Mitig Adapt Strateg Glob Change (2025) 30:36
https://doi.org/10.1007/s11027-025-10223-y

ORIGINAL ARTICLE

Modelling the climate change adaptation potential of no-tillage maize systems in southern Africa

Leonard Rusinamhodzi[1] · David Berre[2] · Christian Thierfelder[3] · Santiago-Lopez Ridaura[4] · Marc Corbeels[2,5]

Received: 2 June 2022 / Accepted: 25 April 2025

Abstract

Southern Africa is a hotspot of climate change where smallholder farmers are particularly threatened because they largely depend on rainfed agriculture for their livelihoods. The objective of the study was to assess the potential of two main principles (no-tillage and crop residue retention) of conservation agriculture (CA) and nitrogen (N) fertilizer management to mitigate the negative effects of future climate (2021–2060) on maize (*Zea mays* L.) productivity using the Agricultural Production Systems Simulator (APSIM). Two tillage practices were considered in the simulations, i.e. the conventional practice of tillage with removal of crop residues (CP) and NT (no-tillage and crop residue mulching), as well as three rates of N input (0, 30, 90 kg ha^{-1}) on mono-cropped continuous maize. Simulations were run for future climate generated by an ensemble of 17 global circulation models (GCMs) using two extreme emission scenarios based on Representative Concentration Pathways (RCP2.6 and RCP8.5) for southern Africa. Results from the simulations suggest that NT management is not more beneficial in the future (2051–2060) than in the current climate, and there is no evidence to support its ability to mitigate the climate change impacts at the study sites, because the effects are principally exerted through increased temperatures. Simulations further show that increased fertilizer N inputs could drastically increase maize productivity, but with increased vulnerability to climate change. Improved crop management practices such a NT need to be combined with improved crop genotypes tolerant to multiple stresses such as drought and heat to maximize resilience under future climatic conditions.

Keywords APSIM model · Global circulation models · Conservation agriculture · Soil fertility management · Crop productivity · Southern Africa

1 Introduction

Climatic volatility and soil fertility depletion are the major biophysical barriers to crop production confronting smallholder farmers in Africa (Challinor et al. 2007). In particular, southern Africa is generally regarded as the region most vulnerable to climate variability

Extended author information available on the last page of the article

Published online: 15 May 2025

and change, and faces major risks of declining crop production and rising food insecurity (Lobell et al. 2008). This is because 90% of maize (*Zea mays* L.), which is the staple food for millions of people, is produced under rainfed conditions. There is a need to develop resilient cropping systems that incorporate superior germplasm in combination with improved agronomy to offset the predicted yield declines due to climate change (Setimela et al. 2018; Thierfelder et al. 2016).

Climate variability can be detected in relatively short periods of time, whereas climate change occurs, and is noticeable, only in the longer term. Overlying the constraints of climate variability and change, soil fertility decline and its spatial heterogeneity as a result of limited resources among smallholder farmers exacerbate the situation (Rusinamhodzi et al. 2013; van Wijk et al. 2009). For example, Rurinda et al. (2013) reported that soil nutrient management is important and plays a key role for sustaining crop productivity in response to climate variability and change in Zimbabwe. Uncertainty in rainfall and resulting soil moisture conditions demand flexibility (not blanket recommendations) in managing nutrients, especially nitrogen (N), in ways that increases efficiency of their use. However, the use of chemical fertilizer is often considered risky by cash-constrained smallholder farmers under variable weather (Thierfelder et al. 2018), and this is one of the reasons for its limited use in sub-Saharan Africa (Morris et al. 2007). In addition, lack of reliable climatic information and weather forecasts make targeted investments by smallholder farmers into fertilizers even more challenging.

Smallholder cropping systems in Africa are diverse in time and space, multi-functional and often not well understood, i.e. there are no simplistic solutions to the constraints faced by smallholder farmers (e.g. Giller et al. 2011). Although an array of possible technologies exists to increase smallholder farm productivity, resilience and profitability, it is not feasible and cost effective to evaluate the impacts of these in an empirical way for every situation. Predictive modeling and decision support systems are therefore important to answer many of the *ex-ante* questions (Jones et al. 2003). *Ex-ante* analysis of promoted technologies is useful to assess how such technologies perform in relation to what farmers are currently practicing as well as how they respond to future changes in climatic conditions (Komarek et al. 2019).

Since the last three decades, conservation agriculture (CA), characterized by minimum soil disturbance, soil cover with crop residues and crop diversification through crop rotations or mixtures (Derpsch et al. 2010), has been introduced through many initiatives and institutes as a possible sustainable agricultural intensification option (e.g. by the Food and Agriculture Organization (FAO), the International Maize and Wheat Improvement Center (CIMMYT) or the French Agricultural Research Centre for International Development (CIRAD). The practice of CA can improve rainfall infiltration and reduce water loss from the soil surface in cropped fields, leading to better water-use efficiency by crops (Thierfelder and Wall 2009). Through crop residue retention, there is also potential for soil fertility build-up via carbon (C) sequestration in the long term if crop diversification components are strongly incorporated (Powlson et al. 2016; Corbeels et al. 2019; Franzluebbers 2010). However, it is not clear to what extent these benefits can mitigate negative impacts of future climatic conditions on crop yields.

