Sensitivity of southern African maize yields to the definition of sowing dekad in a changing climate

Olivier Crespo, Sepo Hachigonta, Mark Tadross

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O. Crespo · S. Hachigonta · M. Tadross

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Abstract Most African countries struggle with food production and food security. These issues are expected to be even more severe in the face of climate change. Our study examines the likely impacts of climate change on agriculture with a view to propose directions to adapt especially in regions where it might be crucial.

We use a crop model to evaluate the impact of various sowing decisions on the water satisfaction index and thus the yield of maize crop. The crop model is run for 176 stations over southern Africa, subject to climate scenarios downscaled from 6 GCMs. The sensitivity of these evaluations is analysed so as to distinguish the contributions of sowing decisions to yield variation.

We present results of the water satisfaction index average change from a 20 year control period before 2000 and a 20 year period surrounding 2050 over southern Africa. These results highlight some areas that will likely be affected by climate change over the study region. We then calculate the sowing decisions contributions to yield variation, first for the control period, then for the future period. The sensitivities computed allow us to distinguish efficient decision to be adapted and long term efficiency of corresponding adaptation options. In most of the studied countries rainfall expected in the sowing dekad is shown to contribute more significantly to the yield variation and appears as a long term efficient decision to adapt. We eventually discuss these results and an additional perspective in order to locally propose adaptation directions.

Keywords Changing Climate · Agriculture · Adaptation

O. Crespo, S. Hachigonta, M. Tadross
Climate Systems Analysis Group,
Department of Environmental and Geographical Science, University of Cape Town,
Private Bag X3, Rondebosch 7701, Cape Town, South Africa.

corresponding author:
Olivier Crespo
Tel.: +27 (0)21 650 2748, Fax: +27 (0)21 650 5773
E-mail: olivier.crespo@csag.uct.ac.za

1 Introduction

Several studies have focussed on the impacts of climate change on agriculture for selected areas within southern Africa. Gbetibouo and Hassan (2005) measured the economic impact of climate change on major South African crops. They used a Ricardian approach to highlight the sensitivity of yield to temperature and rainfall change based on the last 30 years of the 20th century. Though they concluded that net revenue might either increase (*e.g.* Free State, Northern Cape) or decrease (*e.g.* Gauteng, Kwazulu Natal), they noted that both major crops and the cropping calendar may be affected by climate change. More recently Walker and Schulze (2008) simulated the variability of yield, risk and soil organic nitrogen levels over three South African climate regions (Christana, Bothaville and Piet Retief). They focussed on the maize production and simulated the potential outcome of 9 different CO_2 concentration scenarios, concluding that climate scenarios show negative impacts over parts of the country, especially in the drier western areas. Lobell et al (2008) studied crop adaptation in selected regions around the world using multiple General Circulation Models (GCMs). They concluded that southern Africa is one region that is likely to suffer negative impacts on several staple crops, including maize. These studies were conducted over specific regions within southern Africa or utilised large-scale climate data from GCMs.

Climate change is expected to intensify existing problems in developing countries where communities are directly dependent on the natural environment (Parry et al, 2001; Ziervogel et al, 2008; Brown and Funk, 2008), though, changes in climate may have either a positive or negative impact depending on their location and timing. Projected changes in temperature and rainfall will likely change the future agricultural activities of communities, especially in poor rural regions that depend on rain-fed crops (Tadross et al, 2003). Positive changes in rainfall characteristics (*e.g.* reduced number of dry spells) can increase agricultural production but negative changes would require adaptation measures such as changing cropping patterns. In rural regions however, adapting to change can be a very slow process and rural farmers can find it difficult to cope with the changes as they have limited resources. National and regional decision makers within southern Africa are thus looking for adaptation guidelines and decision making tools to help moderate potential negative impacts in these vulnerable regions.

Coping with climate change raises the prospect of novel behaviour and perceptions to cope with changes in the climate. Risbey et al (1999) study was concerned with the crop type decision at the farm and national level. It shows that using seasonal forecast information is significantly overpassing mean, trends and hedge baseline behaviours. It concludes on the importance of climate information for tactical decision making. But these novel behaviour and perceptions may also involve changes in sowing dates, how sowing dates are defined, changes in the application of fertiliser and water at different periods of the crop growth cycle *etc.* (see for example FAO, 2007; Leavy et al, 2008). Additionally such changes will depend on the location, its local climate characteristics, the crop and farm management systems in order to maximise the benefit to agriculture. This is particularly true for rain fed agriculture in southern Africa, where yields are low and the success of the cropping season depends the timing of sowing relative to the start of the rainfall season. One of the most important decisions, therefore, is when to plant and the crop sowing dekad (1 dekad equals 10 days) over southern Africa is often chosen when rainfall exceeds certain thresholds. In our particular case, two parameters defining the sowing dekad are of interest, x_1 which is the expected rainfall within the sowing dekad and x_2 which is the expected rainfall within the following 2

dekads. Our objective is to resolve how the definition of x_1 and x_2 should change for efficient adaptation under a future changed climate. To accomplish this we study the contribution of sowing dekad definition to simulated crop yields over southern Africa using a crop model, which simulates the expected crop response subject to a range of future climate conditions.

