Sub-Saharan African Cities:
Five-City Network to Pioneer Climate Adaptation through Participatory Research and Local Action

Using Climate Projections for Assessing Impacts at the City Scale

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Introduction

Local Governments for Sustainability recently launched a project entitled *Sub-Saharan African Cities: A Five-City Network to Pioneer Climate Adaptation through Participatory Research and Local Action.* One of the aims of this project was to establish a standardised approach for the collection and analyses of climatic base-line data, which will assist in the generation of future localised projections, which, in turn, will assist in planning and decision making.

As Global Climate Model (GCM) climate projections, and their associated downscaled data, are routinely used to infer impacts at a regional and sometimes local level, the question arises as to whether downscaling is useful, in terms of additional insights it may provide regarding the likely direction and magnitude of change, as well as the confidence in those changes.

This paper looks at the results from applying a downscaling methodology, developed at the University of Cape Town, to nine suitable GCMs[1] (forced with the A2 emissions scenario) and the observed rainfall and temperature data from the Cape Town station (only one sample station in one city will be referenced here). The downscaling relates daily weather systems to the observed rainfall and temperature at a particular location on each day. Taking the simulated changes in daily weather systems from each GCM, the expected changes in daily rainfall and temperature were then simulated for each location. The Priestly-Taylor method was used to calculate reference evapotranspiration (ET_0) based on simulated temperatures, solar radiation and altitude.

Attributes of GCMs

The resolving scale of GCMs has improved significantly in the last 10 years with many state-of-the-art GCMs able to resolve at a scale of around 100km. However, most of the GCMs

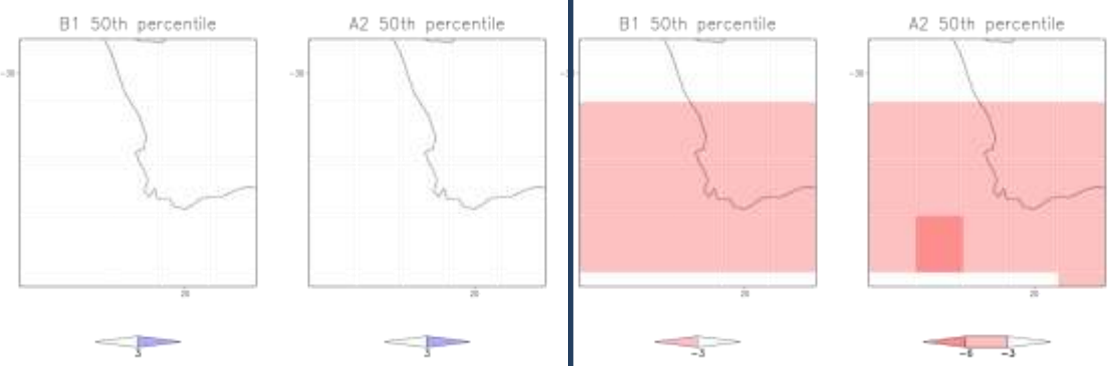
[1] The suitability of GCMs depends on the frequency of data and the type of variable

used for seasonal forecasting are at a scale of the order of 200km, with the skill of the model at this resolution typically low, due to the GCM's simplified topography and representation of regional processes. GCM skill is often higher when aggregated to large scales such 500km to 1000km.

An example of the coarse resolution of GCMs is provided in Figure 1 below. This figure shows how rainfall is expected to change under both B1 and A2 IPCC SRES emissions scenarios; for each season both the median change (15/13 GCMs for the A2/B1 scenario) and the percentage of models agreeing on the sign of the change is shown. The median suggests the most likely change whereas the percentage of models giving a positive change can be taken as an indication of the confidence in whether a positive or negative change is consistently simulated across the GCM models (values less than 50% suggest most models are simulating a negative change, whereas greater than 50% suggest most models simulate a positive change).

If we look for consistency across GCM models (more than 60% of models agreeing on either a positive or negative change) as well as consistency across both the A2 and B1 scenario, then decreases in rainfall are suggested all year round with the greatest changes during the main rainfall season in JJA. During the December-February median changes are small, with consistent model simulations tending towards the western regions over the ocean.

December-February (DJF)	**June – August (JJA)**



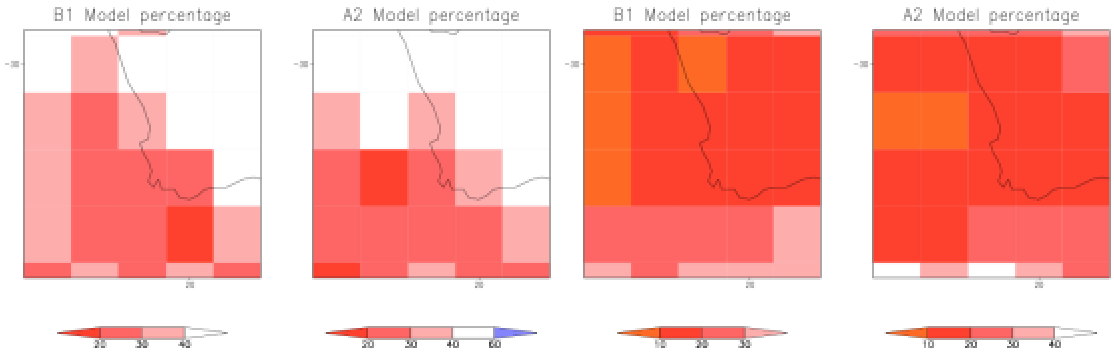


Figure 1: Median GCM simulations of change by 2050 under A2 and B1 emissions scenarios for the summer (DJF) and winter (JJA) seasons. The confidence of the model ensemble simulations is indicated by the percentage of models simulating a positive change.