The underlying hypothesis of this study is that agronomic management involving a combination of no-tillage and residue management practices with increased doses of mineral fertilizer N may provide a pathway to offset the negative effects of climate change. The key question is how resilient these options are under future climate change in the smallholder farming conditions of southern Africa. Therefore, the objective of this study was to forecast maize productivity under different future climatic conditions, applying different tillage and N fertilizer management scenarios in four locations in southern Africa. For the crop growth simulations, we used the APSIM (Agricultural Production Systems sIMulator) model (Holzworth et al. 2014; Keating et al. 2003) because it has been extensively tested in the tropics and specifically for the conditions of southern Africa.

The paper is a result of three activities namely: (a) the APSIM model calibration and testing for the four sites of Chitedze in Malawi, Sussundenga in Mozambique, Monze in Zambia, and Domboshawa in Zimbabwe; (b) the use of global circulation models (GCMs) to generate downscaled climate projections for the four sites and assess patterns of climate change, and (c) the coupling of GCM outputs with APSIM to project future maize productivity in the four locations under different tillage and N fertilizer management scenarios. The simulation results and their implications are discussed in the context of smallholder farming in southern Africa.

2 Materials and methods

2.1 Description of study sites

Four study sites were selected that are representative of the maize-growing areas in the sub-humid savannah zone of southern Africa, and where long-term field experiments with maize are conducted by CIMMYT. These are: the Monze Farmer Training Centre, Zambia (16.24°S, 27.44°E, 1108 m a.s.l.), the Sussundenga Research Station, Mozambique (19.31°S, 33.24°E, 608 m a.s.l.), the Chitedze Research Station, Malawi (13.97°S, 33.65°E, 1145 m a.s.l.), and the Domboshawa Training Centre, Zimbabwe (17.61°S, 31.14°E, 1543 m a.s.l.). Common to all sites is the predominant maize-based mixed crop-livestock farming system, with maize occupying between 50 and 90% of the cultivated land area (Dixon et al. 2001). Maize is commonly grown in monoculture, but also in rotation with different grain legumes (e.g. cowpea (*Vigna unguiculata* L. Walp), groundnut (*Arachis hypogaea* L.), or with cotton (*Gossypium hirsutum* L.) or sunflower (*Helianthus annuus* L.).

The four sites are characterized by a tropical wet and dry climate using the Köppen Climate Classification (Köppen 2020) with most of rainfall occurring between November and April (i.e. a unimodal rainfall pattern). This cwa climate type is the dominant climate where maize is grown in southern Africa. Average seasonal rainfall is around 750 mm (Monze) to 1090 mm (Sussundenga), but rainfall shows high inter-annual and intra-annual variability. Soils are *Lixisols* (Monze, Sussundenga and Domboshawa) and *Luvisols* (Chitedze), with distinct soil water holding capacity and soil fertility levels across the sites (Table 1).

2.2 The APSIM crop growth simulation model

The model used for the maize growth simulations in this study is APSIM, version 7.5. APSIM is a mechanistic model developed to simulate biophysical processes in cropping systems in response to management, in interaction with soil and weather conditions (Keating et al. 2003; Holzworth et al. 2014). The model calculates crop development and growth,

Table 1 Main biophysical characteristics of the four study sites in southern Africa used in the simulation exercise

Site	Altitude (m)	Crop season rainfall (mm)	Average annual temperature (ºC)	Soil type	Soil texture	BD (g/cm3)	Clay + silt (%)	Root depth (cm)	Available water capacity (mm)	OC%	pH
Chitedze	1145	960	21	Chromic Luvisol	Clay loam	1.32	39.5	60	110	1.6	5.2
DTC	1543	880	18.8	Haplic Lixisols	Loamy sand	1.54	16.7	50	33	0.6	5.3
Monze	1108	750	22.2	Chromic Luvisol	Sandy loam	1.56	18	60	65	0.8	5
Sussundenga	608	1090	21.6	Ferric Lixisol	Clay loam	1.57	19.2	60	100	0.6	4.1

soil water, C and N dynamics, and their interactions using a daily time step. APSIM has been tested extensively against field experimental data in a wide range of growing conditions across the globe, including the sub-humid regions of southern Africa (Whitbread et al. 2010; Chikowo 2011). The APSIM modules used in this study include APSIM-Maize (maize development and growth), SOILWAT (soil water dynamics using a multi-layer, cascading approach with soil evaporation calculated via the two-stage evaporation method and plant transpiration calculated using the transpiration efficiency approach), SOILN (C and N transformations in soil, including organic matter decomposition, N immobilization, ammonification, and nitrification), SOILTEMP (soil temperature dynamics), SURFACEOM (the fate of aboveground crop residues, removed from the system, incorporated into the soil or left to decompose on the soil surface), FERTILIZER (the specification of fertilizer applications) and MANAGER (the set of rules using conditional logic during simulations to control the actions of modules within APSIM). In the SOILN module, a soil fresh organic matter (FOM) pool constitutes crop residues together with roots from the previous crop. This pool decomposes to form the BIOM (microbial biomass) and HUM (humus) pools, with immobilization and/or release of mineral N. The BIOM pool represents the more labile soil microbial biomass and microbial products, whilst the more stable HUM pool represents the rest of the soil organic matter (Probert et al. 1998). APSIM-Maize calculates potential crop biomass growth as a function of the intercepted radiation and radiation-use efficiency (RUE). On the other hand, water-limited growth is a function of water supply calculated in the SOILWAT module and the transpiration efficiency of the crop. Actual biomass increase is simulated from either potential or water-limited growth, as modified by temperature and N stresses, the latter depending on crop N demand and soil mineral N supply calculated in the SOILN module (Keating et al. 2003). Partitioning of accumulated biomass to the different plant organs is stage-dependent; from emergence to flowering, leaves have priority over the stems while from flowering to physiological maturity grains comprise the strongest sink for biomass allocation.