Adaptation decision making is a current research focus. Clarke (2008) for example studied the interest of looking for minimax regret rather than looking for 'good' adaptation while the context is extremely uncertain. We agree that uncertainty takes a large part in the problem, and though we are aware that in this context there is no 'best' adaptation, we believe that looking for 'good given our current knowledge' adaptation helps to give decision-maker new and accurate indicators. Pyke et al (2007) introduced an inventory approach that provide systematic information describing the relevant attribute of climate-related decisions. They show the relevance of understanding which decisions are most likely to benefit from decision support. We are following the same direction, though with specific methods (model simulation, evaluation and statistical analysis) concerned with agricultural sowing decision making. The significance of each sowing definition parameter is investigated using the sensitivity analysis approach introduced by Saltelli and Tarantola (1999), which allows the total contribution of each parameter to the output variance to be computed *i.e.* the variation in yield ascribable to x_1 and x_2. Both the projected control (1979-1999) and future (2046-2065) climates are obtained from statistically downscaled General Circulation Models, which simulate the response of the global climate system to increasing greenhouse gas concentrations under an assumed IPCC A2 SRES scenario (see Christensen et al, 2007). GCMs have a low spatial resolution and do not capture many small-scale features, which affect local climates (*e.g.* mountains and lakes) making it advisable to use downscaled climate data where possible. This fine scale data is useful as farming systems, soil types and vegetation also vary on fine spatial scales. Hence adaptation options can be expected to reflect these spatial differences. Gibbons and Ramsden (2008) are concerned with different decision space and temporal scales from the farm to a group of farms. He introduced a multi-scale integrated approach, yet the results presented for the future scenarios are only based on one Regional Climate Model (RCM) forced by one GCM.

In this study we use statistically downscaled (Hewitson and Crane, 2006) data which includes rainfall, minimum and maximum temperatures for 176 station locations in southern Africa to evaluate the likely change in sowing rules for growing maize, the main staple crop (Smale and Jayne, 2003; Akpalu et al, 2008). The advantages of using statistically downscaled data are that: a) there is a greater consistency between the different GCM rainfall responses to anthropogenic forcing; b) hot spots where GCMs agree on the change can be found for smaller, climatically homogeneous regions. It should also be noted that whilst previous studies have mostly evaluated the impacts of climate change (Walker and Schulze, 2008; Lobell et al, 2008; Fischer et al, 2001), the focus of this paper is to evaluate the efficiency, of a restricted set of adaptation options, to mitigate those impacts. The method is expendable to other potential adaptation decisions *e.g.* application of fertiliser and irrigation, though only the sowing decision is investigated here.

2 Methods and data

2.1 Crop model

The crop model used in this study is the AgroMetShell model, developed by the Food and Agriculture Organization (FAO), Environment and Natural Resources Service. The primary reasons for selecting this model is because it has been used by the Regional Remote Sensing Unit (RRSU) for food security assessment (Mukhala and Hoefsloot, 2004) and it demands less data compared to other complex models, *e.g.* APSIM (Keating et al, 2003) or DSSAT (Jones et al, 2003), which require for example detailed soil parameters, while the AgroMetShell model requires only water holding capacity (representative of general soil characteristics).

The AgroMetShell model is a water balance based model (see Doorenbos and Kassam, 1979). Water balance is the difference between the effective amounts of rainfall received by the crop and the amounts of water lost by the crop and the soil due to evaporation, transpiration and deep infiltration (Mukhala and Hoefsloot, 2004). The Water Satisfaction Index WSI is calculated as the ratio of seasonal actual evapotranspiration (ETa) to the seasonal crop water requirement (equation 1). Water requirement (WR) is calculated from the modified Priestley and Taylor potential evapotranspiration method (see Priestley and Taylor, 1972), adjusted using crop coefficients at each stage of crop growth.

$$WSI = \frac{ETa}{WR} * 100 \tag{1}$$

Whenever the soil water content is above the maximum allowable depletion level, ETa will remain the same as the water requirement. But when the soil water level is below the maximum allowable depletion level, ETa will be lower than water requirement in proportion to the remaining soil water content. This method was used because its estimated evapotranspiration values where highly correlated (not shown) with the recommended Penman-Monteith (Allen et al, 1998) over the study area. Required radiation values where calculated using modified Hargreaves and Samani temperature based model (Annandale et al, 2002; Hargreaves and Samani, 1982).

The soil water balance technique requires that crop water availability and consumption be known, with consumption being dependent on several variables including temperature and radiation, all contributing to the calculation of potential evapotranspiration. The crop coefficient and the start of the crop growing season, which is based on rainfall amount needed in a certain period for successful crop germination, are user-defined. The sowing dekad is defined according to the fulfilment of the following conditions:

1. at least x_1 (mm) rainfall falls in the sowing dekad (*e.g.* $x_1 = 25mm$),
2. and at least x_2 (mm) falls in the following 2 dekads (*e.g.* $x_2 = 20mm$).

These rules describe a sowing decision process that guarantees enough moisture at sowing whilst avoiding a false start. Guaranteeing enough moisture (translated by x_1) is directly related to the rainfall in the sowing dekad, and can be directly evaluated by the farmer. Avoiding a fatal deficit of moisture in the following 2 dekads (translated by x_2) is not necessarily evaluable *a priori* by the farmer, but nevertheless is taken into consideration through personal expectations based on historical experiences. Because the crop model is actually capable of evaluating the rainfall in these following 2 dekads, it will make the perfect decision every time and thus simulate the *potential* yield. The

observation of change in the decision making process, as simulated with the crop model, is meaningful in evaluating the change in the decision making process a farmer will be required to make to his perceptions that are based on his experience in the field. Note that if this decision rule is never fulfilled within the time windows specified, no crop is sowed and AgroMetShell will return a missing value for the WSI simulation.

