Agricultural Systems,Volume 103, Issue 2, February 2010, Pages 63-72

A preliminary assessment of climate change impacts on sugarcane in Swaziland

Knox, J.W. [1 *], Rodríguez Díaz, J.A. [2], Nixon, D.J., [3] and Mkhwanazi, M. [4]

[1] Centre for Water Science, Cranfield University, Bedfordshire, MK43 0AL, UK
[2] Department of Agronomy, University of Cordoba, Campus de Rabanales, 14071 Cordoba, Spain
[3] Booker Tate Ltd, Masters Court, Church Rd, Thame, Oxon OX9 3FA, UK
[4] University of Swaziland, Faculty of Agriculture, P/B Luyengo, Swaziland

** Corresponding author*

Abstract

The spatial and temporal impacts of climate change on irrigation water requirements and yield for sugarcane grown in Swaziland have been assessed, by combining the outputs from a general circulation model (HadCM3), a sugarcane crop growth model and a GIS. The CANEGRO model (embedded with the DSSAT program) was used to simulate the baseline and future cane net annual irrigation water requirements (IR_{net}) and yield (t ha^{-1}) using a reference site and selected emissions scenario (SRES A2 and B2) for the 2050s (including CO_2-fertilisation effects). The simulated baseline yields were validated against field data from 1980-1997. An aridity index was defined and used to correlate agroclimate variability against irrigation need to estimate the baseline and future irrigation water demand (volumetric). To produce a unit weight of sucrose equivalent to current optimum levels of production, future irrigation needs were predicted to increase by 20-22%. With CO_2-fertilisation, the impacts of climate change are offset by higher crop yields, such that IR_{net} is predicted to increase by 9%. The study showed that with climate change, the current peak capacity of existing irrigation schemes could fail to meet the predicted increases in irrigation demand in nearly 50% of years assuming unconstrained water availability.

Keywords: *CANEGRO; GIS; irrigation; sugarcane; water; yield.*

1. Introduction

Many studies in the research literature describe how agricultural production in Africa will be one of the sectors most vulnerable to climate change and variability (Challinor *et al*., 2005).

This is because a significant proportion of the African economy is dependent on agriculture, most of Africa's water (85%) is used for agriculture (Downing *et al.*, 1997), farming techniques are relatively primitive and the majority of the continent is already hot and dry (Kurukulasuriya and Mendelsohn, 2008). Spatial and temporal changes in precipitation and temperature patterns will thus have major impacts on the viability of both dryland and irrigated farming (Benhin, 2008). For an important commodity crop such as sugarcane where water is a limiting factor in production, the priorities are to assess the impacts of climate change on both resource availability (for irrigation abstraction) and water demand (for crop production). However, most studies to date have focussed on agriculture and rural livelihoods, with limited attention to impacts on sugarcane in southern Africa (Deressa *et al.*, 2005).

In many African countries, including Nigeria (Binbol *et al.*, 2006), South Africa (Hassan and Olbrich, 2000), Zambia and Zimbabwe, sugarcane forms the mainstay of the economy. In Swaziland, production dates back to the mid-1950s, with the establishment of mills at Big Bend, Mhlume and Simunye. Sugarcane production has grown steadily, and in 2007 accounted for 59% of Swaziland's agricultural output and 24% of gross domestic product (GDP). In 2008 production was reported to be 5,100,456 tonnes with an average annual yield of 102 t ha^{-1} (SSA, 2009). Most cultivation is concentrated on large plantations in the Lowveld and Lower Middleveld regions, where fertile soils and high temperatures provide ideal conditions for production, although all are dependant on irrigation to supplement low rainfall during the growing season. In this context, Swaziland is unique, as sugarcane cannot be grown without irrigation, in contrast to neighbouring countries such as South Africa where 40% of the total cropped area is irrigated (Inman-Bamber and Smith, 2005). As a consequence, the majority of water abstracted for agriculture (96%) in Swaziland is used for sugarcane production (Matondo *et al.*, 2005).

The total cane cropped area is currently 52,071 ha (SSA, 2009) having increased from 14,500 ha in the late 1960s (Murdoch, 1968); further irrigation developments are underway which will result in an additional 19,000 ha being cultivated. This will add pressure on already strained water resources, and is likely to lead to increased tensions with neighbouring riparian states regarding water allocations for agriculture (Nkomo and van der Zaag, 2004). At present, sugarcane irrigation needs vary between 10,000 to 14,000 m^3 ha^{-1} depending on variety, soil and agroclimate conditions. Although traditional methods such as furrow are still popular (39% of the total area), sprinklers (54%), centre pivots (3%) and drip (3%) are gaining favour (Nkomo and van der Zaag, 2004) as estates switch technology to improve water efficiency (more 'crop per drop'), coupled with concerns regarding labour availability (Merry, 2003).

Deressa *et al* (2005) assessed the economic impacts of climate change on sugarcane in South Africa using a Ricadian approach. By combining critical damage point analyses with information on agroclimate variability their analyses showed that sugarcane revenue is more sensitive to predicted increases in temperature, rather than rainfall. Their analysis excluded the impacts of CO_2 fertilisation on productivity. Previous studies have investigated the impacts of climate change on water resources in Swaziland but have not considered sugarcane production (Matondo *et al*., 2004). Other studies have assessed agronomic impacts and the potential for using spatial (GIS) modelling for yield prediction (Kiker, 2000). The objective of this study was to conduct a preliminary assessment of climate change impacts on sugarcane production in Swaziland.

2. Methodology

In summary, the outputs from a general circulation model (GCM), a sugarcane crop growth model and a geographical information system (GIS) have been combined to assess the spatial and temporal impacts of climate change on cane yield and irrigation needs. Using selected IPCC SRES scenarios for the 2050s (Nakicenovic *et al*., 2000), future climate datasets were derived for a reference site using outputs from the HadCM3 model. The net annual irrigation water requirements (IR_{net}) and crop productivity (t ha^{-1}) for the baseline and selected IPCC scenario were then simulated using the CANEGRO model embedded within the DSSAT (Decision Support System for Agrotechnology Transfer) program (Jones *et al.*, 2003). The crop simulations considered future emissions scenarios both with and without CO_2 fertilisation effects. Using potential soil moisture deficit (PSMD) as an aridity index, maps showing future changes in agroclimate were produced. Finally, a linear regression analysis between agroclimate variability and irrigation need was used to estimate current and future volumetric water demand for sugarcane. A brief description of the study site, the climate change scenarios and datasets, crop modelling and GIS mapping, is provided below.

2.1 Study site

The study site was Mhlume (Lon: 26:03:02S; Lat: 31:50:05E), in the eastern Lowveld, an area in which nearly half the total area of irrigated sugarcane in Swaziland is located. The Commonwealth Development Corporation (CDC) established a sugar mill at Mhlume in the 1950s, now owned by the Royal Swaziland Sugar Corporation (RSSC) who manage approximately 20,000 ha of sugarcane which is milled at Mhlume and Simunye factories. RSSC is one of the largest companies in Swaziland, producing two-thirds of the country's sugar. Mhlume has a sub-tropical steppe climate and compared to other parts of the country, the Lowveld region is characterised by low rainfall and high temperatures. For this study, daily weather records for 1969-1996 for the site were available. In January, the mean monthly temperature is 31°C, but with daily maximum temperatures as high as 39°C. The minimum monthly mean temperature (9°C) occurs in winter (June to July), but on some days can be as low as 3°C. Nearly 80% of annual rainfall occurs between October and March. Reference evapotranspiration (ETo) (Allen *et al.*, 1998) exceeds rainfall in all months, with the greatest moisture deficits occurring between May and September (Figure 1). A cropping database for RSSC provided detailed field records on planting and harvest dates, varieties grown, soil types, ratoon periods, irrigation methods, and yields (harvested cane and sucrose) from 1980 to 2007. This database was used for validating the CANEGRO simulation outputs.

2.2 Climate change scenarios and datasets

Climate projections were based on the HadCM3, a third generation coupled atmosphere-ocean general circulation model developed at the Hadley Centre for Climate Prediction and Research (Johns *et al*., 1997). It was developed from the earlier HadCM2 model, used to generate predictions of climate change for the IPCC 3rd and 4th Assessment Reports, and has been widely used in Africa for impact assessments. For example, Tanser *et al* (2003) studied the effects of climate change on malaria transmission in Africa using HadCM3 and three climate scenarios. Thomas *et al* (2005) studied the mobilization of southern African desert dune systems using outputs from three GCMs (HadCM3, HadCM2 and CGCM1). They showed that for the HadCM3 model, index values for dune activity bore a very close relationship to those derived from observed data for the 1961–90 period.