Temperature is a major factor controlling crop development in APSIM. Phenological phases of crops require a thermal time target (degree days, °Cd) to be reached to instigate movement to the next phase. Values of the thermal time targets are cultivar specific. Thermal time simulations for maize use a base temperature of 8°C and an optimal temperature of 30°C. As a result, the maize cycle length is mainly driven by thermal time accumulation. Thermal time also controls leaf appearance rate, the last 14 leaves before the flag leaf appear each 36 °Cd, before which a leaf appears every 65 °Cd (Wilson et al. 1995). In addition, APSIM-Maize has a series of temperature stress functions that can potentially affect photosynthesis, grain number development (during flowering period), and grain filling. Temperature effects on photosynthesis are modelled through a multilinear temperature stress function on RUE, with a base temperature of 8 °C below which full stress is assumed, an optimal temperature between 15 and 30 °C above or below which stress will occur, and a limiting temperature of 44 °C at which full heat stress is reached (Keating et al. 2003). Maize grain number is linearly reduced if maximum temperatures exceed 38 °C during flowering period (Carberry et al. 1989). Finally, the optimum temperature for maize grain filling is set to 30 °C (Carberry et al. 1989).

Water stress in APSIM is calculated as the ratio of water supply to water demand. It can potentially affect phenology, photosynthesis, leaf elongation and senescence, and root growth in APSIM. Water supply is calculated as the amount of water above the lower limit of water content in soil layers containing roots. This amount is multiplied by a factor that accounts for the ability of roots to extract water from a soil layer. Water demand, on the other hand, is driven by the potential biomass growth rate and transpiration efficiency that is adjusted for vapor pressure deficit (VPD) (Keating et al. 2003). An indirect effect of rising temperature on simulated crop growth is that it will increase evapotranspiration and crop water demand, thereby possibly increasing water stress.

2.3 Description of the field experiments for APSIM calibration/testing

At each of the four study sites, data for the APSIM model calibration and testing were obtained from long-term experiments originally designed and established by CIMMYT. They are characterized by continuous maize cultivation in which a conventional crop management practice (CP) based on soil tillage with removal of crop residues, and an partial NT system with no-tillage and with crop residue retention on the soil surface (but no crop rotations or mixtures) were compared with each other. The CP treatments represent the farmers' common local practices. At Chitedze, the CP treatment consists of a ridge and furrow system prepared in September or October with hand hoes, after removal of the crop residues. In the NT treatment, maize is planted on untilled soil through the mulch of retained crop residues with a dibble stick, a pointed stick that creates two holes, one for seed and one for fertilizer distribution. At Monze, Sussundenga and Domboshawa, the CP practice comprises the use of an animal-drawn moldboard plough at shallow soil depth (10–20 cm) and manual planting into the furrows created by the plough. Remaining crop stubbles after residue removal are incorporated during ploughing. For the NT practice, the animal-drawn direct seeder made by Fitarelli Máquinas Agrícolas Ltda. (Aratiba, Rio Grande do Sul, Brazil) is used. At all sites the NT treatment aimed at retaining at least 2500 kg dry matter ha^{-1} of maize residues, that were, however, decomposed very rapidly at Sussundenga due to strong termite attacks at this site. A medium-duration commercial maize hybrid was planted, usually at the beginning of December, at a target plant population of 44,000 plants ha^{-1} at all sites except at Chitedze, where planting was done to achieve 53,000 plants ha^{-1} following local recommendations. Fertilizer application was equal for the CP and NT treatments at each site although rates varied across sites due to differences in site-specific characteristics related to soil and climate (Thierfelder and Mhlanga 2022). At Monze, maize was fertilized with 107 kg N ha^{-1}, 14 kg P ha^{-1} and 14 kg K ha^{-1}, at Sussundenga with 112 kg N ha^{-1}, 17 kg P ha^{-1} and 16 kg K ha^{-1}, at Chitedze with 69 kg N ha^{-1} and 9 kg P ha^{-1} (no K fertilization), and at Domboshawa with 80 kg N ha-^{1}, 6 kg P ha^{-1} and 6 kg K ha^{-1}. Nitrogen was applied as basal and topdressing fertilizer. Weed control at Domboshawa was manual through regular hand hoeing during the cropping season. At the other sites, glyphosate was used before crop emergence at a rate of 2.5 l ha^{-1} followed by manual weeding as necessary (i.e. up to three times during the growing season). The experiments are described in greater detail in an earlier publication (Thierfelder and Mhlanga 2022).