The weather input data needed to drive the crop model include dekad precipitation and potential evapotranspiration. The water balance output variables produced include total water requirement, excess soil water, soil water deficit and water satisfaction index which expresses the percentage of the crop's water requirements that are actually met during the initial, vegetative, flowering and ripening phases. However, as the WSI is the most representative of the yield, it will be our main focus in this study. The shift in the sowing dekad would most probably affect the temperature and radiation regimes experienced during the crop growth, thus impacting the phenology and the yield. This does not however affect the WSI and this is a known limit to our work. Even so, waiting for more rain, when rainfall generally increases, does not necessarily mean the crop being planted later. Indeed our simulations suggest a change of $\pm$ 2 dekads, which means that most simulations remain within the currently experienced sowing window. This issue is not further addressed here, but will be handled in future work by using more complex crop models, *e.g.* APSIM (Keating et al, 2003).

The AgroMetShell model was designed for crop forecasting purposes thus several sources of uncertainties arises, for instance the model has a simple representation of soil parameter (water holding capacity) and does not take into account the irrigation, technological, social and economic factors like prices and fertilizer application which can have a major influence on final crop production. The computed values have thus to be interpreted carefully and we concentrate on extracting valuable information within this given context.

2.2 Sensitivity analysis method

From a formal point of view the crop model simulation process will allow us to associate an outcome $Y = f(X, c)$ to X, which is the set of input parameters, and c which is the climate used to reach the outcome Y by simulating the model f. Uncertainty is involved in both the model f, which is by definition a partial representation of the modeled real system, and in the simulated climate c. If we assume that the crop model uncertainty is small in comparison to the climate scenario uncertainty, then we can consider the problem as stochastic, where climate is the main source of uncertainty. We can then perform a sensitivity analysis of simulated WSI with regard to (sowing) decision parameters under several future climates.

2.2.1 Identifying the most efficient decisions for adaptation

To explore which adaptation decisions provide for efficient adaptation to a future climate we explore the sensitivity of WSI to the definition of sowing dekad for both the present and future climates. Two parameters are used to define the sowing dekad (see section 2.1). Throughout this paper, we call these two input parameters, x_1 and x_2 such that $X = \{x_1, x_2\}$. The crop model simulations provide outputs (*i.e.* the Water Satisfaction Index) that are dependent on the input parameters and the climate. We evaluate combinations and how they affect WSI, which is assigned to a function y_1

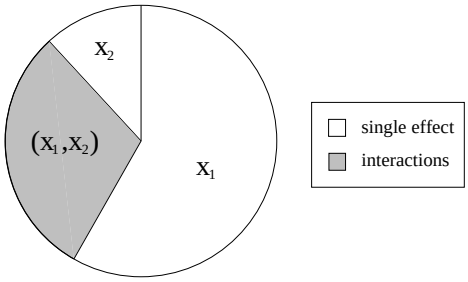

Fig. 1 FAST output simplified example : contribution percentage of single and coupled effects of x_1 and x_2 on the outcome variance.

i.e. $Y = \{y_1\}$. Let us consider a sequence of n climates such that the simulated climate c is included in $[c_1 \dots c_n]$.

Sensitivity analysis of Y as a response to X is based on the Fourier amplitude sensitivity test (FAST), which allows the computation of the total contribution of each input factor to the output's variance. This method was introduced by Saltelli and Tarantola (1999) and here we use its R-project implementation (R Development Core Team, 2009). The analysis consists of three main steps. First an input matrix of all combinations to be simulated is produced. Each combination is simulated with the crop model, and associated with its outcome, after which it undergoes a FAST analysis. Figure 1 shows a simplified representation of the results computed for one station and a single climate representation. In this example the variance of outcome Y is due mostly to the single decision parameter x_1, then by the combination of both x_1 and x_2, and to the least extent due to the single decision x_2. According to the decision rule which involves x_1 and x_2 (see section 2.1), this specific case depicts a station where more than half of the crop yield variability (when x_1 and x_2 are varied under this particular climate) is due to the variation of the rainfall amount in the sowing dekad. Rainfall that occurs in the following 2 dekads explains only slightly more than 10% of the yield variability. This kind of information is useful from an adaptation point of view as it allows the decision maker to identify the sowing decision that should be adapted in order to have a noticeable effect on the desired outcome *i.e.* crop yield.

The sowing decision rule defined in section 2.1 is often taken as $x_1 = 25mm$ and $x_2 = 20mm$ (Reason et al, 2005; Tadross et al, 2003). However, in order to explore both actual and potential combinations of sowing dekad parameters, we explore a much wider range of possible sowing dekads. We choose to consider any combination of (x_1, x_2) with the range of x_1 and x_2 being $\{0, 50\}$. Though neither of the four extreme possible combinations $(x_1, x_2) = \{(0, 0), (0, 50), (50, 0), (50, 50)\}$ will occur in a practical crop sowing process, they define a decision space wide enough to assume it is enclosing most of the possible combinations.

Figures 2 and 3 demonstrates the mean contribution of x_1 and x_2 to WSI simulated subject to observed climate between 1979 and 1999. WSI variability is more sensitive to the amount of rainfall required during the sowing dekad (x_1). It contributes up to 40% in eastern South Africa and some parts of Zimbabwe. The contribution of x_2 to the WSI variability barely rises above 20% in most parts of southern Africa. However in some parts of Malawi and northern Zambia where x_1 and x_2 contributions are low, the combination (x_1, x_2) significantly contributes (not shown).

