that the local and regional climates are primarily a function of synoptic scale forcing which determines the dynamics controlling such attributes as precipitation or cloud cover, as well as the air mass characteristics of humidity and temperature, and source regions. In addition, and perhaps less apparent, is that the procedure assumes that the GCM atmospheric circulation events fall within the span of events in the training data which is used to derive the relationships. If this were not the case, then the methodology requires that the derived relationships are stable enough to extrapolate beyond the bounds of the data on which the relationship is based. This implied attribute is obviously potentially problematic, however, in general the changes in the GCM output-data are affected through changes in frequency, intensity, persistence, and the recurrence period of synoptic events. Hence the GCM data do fall within the span of the observational training, with the exception of very few events denoting rare weather occurrences, and thus the assumption of not using the relationship to extrapolate can be made safely.

Empirical downscaling methodologies have appeared in multiple forms in the literature, and fall within three categories (Figure 1); stochastic (weather generators calibrated to the large scale circulation fields), indirect relationships (a traditional synoptic climatology approach using circulation typing), or direct relationships (using direct quantitative functions to relate circulation to local climate). While each approach demonstrates relative advantages and disadvantages, a common theme in their application has been to use atmospheric predictor variables which describe the circulation dynamics (e.g. geopotential height fields, or vorticity), and occasionally include other variables such as atmospheric temperature.

Stochastic weather generators, perhaps the most common methodology, suffer from the fact that the procedure is "tuned" to the frequency distribution of present day conditions, and hence presents a problem if future climates change in terms of the frequency distribution of events. More traditional synoptic climatology techniques, while avoiding the difficulty with stochastic techniques, afford only a very coarse incremental resolution over the range of the local climate response. Direct relationships attempt to derive quantitative equations in the form of a transfer function between the atmospheric forcing and the local climate response. As such, the direct relationship method, in theory, will provide local climate data to the maximum spatial and temporal resolution afforded by the training data, and to the degree that the local climate is a response to larger scale atmospheric forcing.

3. Empirical transfer function downscaling

The empirical downscaling approach used in this study is a development of initial work undertaken by Hewitson (1996, 1997). The initial study was based around the use of Artificial Neural Nets (ANNs) to derive non-linear relationships between atmospheric circulation (represented by Principal Components Analysis (PCA) of sea level pressure and 500hPa geopotential heights) and local precipitation and temperature. The procedure was shown to demonstrate significant skill in generating the local climate response on a 5-day smoothed temporal scale.

In essence, the ANN methodology works in a manner analogous to multiple regression whereby a function between an independent set of variables (the PCA of atmospheric circulation) and the local climate (temperature and precipitation) is derived. The ANNs, however, provide significant advantages over regression in that they are able to capture arbitrary non-linearities within the data and hence represent, theoretically, the fullest expression of the relationship between the independent and dependent variables. Full details of the ANN approach and how to use ANNs may be found in Hewitson (1997) and Hewitson and Crane (1994), and a short summary of the basic attributes of the ANN are presented here (adapted from the appendix in Wilby *et. al.*, 1998).

ANN fundamentals

ANN downscaling represents a form of direct scale translation, whereby a quantitative function is derived which directly relates two data sets (e.g. atmospheric circulation variables and target local climate). In this regard, ANNs are analogous to multiple regression, although mathematically dissimilar. In the same way that multiple regression develops a quantitative function, so does an ANN, although with no supposition on the form of the function or degree of non-linearity. In theory, an ANN is capable of representing any arbitrary non-linear relationship.

An ANN is composed of multiple simple processing nodes, each of which receives inputs from other nodes, and outputs values to further nodes. The resultant "net" of nodes will have some nodes dedicated to receiving inputs, and some to providing outputs from the overall net. Each node is connected to others via weighted links, and calculates a sum of the weighted inputs. This sum is then transformed with some function, typically a linear or step function, or a bounded differentiable non-linear function (e.g. a sigmoid), which becomes the node output value.

Nodes are generally arranged in layers, with an input layer connected to a "hidden" layer that is in turn connected to an output layer. Figure 2 shows a typical ANN construction. Given this structure, a useful analogy of how the ANN represents a complex function is that of inverse Fourier transforms. In the same way that inverse Fourier transforms combine simple sine and cosine waves to create a complex wave, so ANNs combine simple non-linear functions to create a complex function.

In downscaling applications the ANN is typically configured with only one output node to provide the downscaled information for the target location, and an input layer of nodes and one hidden layer. Development of the actual function represented by the ANN is accomplished through a training procedure. Multiple alternatives are available for training, but all, in some form or other, represent a minimization procedure. Initially the weights in the ANN are set to small random values. The ANN is then presented with input data for which known target output values are available. The full set of input samples is sequentially presented to the ANN, and the error between the ANN output and desired output values noted. The training procedure then adjusts the weights in an attempt to minimize the error, and the training data are again presented to the ANN. In this manner the training algorithm iteratively performs a minimization procedure of the error surface to find the global minimum, or at least a local minimum close to the global minimum.

In this downscaling application, the training algorithm used is back-propagation, whereby the error after each pass of the data is "back-propagated" through the net from the output node to the input nodes, with proportional error assigned to each node. The weights connecting each node are then adjusted in a direction to minimize the error. In the simplest form this represents a gradient descent algorithm. However, the form utilized here makes some assumptions about the shape of the error surface local to each node in order to speed up the convergence, and avoid becoming trapped in a local minimum.

A potential pitfall in the ANN training procedure is that of overtraining. Due to the ability of the ANN to represent highly complex relationships, it is possible for the ANN to start "learning" to relate the noise or unrelated variance in the input and target output data. To avoid this, a random portion of the training data is usually removed from the training process and retained for testing purposes. During the training procedure, the ANN is then repeatedly evaluated against the independent test data until the performance of the ANN on the test data no longer improves. Once the training of the ANN is completed, the ANN function may be applied to further input data with the assumption that the new data falls within the dimensional span of the training data.

Limitations and refinements:

Through experience in the initial downscaling project, and in subsequent comparative methodology studies, it was noted that the ANN procedure as configured contained some limitations that would benefit from further refinements. In particular, the procedure required a potentially problematic step of matching PCA results between observed and GCM data, and had difficulty in generating daily resolution data. As a result, the procedure was restructured in this project, retaining the ANN as the core means of generating the relationship, using alternative means of forming the input atmospheric variables, and including a technique to incorporate the local forcing component.

Fundamentally, the changes to the ANN downscaling procedure are:

- Replacement of the PCA data with the raw assimilation atmospheric data and the inclusion of an index of synoptic state as a predictor.

- Inclusion of atmospheric water vapour content as a predictor.

- Addition of procedures to include local climate variance due to local forcing not represented by the larger scale atmospheric forcing.

Each of the above improvements is discussed separately in the sections below.

4. Using raw atmospheric data as predictors

In the simplest of forms the downscaling needs to incorporate the atmospheric circulation as the primary forcing/predictor of the regional climate. Within this data set the need is to represent the atmospheric dynamics in the lower and upper troposphere, and some indication of the time-dependent development of the synoptic state. In the initial study the circulation was represented by lagged PCA component scores on the presumption that this would provide a dimensionally reduced version of the data representing the primary processes. However, the added complexity of PCA along with the related assumptions introduced appears to add little benefit to the procedure over simply using the raw data values. While the use of raw data does increase the number of predictor variables over that of the PCA version, this only minimally increases the computational requirements.

The indicators of tropospheric dynamics chosen are thus the 500hPa and 700hPa geopotential height fields, while the time-dependant development is included through lagging of the height observations. The geopotential height fields implicitly include the attributes of the dynamics such as vorticity, or divergence, and the subsequent impact on vertical velocity, as well as geostrophic wind speeds and direction. While other derived fields could be used as well, the selection of the circulation variables is constrained in this application to geopotential heights as, if climate change scenarios are to be developed, then there is the added requirement that the fields be valid in the GCM as well.

In theory the above information should not need further manipulation prior to use as predictors with the ANN. However, while the ANN is capable of generating transfer functions of arbitrary complexity, in practice it appears beneficial to provide the predictor information in a form whereby the coarse state of the atmosphere is also represented, and then the ANN can better identify the actual response. The simplest way of representing the basic state of the atmosphere is through some means of synoptic indexing. In this application the synoptic indexing is done with the use of Self-Organising Maps (SOMs). SOMs provide a 2-dimensional non-linear integer index of the state of the atmosphere at a user selectable resolution. In this manner an additional 2-part index of the synoptic state may be added as a predictor. Details of the SOM are further outlined below.

5. Self Organising Maps and "typing" synoptic states.

If one considers the atmospheric data to be samples of a continuum, then ideally a synoptic indexing method should identify the preferential "modes" of state along the continuum. Thus, as samples of the continuous behavior of the atmosphere one would like to identify states along the continuum which represent modes of the atmosphere of primary importance (at least in terms of frequency of occurrence). These "modes" in turn may be non-linearly positioned within the continuum, and thus no supposition in this regard should be made by the method used. While traditional synoptic typing techniques exist, these are linear in nature, assume the data variables to be orthogonal, and work from the presumption that the data represents groups rather than a continuum. Furthermore, it is problematic to quantitatively express the relation of one cluster group to another.

Conversely, a tool that avoids these difficulties, and is particularly suited to the conceptual objective outlined above, is the Kohonen Map, or Self Organizing Map (SOM). A suitable analogy for a SOM is that of an optical camera. In a manner similar to the way that an optical camera projects 3-dimensional space onto a 2-dimensional plane, so a SOM projects N-dimensional data onto a 2-dimensional plane. In the case of the SOM, the 2-dimensional plane is made of a matrix of nodes, and the data is projected onto one of the nodes. Taking the camera analogy a step further, using the SOM is a matter of "focusing" the SOM lens to correctly project the data onto the plane of nodes. The result is that data samples may be mapped to one of N-nodes, where similar data samples will map to adjacent nodes, and hence represent the N-dimensional continuum across a 2-dimensional plane.

Thus, the SOM can be viewed as expressing the continuum of samples non-linearly across a 2-dimensional plane. In short, an explicit definition of the SOM procedure is that the SOM defines a 'nonlinear projection' of the probability density function of the high-dimensional input data onto a two-dimensional display. Full details of SOM procedures, complete reference lists, and details of implementation may be best found with the software package SOM PAK, freely available at ftp://cochlea.hut.fi. Figure 3 provides a conceptual schematic of how the SOM is "focused", or trained.

The SOM is essentially a single layer competitive ANN where each node has a set of weights equal in number to the number of data inputs. As with training the downscaling ANN, training data samples are presented sequentially to the SOM. With each presentation, the outputs of each node are determined and the node with the largest output value is deemed the "winning" node. The weights of this node are then incrementally updated such that the values of the weights approach that of the data sample. Additionally, the weights of the surrounding nodes are updated in a similar manner but to a lesser degree. With greater distance from the "winning" node, the weights are updated to a lesser and lesser degree.

In this manner, similar data samples are "focused" to the same node, and marginally less similar data samples to adjacent nodes, and so on. The data are repeatedly presented to the SOM until each node's weights closely represent the modal value of all samples mapped to that location. After training, any data sample may be presented to the SOM and the node to which it maps identified by the X and Y coordinate of the node matrix, analogous to a cluster group in regular cluster analysis. Smaller matrices of nodes generalize the input data, while larger matrices provide more detail—in the same manner as cluster analysis where few clusters generalize the data clustered, and many clusters provides more detail. The SOM, however, has an additional advantage in that the "clustering" may be easily visualized, as each node in the SOM matrix is related to the adjacent nodes, and the weights on each node represent a point on the continuum of the higher dimensional input-space.

In the downscaling application, the same input data used in training the ANN are used to train the SOM. A SOM of 15 nodes was created as a matrix of 3 by 5 nodes. After training the SOM each node on the SOM matrix represents a state in the circulation input space.

6. ANN basic downscaling procedures.

Figure 4 indicates a typical downscaling procedure, and demonstrates how the SOM indexing becomes a further procedural step and provides the additional inputs for the ANN. The flow diagram indicates how observational data are initially used to create a transfer function *f* between the atmosphere and some given local climate variable. The function is then subsequently applied to independent observational data and later GCM data to generate local climate variables as a function of the atmospheric forcing.

At this stage of development, the downscaling represents only the atmospheric component in determining the local climate. Nonetheless, under the assumption that the synoptic dynamics are the dominant control then it is anticipated that this would provide the fundamental local climate response from the ANN. The ANN was tested following this procedure and demonstrated that this expectation held true.

In this first test the atmospheric observational data used are from the GSFC[1] 4-D data assimilation experiment which spanned the years 1980 to 1993. The geopotential height fields for 700hPa and 500hPa are selected to describe the circulation dynamics, and inherently account for information such as geostrophic wind speed, vorticity, and divergence. The data are twice daily (0Z and 12Z) on a 2° latitude by 2.5° longitude grid. The observational daily precipitation data used as the local climate variable of interest are area averaged station data obtained from the South African Computing Centre for Water Research (CCWR[2]), and provide gridded precipitation on a 0.5° grid. Grid cell averages derived from less than 3 stations are not used. The ANN downscaling procedure is then applied for each of the December-January-February (DJF) and June-July-August (JJA) seasons.

For each target local climate grid cell (0.5° area-averaged precipitation) the 700hPa and 500hPa geopotential heights from the co-located GSFC grid cell, plus the 8 surrounding cells are selected. A moving 48 hour window is then used to incorporate the antecedent conditions, and used as inputs to the ANN and SOM. Initially a SOM classification is performed to obtain the additional indices to use as inputs to the ANN. For both the SOM and ANN training the data are first subset on a random basis into two groups of 75% and 25% of the days. The 75% set is used in training and the 25% set used as independent data to evaluate the training, and determining the point at which to halt training and prevent the ANN from learning to relate noise between the input and output data sets.