2.4 APSIM model calibration and testing

The APSIM model was first calibrated for each of the four study sites using data from the CP treatments of the experiments. For these model runs, on-site collected daily weather data (solar radiation, maximum and minimum temperature, and rainfall) were used. Crop species-specific parameters were assigned the default values for maize defined in the APSIM-Maize module. The values for cultivar-specific phenological parameters (Table 2) required in APSIM-Maize were obtained by fitting the model to the observed dates of emergence, flowering, and maturity. The value for RUE (1.6 g MJ^{-1}) was estimated by fitting the model to the observations of aboveground biomass productivity. In this way we accounted for growth limitations other than water and N. Model parameter values related to grain filling (maximum grain number per head, and grain growth rate, Table 2) were obtained by adjusting model output to observed grain yields. Model input parameters for the soils were quantified from measurements on soil profiles at the experimental sites. A maximum root depth of 90 to 140 cm was used for simulating water extraction by maize, represented by 4 to 7 soil layers in the model, depending on the soil characteristics of the respective sites (Table 3). Water extraction coefficients (KL) over soil depth were the default values for maize (0.06 to 0.08 day^{-1}) and root exploration factors (XF) were set at 1. Soil water contents at saturation (SAT) and at the drained upper limit of plant water availability (DUL) were determined through laboratory measurements; they depend solely on soil properties and are shown in Table 3. On the other hand, we used a crop-determined lower limit of plant water availability (CLL) defined as the lowest field-measured soil water content after plants have stopped extracting water (Tsubo et al. 2005). For plant transpiration, we used the default transpiration efficiency coefficients (Table 2) for maize defined in the APSIM-Maize module. Two parameters, U and CONA, which determine first- and second-stage soil evaporation were set at 6 mm and 3.5 mm day^{-1}, respectively, which are values accepted for sub-humid conditions (Probert et al. 1998; Keating et al. 2003). The proportion of water in excess of field capacity that drains to the next layer within a day is specified via a parameter, SWCON, which varies depending on soil texture (Table 3). Poorly drained clay soils will characteristically have values <0.5 whilst sandy soils that have high water conductivity can have values >0.8 (Probert et al. 1998). The bare soil runoff curve number (CN2b) was set at 74 to account for low runoff due to the flat topography of the four experimental sites. Initial soil conditions for soil moisture and soil organic C (Table 1) were set using measured

Table 2 Crop parameters of maize used in the APSIM simulations

Maize parameters	Chitedze (DKC9089)	Monze (SC625)	DTC (SC627)	Sususn-denga (SC513)	Units	Source
Emergence-end juvenile	280	272	280	265	°C days	Observed
End juvenile- floral initiation	20	20	20	20	°C days	Observed
Flag leaf-flowering	10	10	10	10	°C days	Observed
Flowering-start grain filling	170	170	170	165	°C days	Observed
Flowering - maturity	740	710	750	690	°C days	Observed
Day length photoperiod to flowering	12.5	12.5	12.5	12.5	hours	Default
Day length photoperiod for insensitivity	24	24	24	24	hours	Default
Base temperature	10	10	10	10	°C	Estimated
Grain maximum number per head	560	545	550	540	number	Observed
Grain growth rate	9	9	9	9	mg/day	Estimated
Radiation use efficiency	1.6	1.6	1.6	1.6	g/MJ	Default value
Transpiration use efficiency	0.009	0.009	0.009	0.009	kPa	Default value

Table 3 The physical properties of the soil layers at the experimental sites used in the APSIM simulations for the four study sites

Site	Depth (cm)	BD (g/cc)	Air dry (mm/mm)	L15 (mm/mm)	DUL (mm/mm)	SAT (mm/mm)	Maize LL (mm/mm)	Maize PAWC 52.1	Maize KL (/day)	Maize XF (0–1)	SWCON
Monze	0–10	1.63	0.022	0.111	0.2	0.335	0.111	8.9	0.08	1	0.7
	10–20	1.63	0.067	0.111	0.25	0.335	0.111	13.9	0.08	1	0.7
	20–30	1.49	0.115	0.177	0.282	0.388	0.177	10.5	0.08	1	0.5
	30–40	1.49	0.229	0.229	0.289	0.388	0.229	6	0.08	1	0.5
	40–60	1.49	0.279	0.279	0.303	0.388	0.279	4.8	0.08	1	0.5
	60–80	1.33	0.358	0.358	0.378	0.448	0.358	4	0.06	1	0.3
	80–100	1.33	0.358	0.358	0.378	0.448	0.358	4	0.06	1	0.3
Sussundenga	0–10	1.337	0.08	0.135	0.33	0.44	0.139	19.1	0.06	1	0.95
	10–20	1.367	0.08	0.135	0.33	0.44	0.139	19.1	0.06	1	0.95
	20–30	1.344	0.08	0.135	0.33	0.44	0.139	19.1	0.06	1	0.95
	30–60	1.287	0.08	0.28	0.36	0.45	0.29	21	0.06	1	0.95
	60–90	1.273	0.08	0.33	0.38	0.47	0.341	11.6	0.06	1	0.95
Chitedze	0–10	1.32	0.04	0.11	0.22	0.3	0.11	11	0.08	1	0.7
	10–20	1.41	0.14	0.14	0.25	0.3	0.14	11	0.08	1	0.7
	20–30	1.42	0.15	0.16	0.27	0.32	0.16	11	0.08	1	0.7
	30–60	1.47	0.16	0.17	0.28	0.33	0.17	33	0.08	1	0.7
	60–90	1.54	0.18	0.19	0.3	0.34	0.19	33	0.06	1	0.7
Domboshawa	0–30	1.555	0.12	0.135	0.153	0.166	0.135	5.2	0.06	1	0.7
	30–65	1.541	0.12	0.135	0.153	0.166	0.135	6.1	0.06	1	0.7
	65–130	1.579	0.12	0.135	0.153	0.166	0.135	11.3	0.06	1	0.7
	130–140	1.581	0.12	0.142	0.157	0.17	0.142	1.4	0.06	1	0.7
	140–180	1.596	0.12	0.148	0.162	0.178	0.148	5.4	0.06	1	0.7

data from the experiments. The fractions of stable soil organic matter (HUM and INERT, i.e. proportion of initial organic C assumed to be inactive) were initialized based on silt and clay contents of the topsoil from the experimental sites (see Porter et al. 2010). Other parameters, such as those controlling rates of soil C and N transformations, were given the default values of the APSIM model. Model calibration was completed when good agreement was achieved between observed and simulated values for the variables evaluated (see Results).