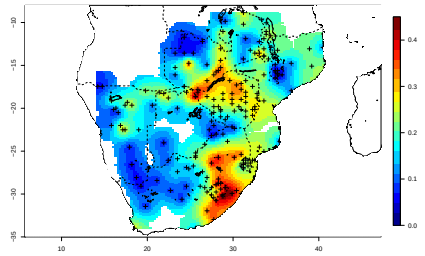

Fig. 2 Observed mean x_1 fractional contribution to WSI variance.

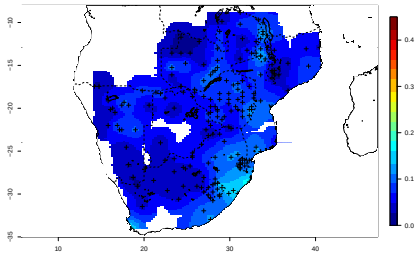

Fig. 3 Observed mean x_2 fractional contribution to WSI variance.

2.2.2 Identifying changes in future decisions

Knowing the significance of sowing dekad decision parameters under current climate conditions is useful, but does not necessarily remain the same in a future climate. Hence we evaluate the change in x_1 and x_2 contributions to WSI variability under both the downscaled GCM control and future climates detailed in section 2.3. The aim is to study the potential evolution of these decisions and evaluate the efficiency and durability of any proposed adaptations based on modifying these decision rules.

2.3 Downscaled data

The Hewitson and Crane (2006) downscaling technique integrates the use of artificial neural networks (Self Organized Maps (SOMs)). The method first derives a statistical relationship between a small-scale feature at a particular location and large-scale GCM variables. SOMs allow for the categorization of specified atmospheric conditions at local scale (*e.g.* specific humidity), using a clustering process to sort groups that are most suited to each atmospheric condition. Detailed description of SOMs can be found in Hewitson and Crane (2006). Training of the SOM on atmospheric variables is done using NCEP reanalysis data. The next step involves performing the SOM technique on observational data (*e.g.* rainfall) to characterize the atmospheric circulation on a localized domain around the target location. This generates probability density functions (PDFs) for the rainfall distribution associated with each atmospheric state. The last part involves mapping of GCM data to a particular SOM characterization of the atmospheric states. This is done for each circulation state in the GCM data, randomly select precipitation values from the associated PDF. The downscaled output data is produced at each of the 176 stations shown in Figure 4 for precipitation, minimum and maximum temperature.

We used downscaled climate scenarios from six GCMs : the CSIRO Atmospheric Research, Australia, MK3.0 Model (CSIRO3.0); the NOAA Geophysical Fluid Dynamics Laboratory, CM2.0 coupled climate model (GFDL); the Météo-France, Centre National de Recherches Météorologiques, third version of the ocean-atmosphere model, CM3 Model (CNRM); the Canadian Centre for Climate Modeling and Analysis, third generation coupled global climate model (CCCMA); the NASA Goddard Institute for

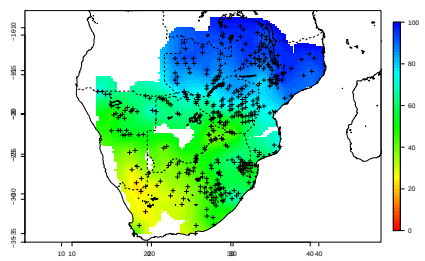

Fig. 4 Mean WSI simulated from observed climates 1979 to 1999.

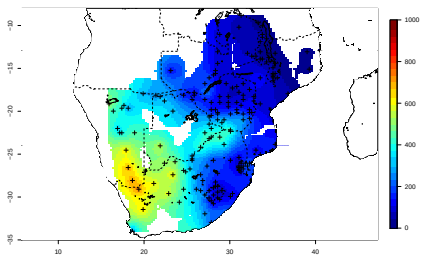

Fig. 5 Average number of crop failure for the control period 1979-1999.

Table 1 WSI relationships to yield and crop performance

Expected percentage of maximum (potential) yield	Classification of Crop Performance	WSI
100	Very good	100
90-100	Good	95-99
50-90	Average	80-94
20-50	Mediocre	60-79
10-20	Poor	50-59
<10	Failure	<50

Space Studies, ModelE20/Russell (GISS); and the Max Planck Institute for Meteorology, Germany, ECHAM5 (ECHAM).

Figure 4 shows the mean maize WSI calculated using the observed climate data for the 1979 to 1999 period. The region can be split into approximately three sub-areas. The first area covers Zambia, Malawi, northern Zimbabwe and northern Mozambique and has a high mean WSI (above 80%) which relates to high yields (see table 1). The second region covers a wide strip from the northern Namibia to the north eastern parts of South Africa, through northern Botswana and parts of southern Zimbabwe, southern Mozambique, Swaziland and Lesotho; here the mean WSI is about between 50-60% suggesting yields are on average poor. The third region covers parts of southern Namibia, south west Botswana and western South Africa: WSI is observed to be below 40 which indicates complete crop failure and unsuitability for growing maize.