A separate downscaling is performed for each target 0.5° grid cell. The best transfer function for a grid cell is determined at the point in training where, when applying the ANN function to the independent 25% test data, no improvement in the match between the ANN derived precipitation and the observed target precipitation is seen. Finally, the ANN predicted daily precipitation produced by the ANN with the independent test data is evaluated against the actual observed precipitation to validate the downscaling functions.

Figures 5 and 6 show the observed DJF and JJA seasonal mean precipitation based on the observational daily precipitation data, and the daily precipitation predicted by the ANN as a function of the atmospheric forcing. As can be seen, the ANN derived precipitation field demonstrates an accurate representation of the spatial pattern, as well as magnitude, of the precipitation, although with a slight tendency to be too wet. Thus, at least in terms of the aggregated seasonal means from the daily downscaled precipitation,

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[1] Goddard Space Flight Center (GSFC) reanalysis project at http://dao.gsfc.nasa.gov/
[2] http://www.aqua.ccwr.ac.za/

the ANN functions may be deemed valid and further applied to GCM simulation data in order to generate climate change scenarios.

7. The relative importance of atmospheric humidity.

As identified earlier, in terms of the controls on regional climate the atmospheric water vapour content plays an important role, particularly in the context of global climate change where global warming would alter global evapo-transpiration. However, in nearly all cases of downscaling in the literature, the absolute atmospheric humidity levels (as opposed to, say, relative humidity) have been left out of the downscaling function, and it is argued that this represents a significant problem.

A study that particularly highlighted the potential significance (albeit negatively) was undertaken as a team project in 1996/7 where 4 downscaling research groups participated to evaluate the respective methodological strengths and weaknesses (Wilby et. al., 1998). Using only circulation data and no atmospheric variable indicative of humidity, four independent downscalings were carried out focused on the USA and using the identical source data. In all cases the climate change scenarios developed showed, contrary to expectations, minimal change in precipitation. Conversely, another study (Crane and Hewitson, 1997), although using different GCM data, included atmospheric humidity and noted a significant climate change signal over similar domains in the USA.

In terms of climate change scenarios one needs to consider seriously the potential consequences of the above approach. As noted earlier, climate change is likely to be primarily manifest at the regional scale in terms of changes in frequency, intensity, and persistence of synoptic events, coupled with a background increase in the direct radiative forcing. However, in addition to this, atmospheric humidity levels are also expected to change significantly as a function of warmer oceans with greater evaporation, and warmer land temperatures driving greater evapo-transpiration. The consequent changes in absolute humidity levels leads to changes in the precipitable water, and would seem, even on a purely conceptual level, to be critical for determining precipitation rates. Thus, when considering regional climate change scenarios and the impacts on precipitation, which is perhaps the variable with the greatest potential to impact society, it would seem vital to include some measure of atmospheric humidity in the downscaling functions.

To evaluate the significance of this aspect, an empirical downscaling is performed where atmospheric humidity is firstly included, and then excluded, from the downscaling function. Regional climate change scenarios are then derived from a GCM simulation, and the response evaluated in the light of the inclusion or exclusion of humidity fields.

An important question related to this is how to represent humidity – a question that has been the subject of some debate. The common variable used is Relative Humidity (RH). However, RH is probably the least useful measure to use in this case, as it is not a measure of the absolute water content, and strongly dependant on temperature – a variable likely to change under global warming. An alternative quantity representative of the absolute water content of the atmosphere would be specific humidity.

As specific humidity is the mass of water vapour per unit mass of moist air, if we warm the air column (in a global warming scenario), volume and pressure change, but specific humidity at any particular level does not change (unless evaporation changes). That is, there are still the same number of water molecules in a Kg of air. On the other hand, RH will change, as it is the ratio of water molecules in a parcel of air to the number of molecules you would have in a saturated sample of the same volume, at the same temperature.

So, if one ignores for the moment increased evaporation and considers what happens if the air simply warms, then specific humidity does not change but RH decreases. In this case a downscaling transfer function using RH as a predictor is likely to produce less rain. In reality, we assume that the processes that produce uplift and cooling cannot change (i.e.: the fundamental physics of the atmosphere remains the same), and so a synoptic situation that produces uplift, condensation, and precipitation under present conditions will do so in the future. What is important in determining the magnitude of the rainfall event is thus not the process that brings the air to saturation, but how much water vapour is present (again assuming that cloud condensation nuclei (CCN) do not change). Thus in this situation, specific humidity is a far better measure of atmospheric water content than RH.

To evaluate the role of atmospheric water content two downscaling experiments were conducted; the first with no atmospheric humidity predictors, and the second using specific humidity as a predictor. In the case including humidity the specific humidity values co-located with the target grid cell at the surface (2m – indicative of boundary layer humidity), 700hPa (lower troposphere), and 500hPa (mid to upper troposphere) levels were included as predictors. Thus the full predictor set represents the column humidity over the target location, and the tropospheric circulation dynamics over the surrounding region. As before, the ANNs are trained, and now in addition applied to the GCM simulation data, as it is in this context that humidity is of primary importance.

For use with GCM data, 5 years of twice daily fields were extracted from each of the control and doubled atmospheric CO_2 simulations of the GENESIS v2.01 GCM. These simulations are not transient runs as are most current generation experiments configured. Nonetheless, they serve well in the current context, and the GENESIS GCM has been validated in terms of circulation over southern Africa (Hudson, 1997). Full details of the GENESIS GCM may be found in Pollard and Thompson (1995) and Thompson and

Pollard (1995). The GCM has 18 vertical levels and T31 horizontal resolution, and uses a mixed layer ocean. The data have the same temporal resolution as the GSFC data, and are spatially interpolated to match the GSFC grid.

Figure 7 and 8 show the DJF and JJA ($2xCO_2$ – control) seasonal mean precipitation anomalies derived from downscaling without the humidity data, and the same mean fields derived from downscaling including humidity as a predictor. While the specifics of the regional climate change implications are of ultimate interest, the point to be made here is that the presence or absence of atmospheric humidity in the downscaling function has a substantial impact on the resultant climate change scenario. As can be seen in Figure 7 and 8, not only is the magnitude of change different, but also in some regions the sign of the change may be reversed.

The results indicate that the regional climate change scenarios need to be considered as more than a response to synoptic forcing, and that the additional factor of atmospheric humidity can play as important a role. For example, in interpreting this scenario the indication is that the changes in synoptic forcing are conducive to a drying in the summer rainfall regions (downscaling without atmospheric humidity), whereas the change in atmospheric humidity (from atmospheric warming and increased evaporation) appears to counter the drying trend. As such, the validity of the scenario needs to be evaluated in the light of not only the GCMs synoptic circulation performance, but also in terms of the humidity changes in a doubled CO_2 world.

The numerous downscaling applications presently in the literature thus potentially represent only the climate change forcing in terms of the synoptic forcing, unless the methodology has explicitly accounted for absolute humidity levels in the atmosphere. While the response to synoptic forcing alone is important information for understanding the potential changes to the climate system, the scenarios need to be considered in the light of whether the role of changing atmospheric humidity has been accounted for, or not.

8. Stochastic addition of local forcing.

Thus far the downscaling has focused on the local climate response in the context of the larger atmospheric forcing. However, as noted earlier, atmospheric factors alone are not perfect predictors, and there will always remain a residual variance unaccounted for by the atmospheric predictors. The net effect of not including the variance from local forcing is for the downscaling to generate far too many trace precipitation days, and to under-predict the peak events.

This effect is due primarily to the downscaling relationships generalising a local climate response for a given atmospheric state. For example, in the training data, very similar atmospheric states have associated with them a (finite) range of local climate responses, and the downscaling relationship provides some generalised value of this range of response. With the ANN, the generalised local response tends toward the *mode* of the individual responses in the training data for days with a similar atmospheric state – or in other words the ANN response tends toward the most frequent response in the target data for the given atmospheric state. For much of the range of local climate variation this does not present a problem, but does become a significant factor at the tails of the distribution.

For example, consider the dry and wet ends of a precipitation distribution. On the dry side, in order for the ANN to differentiate between zero rainfall and trace rainfall, the atmospheric predictors need to incorporate some distinguishing forcing factor. However, with atmospheric circulation the means of distinguishing between a dry day and a trace precipitation day is often not possible, and is rather a function of some other feature, such as antecedent soil moisture, or the particular trajectory of a convective cell. Hence, during training the ANN is presented with days that from an atmospheric standpoint look very similar, yet have local responses of both zero and low precipitation amounts. The ANN generalised response is to converge to the median of these, which in this case becomes a trace rainfall event.

At the extreme wet end of the spectrum the situation arises where the atmospheric distinction between a high rainfall event and a very high rainfall event may be fairly subtle. This is compounded by the fact that there may be very few samples in the data from which to infer the relationship. As with the trace rainfall situation, for the atmospheric forcing of a given set of high rainfall events, the ANN will converge on a median value for this atmospheric state which will be somewhat less than the peak values of the data.

The net effect of the above is that the ANN produces a reduced range of local climate responses characterised by too many wet days – which is the representation of the local climate purely as a function of atmospheric state. While in one sense the residual variance not captured may be considered noise, it is in fact due to local processes for which information is not contained within the predictors used. Fortunately, the local forcing on local climate, unlike the synoptic circulation forcing, is likely to be largely independent of a climate change signal, for example the "random" sources of variance such as the particular trajectory taken by a convective cell over the landscape. These are not truly random in that there are definite physical processes governing the behaviour of such features, yet in the downscaling context they may be considered as an unpredictable component with some distribution of behaviour not responsive to a climate change signal.

The importance of incorporating this source of variance lies in the fact that for many sectors of impacts research there is a strong need for daily temporal-scale scenario information. Seasonal means, as have been shown so far, are informative only so far as to indicate the general climate response. If one is to assess effectively the consequence on society and infrastructure, then the information about the distribution of daily events, such as extremes, median, sequencing, etc., become as important. Without the variance from the local forcing, the climate change scenarios dependant only on the atmospheric forcing are not sufficient for the effective prediction of impacts.

As the local sources of variance are largely non-responsive to a climate change signal it should be possible to treat them stochastically, although the stochastic attributes are likely to be a function of the synoptic scale circulation mode or state at any given time. Given this, it would seem reasonable that a downscaling procedure which included the synoptic scale circulation forcing and atmospheric humidity, and which models the local forcing stochastically, should be able to replicate empirically the overall local climate response, and hence generate viable regional climate change scenarios. This is, however, always assuming that GCMs can reasonably simulate the synoptic circulation and humidity fields.

Thus, in general the locally forced variance component on the local climate signal can be considered as a stochastic factor with a given distribution, and importantly, as a function of synoptic mode. For example, while some stochastic downscaling techniques do try to incorporate this distribution (e.g. Wilby et. al., 1998) (although they do not account for atmospheric humidity), they treat the distribution of local variance as a constant across all synoptic situations.

A constant distribution curve, however, is unlikely to be the case. One can easily envisage synoptic situations which may dominate the local climate response (e.g. frontal activity) and hence lead to very small input from local factors. Alternatively, where the synoptic forcing is very weak (e.g. weak pressure fields with convective activity, where the synoptic state merely inhibits or enhances the general local climate dynamics), the degree of local forcing is likely to be large. This may be found, for example, in the dependence of the rainfall response on the particular trajectory of a convective cell.

The basic distribution for the stochastic model may be derived from the distribution of residuals (from the circulation + humidity downscaling) of the ANN training. i.e. when training the ANN, the ANN predicts a precipitation time series which will imperfectly match the target observed precipitation due to the local forcing not incorporated in the predictors. These residuals then represent the variance due to local forcing, and the distribution of residuals can then be used to add a random factor representative of local forcing back into the downscaled data derived from circulation and humidity alone.

First, however, the residuals from the ANN training need to be evaluated as a function of synoptic state in order to determine the distribution pattern. For this the SOM classification used earlier in the downscaling procedure provides a convenient means to develop the distribution of residuals as a function of the synoptic mode. The different modes of the daily synoptic and humidity input fields to the ANN have already been identified, and the residuals can be subset accordingly. Subsequently, for any given day downscaled, the synoptic mode may be identified, and a random value to incorporate in the downscaled data selected from the appropriate distribution of residuals.

Figure 9 outlines the modifications to the basic downscaling to include the stochastic local forcing. After training the SOM with the composite circulation-humidity data, each node on the SOM matrix represents a state in the circulation-humidity input space. The SOM nodes to which each input sample is mapped is then identified, and the residuals from the ANN training data collated for each SOM node. The selection of residuals for each SOM node (synoptic state) then represents the variance of the local climate signal that cannot be accounted for by the synoptic circulation and humidity predictors in the downscaling.

The distribution of residuals on each SOM node are themselves very illuminating. Figure 10 shows the histogram of a selected three of the SOM nodes and illustrates this point. Of the 3 distributions, one demonstrates a narrow distribution centered on rainfall category 5, indicating that under this synoptic state the atmospheric predictors are the dominant forcing. On the other hand, one distribution is nearly flat indicating that under these conditions the synoptic forcing is a poor predictor, and that other forcing factors are significant. The third distribution indicates a situation somewhere between these two states.

9. Downscaling with atmospheric circulation and humidity sources of forcing.

The SOM may now be used with the downscaled data to incorporate the variance due to local forcing. For each downscaling data sample the SOM identifies one of N (in this case 15) nodes, each associated with a distribution of residuals. Using a random number generator a value is randomly selected from the distribution and added to the downscaled value. In order to evaluate the effectiveness of the stochastic addition of local variance, a number of measures of daily precipitation are used to represent comprehensively attributes of the precipitation behavior.