Then, NT treatments were simulated by turning off 'tillage' in the SURFACEOM module and initializing the model with a crop residue cover to simulate its effects on soil properties and processes describing the soil water and, C and N dynamics (Keating et al. 2003). Simulated maize aboveground biomass and grain yield values were then compared with observed values. The amount of maize surface residues was initially set at 3000 kg dry matter ha^{-1} at planting but in subsequent years the simulated crop residues at harvest were retained. The C: N ratio of maize residues is a user-specified input value in APSIM and was set at 80, whilst that of roots was set at 40 (Cichota et al. 2021). Depending on the initial amounts, the maize residues represented an input of between 20 and 30 kg N ha^{-1}. Part of this organic N is simulated as mineralized during the growing season and becomes available as mineral N for the crop. Values for all other model parameters were kept the same as for the CP treatment.

2.5 Projected weather data

We generated future (2021–2060) daily weather data files (solar radiation, maximum and minimum temperature, and rainfall) through an ensemble of 17 GCMs for the four study sites, and for the contrasting Representative Concentration Pathway (RCP) 2.6 (lowest emissions) and 8.5 (highest emissions). The use of multiple GCMs is a way of considering the uncertainty related to these models.

Downscaled weather data were produced using the MarkSim web version for the Coupled Model Intercomparison Project, Phase 5 dataset (CMIP5) (http://gisweb.ciat.cgiar.org/MarkSimGCM, Jones and Thornton, 2013). MarkSim uses a third order Markov chain process, in addition to stochastic resampling of the model parameters, to generate rainfall and temperature variances for a given location. These variances are then used in conjunction with a set of interpolated climate surfaces to downscale and simulate the weather variables (Jones and Thornton 2000). Mean seasonal temperature and cumulative seasonal rainfall were calculated based on a pre-defined length of the cropping season, i.e. from the 1 st October to the 31 st May of the following year. The climate data was corrected for bias using the procedure described by Hawkins et al. (2013) before use in crop modeling.

2.6 Model simulations and scenario analyses

The calibrated and tested APSIM model was used to assess the impact of NT management on maize yield at the four sites under current (2011–2020) and future (2021–2060) climate. The NT practice was hereby simulated, and compared with the simulated CP practice, under three scenarios of N fertilization: (1) no N fertilization; (2) 30 kg N ha^{-1} applied as 15 kg N ha^{-1} at sowing and 15 kg N ha^{-1} as topdressing, i.e. 35 days after sowing, and (3) 90 kg N ha^{-1}, i.e. 45 kg N ha^{-1} at sowing and 45 kg N ha^{-1} as topdressing.

To assess the effects of climate change on maize productivity, the period between 2011 and 2020 was taken as the baseline scenario and compared with the 2051–2060 simulation period of future climate - under the two contrasting emission scenarios, RCP2.6 and RCP8.5. The scenarios of improved/intensified crop management through the practice of NT and increased fertilizer N doses were evaluated for their impact on maize grain yield under baseline/current climate ($IMPACT_{BASE}$) and for their adaptation potential to future climate ($ADAPT_{POT}$) as follows (Lobell 2014):

$$\mathrm{IMPACT_{BASE}} = (\mathrm{Y_A} - \mathrm{Y_B})/\mathrm{Y_B}*100$$
$$\mathrm{ADAPT_{POT}} = [(\mathrm{Y_C} - \mathrm{Y_D}) - (\mathrm{Y_A} - \mathrm{Y_B})]/\mathrm{Y_B}*100,$$

where Y_A is the maize grain yield of NT under the baseline/current climate, Y_B is the yield of the CP under the baseline/current climate, Y_C is the yield of NT under future climate and Y_D is the yield of CP under the future climate. $IMPACT_{BASE}$ and $ADAPT_{POT}$ were calculated for the three levels of N fertilization.

During the simulations, soil organic matter, mineral N, and water contents were re-initialized at the start of each planting window for each growing season. Sowing date was defined as the last day of three continuous days with rainfall accumulation of 20 mm within the defined sowing window of 1 November to 31 December. The crop response to CO_2 was not included, because the direct CO_2 fertilization effect on photosynthesis in C4 crops such as maize is minor and the secondary effect of reducing crop transpiration is not well captured in crop growth models such as APSIM (Durand et al. 2018). For all simulations, CO_2 concentrations were held constant at 370 ppm. We assessed attainable yield (water and N limitation), the model runs assumed that weeds, insect pests and diseases were well controlled, and hence their effects on crop growth and yield were not simulated.

2.7 Model evaluation and statistical analyses

The ability of the model to reproduce aboveground maize biomass and grain yield data from the long-term experiments (Sect. 2.3) was evaluated by calculating the root mean square error (RMSE) and graphically by regressing observed values against simulated values. RMSE is a measure of the difference between values predicted by the model and the values observed (Wallach and Makowski 2006). The RMSE is calculated as:

$$RMSE = \sqrt{\frac{\sum_{1}^{n} \left(X_{obs,\,i} - X_{model,\,i}\right)^2}{n}},$$

where X_{obs} are observed values and X_{model} are modeled values at time i.

The graphical analysis was performed in R-Studio using the ggplot2 r-package (Wickham 2009). The 1:1 line was used as the reference of high precision for the model output.