AgroMetShell returns a missing value of WSI if the defined sowing dekad is not met within a set time period. For instance the time window for sowing dekad calculation was set to be any dekad between 1st august to end of March. Not surprisingly the dry arid regions to the south west (lowest WSI values in figure 4) most often fail to simulate a valid WSI. The mean number of these failures (out of 1000 simulations) for all the years is indicated in figure 5. Whilst this suggests that model simulations in these regions should be ignored, the large number of crop failure, either due to the unfulfilled requirement of the sowing decision rule or due to the achievement of a WSI lower than 50, describe the current situation and promotes confidence that the crop model responses are accurate. Furthermore whilst maize is not cropped over the arid parts of southern Namibia and western South Africa at present, this is not to say that these regions may be more viable in a future climate. Thus, simulating regions or conditions that do not currently grow maize is necessary to deal with potentially

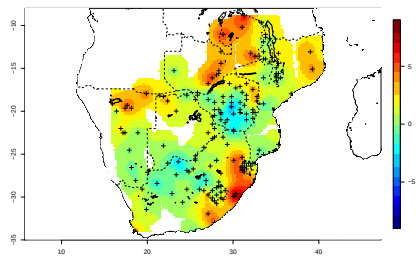

Fig. 6 Simulated mean change in WSI (average of 6 GCMs).

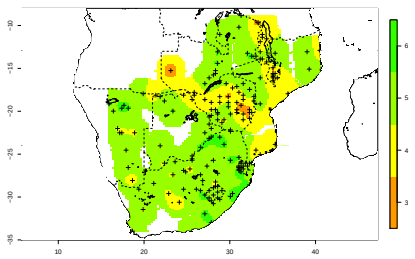

Fig. 7 Model agreement on the sign according to the WSI mean change (figure 6).

new climatic conditions in the future (*e.g.* it can help us consider changes in cultivars and/or re-localisation of crops). Since the future climate could decrease WSI over current good yield areas, or increase WSI over poor or failing areas, we choose to make no distinction between whether a crop fails with $WSI = 10$ or with $WSI = 30$. We translated this decision rule by substituting and setting all results with WSI below 50, including missing values, to $WSI = 50$, in accordance to the failure threshold proposed by the FAO (Frère and Popov, 1986) and outlined in table 1.

3 Results

The results presented below are based on the average of 1000 simulations of AgroMetShell (using different parameter combinations) for each year of the control (21 years) and future (20 years) climates of each of the 6 downscaled GCMs and for each of the 176 stations available across southern Africa. Any WSI response below 50 is assumed to represent crop failure (see table 1) and the results are shown as the average of the 6 GCMs and for each control and future climate. We firstly demonstrate expected changes in WSI (future-control), and whether the GCMs agree on simulating this change. We then present the contribution of x_1 and x_2 to WSI variability in the control climates and compare it with those contributions under future climate conditions.

3.1 Simulated changes in WSI

Figure 6 shows the difference between average WSI from the 6 GCMs simulated for the 20-year future climate (2046-2065) and WSI as an average of the 6 GCMs for the 20-year control climate (1979-1998). The results indicate three broadly consistent regions of change. Two regions where WSI is expected to increase are eastern South Africa and northern Zambia, where WSI is expected to improve by approximately 5%. Over northern Zambia WSI is already high (see figure 4). The eastern parts of South Africa, however, indicate much lower WSI values where an increase in WSI could be beneficial. The central and southern parts of Zimbabwe, however, are expected to face a reduction in WSI, which is potentially problematic as these regions are clearly on the threshold of crop failure. Negative impacts on crop production in this region will need suitable adaptation options.

Figure 7 shows the number of GCMs which agree on the sign ($^{+}/_{-}$) of change in WSI as indicated in figure 6. Except for a few stations where the models disagree on the sign of change, at least 5 of the GCMs agree on the positive impacts in Zambia and eastern South Africa, while 4 GCMs or more agree on the negative impact expected in the central and southern regions of Zimbabwe.

These results have to be considered in relation to crop failure (sowing conditions never met or WSI below 50). We observed earlier (figure 5) that the frequency of such failure for the GCM control climates are realistic. The mean change in crop failures from the control to the future period is plotted in figure 8. Though there is a consistent increase over the arid area of south Namibia and west South Africa, the rest of the region indicates less frequent crop failures, except for little change over south Mozambique and Zimbabwe.

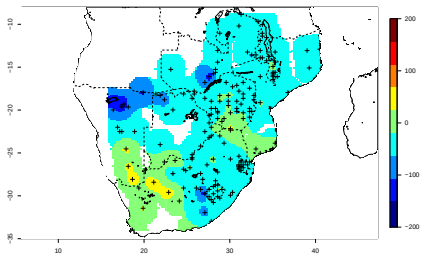

Fig. 8 Change in average number of crop failures (future-control).

Comparison with figure 6 suggests that whilst the mean increase in WSI over eastern South Africa is associated with more frequent crop opportunities, the decrease in mean WSI over south Zimbabwe is not necessarily associated with more cropping failures. The increases in cropping opportunities reflect a general increase in rainfall and length of the rainfall season in the downscaled climate data over these regions.

3.2 Control climate WSI sensitivity to sowing parameters

Figure 9 shows the x_1 mean contribution to WSI variability across all 6 GCM control climates, and figure 10 shows the corresponding x_2 contribution. The contribution of x_1 using observed weather data (figure 2) also shows very high values over central northern Zimbabwe and east South Africa, with lower contributions to the west. The contribution

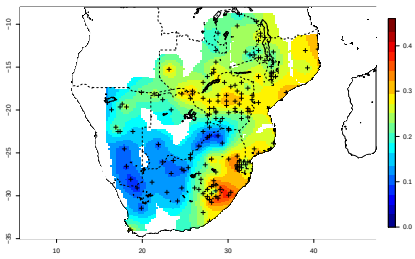

Fig. 9 Control WSI sensitivity to x_1 (mean of 6 GCMs).