Validation of Downscaling

Figures 11 to 16 shows selected parameters of the DJF and JJA conditional wet day probability, standard deviation, and mean wet spell length. For each of the parameters the observational data, the downscaled data from observed circulation with no stochastic local forcing, and the downscaled data from observed circulation with stochastically modelled local forcing are shown for the DJF and JJA seasons. As can be seen the downscaling from circulation and humidity alone is characterized by far too many wet days. However, with the addition of the local forcing derived from the stochastic procedure, the results again are a close match to the observed data.

Although only a sub-sample of statistics is presented here, some generalization attributes are consistent across a wide range of measure of daily temporal behavior. By noting the range of the shading bar on the plots it is apparent that the stochastic procedure brings the variance of the downscaled fields back to values that are comparable to the observed data. However, in statistics that are a measure of the span of precipitation events, the stochastic procedure benefits the data set, but still falls short of raising the variance back to levels on a par with the observed data. This is primarily due to the peak downscaled events still having a magnitude lower than the observed peak events, and may be due to the relatively short period of training data used in developing the downscaling functions. Further work is underway with a 40 year period of observed data to evaluate this. The relatively short training data initially used may also impact on the residuals used in developing the distributions, and here again the new longer data set will allow evaluation of this.

Overall the stochastic procedures bring the downscaled precipitation into close approximation with the temporal and spatial characteristics of the observed data.

Climate change scenarios

The climate change scenarios presented here are not intended as definitive projections for the future, especially as the scenarios represent a climate projection from an older generation experiment. This is not to say the GCM derived scenario has no credibility, but rather that the scenarios presented here need to be considered in the correct context. Pertinent caveats are that the GCM represents a short time period (5 years), uses only a mixed later ocean, and is a quasi-equilibrium solution after an instantaneous doubling of the atmospheric CO_2.

Having said that, the scenarios do indicate interesting characteristics. The seasonal mean scenario has already been shown in Figures 7 and 8. Figures 17 to 20 show additional scenario attributes in terms of the daily statistics that reflect characteristics of the temporal behavior. The primary point to be made here is the impact on the scenario when humidity is included as a predictor. As was indicated earlier when evaluating the role of humidity with seasonal averages, it can be seen that the regional scenarios in terms of daily statistics can change substantially when the humidity factor is included.

Overall the scenarios indicate a summer situation where changes in synoptic circulation are conducive to drier conditions and decreased variability in the north-east (as seen in the downscaling excluding humidity), but which are offset by the increased atmospheric humidity (downscaling with humidity). The reverse is seen over the central, southern, and western regions. In JJA the winter rainfall regions appear to receive a nominal increase in rainfall, with a fairly marked decrease in variability over the south-western Cape.

10. Summary.

Regional climate change poses an important threat to the already variable and drought and flood-prone climates of South Africa. Current scenarios of potential change are severely limited in spatial and temporal resolution, especially with regard to precipitation, and are in critical need of alternatives in order to plan for the future. Downscaling is one widely recognized methodological approach for dealing with GCM inadequacies in developing regional scale climate change scenarios, and is considered the most viable for the South African context.

Multiple approaches to downscaling are available, although many have significant infrastructural constraints or problematic assumptions which underlie their procedures. The approach adopted in this work has thus focused on the empirical downscaling option, and the variant of empirical solutions has been to directly relate atmospheric forcing to local climate through the application of ANNs. This represents further development of earlier methodological work undertaken for the WRC. An early formal evaluation of the initial methodology against 3 other downscaling approaches has shown that the ANN approach is able to capture important aspects of regional climates not managed by other techniques. Problems identified in the comparative study have also greatly assisted in refining the new work undertaken here.

Of all empirical downscaling techniques, the ANN approach is arguably the method with the least problematic assumptions, and provides a tractable procedure for developing regional scenarios from long term GCM simulations, and for use with multiple GCM data sets. Validation of the ANN techniques has shown the procedure to be viable and effective in capturing the primary forcing over a wide range of climate regimes and seasonal variation. Using geopotential height fields representing circulation dynamics, and atmospheric humidity as an indicator of precipitable water, the ANN procedure is able to effectively capture the spatial and seasonal attributes of precipitation over South Africa.

It is in recognizing the important role played by atmospheric humidity that the methodology has been further refined in comparison to work carried out by other research groups in recognition of. Atmospheric humidity has been shown to be a critical variable in terms of the local climate response to global change. In particular the inclusion or exclusion of humidity in the procedure can influence the results to such an extent that over certain regions the sign of the climate change may alter, let alone the magnitude. Consequently it is argued that downscaling without cognizance of the role of atmospheric humidity leads to scenarios that only represent climate response to circulation dynamics, which, while informative, may be substantially different from actual climate response.

Similarly, as much of the potential climate impact within different components of the physical system may be sensitive to the daily temporal characteristics of climate, it is important that the downscaled climate reasonably reflects daily variance. Since the downscaling cannot include local forcing factors, and since these are largely insensitive to the global climate change signal, the methodology incorporates this source of variance through stochastic modeling. The addition of this source of variance substantially improves the daily characteristics of the downscaled climates and allows scenarios to be constructed in terms of the daily behavior of the downscaled climate.

The remaining errors in the downscaled climate are manifest primarily as a tendency toward nominally wetter than observed conditions. However, in the context of GCM skill, and given the level of accuracy of alternative sources of climate change scenarios, the downscaled procedure and subsequent climate projections represent a viable, justifiable, and pragmatic solution for the immediate and near future climate change impact research needs.

11. Products, Recommendations, and Future directions.

In addition to a preliminary set of climate change scenarios, the primary product of the project is the suite of software tools to perform ANN-based downscaling. The software has been packaged into a (relatively) user-friendly package running on UNIX based computer systems. Two other research groups in the USA have already used preliminary versions of the software package, and two new projects within the USA have also adopted the software package, and are working in collaboration with UCT in this regard. In addition, the procedure has been adopted as a major component of the scenario development for the South African FCCC (Framework Convention on Climate Change) assessment project. The software package will be made available to relevant researchers on request, with collaboration encouraged.

However, within the South African context the primary need is to now apply the procedure to as wide a range of recent generation GCM experiments as possible. In response to this, data has already been collected from two GCM transient coupled ocean runs and will form the basis of the FCCC scenario development work currently underway. This activity needs to be extended.

A number of GCM experiments are currently underway at overseas institutions focused on the next IPCC (Intergovernmental Panel on climate Change) report, and will be completed over the remainder of this year. Contact has already been made with the relevant scientists in this regard about access to the data, and it is recommended that further work be undertaken to develop a full suite of scenarios and apply further analysis of the potential impacts, and investigate the level of consensus between scenarios.

This last point must not be underemphasized. In light of the variable nature of the South African climate system, and the high degree of vulnerability to climate change, a clear view of possible future impacts is needed, with rational interpretation and associated levels of confidence in the scenarios. The only tractable means of approaching this objective within the next few years is through analysis of ensembles of current generation long term (100 year+) GCM derived data sets through empirical downscaling.