> Box 1. The resolvable scale of a projection indicates the size of the discrete grid boxes that are produced by the models. Within each grid cell there is only value, thus the smaller the grid box (and larger the scale) the greater the variation can be displayed over the same area. Thus GCMs have small (or coarse) scales and downscaling's intention is to increase this scale, or making it finer.

The problem is that the scales used above are far too coarse for most users dealing with regional issues such as water management and agriculture. Society and ecosystems typically operate at much finer scales. Downscaling of these GCM simulations is therefore often applied to produce data that is useful at the local level. This is based on the assumption that local scale climate is largely a function of the large scale climate modified by local influences such as topography, surface water bodies and proximity to the coast etc. There are two main types of downscaling; dynamical and statistical.

Dynamical downscaling utilises a higher resolution, limited domain, dynamical model that follows the same principles as a GCM but, because of the limited domain, is able to be run at much higher spatial resolutions with moderate computation costs. Dynamical downscaling offers a physically based regional response to the large scale forcing. However, dynamical modelling is complicated by similar problems to those of GCMs, namely bias and errors due to parameterisations and scale, as well as being computationally expensive and difficult to downscale more than one or two GCMs. This latter reason makes it difficult to account for much of the uncertainty in the future projections, which is represented by the many different projections coming from many GCMs.

Statistical downscaling utilises statistical methods to approximate the regional scale response to the large scale forcing (Wilby *et al*., 2004). Various methods have been developed, including the SOMD (Self Organising Map based Downscaling) developed at the University of Cape Town which is used in this report. Details of the method can be found in Hewitson and Crane (2006). The method recognises that the regional response is both stochastic as well as a function of the large scale synoptic features. As such it generates a statistical distribution of observed responses to past large scale observed daily synoptic states. These distributions are then sampled based on the GCM generated daily synoptic states in order to produce a time series of GCM downscaled daily values for the observed variables on which it is trained (typically temperature and rainfall). An advantage of this method is that the relatively poorly resolved grid scale GCM precipitation and surface temperature are not used by the downscaling, but the relatively better simulated large scale circulation (pressure, wind and humidity) fields are used. Because the method is easily applied to multiple GCMs it can allow a sampling of the uncertainty within an ensemble of multiple GCMs (Mearns *et al*., 2003).

In the following example for a station situated in the city of Cape Town, 9 GCMs forced using an SRES A2 emissions scenario was obtained (from the CMIP3 archive) for the periods 1961-2000 and 2046-2065. These coarse scale climate projections were used to downscale available observations of rainfall and minimum/maximum temperature from climate stations, using the statistical downscaling technique described below.

- For each day of the observations, the daily synoptic state was classified using a SOM of 10m u and v winds, 700 hPa u and v winds, 500-850hPa lapse rate, 2m surface temperature, relative humidity and specific humidity taken from the NCEP reanalysis;
- A cumulative distribution function (CDF) of the observed variable for each synoptic type was created;
- Map the GCM daily synoptic states to the SOM using the same variables as above;
- A Random sample taken from CDF of each synoptic state.

This, then, allows a stochastic sampling of the local observed variable, conditioned by the large-scale synoptic state.

Downscaled results

Taking the median of all the statistically downscaled GCMs, the maps for winter and summer rainfall change over South Africa are shown in figures 2 and 3