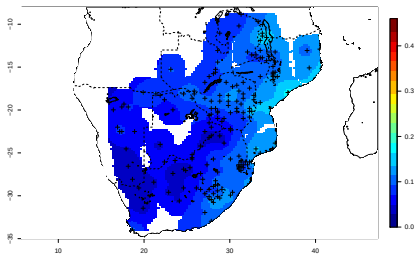

Fig. 10 Control WSI sensitivity to x_2 (mean of 6 GCMs).

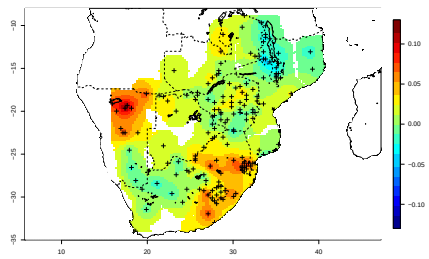

Fig. 11 Change in WSI sensitivity to x_1. Mean difference (future-control) for all 6 GCMs.

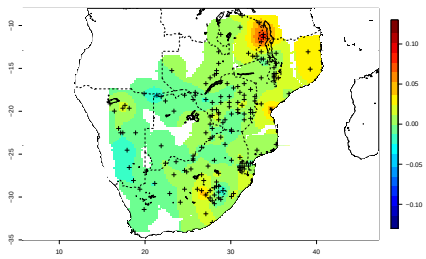

Fig. 12 Change in WSI sensitivity to x_2. Mean difference (future-control) for all 6 GCMs.

of x_2 in the GCM control climates also reflects that in the observations (figure 3), except with higher contributions over northern Mozambique and Malawi. The downscaled GCM control simulations, therefore, well represent the observed sensitivity of WSI to the definition of x_1 and x_2, especially over Zimbabwe, eastern South Africa and further west.

The results also indicate that x_1 contributes as much as 40% to the variation in WSI over eastern South Africa, while the x_2 contribution is below 15%, whilst over central Zimbabwe the x_1 contribution is above 30% while the x_2 contribution is around 10%. Clearly in these regions the definition of x_1 is important. Over southern Zimbabwe, Limpopo and further west, however, the contribution of both single x_1 and single x_2 is small, implying that the combined effect of the two parameters is the most significant contributor to WSI variability.

3.3 Future climate WSI sensitivity to sowing parameters

Any decision that may be taken in anticipation of future climate change impacts should also take into account potential changes in the ability of these decisions to mitigate the impact in a future climate *i.e.* its effectiveness may change under different climate conditions. Figures 11 and 12 show the mean change in WSI sensitivity to x_1 and x_2 respectively between the downscaled GCM control (1979-1998) and future (2046-2065) climates. The contribution of x_1 increases over most regions, especially so over northern Namibia and eastern South Africa, whereas the x_2 contribution to WSI variation increases slightly in regions further east, and up to 10% in the northern Malawi.

Generally the sensitivity to x_1, which is already high in the control climates (figure 9) is increased in the future climate. In the case of eastern South Africa and central Zimbabwe the increase in x_1 and x_2 contributions increase the total contribution of the two parameters close to 50%, which suggests that we can propose efficient adaptation options based on x_1 and x_2, in order to mitigate the negative impact expected in this region (see figure 6). Over Malawi, however, the relative effectiveness of x_1 decreases in the future climate, whereas the effectiveness of x_2 increases. Whilst there is little mean change in WSI (figure 6) this still implies that the sowing decision will need adapting in the future.

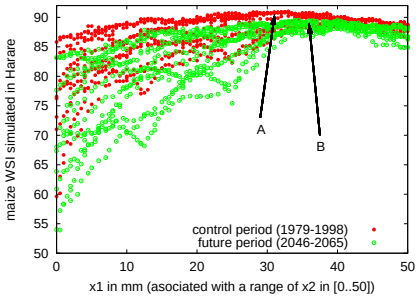

Fig. 13 Simulated WSI dependence on x_1 at Harare (Zimbabwe) under different control and future climates.

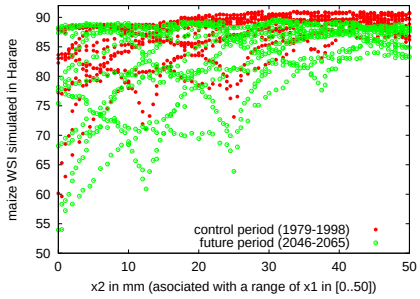

Fig. 14 Simulated WSI dependence on x_2 at Harare (Zimbabwe) under different control and future climates.

4 Discussion

Given the demonstrated ability of the sowing parameters to affect simulated yields and the change in their effectiveness in a different climate, the question is often raised about which decision to adapt and if so in what way to adapt the decision. As an example, figures 13 and 14 demonstrate (for Harare, Zimbabwe) the variation in WSI with both the x_1 and x_2 sowing parameters for both control and future climates. The decrease in WSI from the control climate to the future climate is seen as a shift of the maximum WSI reached for each period, which is of the order 3% in both figures 13 and 14. The variation of the maximum WSI in both figures also reveals that the variation of x_1 is contributing to changes of up to 5% along the crest of the highest WSI during the control period, while x_2 is not contributing more than 3% change. Under the future climate, the x_1 contribution to WSI change is quite similar, while the x_2 contribution is much less than under the control climate *i.e.* maximum WSI varies little with x_2 in the future period. It is also clear from figures 13 and 14 that beyond a certain limit (approximately 30mm) variation in x_2 has little effect on WSI, whereas x_1 continues to affect WSI at all values below 50mm.