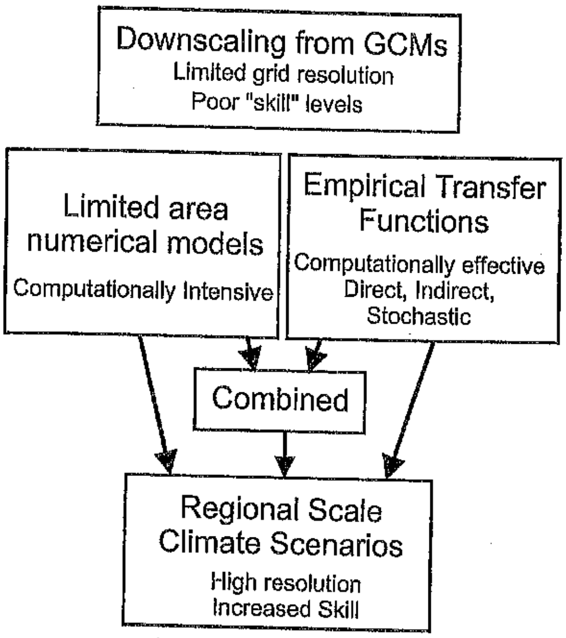


Figure 1: Downscaling options

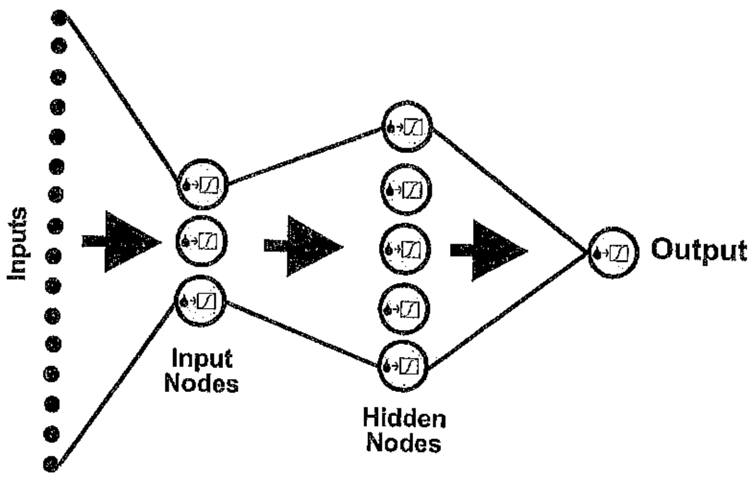


Figure 2: Configuration and information flow in a typical ANN

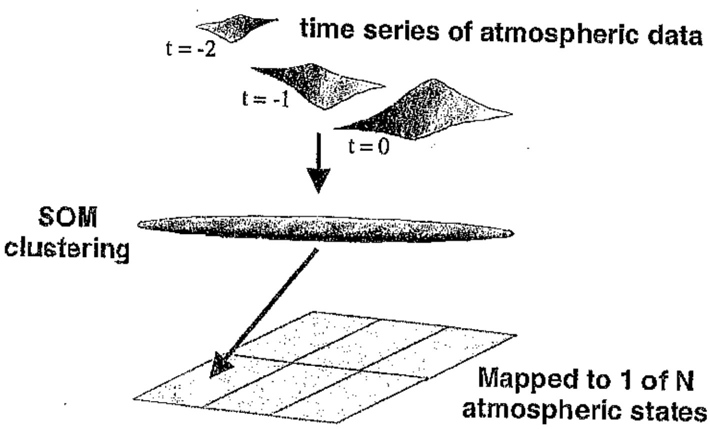


Figure 3: Mapping of atmospheric samples to 1 of N states

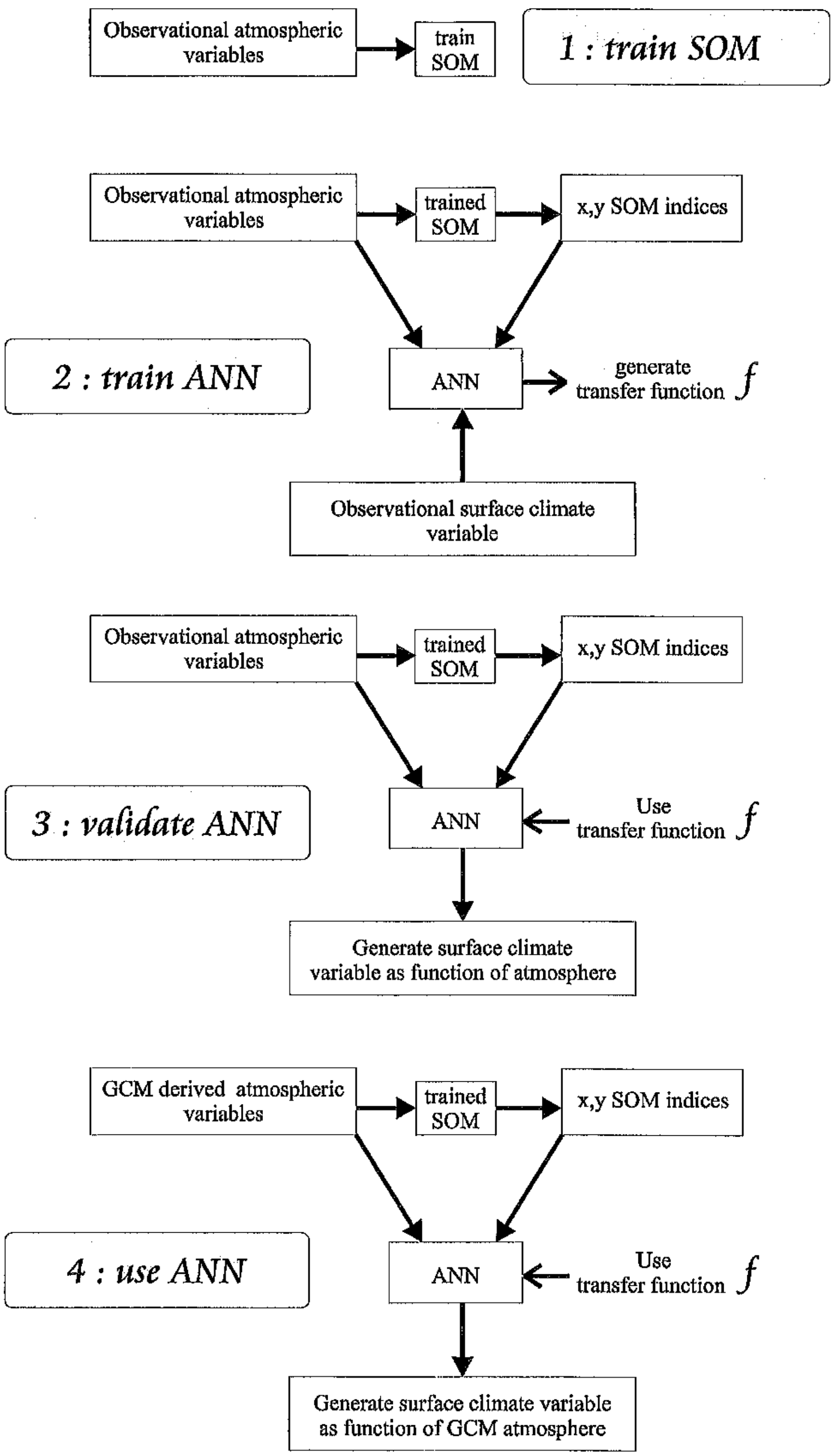


Figure 4: Procedural steps in downscaling

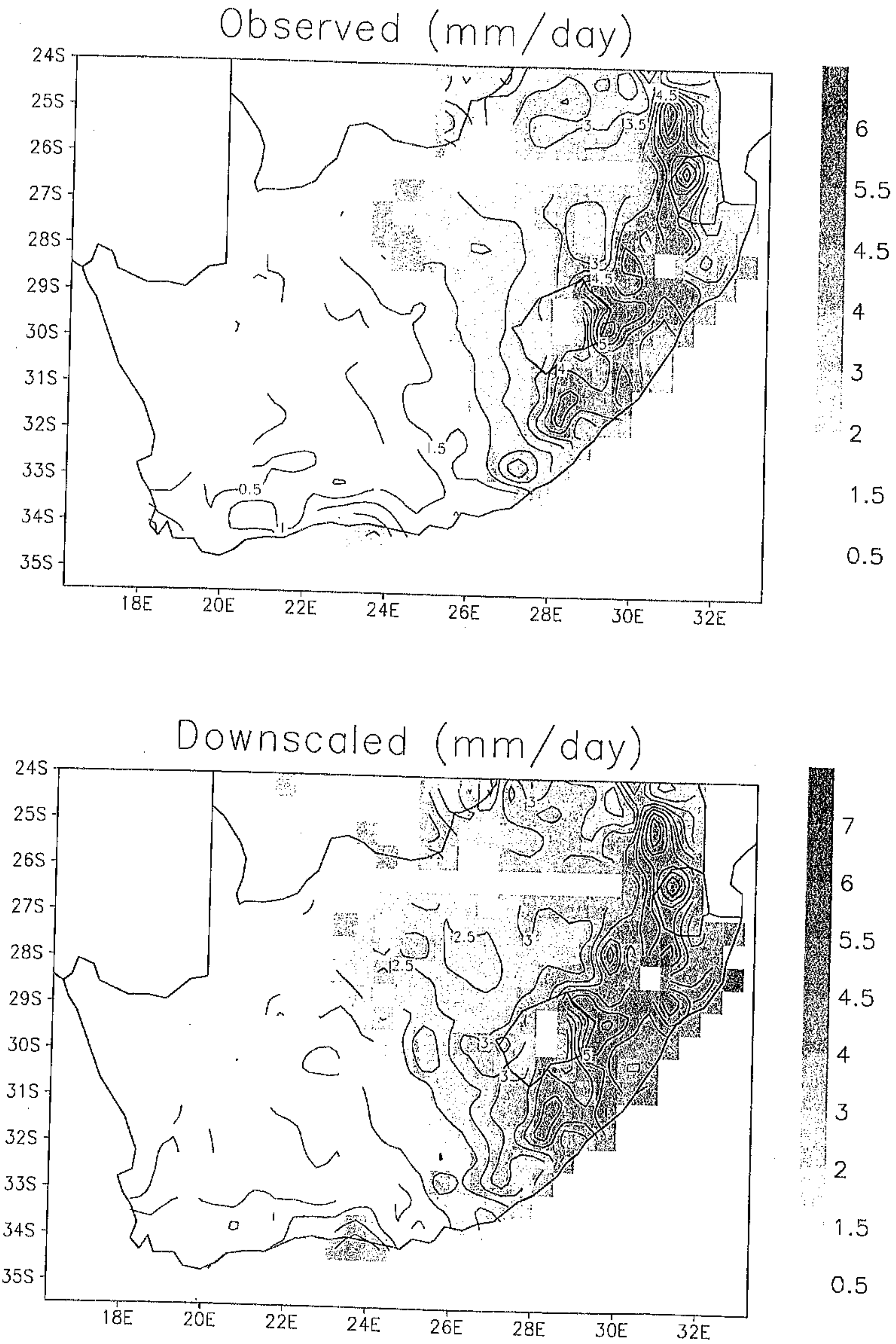


Figure 5: DJF observed preciptation and downscaled precipitation (from observed circulation)

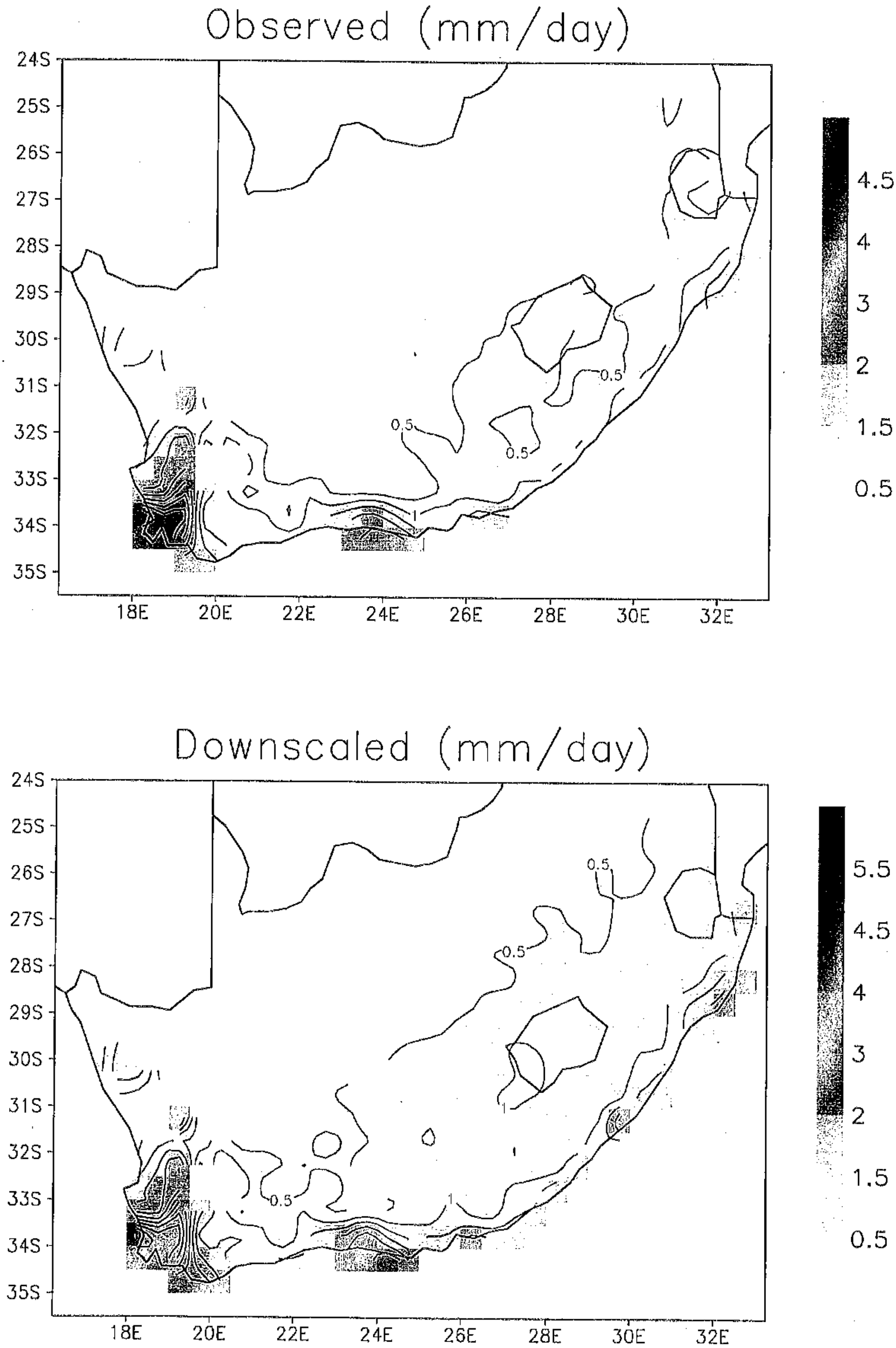
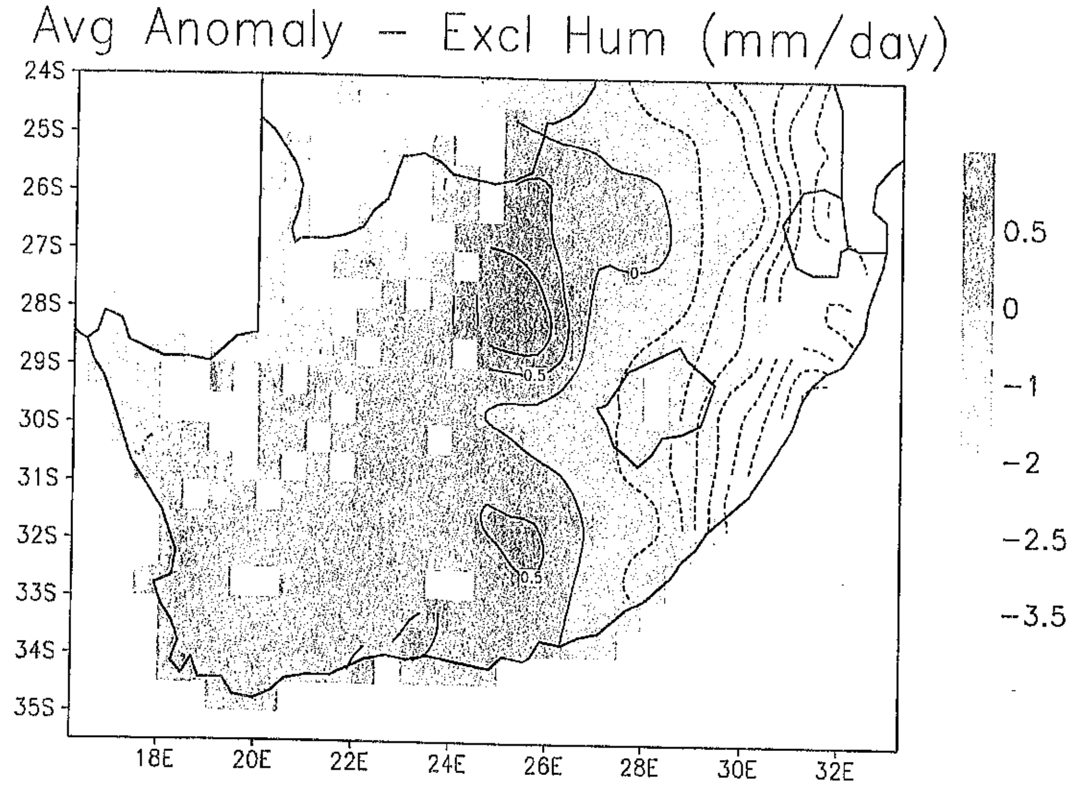


Figure 6: JJA observed preciptation and downscaled precipitation (from observed circulation)



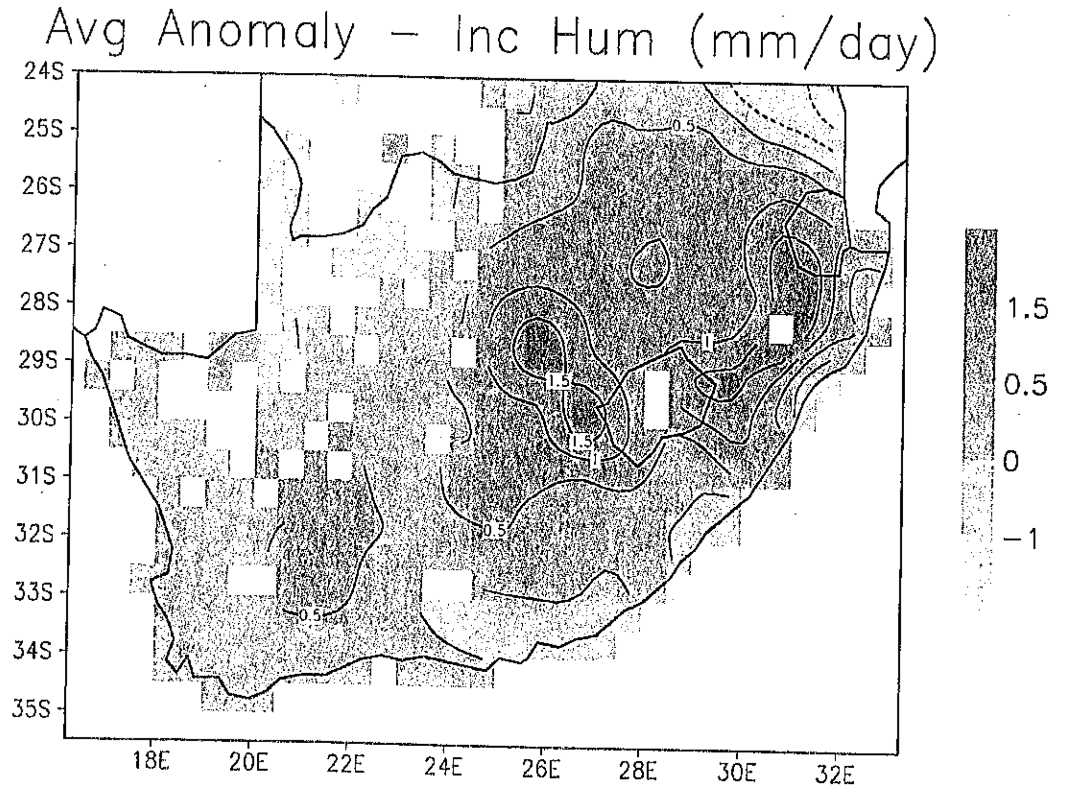


Figure 7: DJF climate change scenario expressed as seasonal mean precipitation anomalies. The top figure is derived from downscaling excluding humidity as a predictor, while the lower figure includes humidity as a predictor.