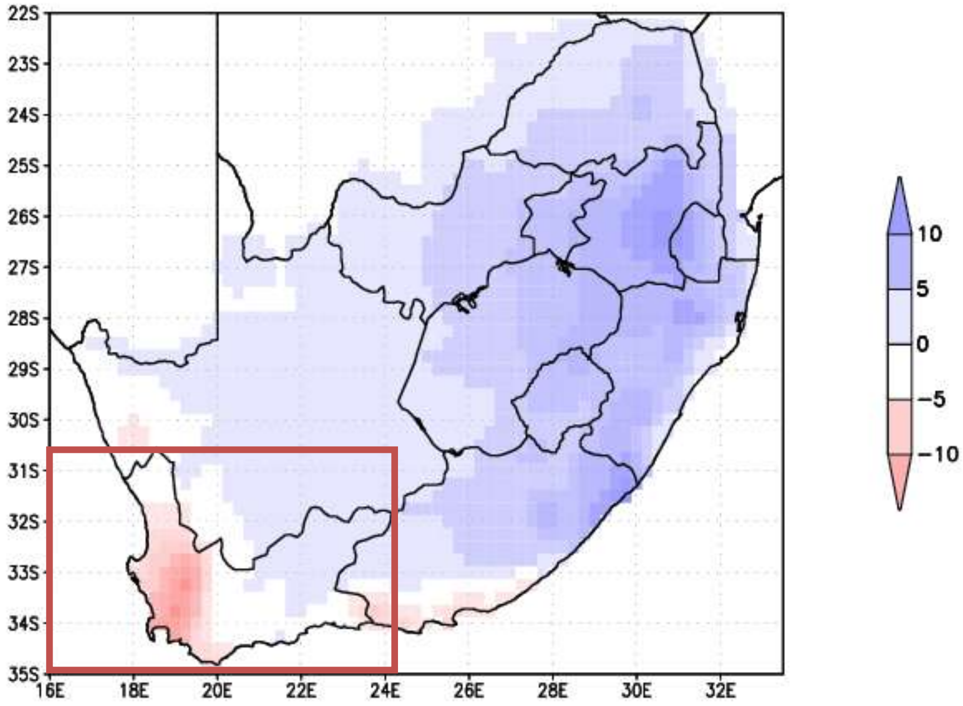


Figure 2 Winter (JJA) rainfall anomaly projections (2046-2065) for SA (Hewitson, in South African Risk and Vulnerability Atlas (SARVA), 2010)

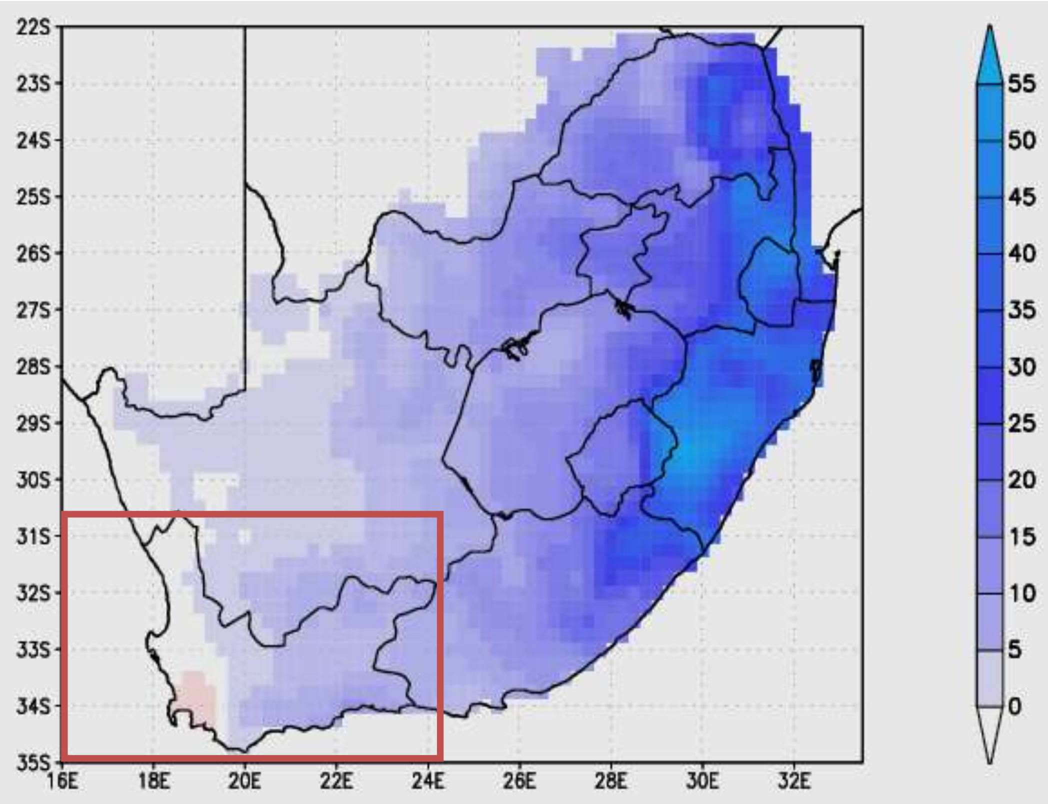


Figure 3 Summer (DJF) rainfall anomaly projections (2046-2065) for SA Hewitson, in South African Risk and Vulnerability Atlas (SARVA), 2010)

Comparing the downscaled figures (2 and 3) with figure 1 demonstrates how the downscaling is able to improve on the large-scale information provided by the GCMs. This is particularly apparent during the winter JJA season where figure 1 indicates a median decrease in rainfall across the whole of the western Cape region, whereas figure 2 suggests that the negative changes will be confined to the far western regions of the western Cape. There is an implied level of detail in the downscaled results that suggests the local response to the large scale forcing in the GCMs is different between the western and eastern regions of the western Cape. However, it is still unclear how confident the downscaled model ensemble is – do most of the models suggest a decrease or is there still a wide range of model results, some of which suggest negative and some positive change? In order to investigate this the following section examines the downscaled GCMs for a single station near Cape Town (SA Astronomical observatory), the location for which is given in figure 4. Several stations were available in the vicinity of Cape Town and of these the SA Astronomical Observatory has the longest record, including data for the last 10 years which gives a longer time-series for which to train the downscaling model.