Earlier we saw that the x_1 sowing parameter can produce effective changes over Zimbabwe if adapted, and that this adaptation capacity will likely last. If we can assume that farmers are taking the best decisions that can be taken at present, these decisions are represented in figure 13 by the maximum control climate WSI, marked **A**. Furthermore, if we can assume that the best sowing decisions in the future climate will be about the maximum future climate WSI, marked **B**, then this implies a change in the sowing decision parameter x_1 in the future. Whilst we do not want to put fixed and limiting values to this shift (it will depend on both the range of climate scenarios and aspects of crop model parametrisation), it gives the decision maker a fair idea of the direction in which to adapt decisions. For the Harare example, figure 13 shows that expected rainfall within the sowing dekad will likely need to be increased to eventually reach the higher WSI possible in the future period. Except for the arid south western area, a slight increase in rainfall is expected. This increase in available water for agriculture would explain the general though slight increase in cropping opportunities. However temperatures are also expected to increase, especially at the end of the dry season, thus increasing evapotranspiration before planting. In such conditions the best

WSI are simulated when sowing is delayed until more rain falls, thus overcoming the increases in evapotranspiration.

In this paper we have presented an approach for assessing the effectiveness of decisions related to adaptation in the agriculture sector over southern Africa. As an example of the approach we have used some of the latest downscaled climate change scenarios from multiple GCMs and a crop model, combined with a sensitivity analysis to show how decisions related to sowing can affect yields and how the effectiveness of these decisions may change in a future climate. This new approach involves identification of significant decision parameters, *i.e.* decision parameters that will make a difference in the expected yield if adapted. Given our 2-decision parameter case study, it was shown that over most regions of southern Africa the water amount required during the sowing dekad of the decision process (x_1) contributes more to yield variation than the water amount required during the following 2 dekads (x_2). From a practical point of view this means that if we want to be efficient at changing the expected yield, then we have a better chance of success by adapting x_1.

The contribution of the x_1 decision parameter to WSI variability was also shown to increase in the future climate over many regions, including Zimbabwe and eastern South Africa. Over eastern South Africa WSI was projected to increase whereas over Zimbabwe it was projected to decrease, implying that adaptation will be necessary over Zimbabwe and that x_1 is a potentially efficient adaptation tool both now and in the future. Even though a beneficial increase in WSI is simulated over eastern South Africa, the need for adaptation will depend on the farming system (*e.g.* irrigated, non-irrigated) and how close they are to critical thresholds of climate. If new opportunities become available, they also may be close to these critical thresholds, and in either case adapting x_1 is suggested as a potentially useful mitigation measure. Over Malawi, however, the ratio between x_1 and x_2 is changing in a completely different way in the future than it is experienced in the current climate. This provides the decision maker with the warning that (1) an efficient current adaptation might not be efficient for a long time, and (2) that the decision process by itself, even if no production decrease is to be expected, is likely to change from current 'optimal' decisions to reach the highest WSI. This clearly demonstrates that seeking adaptation options in the current climate *e.g.* to current climate variability, is not necessarily the most effective way to mitigate against the impacts of future climate change.

In general, this approach allows any decision-maker to center his/her interest and efforts on a small ensemble of decisions that are currently making a significant difference with regard to his/her objectives. In this way we can investigate the effectiveness of any decision given current and future climates, as long as the effect of that decision on the decision-makers objectives can be simulated *e.g.* in this case using a crop model. We could, for example, study the contribution to yield variation of irrigation or changing crops in an area expected to be drier in the future. Some areas might show that changing irrigation procedures will have the highest impact on expected yields, while other areas might show that changing crops is a more effective adaptation.

5 Conclusion

Our study has presented a new approach to help decision makers assess adaptation options for agriculture in southern Africa. An example of the approach, using only two decision parameters which together decide the sowing dekad, indicates three important

aspects related to adaptation: (1) it highlights which of the two parameters is most likely to impact yields if adapted; (2) using future climates it was possible to show if this adaptation would likely be effective in the future and (3) it indicates how to adapt these decision parameters so as to keep yields as high as possible in the absence of other adaptation.

In the southern Africa context, where food production is already a risky activity for many smallholder farmers, who are constrained by water management and economics, yet whose ability to produce food might be stressed further by climate change, being able to focus on effective decisions for adaptation can help to make adaptation possible and efficient. However, before advise on adaptation can be given it will be necessary to explore other possible objectives (maximising yields may not be the main priority), as well as other decisions that affect those objectives. The results presented here are only applicable for the case of maximising yields by shifting sowing dekads. Furthermore these results are dependent on the accuracy of the crop model, its ability to translate the effect of changing decisions and uncertainty in the climate change scenarios. In this regard future work will encompass a wider range of downscaled GCMs, emissions scenarios and crop models which include the potential effects of changing crops and the application of fertiliser and irrigation.