The HadCM3 has a higher spatial resolution than previous versions (2.5° x 3.75°, latitude by longitude) and allows the radiative effects of CO_2 and other minor greenhouse gases, including water vapour and ozone to be represented. In order to provide information on possible changes in global climate, the model is forced to consider future scenarios where changes in atmospheric CO_2 concentration are assumed depending on anthropogenic activity for three 30-year mean periods (2020s, 2050s, and 2080s). The scenarios reflect different 'storylines' based on differing rates of demographic change, industrial activity, dependence on fossil fuels, and other socio-economic indicators. These represent mutually consistent characterisations of future states of the world during the 21st century, and are neither predictions nor forecasts of future conditions. Rather, they describe alternative plausible futures that conform to sets of circumstances or constraints within which they arise. The true purpose of scenarios is thus to determine the possible ramifications of climate change along one or more plausible (but indeterminate) paths.

The emissions are based on those developed by the IPCC (Nakicenovic *et al.*, 2000) and known as SRES (Special Report on Emission Scenarios). In simple terms, there are four ‘marker scenarios’ that combine two sets of divergent tendencies. One set varying between strong economic values and strong environmental values, the other set varying between increasing globalisation and increasing regionalisation (IPCC-TGCIA, 1999). The scenarios are commonly referred to as A1 (economic-global), B1 (environmental-global), A2 (economic-regional), and B2 (environmental –regional). For this research, the A2 and B2 scenarios for the 2050s were chosen. The A2 scenario has the higher atmospheric CO_2 concentration and temperature increase with the highest population increase, the B2 is less extreme, assuming greater efforts to control global CO_2 emissions (de Silva *et al.*, 2007) (Table 1). Strzepek and McCluskey (2006) assessed the impacts of climate change on regional water resources and agriculture in Africa using five different models (CSIRO2, HadCM3, CGCM2, ECHAM and PCM) using the same emission scenarios. An approach involving downscaling the HadCM3 outputs for each scenario was chosen in preference to using a regional climate model (RCM) as previously used in South Africa (Hudson and Jones, 2002; Tadross *et al*., 2005) since these studies considered only one socioeconomic scenario (SRES A2) for 2100. The challenges of choosing an appropriate GCM, a representative number of emissions scenarios and time slices and the downscaling approach in order to capture an appropriate degree of uncertainty in the modelling are considered under the methodological limitations section.

When downscaling, changes in climate need to be considered relative to a ‘baseline’. In this study, a baseline climatology developed by the International Water Management Institute (IWMI) was used (New *et al*., 2002). This 10’ resolution dataset includes gridded mean monthly surface climate data, derived from observed data for 1961 to 1990, to match the World Meteorological Organisation (WMO) standard. However, it is important to check that the baseline (historical) climate for a study site is consistent with the equivalent gridded baseline climatology data. For Mhlume, the historical baseline referred to 1969 to 1996. A comparison between Mhlume and the equivalent IWMI grid pixel (1961-90) using mean monthly data for rainfall and reference evapotranspiration (ETo) is shown in Figure 2. Although the time series are different, linear regression analyses showed a very high correlation between the two datasets (Rainfall R^2 = 0.96 and ETo R^2 = 0.98) confirming that the IWMI baseline climatology was appropriate for the downscaling process.

It is acknowledged that GCMs do not simulate the present climate perfectly, and that model changes predicted from the present to the future are generally more reliable than the present or the future climate predicted alone (Carter *et al*., 1994). Downscaling GCM outputs for the study site was undertaken using a well established procedure using 'change factors' (Diaz-Nieto and Wilby, 2005). A baseline climatology for the site was first established. Changes in the equivalent climate variables for the GCM grid box closest to the target site (Mhlume) were calculated by taking the difference between the transient HadCM3 GCM runs with the IWMI observed climate data from the 30 year baseline period (Table 2). Finally, these 'change factors' (CF) were applied to the historical baseline – adding the changes in temperature to the observed temperature, and multiplying ratio changes for precipitation and other variables (e.g. solar radiation, wind, ETo) by their observed daily values during the period 1961-90 (Alexandrov and Hoogenboom, 2000). Two new datasets were generated, to represent the future climate at Mhlume under each SRES scenario (2050_A2 and 2050_B2). Using this approach, all the daily climate values in each month are altered by the same percentage, each day and in each year of record. This approach has the virtue of simplicity and maintains a realistic temporal structure of climate data. It also assumes that the relative variability in climate from day to day and year to year (the shape of the frequency distribution) remains constant. Whilst it is recognised that this is not necessarily true of future climate, it avoids introducing additional uncertainty into the analysis. Similar CF approaches for downscaling have been applied in the UK (Pilling and Jones, 1999), Bulgaria (Alexandrov and Hoogenboom, 2000), Spain (Rodriguez Diaz *et al.*, 2007) and Sri Lanka (de Silva *et al.*, 2007). The historical baseline and perturbed future climate datasets for Mhlume were used as inputs for the sugarcane crop modelling.

2.3 Modelling sugarcane yield and water use

For simulating baseline and future sugarcane yield and irrigation needs, the CANEGRO model was used; this is one of 16 crop models embedded within the DSSAT (v4.0) program (Jones *et al*., 2003). A brief description of the CANEGRO model is given below, but readers interested in a detailed description are referred to Inman-Bamber (1991; 1995) and O'Leary (2000). The CANEGRO model was originally developed by the South African Sugar Association Experiment Station (SASEX) to determine optimal harvest age because of risks from the stalk borer *Eldana sacchararina* (Inman-Bamber, 1995). It has since been embedded into DSSAT and used in Africa (Inman-Bamber and Kiker, 1997), Asia (Jintrawet and Prammanee, 2005) and America. The model contains carbon simulation, crop development, energy and water simulation components. Although it was coupled to a soil and plant nitrogen model from the CERES-Maize model (Jones and Kiniry, 1986) in the DSSAT program this has not yet been validated, and hence CANEGRO remains a radiation-water-temperature limited model that takes no account of nutrient status (O'Leary, 2000). The model has, however, been extensively tested for simulating above ground biomass and water status for NCo376, a popular cultivar grown in Swaziland. Keating *et al* (1995) has shown CANEGRO to be robust for simulating biomass with water or nitrogen stress and Inman-Bamber (1994, 1995) reported on its application at two different locations. The model requires input data relating to the local weather, crop and soil characteristics, and management practices (fertilizer and irrigation regimes) and runs on a daily time-step to calculate crop phasic and morphological development using temperature, day length and genetic characteristics. The weather, crop and soil datasets and assumptions used for parameterising CANEGRO are outlined below.

Three weather datasets were used. A historical baseline dataset containing daily maximum and minimum temperature, wind speed, solar radiation, rainfall, and relative humidity for Mhlume for 1969-1996, and two equivalent perturbed datasets for the SRES 2050_A2 and 2050_B2 scenario, respectively, as described previously. Crop modelling was based on NCo376, a cultivar which is grown extensively in Swaziland. An analysis of RSSC field data for 1980-2007 showed that on average this variety accounts for 66% of the total cropped area. The study assumed a plant cane crop; however, in reality, sugarcane is ratooned and only a small proportion (typically 10%) is plant cane. At Mhlume, over three-quarters (77%) of the annual cropped area is ratooned cane aged 1 and 6 years (Figure 3). This was acknowledged to be a methodological limitation as plant cane yields are higher than ratooned cane. However, analysis of RSSC field data actually showed that the average yield for plant cane was not significantly different from ratooned cane aged 1-6 years (Figure 3). It was therefore assumed that simulating plant cane yield would provide a reasonable indication of ‘typical’ yield for cane under both current and future climates.

Planting and emergence dates were assumed to be identical. This is because in ratoon cane the stems are cut to ground level and the stumps appear above ground, as in emergence. Normal practice is to stagger planting in order to optimise cane supplies to the factory. For the modelling exercise, November planting was chosen as this coincides with higher temperatures and rainfall (Figure 1) which is the ideal condition for germination and filleting (Doorenbos and Kassam, 1979). The assumed irrigation method was furrow as this represented 52% of the irrigated area in the region. An automatic irrigation schedule (defining the timing and amount of irrigation) was chosen, with irrigation scheduled to return the soil back to field capacity when the profile soil water content dropped below 65% of total available water. This is assumed typical of current irrigation management practices in the region. Irrigation efficiency was assumed to be 100%, as net irrigation water requirements were being modelled, although in practice surface irrigation efficiencies are considerably lower.

At RSSC, the soils are grouped into three classes ranging from good (1) to poor (3) in terms of sugarcane suitability. For modelling, the fields were assumed to have 'R-set' soils. These are Class 1 soils, equivalent to heavy textured Shortlands and Hutton Forms in the South African Binomial Soil Classification, with an effective rooting depth of 1 m and an available water capacity (AWC) of 140-180 mm m^{-1} (SASEX, 1999). They are defined as moderate to well structured red or reddish brown clay loam to clay soils with moderate organic matter content, and usually occur in mid-slope positions on well draining gentle slopes (Nixon, 2006). They are one of the best soils, giving higher cane yields than other local soils (Murdoch, 1968). An analysis of RSSC field data showed that 65% of the cropped area were on Class 1 soils, and 76% of all fields contained R-set soils.