Significant differences (at $P \leq 0.05$) in the projected seasonal temperature and rainfall data among decades, GCMs and emission scenarios were tested using analysis of variance (ANOVA). Effects of (no)tillage system, N fertilization rate, site, and emission scenario on simulated (for the 2011–2020 and 2051–2060 periods) maize aboveground biomass and grain yield were estimated by the generalized linear mixed model (GLMM) functions of the *stats* r-package version 4.1.2 (R Core Team 2021). Data was first log-transformed to achieve normality. The (no)tillage system, N fertilization rate, and emission scenario were considered fixed factors while the site was considered a random factor. ANOVA was then done on the fitted models. Separation of means was done using the post hoc Tukey test at at $P \leq 0.05$ using the *emmeans* function from the *emmeans* package (Searle et al. 2012).

3 Results

3.1 APSIM model performance

Results of the APSIM model calibration for the CP treatment are shown in Fig. 1. The APSIM model reproduced the observed maize aboveground biomass and grain yield reasonably well across all the sites, although it was more accurate for Chitedze and Monze than it was for Domboshawa and Sussundenga. The calculated overall RMSE for the four sites was 1260 kg ha^{-1} for grain yield and 2280 kg ha^{-1} for aboveground biomass productivity, with good correlations between simulated and observed data (R^2= 0.74 and 0.63 for grain

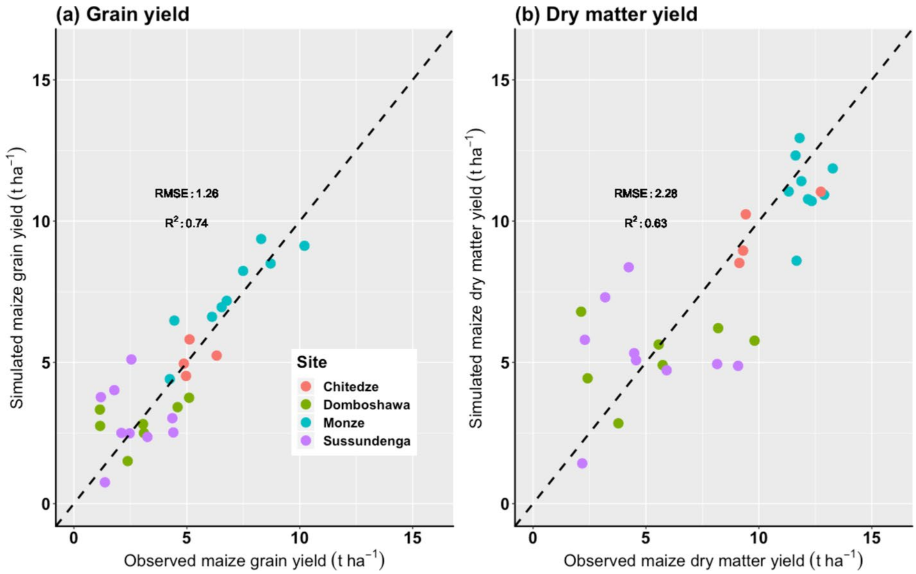

Fig. 1 A graphical representation of the model performance in simulating conventional tillage (CP) maize production in the four sites used in the case study, (**a**) maize grain yield, and (**b**) dry matter yield

yield and aboveground biomass, respectively). Next, with tillage removed and maize residues added as mulch in the SURFACEOM module of APSIM, the model (as calibrated for CP) simulated reasonably well maize grain and aboveground biomass productivity of the NT treatments at the four sites (Fig. 2). However, there was a tendency of overestimating observed values at all four sites. The calculated RMSE for the four sites was 1630 kg ha^{-1} (R^2= 0.69) and 2510 kg ha^{-1} (R^2= 0.62) for grain yield and aboveground biomass productivity, respectively. The variability in model predictions are similar to the variability of the measured yield reported from the study sites – variability among repetitions of the same treatment in a single season, and across seasons for the same treatment (Thierfelder and Mhlanga 2022). We conclude that there is good evidence that the performance of APSIM in simulating maize yields under contrasting tillage systems across a range of environments in southern Africa is adequate, and the model can be used for exploring management and climate change effects on maize yields.

3.2 Climate change projections

The results of the climate change projections (2021–2060) for the four study sites are shown in Figs. 3 and 4 for average seasonal maximum and minimum temperature, and total seasonal rainfall, respectively. Projected changes in seasonal temperatures and rainfall were highly variable largely depending on the GCMs. There were significant (P< 0.05) differences in projected seasonal temperature and rainfall between GCMs but without any consistency across the different sites, thus we used the whole ensemble of 17 individual GCM outputs for the subsequent APSIM maize growth simulations and scenario analysis.