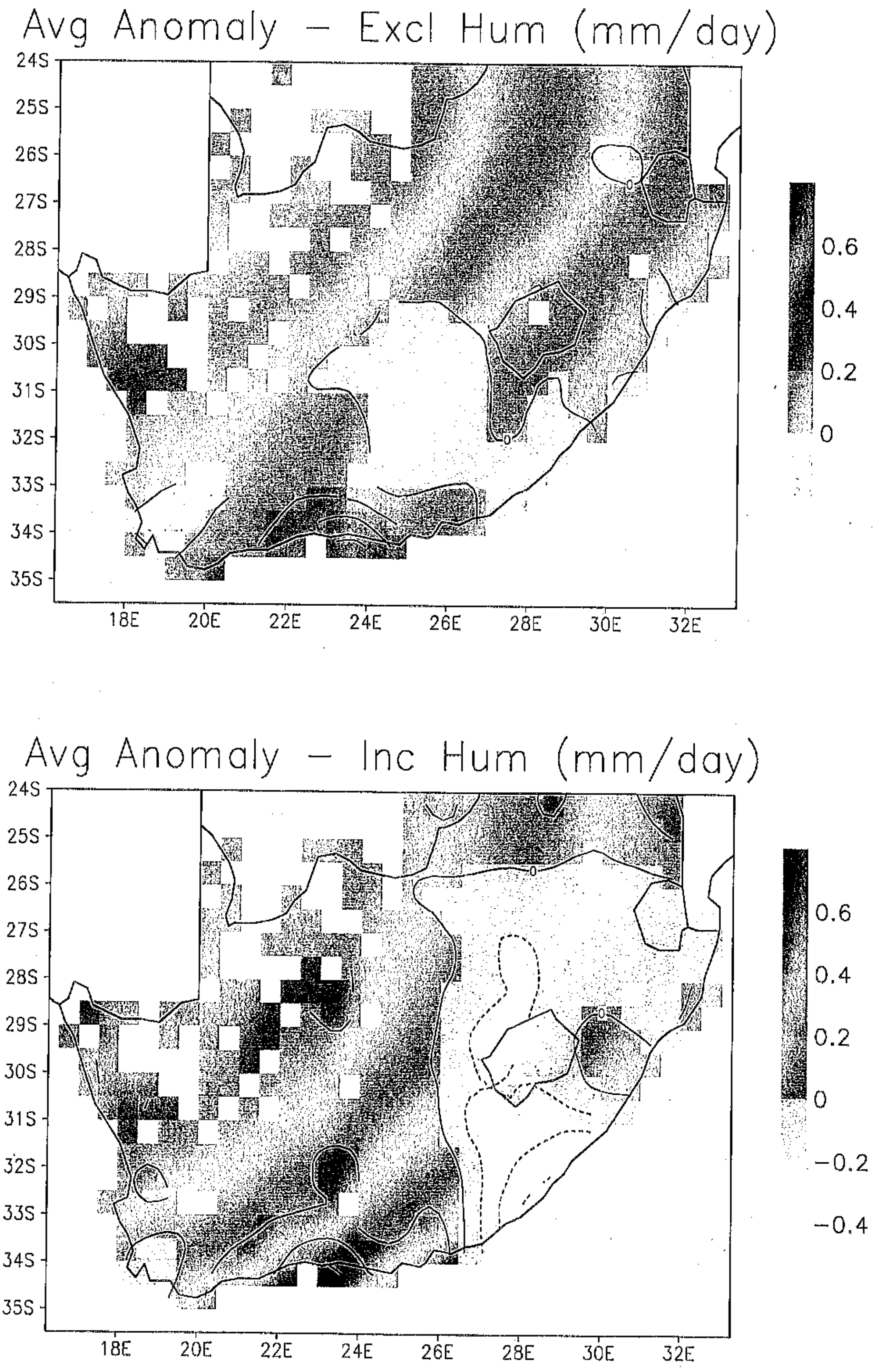


Figure 8: JJA climate change scenario expressed as seasonal mean precipitation anomalies. The top figure is derived from downscaling excluding humidity as a predictor, while the lower figure includes humidity as a predictor.

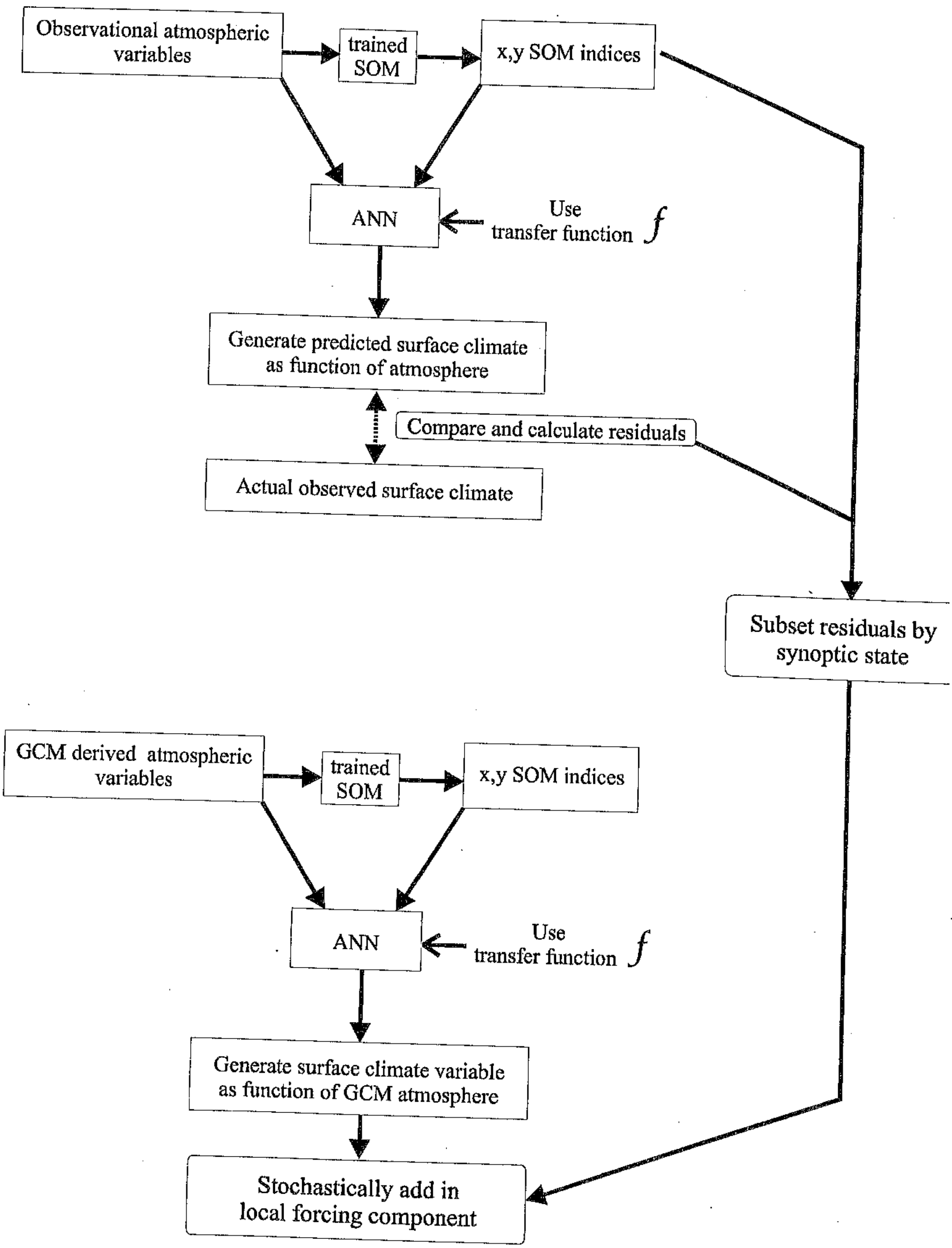


Figure 9: Procedural steps to include stochastically modeled local forcing.

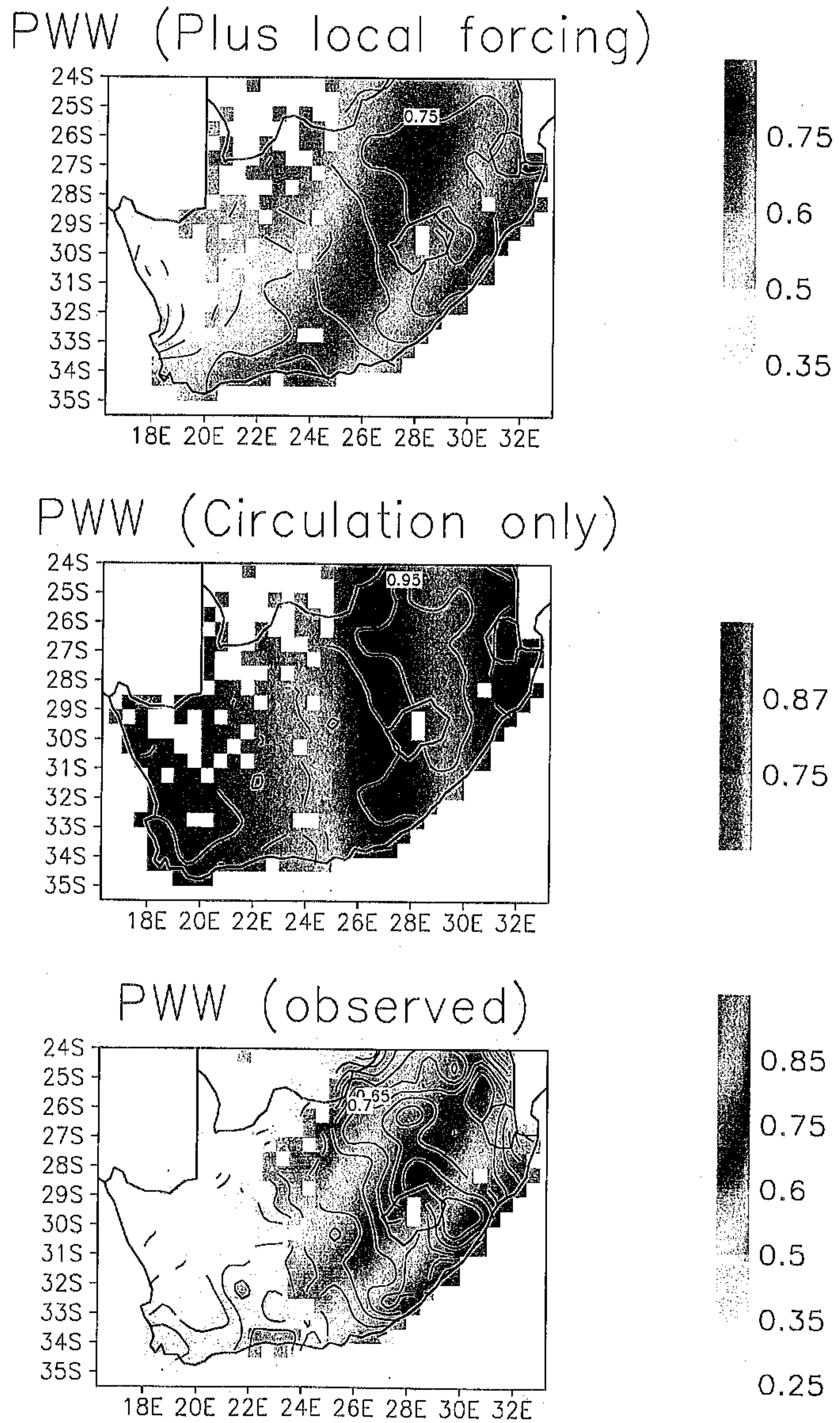


Figure 10: DJF conditional wet-day probability (PWW) for observed precipitation (bottom), and for precipitation downscaled from observed circulation and humidity excluding local forcing (middle), then with stochastically modeled local forcing (top).