The CANEGRO model was parameterised and used to simulate annual sugarcane yield and irrigation needs for a baseline 'scenario' using data from 1980-96. The model was then re-run for each SRES scenario (with and without CO_2 fertilisation effects) using the same crop and soil files, but with the future climate datasets. For each year of simulation, model outputs included biomass yield (t ha^{-1}), sucrose yield (t ha^{-1}), irrigation needs (mm), and water use efficiency (WUE) defined as kilograms of sucrose production per cubic metre of irrigation water usefully applied (kg^{-1} m^{-3}).

2.4 Model validation

It is important to have confidence that a crop model can predict with reasonable accuracy historical variations in yield, before imposing further uncertainty through climate change. The CANEGRO model was used to simulate yields for 1980-96. For validation purposes, RSSC field data for the same period were obtained. These contained information on cane yield, including variety, ratoon year, planting and harvest dates, and soil type (18,000 records in total) on a field by field basis. From this, a validation dataset was produced (based on 1549 fields) containing yields for all fields growing plant cane (variety NCo376) on R-set soils. A comparison between the CANEGRO modelled and RSSC observed cane yields was completed (Figure 4). Visually, for most years, the modelled yield compared well to the average observed yield and within ±1 SD (as shown by the error bars). In some years, the modelled and observed average yields were very similar. To assess whether bias of modelled yields versus observed yields were statistically significant, the model outputs were analysed for lack of fit (LOFIT) with the observed data using a method described by Whitmore (1991). This test was chosen in preference to more widely used goodness-of-fit statistics such as the correlation coefficient (*r*) and root mean squared error (RMSE) because rather than comparing a single modelled value against a single observed value, it considers multiple observed values and differing numbers of observed values in a temporal series. The calculated F value (1.50) was not significant, confirming there was no evidence to suggest that the modelled and observed data were statistically different.

2.5 Modelling agroclimate and irrigation demand

The variables that directly influence soil moisture and hence irrigation are rainfall and reference evapotranspiration (ETo). To assess the spatial impacts of climate variability on sugarcane irrigation needs, an approach was needed to extrapolate the CANEGRO modelled outputs for a single site (Mhlume) across Swaziland. Previous research has shown that a strong relationship exists between irrigation need and potential soil moisture deficit (PSMD) for a range of crops and climates, including rice in Sri Lanka (de Silva *et al.*, 2007) and horticulture in Spain (Rodriguez Diaz *et al*., 2007). The advantage of this index over others such as the Wetness Index (ratio of total annual rainfall and total annual evapotranspiration) is that the distribution of rainfall and ET throughout the year is taken into account. Furthermore, in many African countries where spatial information is sparse or non-existent, the PSMD agroclimate index is more appropriate than the Palmer Drought Severity Index (PDSI) which requires detailed spatial soils information (Narasimhan and Srinivasan, 2005). To assess agroclimate (PSMD) variability across Swaziland a water balance model was used, working from mean monthly rainfall and ETo gridded data from the IWMI baseline climatology. The PSMD for each grid pixel at the end of each month is calculated from:

$$PSMD_i = PSMD_{i-1} + ET_i - P_i \qquad [1]$$

Where

$PSMD_i$ = potential soil moisture deficit in month i, mm

ET_i = reference evapotranspiration in month i, mm

P_i = rainfall in month i, mm

At the start of the sugarcane irrigation season the PSMD is assumed to be zero. In months where $P_i > (PSMD_{i-1} + ET_i)$, no soil moisture deficit is assumed to occur and $PSMD_i = 0$. In Swaziland, soil moisture deficits start to build up each month as ET > P, peak in late summer (August) and then continue through the autumn and winter. Therefore in Swaziland, the estimation of PSMD starts with January as month i = 1. The maximum PSMD of the 12 months of the year is the $PSMD_{max}$ for that grid pixel. A gridded dataset containing the $PSMD_{max}$ for each grid pixel at a resolution of 10 min latitude/longitude (16 km x 16 km) for Swaziland was produced.

A modified approach was required to generate an equivalent $PSMD_{max}$ dataset for each SRES scenario. This involved using a GIS to first downscale the HadCM3 GCM data from a grid mesh of 2.5° x 3.75° (latitude by longitude) down to a 10 minute grid to match the IWMI baseline climatology (New *et al*., 2002) using a krigging interpolation technique. Tanser *et al* (2003) used a similar approach to interpolate the future climate scenario surfaces to the resolution of their long-term mean data using bilinear interpolation. The relative change between the baseline and future for each scenario, grid pixel and climate variable was then calculated:

$$CF_{v\_m,j} = \frac{V_{HadCM3\_fut\_m,j}}{V_{HadCM3\_bas\_m,j}} \qquad [2]$$

Where:

$CF_{v\_m,j}$ is the change factor for variable v in month m for pixel j from the HadCM3 model;

$V_{HadCM3\_fut\_m,j}$ is the predicted value for a climate variable from the HadCM3 model, and;

$V_{HadCM3\_bas\_m,j}$ is the baseline value for a climate variable in the HadCM3 model.

Using krigging interpolation techniques, the change factors calculated in Equation 2, were then interpolated to the grid pixels in the IWMI baseline climatology. The relative change between the IWMI baseline climatology and the HadCM3 future scenario for each climate variable (temperature, precipitation, solar radiation, wind speed and relative humidity) for each month and grid pixel was then calculated. These ‘change factors’ were then applied to the IWMI baseline climatology to derive two future climate datasets at 10’ resolution:

$$V_{10'\_fut\_m,i} = CF_{v\_m,i} \cdot V_{10'\_bas\_m,i} \qquad [3]$$

Where:

$CF_{v\_m,i}$ is the interpolated change factor for variable v in month m and pixel i;

$V_{10'\_bas}$ is the pixel value for a climate variable in the IWMI baseline climatology, and;

$V_{10'\_fut}$ is the predicted value for a climate variable in the IWMI baseline climatology.

Two datasets containing gridded $PSMD_{max}$ values for each SRES scenario at 10’ resolution were produced. Using a GIS, the $PSMD_{max}$ data were classified and mapped to show the spatial variability in agroclimate across Swaziland for the baseline and each SRES scenario.

To assess the impacts of climate change on volumetric irrigation demand, a correlation between irrigation need and agroclimate is necessary. One of the outputs from the CANEGRO model is annual irrigation need (mm). Using Equation 1 and the climate data for Mhlume, the $PSMD_{max}$ in each simulated year (1980-96) was calculated. A correlation between annual $PSMD_{max}$ and annual irrigation need was derived by linear regression analysis

(Figure 5). Using a GIS, the $PSMD_{max}$ dataset for Swaziland was combined with the regression equation (Figure 5) to estimate the irrigation need (mm) in each grid pixel. Data on the location and cropped area (ha) of sugarcane in Swaziland was obtained and imported into the GIS. The volumetric irrigation demand (m^3) was then calculated by multiplying the reported sugarcane cropped area (ha) with the estimated irrigation need (mm) in each grid pixel. The total volumetric irrigation demand for sugarcane grown in Swaziland taking into account the agroclimate variability across the country, for the baseline and each SRES scenario, was estimated.

3. Results and Discussion

3.1 Impacts on sugarcane yield and water use efficiency

The estimated changes in sucrose, biomass yield and WUE from the baseline for each SRES scenario (with CO_2 fertilisation for the 2050_A2 SRES scenario) are summarised in Table 3. With climate change, relatively minor increases in productivity are estimated, principally due to increased radiation levels and higher temperatures (1-6% and 10-29% above the baseline, respectively). This is consistent with Batchelor (1992) who observed trends of increasing growth with increasing temperature. Whilst predicted increases in sucrose yield are small (2-3%), ET was estimated to increase by between 11-14%. This results in a reduction in WUE by 10% for both SRES scenarios. However, when the CO_2 concentration for the baseline (330 ppmv) was increased (600 ppmv) for the 2050s, there was a noticeable increase in biomass and sucrose yield. This is consistent with Watson *et al.* (1996) who reported that a doubling of CO_2 concentration from present levels would increase biomass by 10-30%. CO_2 enrichment of the atmosphere increases the rate of photosynthesis, and thus yields, and is expected to reduce water use. In this study, the crop modelling suggests that sucrose yield under the SRES 2050_A2 scenario, with CO_2 fertilisation would be 15% higher than the baseline yield. There seems to be only a minor effect of CO_2 fertilisation on WUE. According to Downing *et al*.