References

Akpalu W, Hassan RM, Ringler C (2008) Climate variability and maize yield in south africa. Tech. rep., International Food Policy Research Institute (IFPRI)

Allen R, Pereira L, Raes D, Smith M (1998) Crop evapotranspiration - guidelines for computing crop water requirements. In: FAO Irrigation and drainage paper, vol 56, Food and Agriculture Organization (FAO), Rome, Italy

Annandale J, Jovanic N, Benade N, Allen R (2002) Software for missing data error analysis of penman-monteith reference evapotranspiration. Irrigation Science 21(2):57–67

Brown M, Funk C (2008) Food security under climate change. Science 319(5863):580–581

Christensen J, Hewitson B, Busuioc A, Chen A, Gao X, Held I, Jones R, Kolli R, Kwon WT, Laprise R, Rueda VM, Mearns L, Menéndez C, Räisänen J, Rinke A, Sarr A, Whetton P (2007) Regional climate projections. In: Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt K, Tignor M, Miller H (eds) Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp 847–940

Clarke H (2008) Classical decision rules and adaptation to climate change. The australian journal of agricultural and resource economics 52:487–504

Doorenbos J, Kassam A (1979) Yield response to water. In: FAO Irrigation and Drainage Paper, vol 33, Food and Agriculture Organization (FAO), Rome

FAO (2007) Adaptation to climate change in agriculture, forestry and fisheries: Perspective, framework and priorities. Tech. rep., Food and Agriculture organization (FAO), Rome, Italy

Fischer G, Shah M, van Velthuizen H, Nachtergaele F (2001) Global agro-ecological assessment for agriculture in the 21st century. In: IIASA Research Report, International Institute for Applied Systems Analysis (IIASA) and Food and Agriculture Organization (FAO), Laxenburg, Austria

Frère M, Popov G (1986) Early agrometeorological crop yield assessment. In: FAO Plant Production And Protection Paper, vol 73, Food and Agriculture Organization (FAO), Rome, Italy

Gbetibouo G, Hassan R (2005) Measuring the economic impact of climate change on major south african field crops: a ricardian approach. Global and Planetary Change 47:143–152

Gibbons J, Ramsden S (2008) Integrated modelling of farm adaptation to climate change in east anglia, uk: Scaling and farmer decision making. Agriculture, Ecosystems and Environment 127:126–134

Hargreaves GH, Samani ZA (1982) Estimating potential evapotranspiration. Journal of Irrigation and Drainage Engineering 108:225–230

Hewitson B, Crane R (2006) Consensus between gcm climate change projections with empirical downscaling: precipitation downscaling over south africa. International Journal of Climatology 26(10):1315–1337

Jones J, Hoogenboom G, Porter C, Boote K, Batchelor W, Hunt L, Wilkens P, Singh U, Gijsman A, Ritchie J (2003) Dssat cropping system model. European Journal of Agronomy 18:235–265

Keating B, Carberry P, Hammer G, Probert M, Robertson M, Holzworth D, Huth N, Hargreaves J, Meinke H, Hochman Z, McLean G, Verburg K, Snow V, Dimes J, Silburn M, Wang E, Brown S, Bristow K, Asseng S, Chapman S, McCown R, Freebairn D, Smith C (2003) An overview of apsim, a model designed for farming systems simulation. European Journal of Agronomy 18:267–288

Leavy J, Lussier K, Solomon I (2008) Time is now - lessons from farmers adapting to climate change. Tech. rep., ActionAid International, The Hague, The Netherlands

Lobell DB, Burke MB, Tebaldi C, Mastrandrea MD, Falcon WP, Naylor RL (2008) Prioritizing climate change adaptation needs for food security in 2030. Science 319:607–610

Mukhala E, Hoefsloot P (2004) AgroMetShell Manual

Parry M, Arnell N, McMichael T, Nicholls R, Martens P, Kovats S, Livermore M, Rosenzweig C, Iglesias A, Fischer G (2001) Millions at risk: defining critical climate change threats and targets. Global Environmental Change 11(3):181–183

Priestley C, Taylor RJ (1972) On the assessment of surface heat flux and evaporation using large-scale parameters. Monthly Weather Review 100(2):81–92

Pyke CR, Bierwagen BG, Furlow J, Gamble J, Johnson T, Julius S, West J (2007) A decision inventory approach for improving decision support for climate change impact assessment and adaptation. Environmental Science & Policy 10:610–621

R Development Core Team (2009) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, URL http://www.R-project.org, ISBN 3-900051-07-0

Reason C, Hachigonta S, Phaladi R (2005) Interannual variability in rainy season characteristics over the limpopo region of southern africa. International Journal of Climatology 25(14):1835–1853

Risbey J, Kandlikar M, Dowlatabadi H, Graetz D (1999) Scale, context, and decision making in agricultural adaptation to climate variability and change. Mitigation and Adaptation Strategies for Global Change 4:137–165

Saltelli A, Tarantola S (1999) A quantitative model-independent method for global sensitivity analysis of model output. Technometrics 41(1):39–56

Smale M, Jayne T (2003) Maize in eastern and southern africa: seeds of success in retrospect. In: Environment and Production Technology Division (EPTD) Discussion

Paper, vol 97, International Food Policy Research Institute, Washington, U.S.A.

Tadross M, Hewitson B, Usman M (2003) Calculating the onset of the maize growing season over southern africa using gts and cmap data. CLIVAR Exchanges 27:48–50

Walker N, Schulze R (2008) Climate change impacts on agro-ecosystem sustainability across three climate regions in the maize belt of south africa. Agriculture Ecosystems & Environment 124:114–124

Ziervogel G, Cartwright A, Tas A, Adejuwon J, Zermoglio F, Shale M, Smith B (2008) Climate change and adaptation in african agriculture. Tech. rep., Rockefeller Foundation