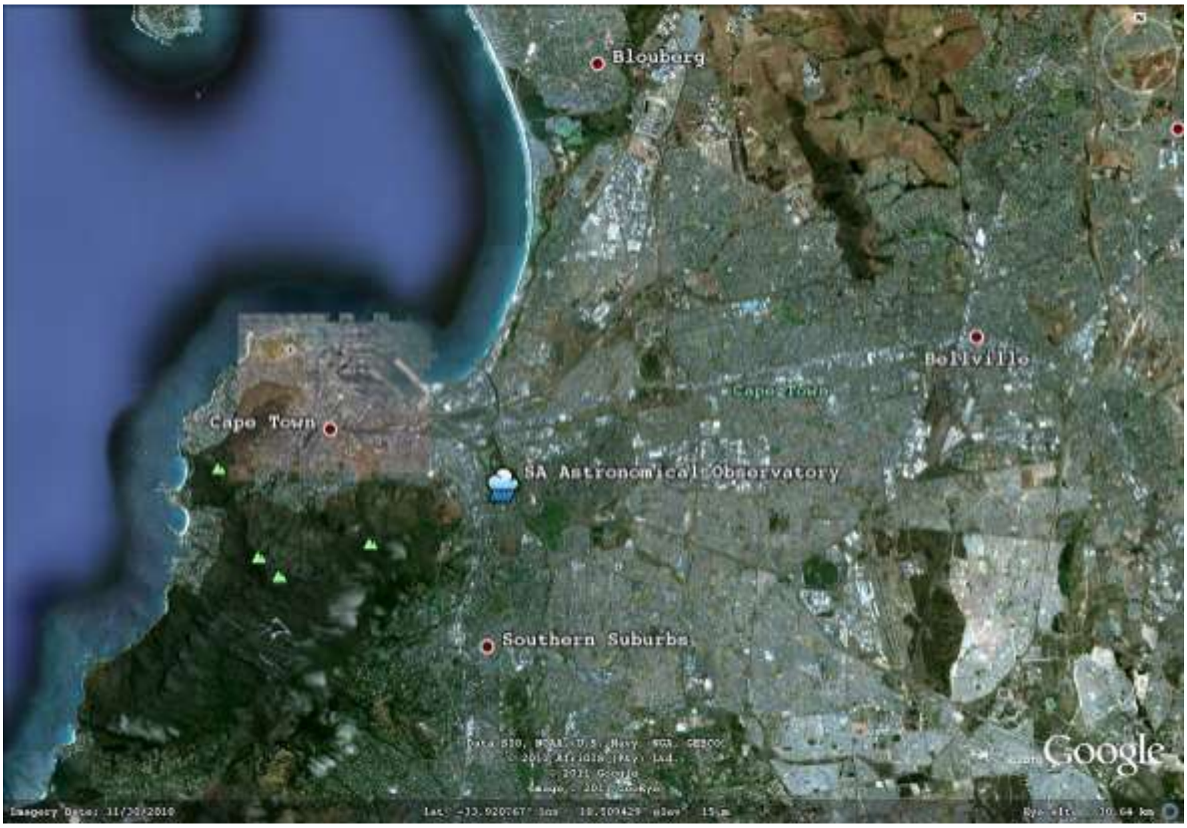


Figure 4: Location of SA Astronomical Observatory (Googlemaps)

Rainfall

Figure 5 below compares the downscaled GCM control climates (1961-2000) with the observed climate for Cape Town. The GCM control climates are close to the observed climate (black line), replicating the observed seasonal cycle and peak rainfall during June. This gives us confidence that the downscaling methodology applied to these GCMs is simulating the local climates correctly, though it is worth noting that the downscaled climates tend to underestimate the observed rainfall and shift the peak rainfall month later.

Figure 6 presents the simulated changes in rainfall for the SA observatory site. The shaded regions indicate the spread between the different downscaled GCMs; between the 10th and 90th percentiles, which indicates the range between the lowest 10% and highest 10% of the GCM downscaled values. This range is provided so that the range of different changes simulated by the different downscaled GCMs, ignoring the outlying extreme model changes (i.e. the 0 and 100 percentiles), can easily be see. Where the range straddles the 0 change line then some models simulate positive changes and others simulate negative changes. However, the tendency of the distribution of models (the majority of models) to simulate positive or negative change is indicated by the solid lines, which represent the median downscaled response i.e. the equivalent of the 50th percentile of the distribution simulated by the downscaled GCMs. The green line and shading is for the change (median and range between the 10th and 90th percentiles) simulated for the 2046-2065 period and blue shading and line similarly for the 2081-2100 period (relative to 1961-2000). The median models suggest an increase in rainfall during late June / early July for the 2046-2065 period but a decrease for other months and all months during the 2081-2100 period. There is significant spread between the 10th and 90th percentile models, particularly during the rainfall months. On the whole these changes are not dissimilar to those simulated by the GCMs, though the slightly wetter simulations on average may be due to the downscaling process, or the influence of Table Mountain on rainfall which is better resolved in the downscaled climate.