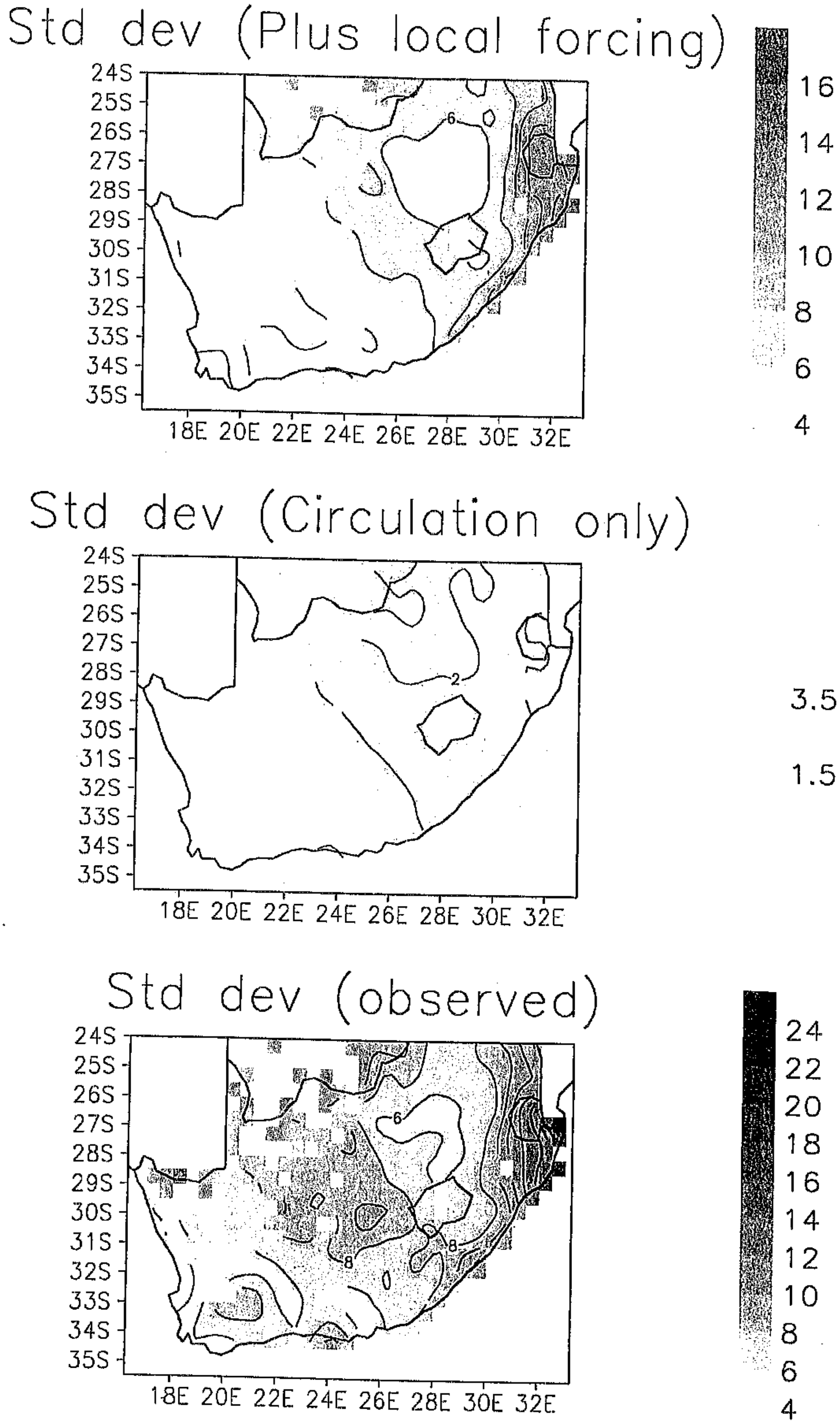


Figure 11: DJF standard deviation of daily precipitation. Observed precipitation (bottom), precipitation downscaled from observed circulation and humidity excluding local forcing (middle), then with stochastically modeled local forcing (top).

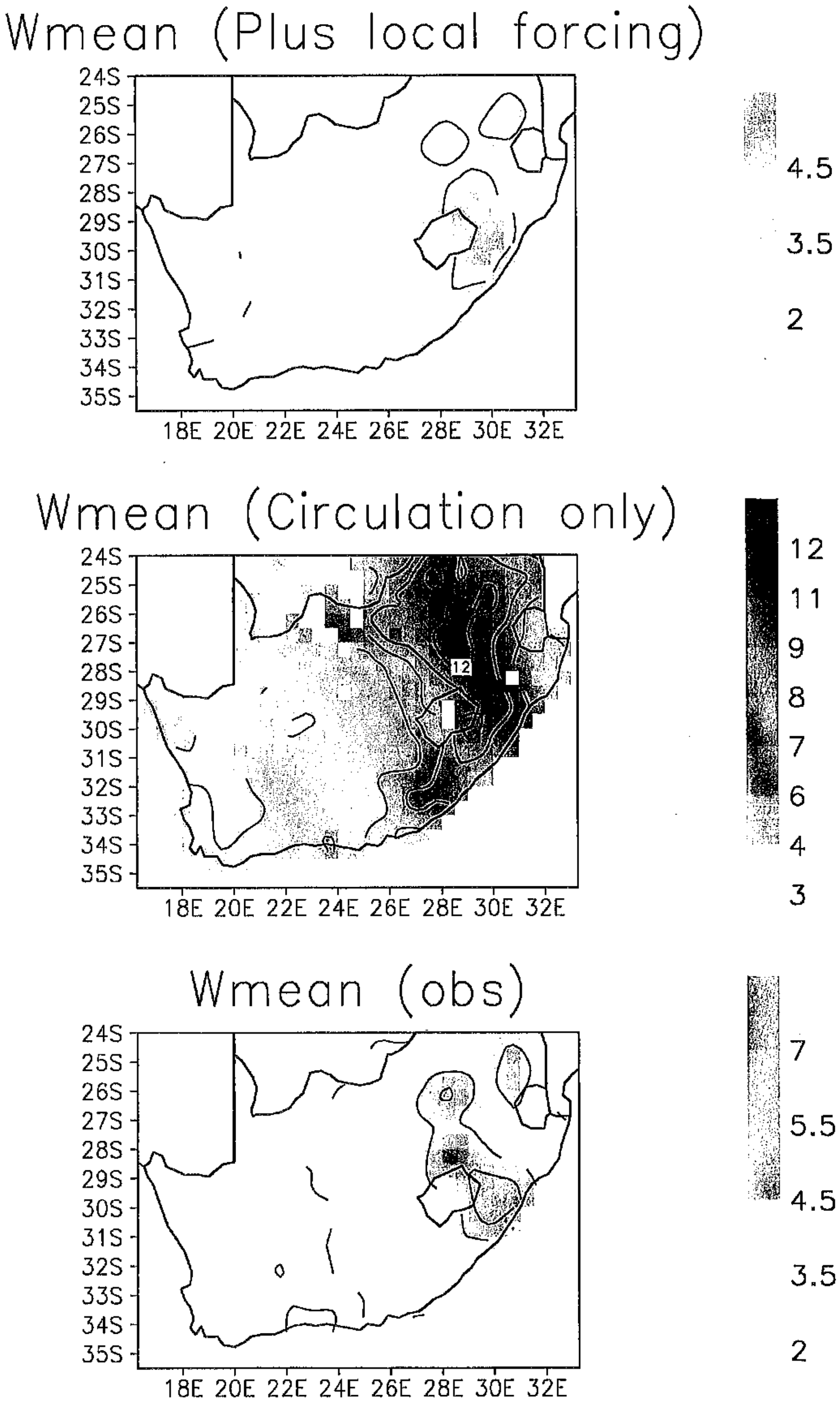


Figure 12: DJF mean wet spell length (in days) of daily precipitation. Observed precipitation (bottom), precipitation downscaled from observed circulation and humidity excluding local forcing (middle), then with stochastically modeled local forcing (top).

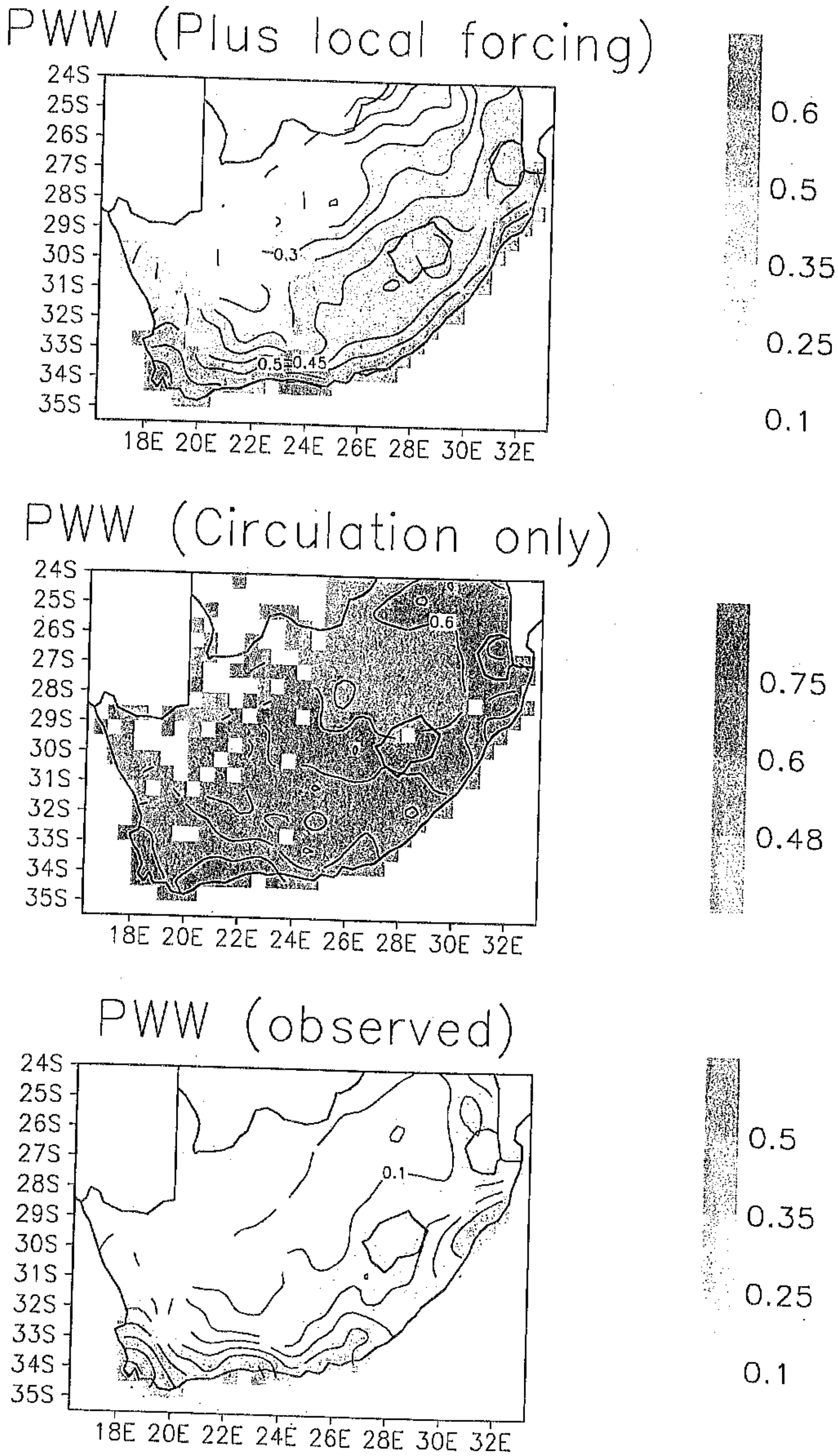


Figure 13: JJA conditional wet-day probability (PWW) for observed precipitation (bottom), and for precipitation downscaled from observed circulation and humidity excluding local forcing (middle), then with stochastically modeled local forcing (top).

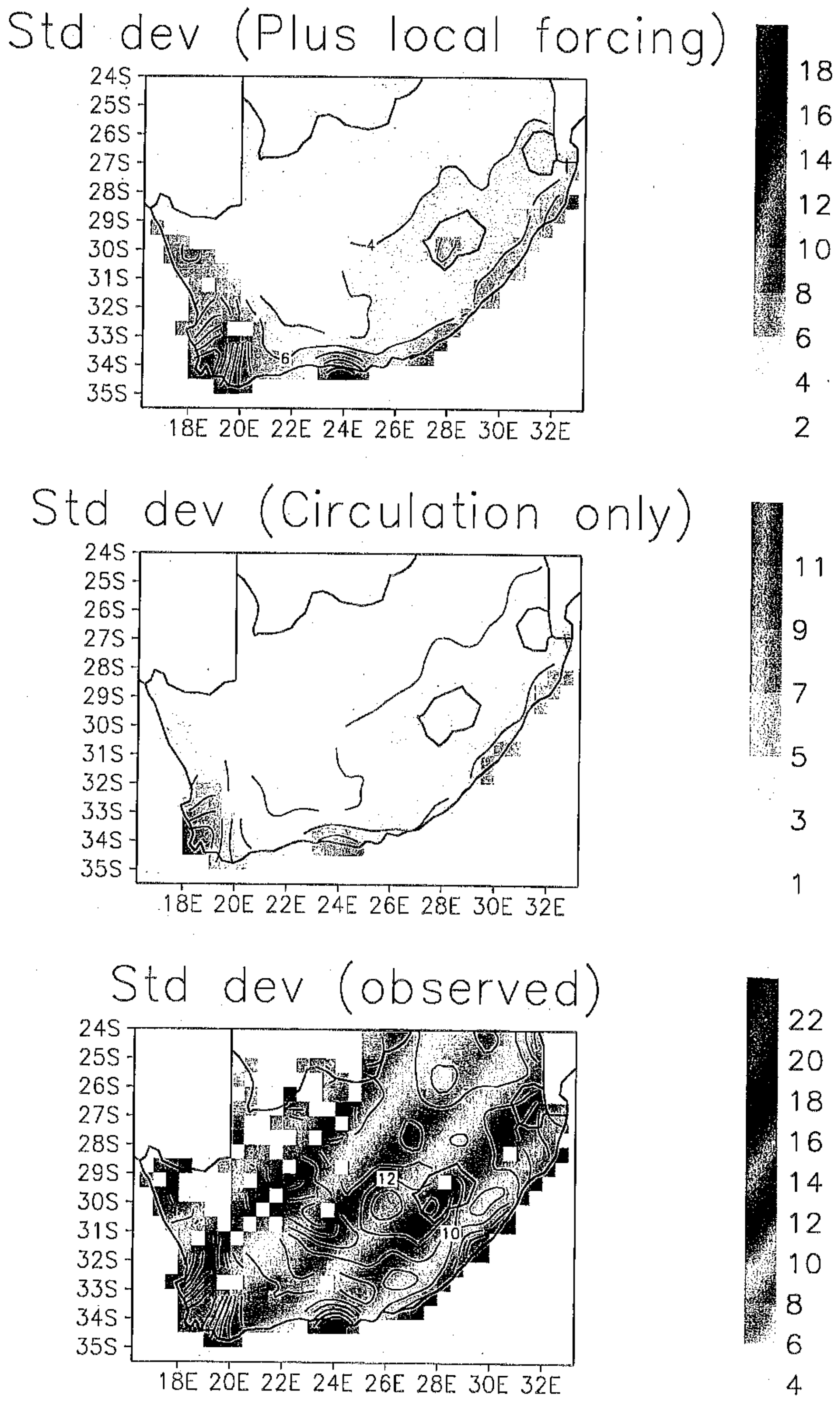


Figure 14: JJA standard deviation of daily precipitation. Observed precipitation (bottom), precipitation downscaled from observed circulation and humidity excluding local forcing (middle), then with stochastically modeled local forcing (top).