On average over the 17 GCMs, both projected maximum and minimum temperatures showed an increasing trend from the first 10-year average (2021–2030) to the last decade

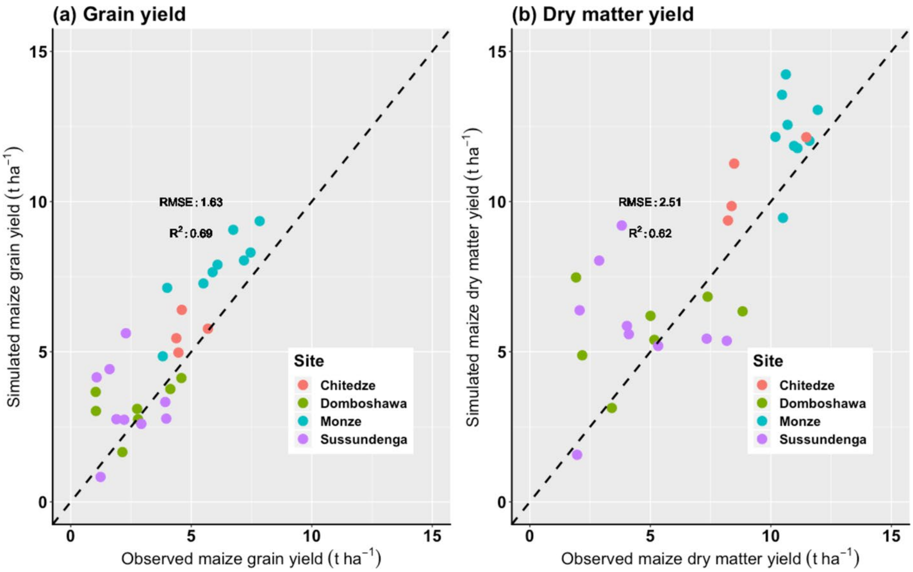

Fig. 2 Simulation of NT (no-till plus residues) maize productivity in the four sites used in the case study, by turning off the tillage module and applying crop residues (**a**) maize grain yield, and (**b**) dry matter yield. Model performed reasonably well and could be used to simulate maize production under NT

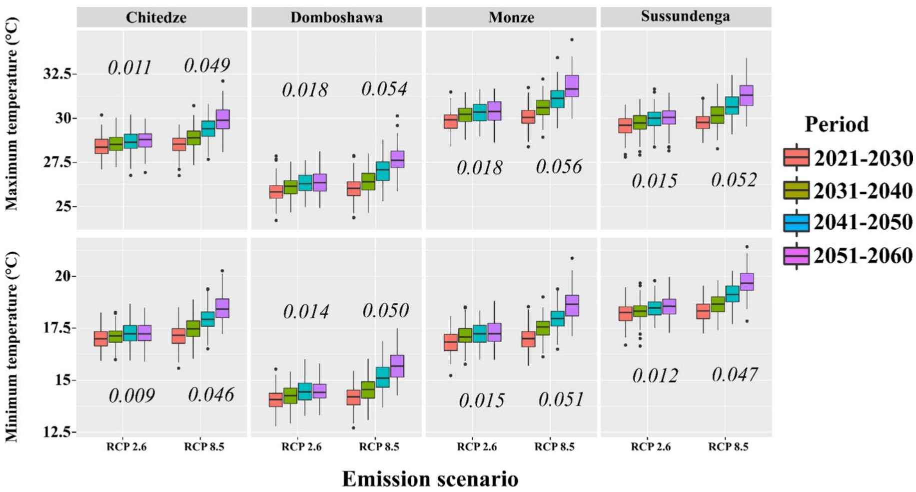

Fig. 3 Boxplots of projected seasonal maximum and minimum temperature for the period 2021–2060 under climate scenarios RCP2.6 (low emission) and RCP8.5 (high emission) at the four study sites in southern Africa. Upper and lower edges of boxes indicate 75 th and 25 th percentiles, horizontal line within box indicates median, whiskers below and above the box indicate the 10 th and 90 th percentiles. Each boxplot represents the projections from all the 17 GCMs

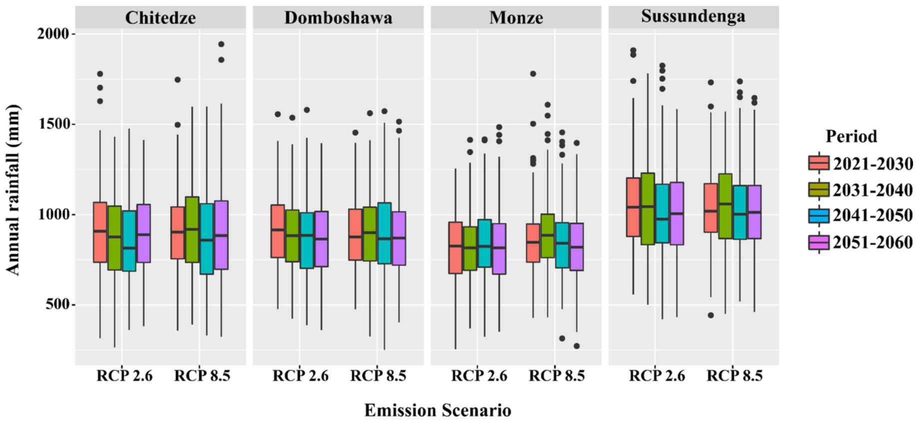

Fig. 4 Boxplots of projected total seasonal rainfall for the period 2021–2060 under climate scenarios RCP2.6 (low emission) and RCP8.5 (high emission) at the four study sites in southern Africa. Upper and lower edges of boxes indicate 75 th and 25 th percentiles, horizontal line within box indicates median, whiskers below and above the box indicate the 10 th and 90 th percentiles. Each boxplot represents the projections from all the 17 GCMs

average (2051–2060) for all sites (Fig. 3). In the RCP8.5 scenario, average seasonal maximum and minimum temperatures increased, respectively, by 0.049 to 0.056 °C and by 0.046 to 0.051 °C per year, corresponding to an average temperature increase of about 2.0 °C by 2060. As expected, warming was less pronounced under the RCP2.6 scenario, with an average increase of about 0.6 °C by 2060. Projected seasonal rainfall instead did not change significantly ($P > 0.05$) over the 2021–2060 period at all sites, with no significant ($P > 0.05$) differences between the two emission scenarios (Fig. 4). All sites showed high variability in projected seasonal rainfall amounts.