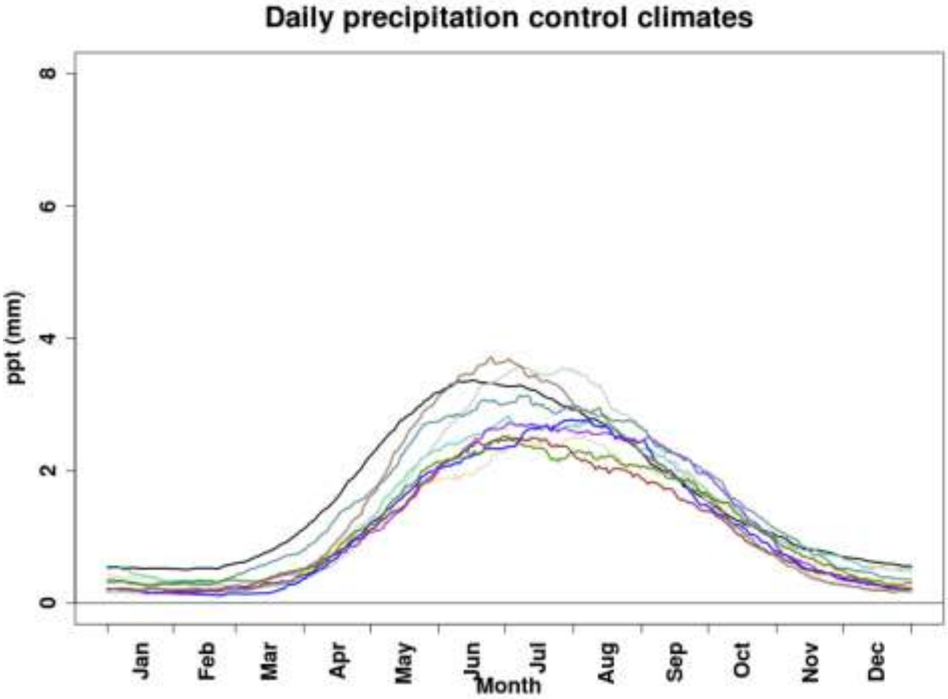


Figure 5: GCM downscaled control rainfall climates (mm per day), for the period 1961-2000 at Cape Town. Black line is observed climate and coloured lines are downscaled GCM climates.

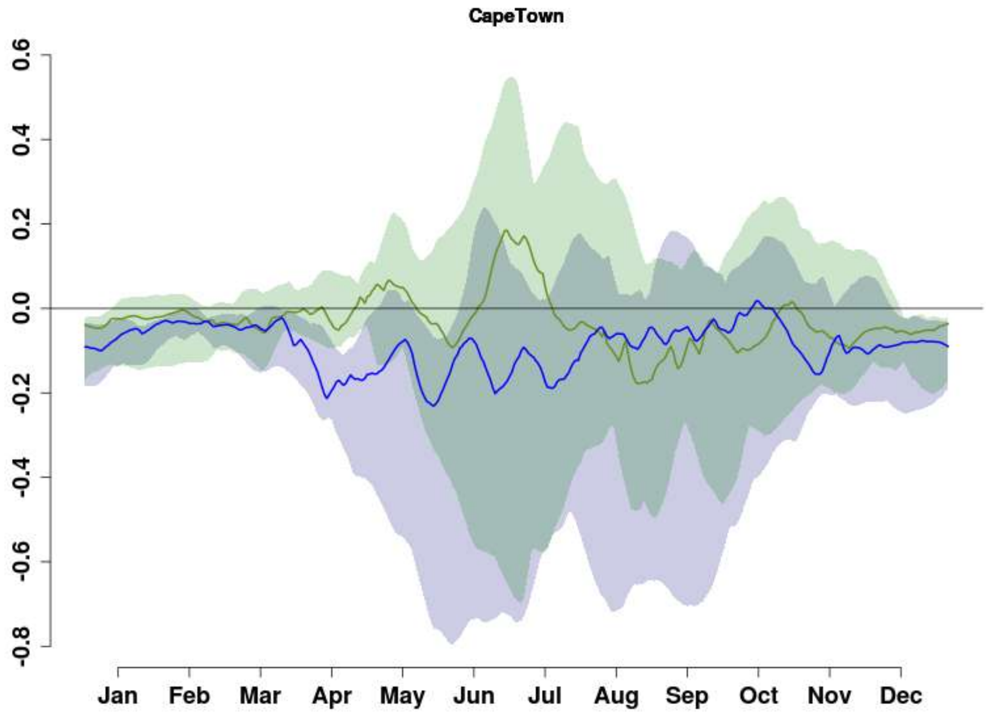


Figure 6: Downscaled rainfall anomalies (mm day^{-1}) for the 2046-2065 period (green) and 2081-2100 period (blue). Shading indicates model spread (10th to 90th percentile change) and solid lines the median model response.

Temperature

The downscaled changes in temperature are similar to those from the GCMs presented earlier and are similar for both minimum and maximum temperatures. Maximum temperature changes are shown in figure 7. Increases are similar during all months, with median changes for the 2081-2100 period as high as 3.4°C and changes for the 2046-2065 period peaking at 1.9°C during May.