(1997) a doubling of CO_2 concentration may increase WUE by up to 50%, with stronger effects for plants with C_3 pathways. The 5% WUE increase in this study is low, and possibly due to sugarcane having a C_4 pathway, which is less water-efficient.

The beneficial effects of climate change on yield due to increased CO_2 concentration might offset the potentially negative impacts of increased irrigation need, particularly in countries where water resources are scarce. Defining any increase in irrigation need is thus important, because if the increase in irrigation need is accompanied by an increase in yield, then in producing a unit weight of economic yield, the same amount of water may still be used, or even less. Therefore a net increase in irrigation will be when more irrigation water is required for the same unit weight of yield (defined as a standard yield). Figure 6 shows the ranked annual irrigation needs for the baseline and each future scenario for a 'standard' yield. The 'standard' yield is defined as one obtained when the crop has no limitations of water. The results show that for all scenarios, there is an average increase in irrigation need from the baseline of between 19-21%. However, with CO_2 fertilisation, the increase in irrigation need is nearly halved (9%).

3.2 Impacts on sugarcane irrigation water requirements

The predicted changes in seasonal irrigation need (depths applied, mm) from the baseline for each SRES scenario are summarised in Figure 6. The crop modelling suggested an increase in crop water requirement (ET_{crop}) of between 11-14% (Table 3). With climate change, the combined effect of reduced summer rainfall and increased evapotranspiration rates, results in an increase in average irrigation need of 22-26%, depending on scenario. This could have major implications for both existing sugarcane plantations and new developments because irrigation schemes (pipe distribution and canal networks, and application equipment) are designed to meet a certain 'peak' daily and seasonal need. Designing for an 'average' year would result in under-capacity in dry years when returns from irrigation are highest. Similarly, designing for the driest year would lead to unnecessarily large pipes and canals and would be uneconomical. Hence most irrigation schemes are designed to meet peak need for a ‘design’ dry usually defined as a return period equivalent to an 80% probability of non-exceedance. However, with increasing reliance on irrigation to attain high quality production (rather than just yield increment), combined with concerns regarding the increased likelihood of future dry years, many new irrigation schemes are now being designed to cope with more extreme events (greater than the 80% probability of non-exceedance). Figure 6 shows the potential increase in ‘design’ dry year need from the baseline for each scenario. The important point is that a future ‘average’ year in irrigation terms could well be more akin to a current ‘design’ dry year, meaning that with climate change future peak irrigation needs could well exceed current design criteria for existing irrigation schemes, and in approximately 50% of years.

3.3 Impacts on agroclimate and irrigation demand

The spatial variability in agroclimate for the baseline and each SRES scenario are shown in Figure 7. For the baseline, the agroclimate zones show a strong north-south delineation, with the highest aridity values observed in the west around Big Bend (700-800 mm) then declining westwards towards Malkerns (300-400 mm). The highest aridity values correspond to where irrigation needs are highest. With climate change, the zones of highest aridity are predicted to increase in area and magnitude, moving further north towards the sugarcane growing areas of Mhlume and Simunye. Under both SRES scenarios, major changes in the spatial variability in agroclimate are predicted, with large regions of the country predicted to experience conditions more arid than those currently experienced anywhere in the country.

For the baseline, the total theoretical volumetric irrigation water demand is estimated to be 24138 x 10^6 m^3 $year^{-1}$, with nearly three quarters (72%) concentrated within three production areas of Mhlume, Simunye, and Big Bend. With climate change, the volumetric irrigation demand in these areas is projected to increase by 18-21%. This could have major repercussions on other abstractors, particularly in water scarce and trans-boundary catchments. For example, Nkomo and van der Berg (2004) investigated water availability and abstraction in the Komati river basin, which is shared by Swaziland, South Africa and Mozambique, and where irrigated sugarcane constitutes the dominant land use. They investigated the impacts of two new dams on water reliability, and found that improved water supply for irrigation in Swaziland and South Africa had been achieved. However, they reported that future water demands in 2015 even without climate change would result in appreciable shortages for irrigation. The preferred adaptation options included increasing irrigation efficiency (from surface to micro-irrigation) and reducing the sugarcane cropped area in favour of other less water demanding higher value crops, including horticulture and flowers.

5. Methodological limitations

Inevitably, the approaches developed in this study which have linked climate, crop and GIS modelling have numerous limitations. The crop and agroclimate modelling were based on one GCM, two scenarios and one time-slice. Although the HadCM3 and SRES scenarios (A2, B2) have previously been used in various African studies (Hulme *et al*., 2001) a more detailed assessment would need to consider a range of GCM outputs (to account for individual model error), additional time slices (2030s, 2080s) and the full ensemble of SRES scenarios (to consider alternative demographic, socio-economic and technological changes). By considering only one GCM the level of uncertainty in the model outputs cannot be easily quantified. For example, the ECHAM4 GCM has been shown to significantly increase predicted changes in irrigation demand for some regions compared to the HadCM3 GCM (Doll, 2002).

Arnell *et al* (2003) analysed different ways of constructing climate change scenarios using output from three climate models (HadRM3H, HadCM3, HadAM3H). Sixteen scenarios were constructed, representing different combinations of model scale (GCM, RCM), whether the simulations were used directly or changes were applied to an observed baseline, and whether observed or simulated variations from year-to-year were used. The different ways of deriving climate scenarios resulted in a range in change in average annual runoff of between 10-20% by 2071-2100, depending on the model and approach used. Using a regional climate model over-estimated rainfall across much of southern Africa and resulted in excessive simulated runoff. This led to smaller estimates of change in future runoff than when changes in climate were applied to an observed climate baseline. Arnell *et al* (2003) concluded that it was preferable to apply modelled changes in climate to observed data to construct climate scenarios (as used in this study) rather than derive these directly from the regional climate model (RCM) simulations.

Although there has been a marked increase in the number of RCM simulations, very few studies have been conducted over southern Africa as most research institutions in this region lack access to the necessary technology. Regional models, such as HadRM3 are also able to resolve tropical cyclones, which affect eastern tropical regions of southern Africa in summer. The hydrological cycle is stronger in the RCM, with consequent increases in the intensity of rainfall, in the magnitude of the moisture fluxes and in soil moisture compared to the driving GCM (Hudson and Jones, 2002). Further studies should therefore investigate the differences in climate change signal derived from using a suitable RCM compared against using established GCM outputs to provide a better assessment of the uncertainty associated with the climate change modelling aspects of this work. Linked to this, is the method of downscaling. In this study, a popular approach using change factors (CF) was used, but this has limitations compared to statistical downscaling (SD) using transfer functions and stochastic weather generators (Diaz-Nieto and Wilby, 2005). The problem is that the future temporal pattern of wet and dry days remains unchanged, and so changes in the intensity and frequency of rainfall events can not be investigated. Further studies should consider using an alternative SD approach which would allow more detailed analysis of climate change uncertainty and exploration of temporal sequencing of meteorological events (e.g. droughts, rainfall). The effect of different resolution between the HadCM3 model (2.5 x 3.75 degrees) and the IWMI baseline climatology (10' latitude/longitude) datasets, and choice of interpolation may also have introduced some distortion. Finally, the GCM outputs were used to generate future datasets based on predicted ‘average’ changes in climate. However, in agricultural irrigation, a statistically defined ‘design’ dry year with a defined probability of non-exceedance is used, rather than an ‘average’ year. The predicted future ‘average’ irrigation needs presented in this study are thus likely to significantly under-estimate future ‘dry’ year irrigation demand.

The crop model outputs are of course sensitive to model parameterisation. Further modelling would benefit from a sensitivity analysis of the key variables known to influence water use and cane yield, including modifying crop characteristics to capture the effects of varying planting dates for different ratooned cane, simulating different soil types (textures and depths), assessing the proportion of effective rainfall, and assessing the impacts of different irrigation scheduling strategies to reflect either traditional (furrow) or more efficient (micro) application methods. Modelling could also investigate the impacts of future changes in reliability of water supply; this study assumed unconstrained demand, but reducing the availability of water for irrigation at differing times during the season (for example, due to low flows or seasonal droughts) would impact on cane development and yield.

6. Conclusions

To produce a unit weight of sucrose equivalent to current optimum levels of production, future irrigation needs were predicted to increase by 20-22%. With CO_2-fertilisation, the impacts of climate change are offset by higher crop yields, such that IR_{net} is predicted to increase by 9%. The study showed that with climate change, the current peak capacity of existing irrigation schemes could fail to meet the predicted increases in irrigation demand in nearly 50% of years assuming unconstrained water availability.