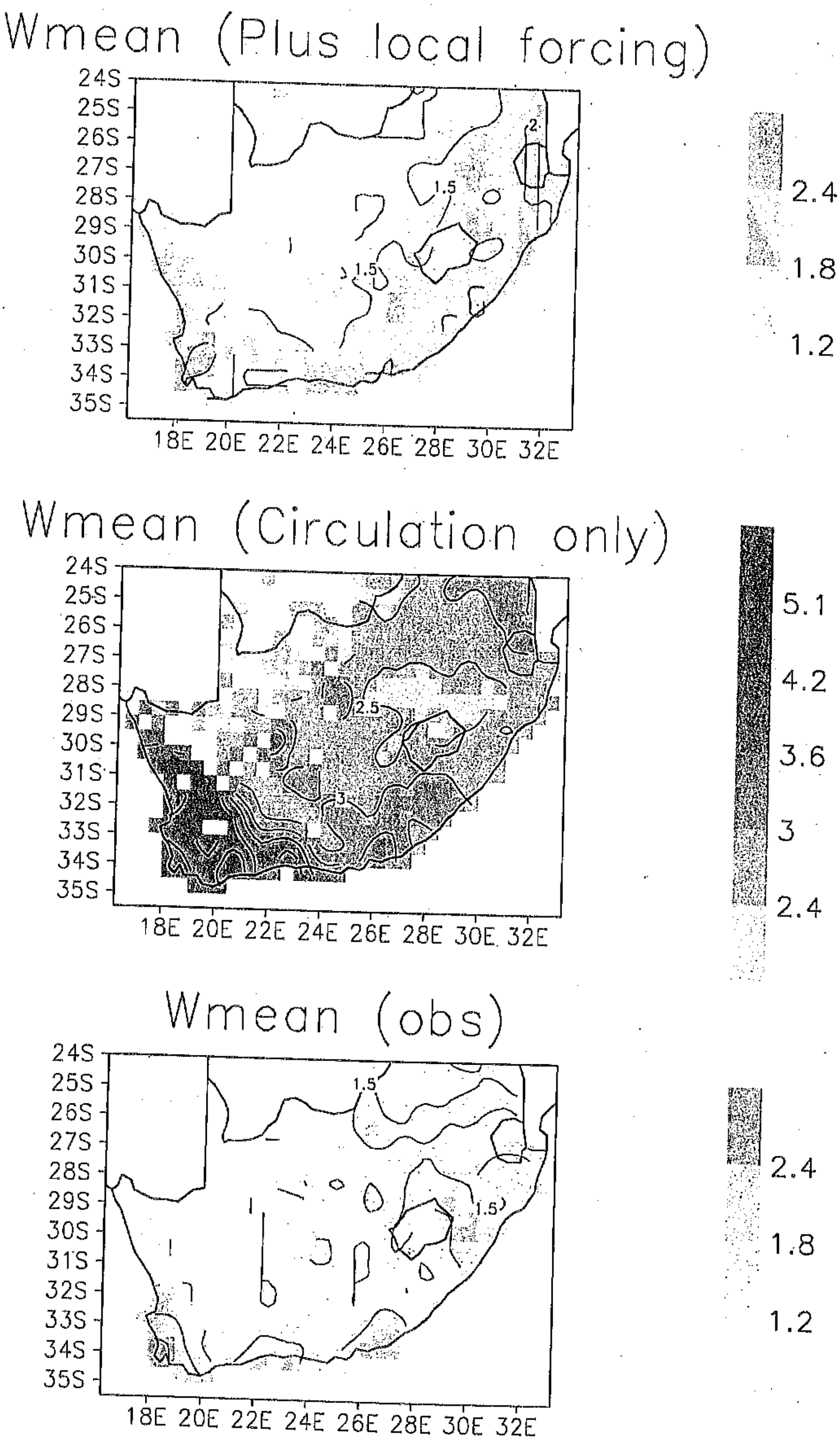


Figure 15: JJA mean wet spell length (in days) of daily precipitation. Observed precipitation (bottom), precipitation downscaled from observed circulation and humidity excluding local forcing (middle), then with stochastically modeled local forcing (top).

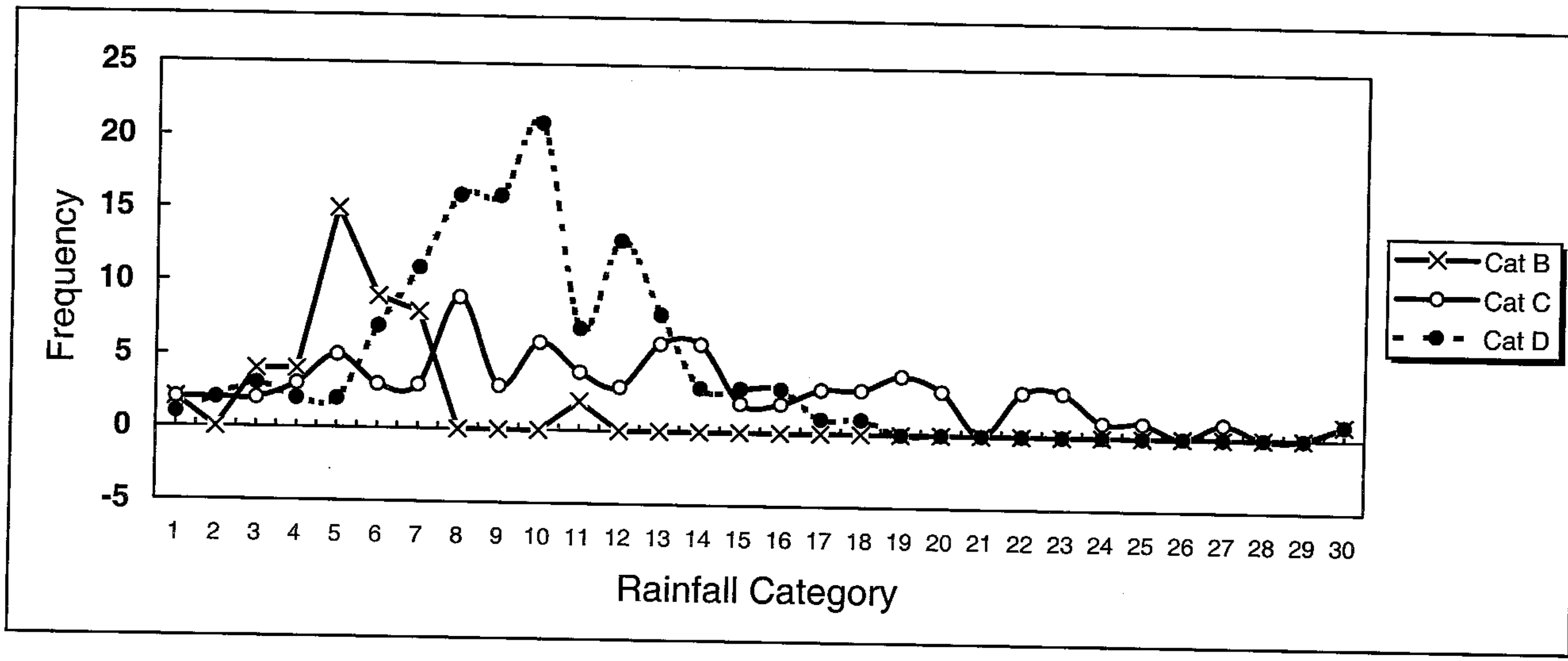


Figure 16: Frequency distribution of residuals for three selected SOM nodes.

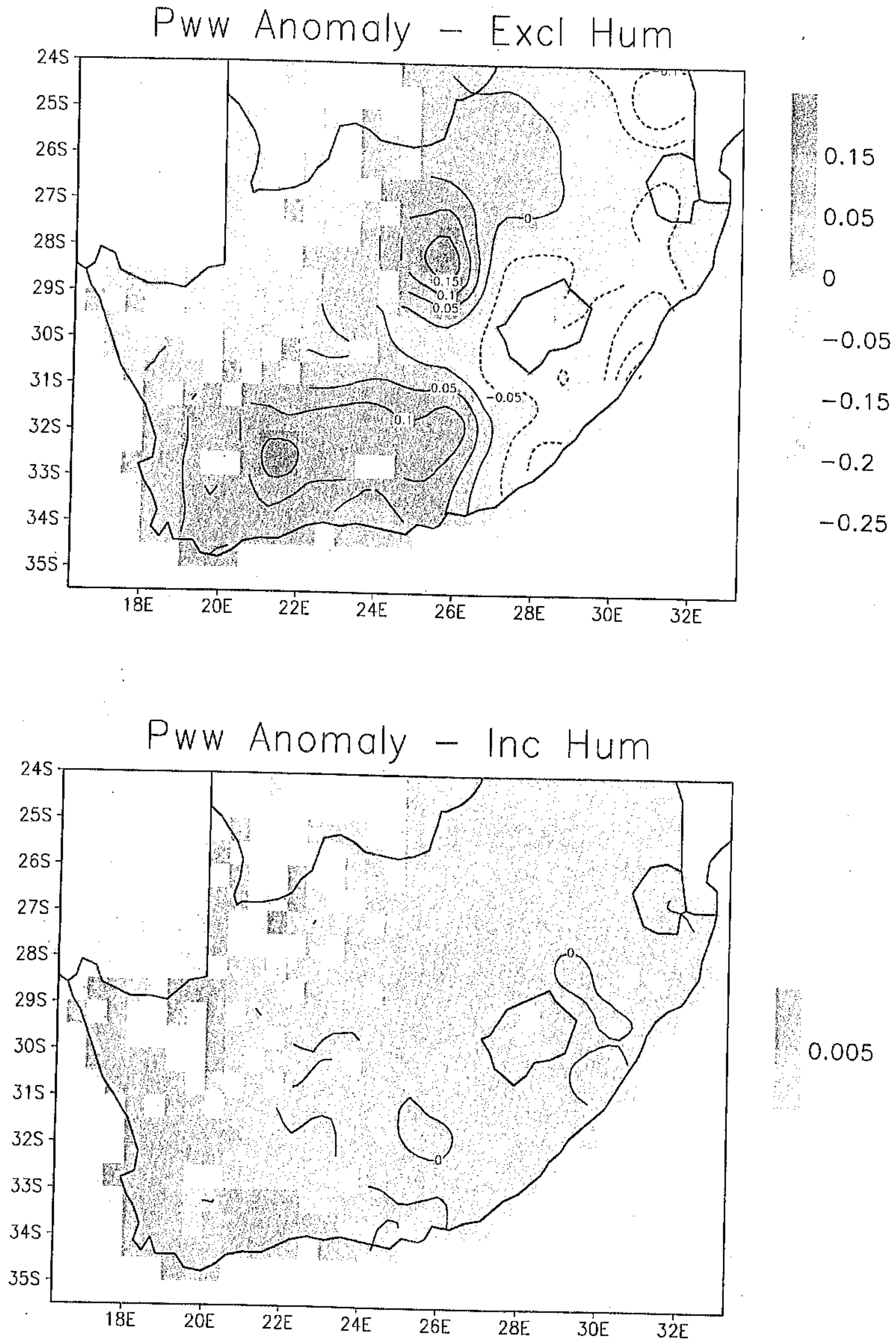
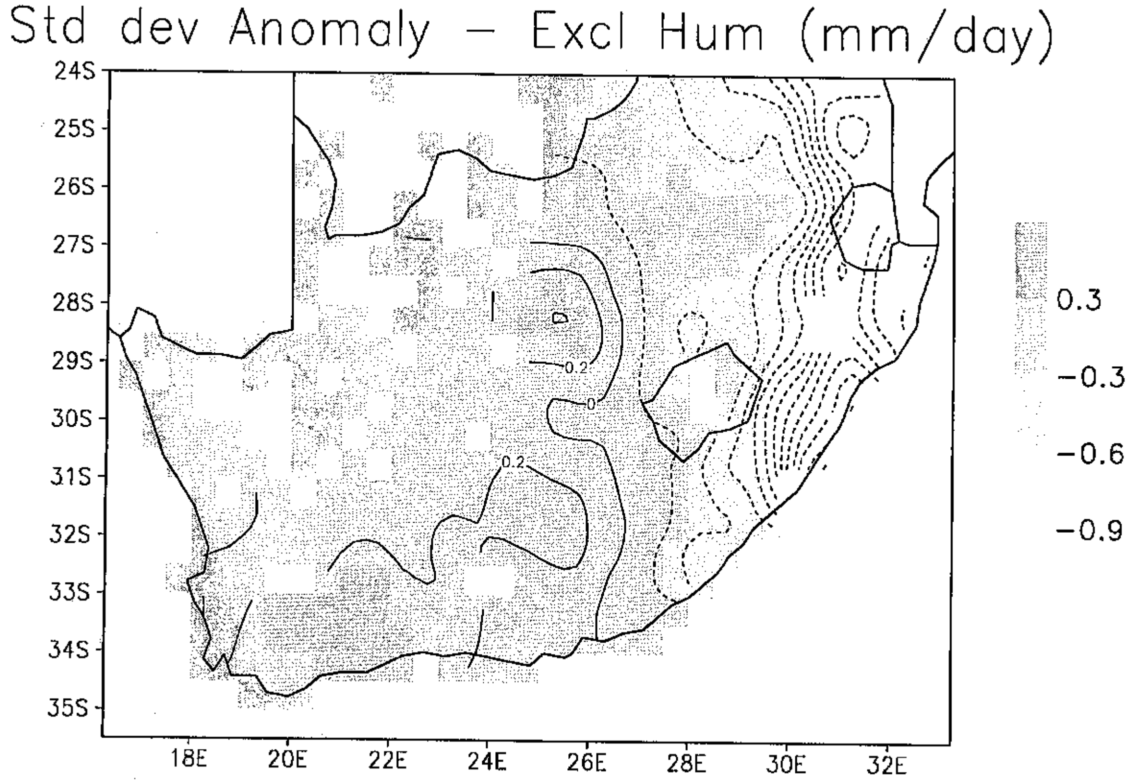


Figure 17: DJF climate change scenario of conditional wet-day probability. Derived from downscaling without humidity as a predictor (top), and then including humidity (bottom).