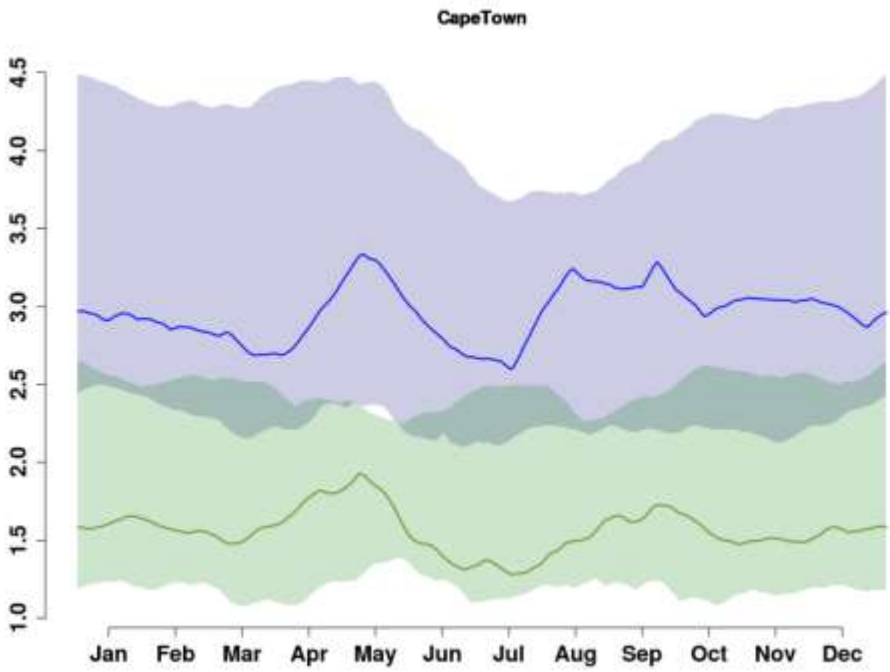


Figure 7: Downscaled maximum temperature anomalies (°C) for the 2046-2065 period (green) and 2081-2100 period (blue). Shading indicates model spread (10th and 90th percentile) and solid lines the median model response.

Evaporation and effective rainfall

One major consequence of the changes in temperature is to increase reference evapotranspiration (ET_0) – assuming only small changes in winds, humidity and solar radiation - the changes for which are shown in figure 8. Increases are highest during December and the peak summer months, with highest median increases of 0.4 mm day-1 during the 2081-2100 period and 0.2 mm day-1 during the 2046-2065 period.

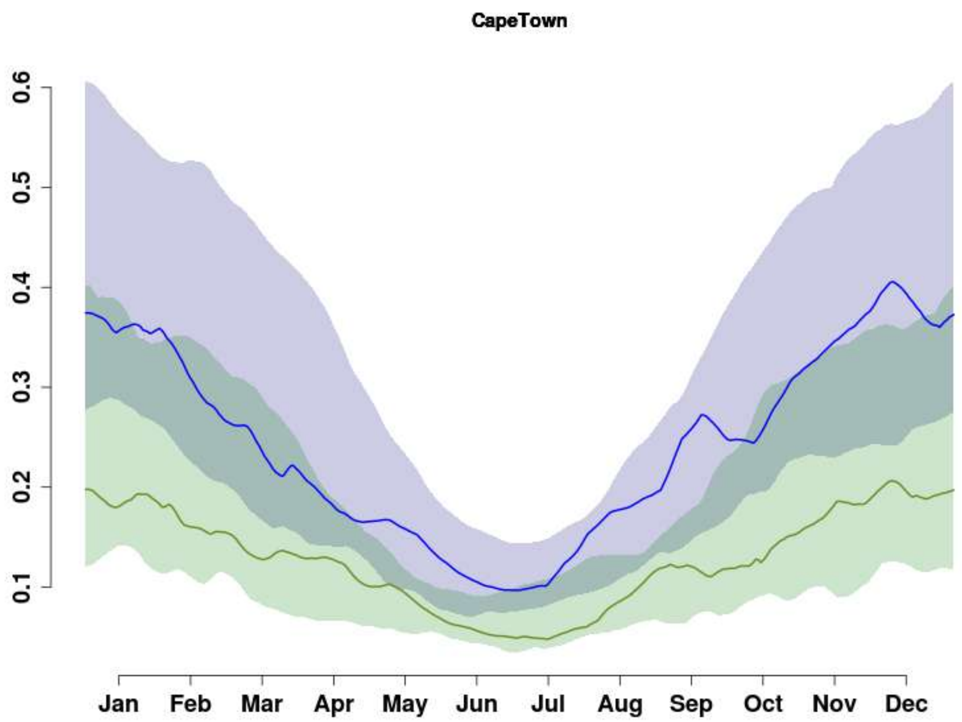


Figure 8: Downscaled reference evapotranspiration (ET_0) anomalies (mm day^{-1}) for the 2046-2065 period (green) and 2081-2100 period (blue). Shading indicates model spread and solid lines the median model response.