GIS modelling confirmed that climate change will impact strongly on the spatial variability in agroclimate and hence demand for irrigation. Although the study was based on only one GCM, and considered a limited number of scenarios, these preliminary findings do highlight some of the potential risks that climate change could impose on sugarcane production in Southern Africa. The approaches developed in this paper and results serve to provide a useful baseline from which more detailed investigations should be undertaken, from which more strategic interventions, including adaptations could then be planned.

Acknowledgements

The authors acknowledge the financial support of the Marshal Papworth Fund, the Royal Swaziland Sugar Corporation (RSSC) for provision of extensive field datasets for model validation, and guidance from by Dr. Tim Hess and Mrs. Pat Belamy regarding statistical analysis.

References

Allen, R.G., Pereira, L.S., Raes, D., and Smith, M. (1998) *Crop Evapotranpiration – Guidelines for computing crop water requirements*. FAO Irrigation and Drainage Paper 56. Rome: FAO.

Alexandrov, V.A., and Hoogenboom, G. (2000). The impact of climate variability and change on crop yield in Bulgaria. *Agricultural and Forest Meteorology* 104, 315-327.

Arnell, N.W., Hudson, D.A., Jones, R.G. (2003). Climate change scenarios from a regional climate model: Estimating change in runoff in southern Africa. *Journal of Geophysical Research* 108(D16), 4519, doi:10.1029/2002JD002782.

Batchelor, C.H. (1992). *Water use and growth of drip-irrigated sugarcane*. Unpublished PhD Thesis, University of Reading, UK.

Benhin, J.K.A. (2008). South African crop farming and climate change: An economic assessment of impacts. *Global Environmental Change* 18(4), 666-678.

Binbol, N.L., Adebayo, A.A., and Kwon-Ndung, E.H. (2006). Influence of climatic factors on the growth and yield of sugar cane at Numan, Nigeria. *Climate Research* 32(3), 247-252.

Carter, T.R., Parry, M.L., Harasawa, H., and Nishioka, S., (1994). IPCC technical guidelines for assessing climate change impacts and adaptations. University College London and Center for Global Environmental Research, United Kingdom and Tsukuba, Japan, pp52-53.

Challinor, A., Wheeler, T., Garforth, C., Craufurd, P., and Kassam, A. (2005). Assessing the vulnerability of food crop systems in Africa to climate change. *Climatic Change* 83, 381-399.

Deressa, T., Hassan, R., and Poonyth, D. (2005). Measuring the impact of climate change on South African agriculture: The case of sugar-cane growing regions. *Agrekon* 44 (4), 524-542.

de Silva, C.S., Weatherhead E.K., Knox .J.W, and Rodríguez Díaz, J.A. (2007). Predicting the impacts of climate change - A case study on paddy irrigation water requirements in Sri Lanka. *Agricultural Water Management* 93: 19-29.

Diaz-Nieto, J., and Wilby, R. (2005). A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the River Thames, United Kingdom. *Climatic Change*, 69, 245-268.

Doll, P. (2002). Impact of climate change and variability on irrigation requirements: A global perspective. *Climatic Change* 54, 269-293.

Doorenbos, J., and Kassam, A.H. (1979). *Yield Response to Water*. FAO Irrigation and Drainage Paper 33. Rome, FAO.

Downing, T.E., Ringius, L., Hulme, M., and Waughray, D. (1997). Adapting to climate change in Africa: prospects and guidelines. *Mitigation and Adaptation Strategies for Global Change* 2, 19-44.

Hassan, R., and Olbrich, B. (2000). A comparison of the economic efficiency of water use of plantations, irrigated sugarcane and sub-tropical fruits: A case study of the Crocodile Catchments, Mpumulanga Province. WRC Report No 666/1/99, Water Research Commission, Pretoria.

Hudson, D.A., and Jones R.G. (2002). Regional climate model simulations of present-day and future climates of Southern Africa. Hadley Centre Technical Note 39, UK.

Hulme, M., Doherty, R., Ngara, T., New, M., and Lister, D. (2001). African Climate Change: 1900-2100. *Climate Research* 17, 145-168.

ICASA (2006). DSSAT Version 4. (Accessed: 11 Aug 2006). http://www.icasa.net/dssat

Inman-Bamber, N.G. (1991). A growth model for sugar-cane based on a simple carbon balance and the CERES-Maize water balance. *South African Journal Plant and Soil* 8, 93-99.

Inman-Bamber, N.G. (1994). Effect of age and season on components of yield of sugarcane in South Africa. *Proc. S. Afr. Sugarcane Technol. Assoc*. 68, 23-27.

Inman-Bamber, N.G. (1995). CANEGRO: Its history, conceptual basis, present and future uses. In: Robertson, M.J. (Ed.), Research and Modelling Approaches to Assess Sugarcane Production Opportunities and Constraints. Workshop Proceedings, University of Queensland, St. Lucia, Brisbane, November 1994, pp. 31-34.

Inman-Bamber, N.G., Kiker, G. (1997). CANEGRO 3.10. DSSAT version 3.1 1998 distribution software. IBSNAT, University of Hawaii, Honolulu.

Inman-Bamber, N.G., and Smith, D.M. (2005). Water relations in sugarcane and response to water deficits. *Field Crops Research* 92, 185–202.

IPCC (1999). Guidelines on the Use of Scenario Data for Climate Impact and Adaptation assessment. Version 1. Prepared by Carter, T.R.; Hulme, M. and M. Lal. Intergovernmental

Panel on Climate Change, Task Group on Scenarios for Climate Impact Assessment, Switzerland.

Jintrawet, A., and Prammanee, P. (2005). Simulating the impact of climate scenarios production systems in Thailand. *International Society of Sugar Cane Technologists: Silver Jubilee Congress. January 30-February 4, 2005*. Guatemala.

Johns T.C., Carnell, R.E., Crossley, J.F., Gregory, J.M., Mitchell, J.F.B., Senior, C.A., Tett, S.F.B., and Wood, R.A. (1997). The Second Hadley Centre Coupled Ocean–Atmosphere GCM: model description, spinup and validation. *Climate Dynamics* 13, 103-134.

Jones, C.A., and Kiniry, J.R. (1986). CERES-Maize: a simulation model of maize growth and development. Texas A&M University Press, College Station, 194 pp.

Jones, J.W., Hoogenboom, G., Portera, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., and Ritchie, J.T. (2003). The DSSAT cropping system model. *European Journal of Agronomy* 18, 235-265.

Keating, B.A., Liu, D.L., Inman-Bamber, N.G., Robertson, M.J., Muchow, R.C., Kingston, G. (1995). Comparison of levels of approach in modelling sugarcane potential yield. In: Robertson, M.J. (Ed.), Research and Modelling Approaches to Assess Sugarcane Production Opportunities and Constraints. Workshop Proceedings, University of Queensland, St. Lucia, November 1994, pp. 43-51.

Kurukulasuriya, P., and Mendelsohn, R. (2008). How will climate change shift agro-ecological zones and impact African agriculture? Policy Research Working Paper 4717. World Bank Development Research Group.

Kiker, G.A. (2000). Canegro-DSSAT linkages with geographical information systems: Applications in climate change research for South Africa. *Proceedings of International CANEGRO Workshop, 4-7 August 2000.* Mount Edgecombe, South Africa.

Matondo, J.I., Graciana, P., and Msibi, K.M. (2004). Evaluation of the impact of climate change on hydrology and water resources in Swaziland: Part I. *Physics and Chemistry of the Earth* 29, 1181-1191.

Matondo, J.I., Graciana, P., and Msibi, K.M. (2005). Managing water under climate change for peace and prosperity in Swaziland. *Physics and Chemistry of the Earth* 30, 943-949.

Merry, R.E. (2003). Dripping with success: the challenges of an irrigation redevelopment project. *Irrigation and Drainage* 52, 71-83.

Murdoch, G. (1968). *Soils and Land Capability in Swaziland*. Ministry of Agriculture, Swaziland. Bulletin 24.

Nakicenovic, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Grübler, A., Jung, T.Y., Kram, T., La Rovere, E.L., Michaelis, L., Mori, S., Morita, T., Pepper, W., Pitcher, H., Price, L., Raihi, K., Roehrl, A., Rogner, H., Sankovski, A., Schlesinger, M., Shukla, P., Smith, S., Swart, R., van Rooijen, S., Victor, N., and Dadi, Z. (2000). IPCC Special Report on Emissions Scenarios. Cambridge University Press, Netherlands.

Narasimhan B., and Srinivasan, R. (2005). Development and evaluation of soil moisture index (SMDI) and evapotranspiration deficit index (ETDI) for agricultural drought monitoring. *Agricultural and Forest Meteorology* 133, 69-88.

New, M., Lister, D., Hulme, M., and Makin, I (2002). A high resolution data set of surface climate over global land areas. *Climate Research* 21, 1-25.

Nixon, D.J. (2006). Guide to the soils of the Swaziland sugarcane industry. Produced by the Swaziland Sugar Association and the South African Sugarcane Research Institute (pp 44).