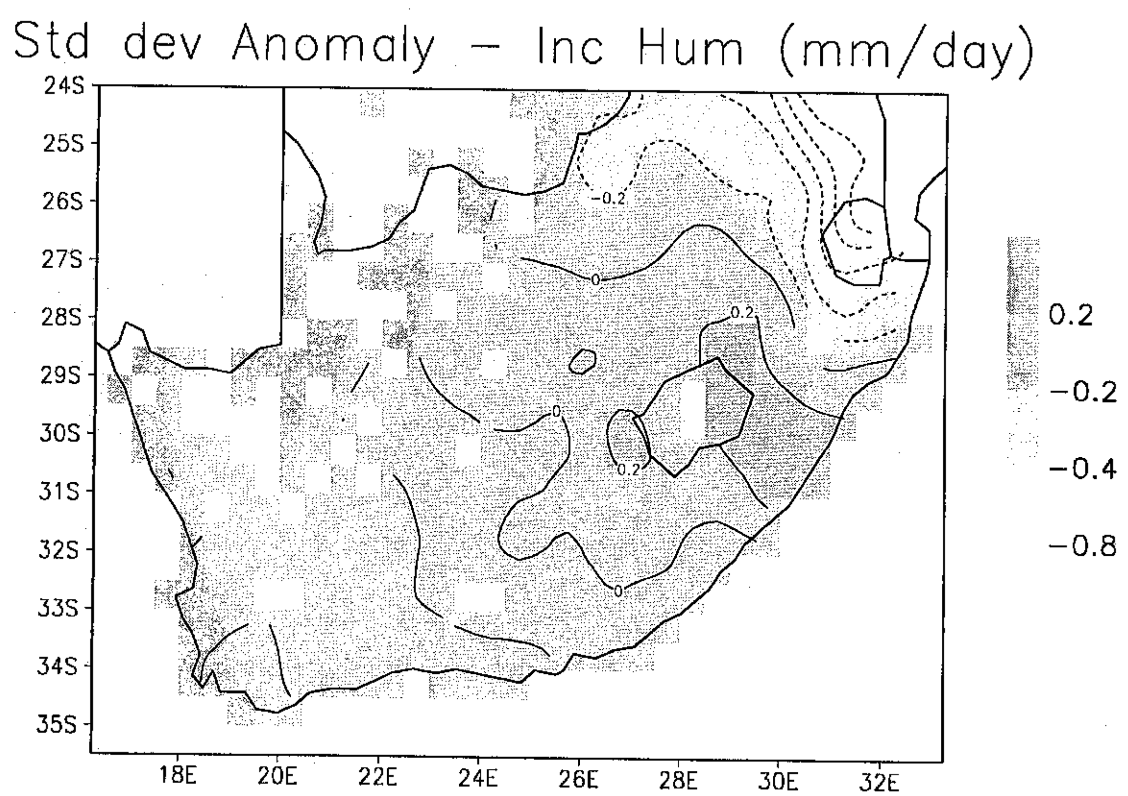
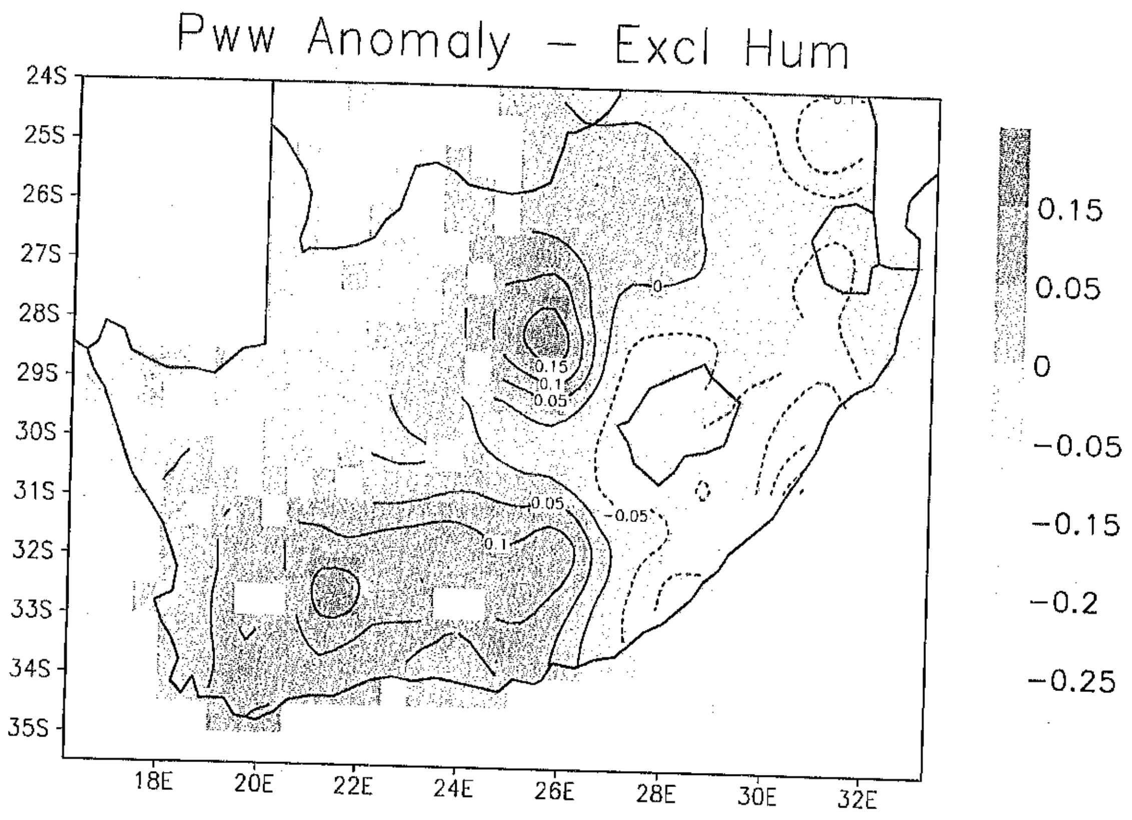


Figure 18: DJF climate change scenario of standard deviation of daily precipitation. Derived from downscaling without humidity as a predictor (top), and then including humidity (bottom).



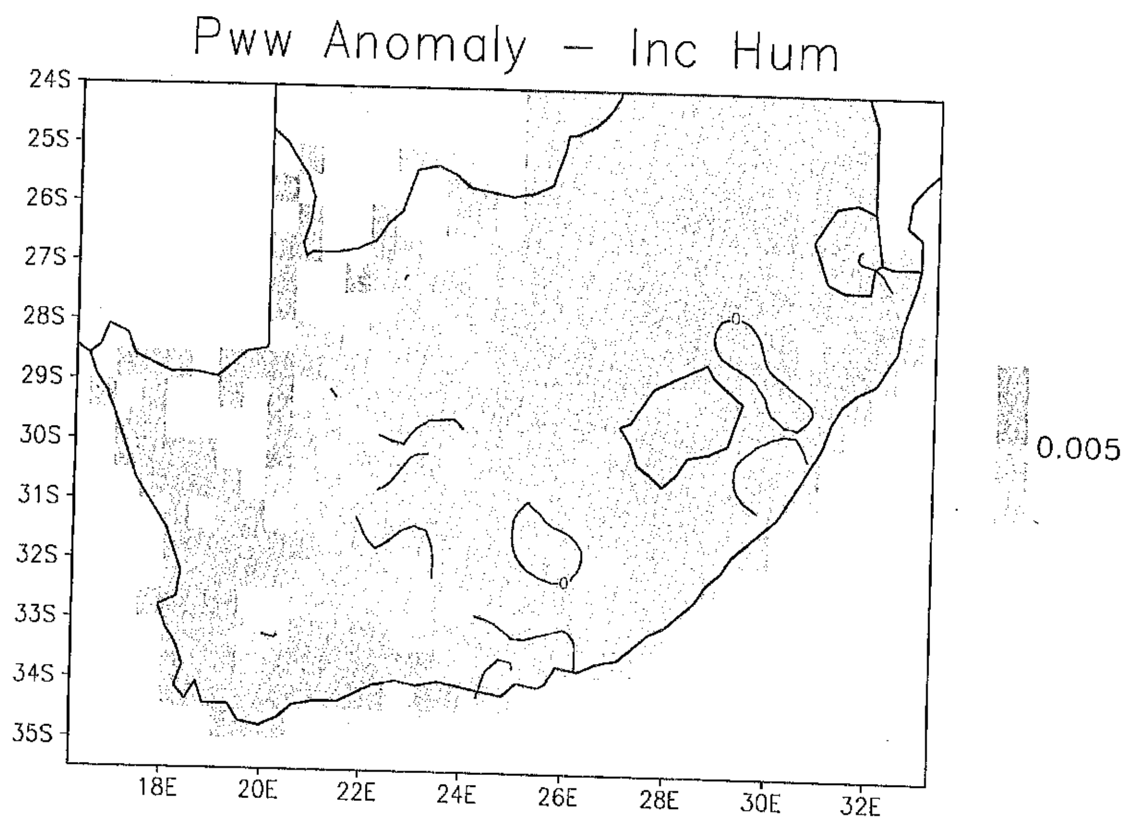


Figure 19: JJA climate change scenario of conditional wet-day probability. Derived from downscaling without humidity as a predictor (top), and then including humidity (bottom).

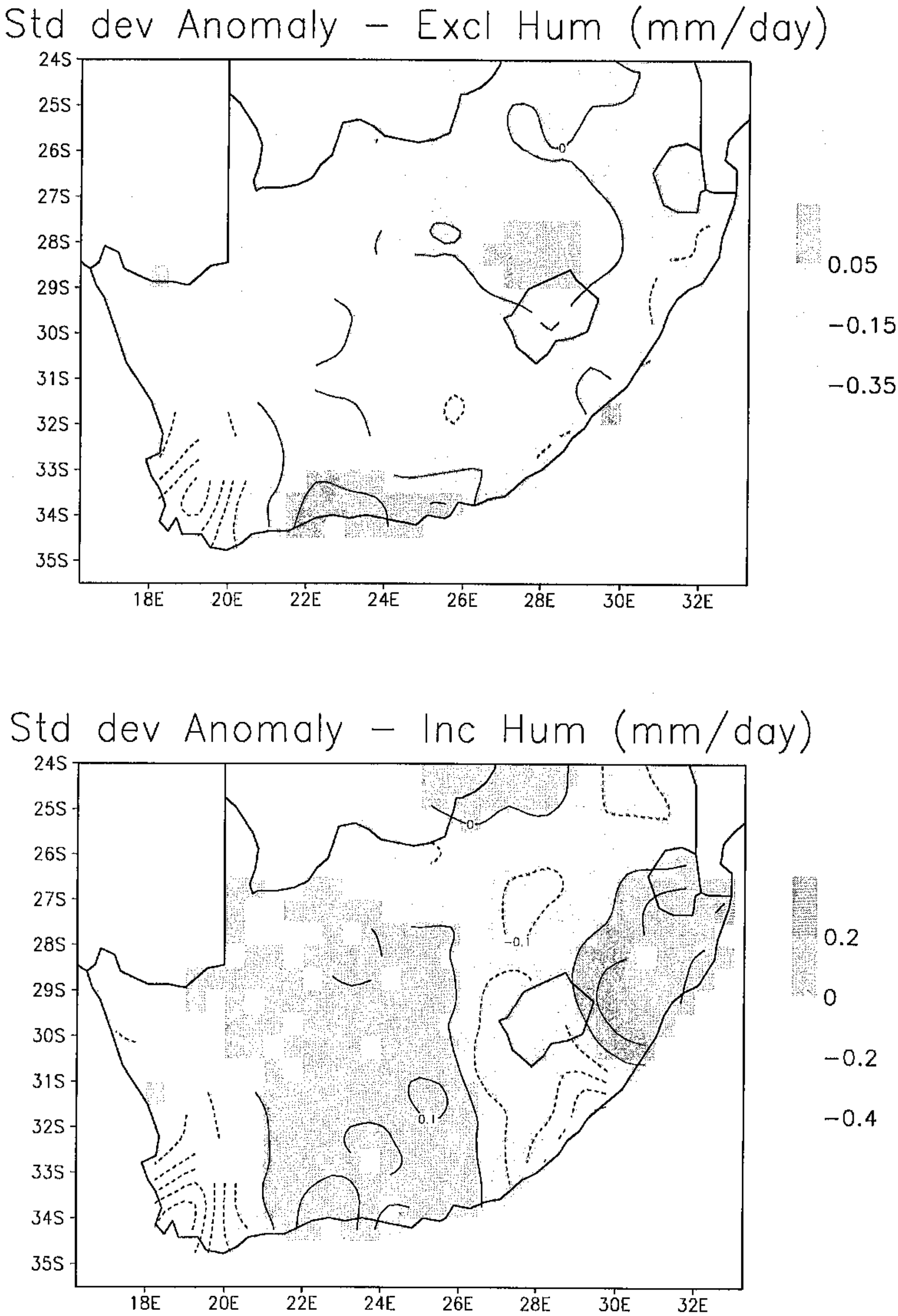


Figure 20: JJA climate change scenario of standard deviation of daily precipitation. Derived from downscaling without humidity as a predictor (top), and then including humidity (bottom).

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