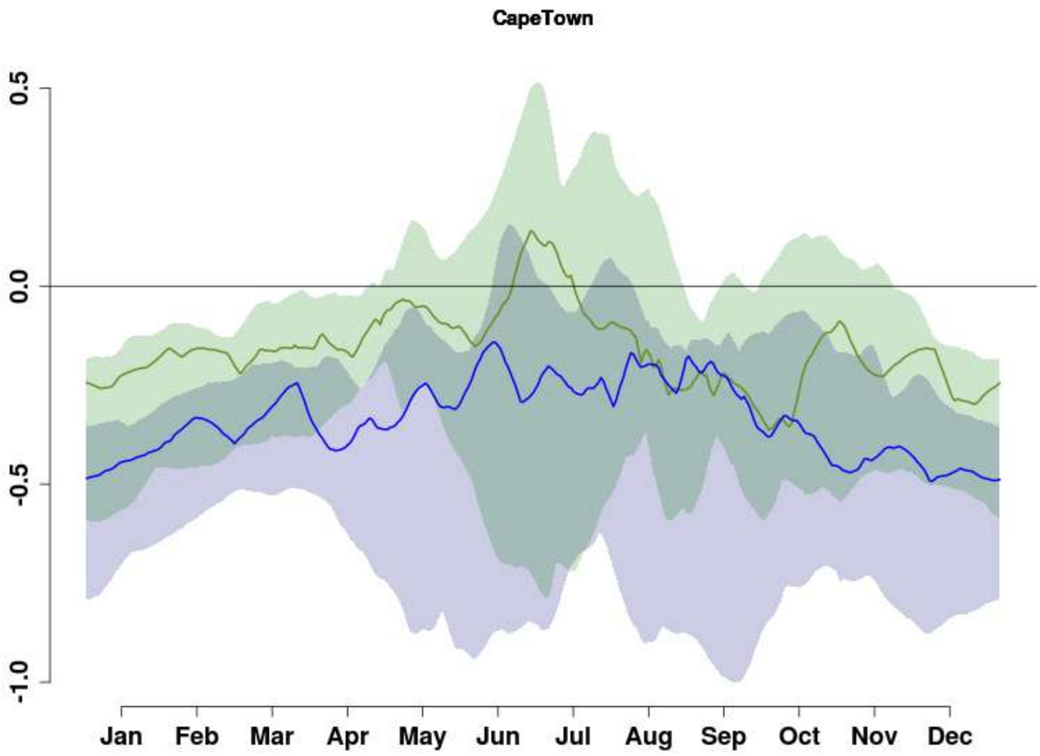


Figure 9: Downscaled effective rainfall (ppt - ET_0) anomalies (mm day^{-1}) for the 2046-2065 period (green) and 2081-2100 period (blue). Shading indicates model spread (10th and 90th percentiles) and solid lines the median model response.

One consequence of these increases in ET_0 is that effective rainfall (rainfall – evaporation) decreases, even without a decrease in rainfall. Assuming that evaporation occurs at the reference level (typical of a surface covered in short grass), figure 9 shows the change in effective rainfall. Comparing it with figure 10, it can be seen that the change in evaporation results in reductions in effective rainfall in nearly all simulations and all months, with the exception of the earlier 2046-2065 period during the peak of the winter rainfall season. This implies less surface water available for dams, plants and agriculture at most times of the year, except, potentially, during the peak of the rainfall season in the mid-century period.

Climate extremes are harder to simulate than changes in the mean climate, largely because GCMs are low resolution parameterised versions of the real climate and may fail to capture important mechanisms e.g. intense and localised convective rainfall. Whilst the downscaling here relates the large scale atmospheric GCM fields to observed rainfall and temperature, and is therefore good at projecting realistic climate on average, it still relies on the GCM simulations to model the change in atmospheric dynamics. This, and the infrequent nature of extreme events (poor sampling in the historical record), means that it is difficult to project future changes.

Until there are fundamental improvements in the GCMs, better estimates of extreme climate events will be difficult; new simulations from the CORDEX programme will offer some high resolution dynamic simulations from multiple regional climate models (RCMs) for the first time, and these simulations may be able to better simulate the complex dynamics of extreme events leading to improved estimates of change.

Changes in extreme temperatures

Changes in extreme temperatures are likely to rise in all simulations from GCMs and the statistical downscaling used here. Figure 10 indicates the cumulative probability of exceeding different maximum daily temperatures for different periods at Cape Town under an assumed A2 emissions scenario. The risk of exceeding high values (e.g. 35°C) is higher during future periods, though this might be an underestimate given that the GCM control climates slightly underestimate the observed exceedance. Table 1 below shows the probability of exceeding several temperatures for Cape Town, as well as for each period.

Box 2. Probability in this context is a measure of the expectation that an event will occur. Probabilities are given a value between 0 (will not occur) and 1 (will occur). The higher the probability of an event, the more certain it is that the event will occur. The cumulative probability is the probability of observing less than or equal to the observed value. The graph shows how this probability of exceeding a maximum temperature increases over the 3 time periods