Nkomo, S., and van der Zaag, P. (2004). Equitable water allocation in a heavily committed International catchment area: the case of the Komati catchment. *Physics and Chemistry of the Earth* 29, 1309-1317.

O'Leary, G.J. (2000). A review of three sugarcane simulation models with respect to their prediction of sucrose yield. *Field Crops Research* 68, 97-111.

Pilling, C. and Jones, J.A.A. (1999). High resolution climate change scenarios: Implications for British runoff. *Hydrological Processes* 13, 2877-2895.

Rodríguez Díaz, J.A., Weatherhead, E.K., Knox, J.W. and Camacho, E. (2007). Climate change impacts on irrigation water requirements in the Guadalquivir River Basin in Spain. *Regional Environmental Change* 7, 149-159.

SASEX (1999). Identification and Management of the Soils of the South African Sugar Industry. Bulletin 19, South African Sugar Association, Mt. Edgecombe.

SSA (2009) Importance of the sugar sector to Swaziland's economy. (Accessed: 8th May 2009). http://www.ssa.co.sz/

Strzepek, K., and McCluskey, A. (2006). District level hydroclimatic time series and scenario analyses to assess impacts of climate change on regional water resources and agriculture in Africa CEEPA Discussion Paper No. 13 Special Series on Climate Change and Agriculture in Africa ISBN 1-920160-01-09 Discussion Paper ISBN 1-920160-13-2.

Tanser, F.C., Sharp, B., and le Sueur, D. (2003). Potential effect of climate change on malaria transmission in Africa. *The Lancet* 362(9398), 1792-1798.

Tadross, M., Jack, C., and Hewiston, B. (2005). On RCM-based projections of change in southern African summer climate, *Geophysical Research Letters* 32, L23713, doi:10.1029/2005GL024460.

Thomas, D.S.G., Knight, M., and Wiggs, G.F.S. (2005). Remobilization of southern African desert dune systems by twenty-first century global warming. *Nature* 435, 1218-1221.

Whitmore, A. P. (1991). A method for assessing the goodness of computer simulation of soil processes. *Journal of Soil Science* 42, 289-299.

Figure 1 Mean monthly rainfall and reference evapotranspiration (ETo) at Mhlume, Swaziland, based on daily historical data from 1969 to 1996.

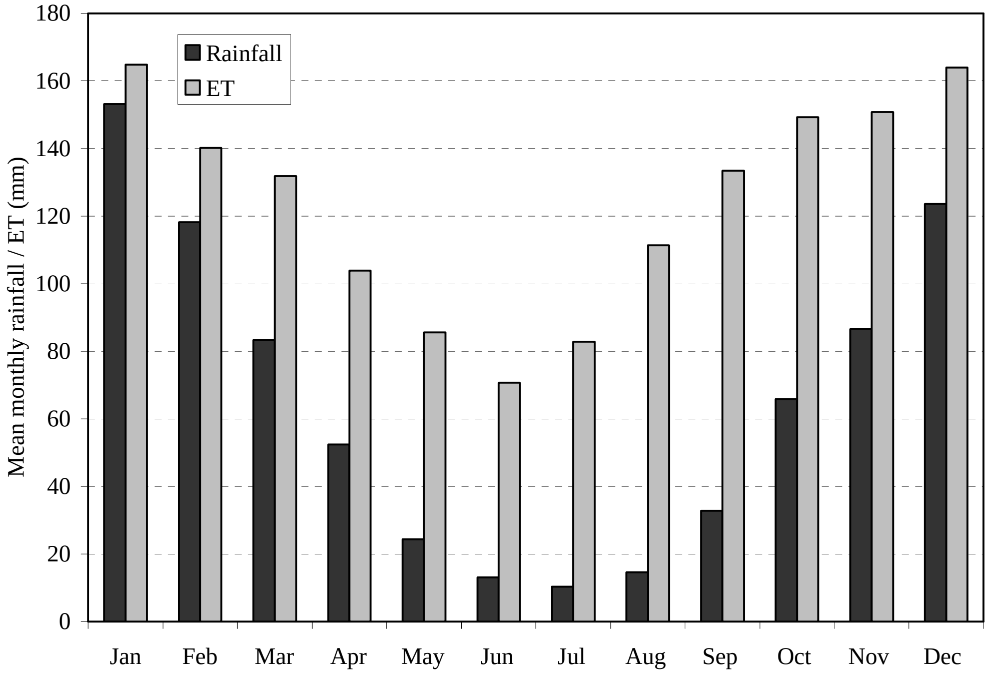
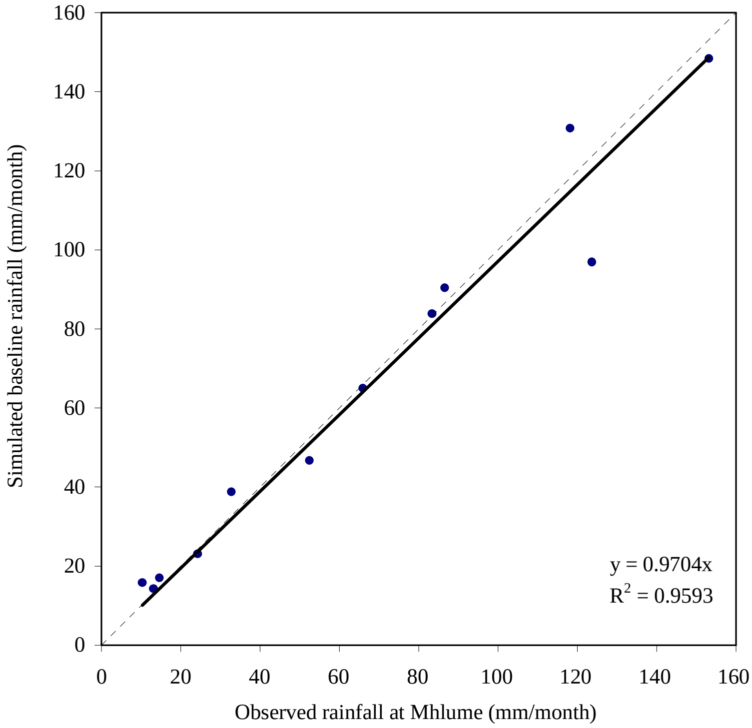


Figure 2 Comparison of observed mean monthly rainfall (mm/month) and mean daily (mm/day) reference evapotranspiration (ETo) for Mhlume against simulated grid pixel data from the IWMI baseline climatology.



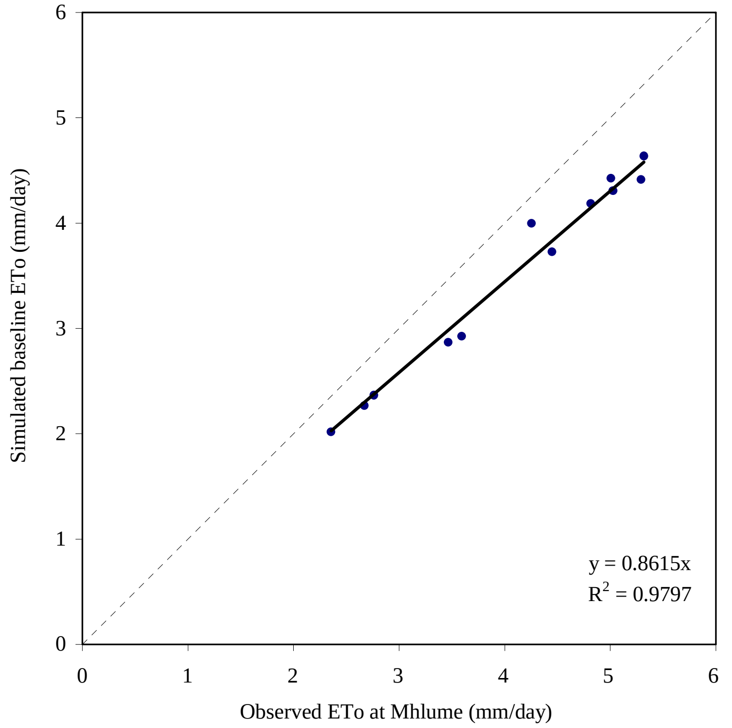


Figure 3 Reported average cane yield (t/ha) and cumulative proportion (%) of total cropped area, by ratoon year, at Mhlume, based on data for 1980-2007.