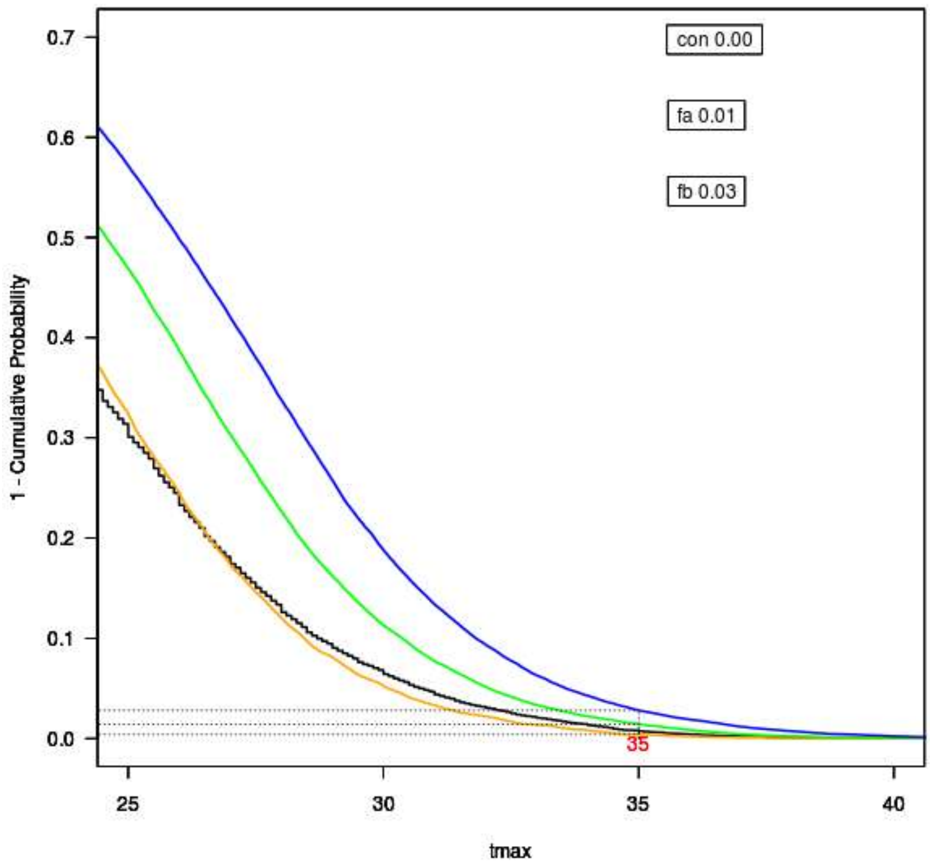


Figure 10: Cumulative probability of exceeding maximum temperatures under current (black), downscaled control (orange), downscaled 2046-2065 (green) and downscaled 2081-2100 (blue) periods at Cape Town.

Temperature threshold	Probability of exceedance under present climate (1960-2000)	Probability of exceedance under future climate (2046-2065)	Probability of exceedance under future climate (2081-2100)
30°C	5%	11%	19%
32°C	2%	5%	9%
35°C	0%	1%	3%

Table 1. The probability of exceeding several temperatures for Cape Town for the 3 periods

As a rough rule we can therefore expect the frequency of days exceeding these different thresholds to more than double by 2055 and approximately quadruple by 2090 under the A2 emissions scenario.

One improvement on these estimates of change for the future would be to downscale using a higher resolution RCM which would be better able to resolve graded temperature changes in regions of steep topography (Tadross *et al*., 2005), something that the GCMs and statistical downscaling used here is not able to do. The multiple RCM simulations generated as part of the CORDEX programme (Jones *et al*., 2011) could be used in this regard.

Changes in extreme rainfall

Changes in extreme rainfall will be at least partly difficult to estimate due to the problems in simulating extreme atmospheric conditions mentioned earlier. Additionally the statistical downscaling technique used here can only simulate daily rainfall values seen in the historical record. This means that it may underestimate increases in rainfall due to increases in intensity, especially at the extreme tail of the distribution. Given that increases in intensity are possible in a hotter climate with more moisture for rainfall, this is a shortcoming of the downscaling methodology employed here. Using RCMs (which are not restricted by such limits) is currently not an option as there are not enough RCM simulations for multiple GCMs available for the region (in order to construct envelopes of change and assess the probability/risk of particular changes). Again this may change when the CORDEX data becomes available.

Analysis

Whilst using an ensemble of GCMs to project change at the large scale is clearly a viable option, it seems to be clear from the work presented here, that this is not the case when smaller regions are considered. In the case of the western Cape and the simulation of rainfall this may be a consequence of several factors:

1. the dominant rainfall mechanism during winter are mid-latitude cyclones which are crudely resolved by the GCMs;
2. rainfall is too simply parameterised in the GCMs;
3. the varied topography and coast is only crudely represented in the GCMs

A downscaled model is shown to be able to provide an enhanced ability to resolve some of these differences, though it is still based on the information and simulations provided by the GCM. In particular, it is able to suggest different regions of positive and negative rainfall change. This is largely a consequence of being able to improve on aspects 2 and 3 above, though it is still fundamentally dependent on the GCMs ability to simulate the first aspect above.

Conclusion

The question posed at the outset was whether a downscaling technique such as the one used here could be used to assist decision-making on the localised scale compared to lower scale GCM output. Whilst there is an indication that the downscaling improves on the ability of the model ensemble to distinguish between regions where different changes might be expected, it still produces an ensemble which is characterised by a wide range of simulated change (both positive and negative rainfall changes). So it remains a possibility that the downscaling does not necessarily reduce uncertainty, but rather simulates a more realistic range of changes given the large scale changes simulated by the GCMs. If this is the case then this is an important improvement, especially when it comes to simulating realistic impacts, either in hydrology or agriculture. In this respect it is especially important to note that the downscaled changes in rainfall need to be realistic, especially if we are to understand whether more or less water will be available in the future – even increases in rainfall may be insufficient to overcome potential increases in evaporation.

Changes in rainfall extremes were shown to be difficult to simulate using the statistical downscaling technique used in this study, though this does not necessarily apply to all downscaling techniques. However, changes in extreme temperatures were easier to estimate and provided useful estimates which can be important for estimating impacts on human and animal health, damages to crops and vegetation etc.

The utility of downscaled data therefore depends on the application of the data and it is not a product free from the problems associated with GCMs. It is rather a translation of the GCM data that is able to provide potentially more realistic changes (in the mean climate) that can better serve as input to an impact analysis, whilst still being limited by methodological constraints. Any use of this data for assessing impacts at the local scale should therefore bear in mind both its advantages and constraints.

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