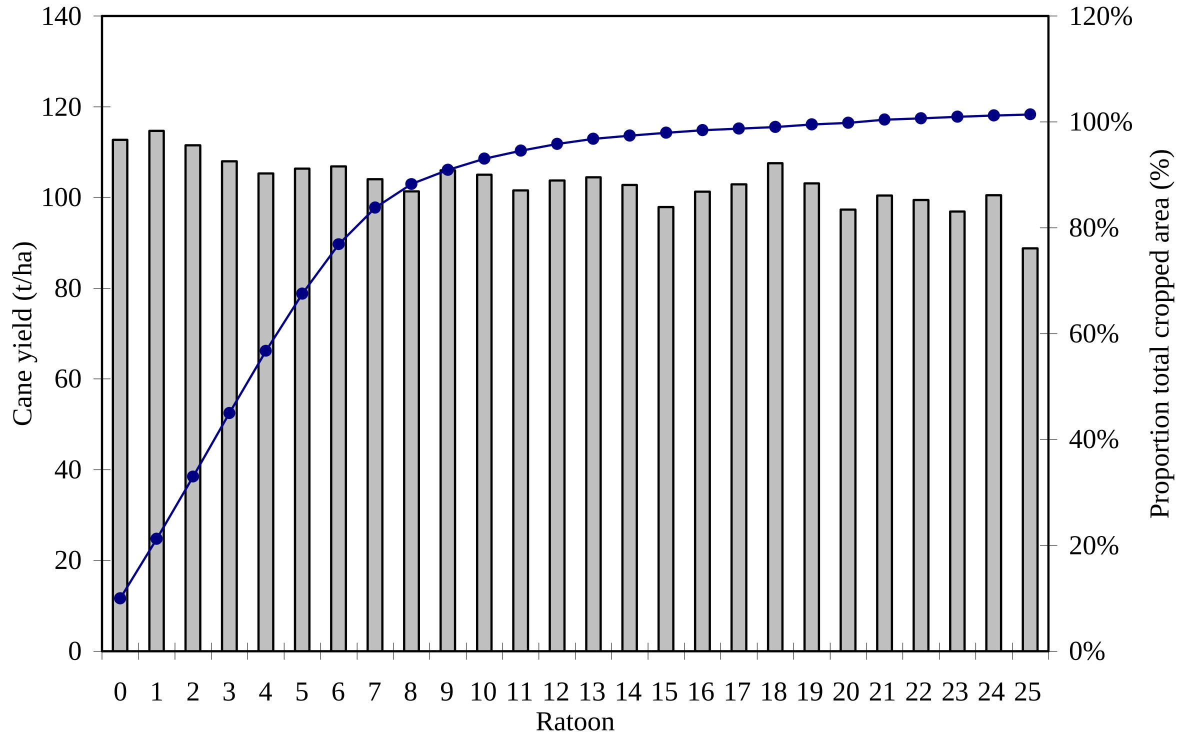


Figure 4 Comparison between CANEGRO simulated average annual yield (t/ha) and RSSC average annual field yield (observed) between 1980-1996.

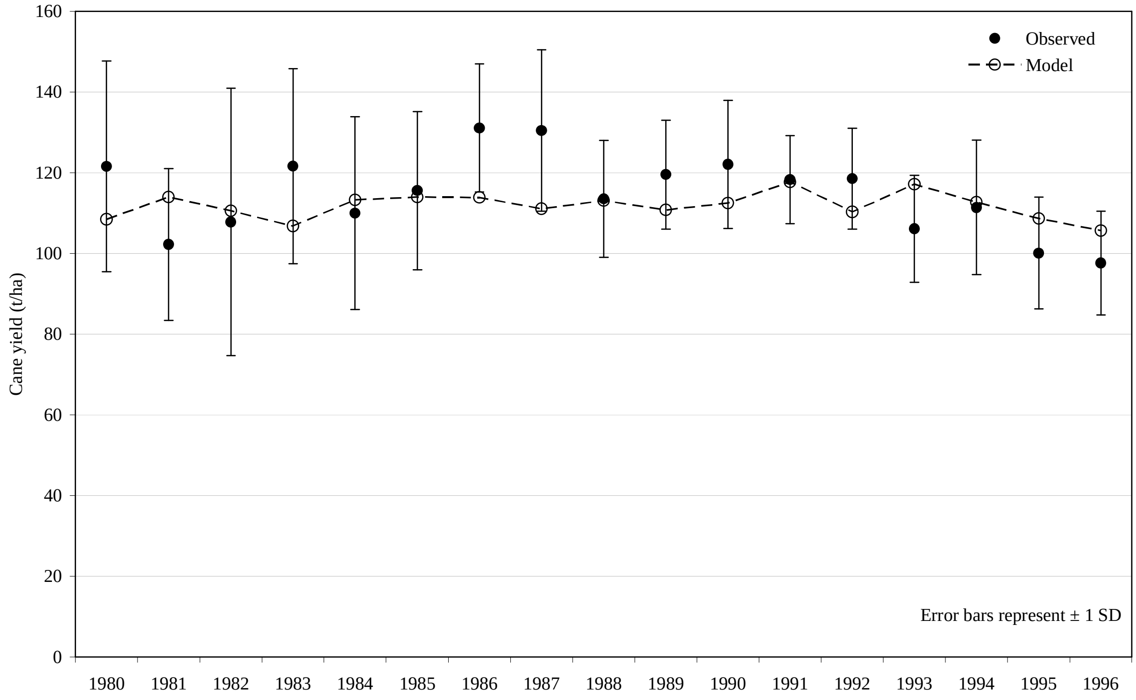


Figure 5 Relationship between annual maximum potential soil moisture deficit (calculated using a monthly water balance Eq. 1) and annual irrigation need (calculated using CANEGRO) for Mhlume for the baseline. A linear regression was fitted to the data points.

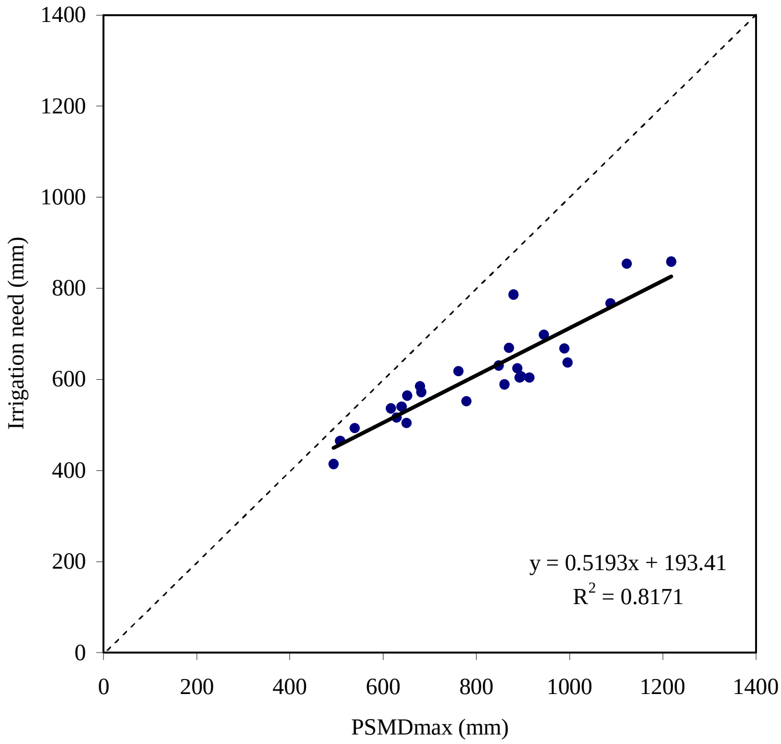


Figure 6 CANEGRO simulated annual irrigation needs (ranked) for sugarcane at Mhlume, for the baseline and each SRES scenario (2050_A2 and 2050_B2). The average irrigation need for the baseline is shown in black.

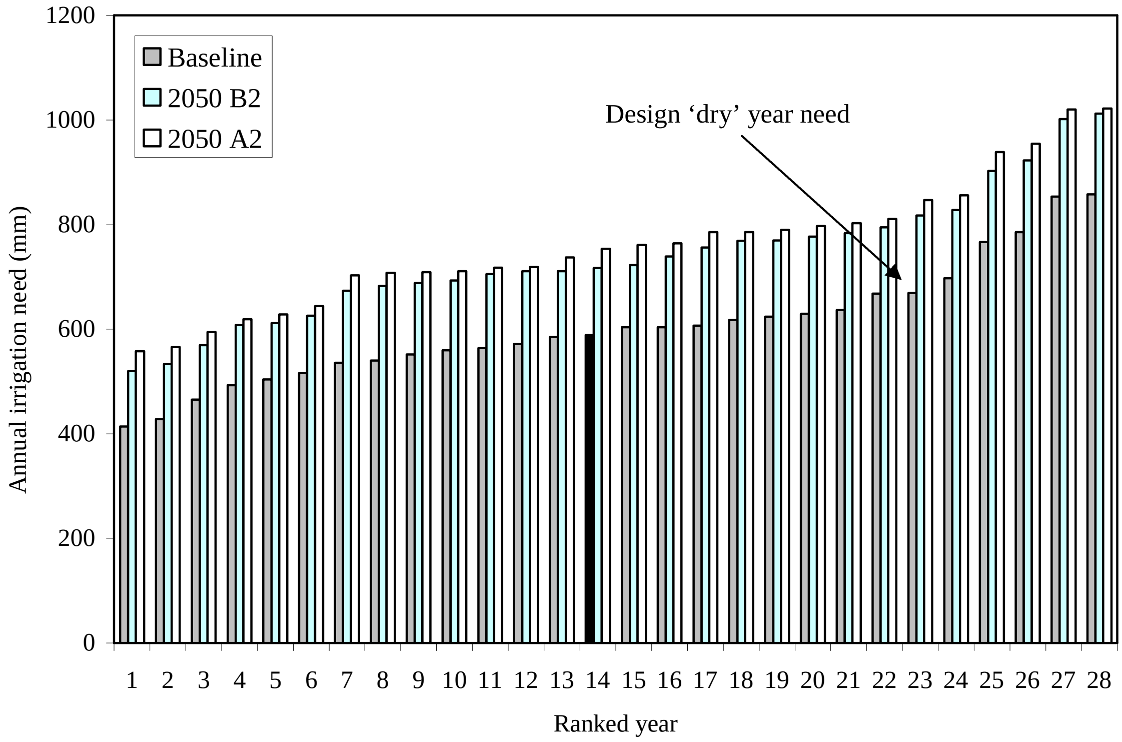


Figure 7 Spatial variability in agroclimate (PSMD) for Swaziland for the baseline (1961-90) and IPCC SRES 2050_A2 and 2050_B2 scenarios.

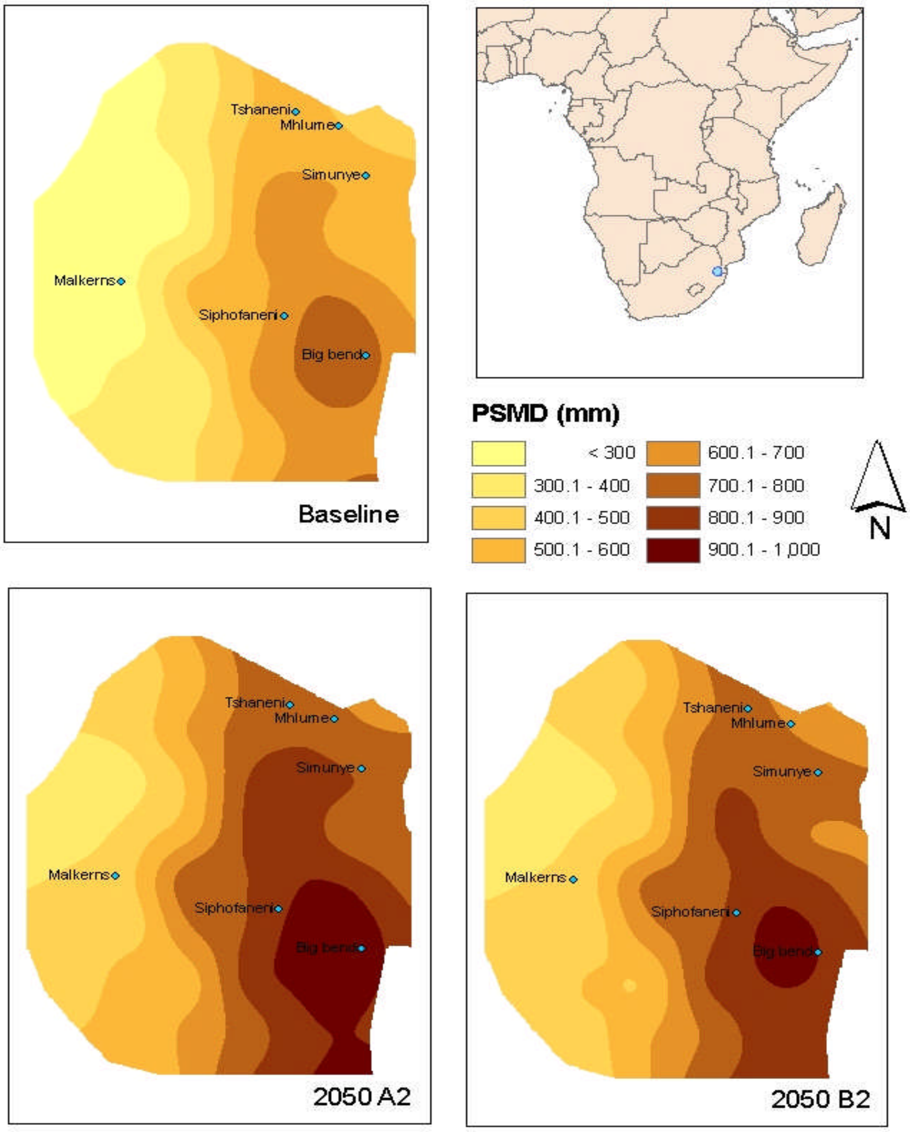


Table 1 IPCC defined climate change scenarios (A2 and B2) and their characteristics for the 2050s (Source IPCC, 1999).

Characteristic	**IPCC scenario**	
	A2	**B2**
Population growth	High	Medium
GDP growth	Medium	Medium
Energy use	High	Medium
Global CO_2 emissions (GtC/yr)	17.43	11.01
Atmospheric CO_2 concentration (ppmv)*	547	601
Land-use changes	Medium /high	Medium
Resource availability	Low	Medium
Technological change	Slow	Medium
Change favouring	Regional	Dynamics as usual

* Bern-CC model predictions

Table 2. Derived changes in mean monthly climate, between the baseline and each SRES emissions scenario, by variable and month, for Mhlume.

Scenario	Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	Temp (^{o} C)	2.70	2.44	2.33	2.91	3.89	4.80	4.96	3.77	3.33	3.87	2.30	2.68
	Rainfall (%)	-5.80	18.60	-23.01	-7.35	22.62	5.07	-32.71	-26.21	-21.91	-28.82	-2.73	-2.73
	Solar radiation (%)	5.06	-1.07	4.31	1.56	-3.86	-4.35	3.89	1.57	1.99	6.30	-4.69	1.67
	Wind (%)	3.03	-1.18	0.79	0.80	4.03	-7.08	1.73	5.84	6.78	9.13	0.51	0.51
	RH (%)	-3.31	-4.63	-2.61	-2.70	3.93	6.49	1.98	-8.35	-10.05	-12.20	-17.62	-2.48
2050 A2	ETo (%)	12.47	7.56	10.65	11.29	9.39	8.42	18.22	20.23	19.07	24.06	12.72	9.34
	Temp (^{o} C)	1.87	2.19	2.21	1.98	3.30	4.33	4.81	3.36	2.97	2.54	1.45	1.92
	Rainfall (%)	-5.80	18.60	-23.01	-7.35	22.62	5.07	-32.71	-26.21	-21.91	-28.82	-2.73	-1.03
	Solar radiation (%)	2.68	2.37	4.37	3.17	-3.01	-2.83	-1.14	1.04	2.34	2.89	-3.23	4.56
	Wind (%)	-2.93	-0.28	1.43	0.09	-3.50	-3.99	7.00	3.80	6.41	7.60	1.09	-0.99
	RH (%)	-1.90	-3.25	-2.61	-2.58	4.66	7.04	0.44	-4.78	-9.24	-11.62	-12.18	-1.51
2050 B2	ETo (%)	7.15	8.86	10.45	9.19	5.49	8.08	18.76	15.58	17.46	17.09	8.51	8.60

Table 3 Modelled cane yield (t/ha), 'design' dry year irrigation need (mm/year) and water use efficiency (kg^{-1} m^3) for the baseline (BL) and each climate change scenario.

Output	**BL**	**2050_A2**		**2050_B2**		**2050_A2 fert**	
	mm	mm	%	mm	%	mm	%
Average annual rainfall (mm)	778	738	-5	737	-5	738	-5
Average annual ETo (mm)	1161	1320	14	1292	11	1320	14
ET_{crop} (mm)	1162	1320	14	1292	11	1320	14
IR_{net} (mm)	605	761	26	738	22	761	26
Design irrig. need (mm)	668	811	21	795	19	811	21
Sucrose yield (kg ha^{-1})	24747	25466	3	25168	2	28429	15
Biomass yield (kg ha^{-1})	65835	69056	5	68202	4	75520	15
Stalk yield (kg ha^{-1})	45457	47911	5	47262	4	52790	16
WUE (kg/m^3)	2.1	1.9	-10	1.9	-10	2.2	5
IR_{net} 'standard' yield (mm)	605	739	22	726	20	662	9