3.3 Maize yield simulations

3.3.1 Current climate (2011–2020)

At all study sites, the APSIM simulations clearly showed the importance of increasing N fertilizer rates in improving current (2011–2020) maize productivity, and that non-application of N depressed grain yields in NT compared with CP (Fig. 5a). Simulation results of aboveground biomass yield showed the same patterns as grain yield, though on some occasions the maize crop could accumulate a substantial amount of biomass in the model simulations during the vegetative stage but without subsequent grain filling (Fig. 5b).

At Chitedze, without any N fertilizer input, the average simulated maize grain yields (over the 2011–2020 period) were extremely low (CP) and close to zero (NT), but there was a significant ($P < 0.05$) effect of 30 kg N ha^{-1}, with CP recording an average yield of 3023 kg ha^{-1} and NT yielding 2503 kg ha^{-1} (Fig. 5). When N input was increased to 90 kg N ha^{-1}, equal yields were simulated for the two tillage systems, with grain yields reaching on average 4070 kg ha^{-1}. At Domboshawa, in the absence of N fertilizer, the average simulated maize grain yield under current climate (2011–2020) was significantly ($P < 0.05$) lower for NT (on average 522 kg ha^{-1}) than for CP (1119 kg ha^{-1}) (Fig. 5). The simulated impact of

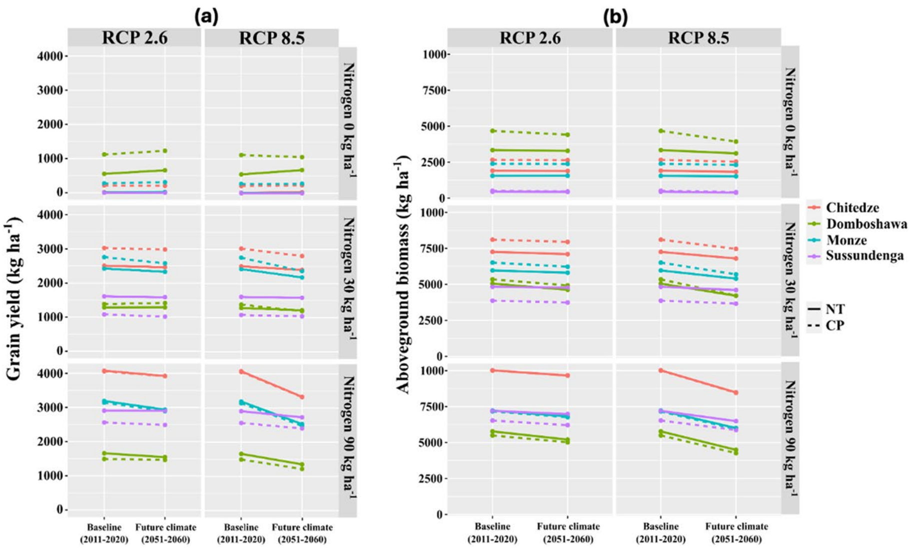

Fig. 5 Simulated mean (**a**) maize grain yield and (**b**) aboveground biomass of conventional tillage practice (CP) versus no-till (NT) management for three levels of nitrogen fertilization in the current climate (2011–2020) and future climate scenarios (under RCP2.6 and RCP8.5) for all study sites

N fertilizer application was relatively low for CP (25%), but larger for NT (up to 200%); as a result, there were no significant ($P > 0.05$) differences in yield between NT and CP at both 30 and 90 kg N ha^{-1}. At Monze, simulated maize productivity without N fertilizer under current climate was extremely low with average yields of 272 kg ha^{-1} for CP and zero for NT (Fig. 5). Simulated grain yields were similar for CP and NT when N fertilization was 30 kg N ha^{-1}, reaching 2590 kg ha^{-1}. With application of 90 kg N ha^{-1}, equal yields were simulated for CP and NT, with average yields of 3320 kg ha^{-1}. At Sussundenga, simulated grain yields for both CP and NT were zero under current climate when the amount of N fertilizer input was zero (Fig. 5). Application of 30 kg N ha^{-1} increased yields significantly ($P < 0.05$) with an average of 1080 kg ha^{-1} for CP and 1609 kg ha^{-1} for NT. When the fertilizer input was increased to 90 kg N ha^{-1}, the average simulated yields further increased significantly ($P < 0.05$) reaching 2562 kg ha^{-1} for CP and 2907 kg ha^{-1} for NT.

Hence, the impact of NT management on maize grain yield under current climate depended on the site and N fertilizer rates (Fig. 6). At Sussundenga, NT had a significantly ($P < 0.05$) positive impact on grain yield for 30 and 90 kg N ha^{-1}, with a maximum increase of 49% at 30 kg N ha^{-1}. At Domboshawa, the impact of NT was positive at 90 kg N ha^{-1} (with an average yield increase of 11%), whilst at lower or zero N fertilizer rates the impact was negative, with a yield decrease of up to 50%. At Chitedze and Monze, there was no significant ($P > 0.05$) impact of NT at 90 kg N ha^{-1}, whilst at lower or zero N fertilizer rates the predicted impact of CA was negative (Fig. 6).

3.3.2 Future climate (2021–2060)

In most model scenarios, maize grain yield and aboveground biomass were simulated to decrease over time under future warmer climate (Fig. 5). As expected, productivity decline

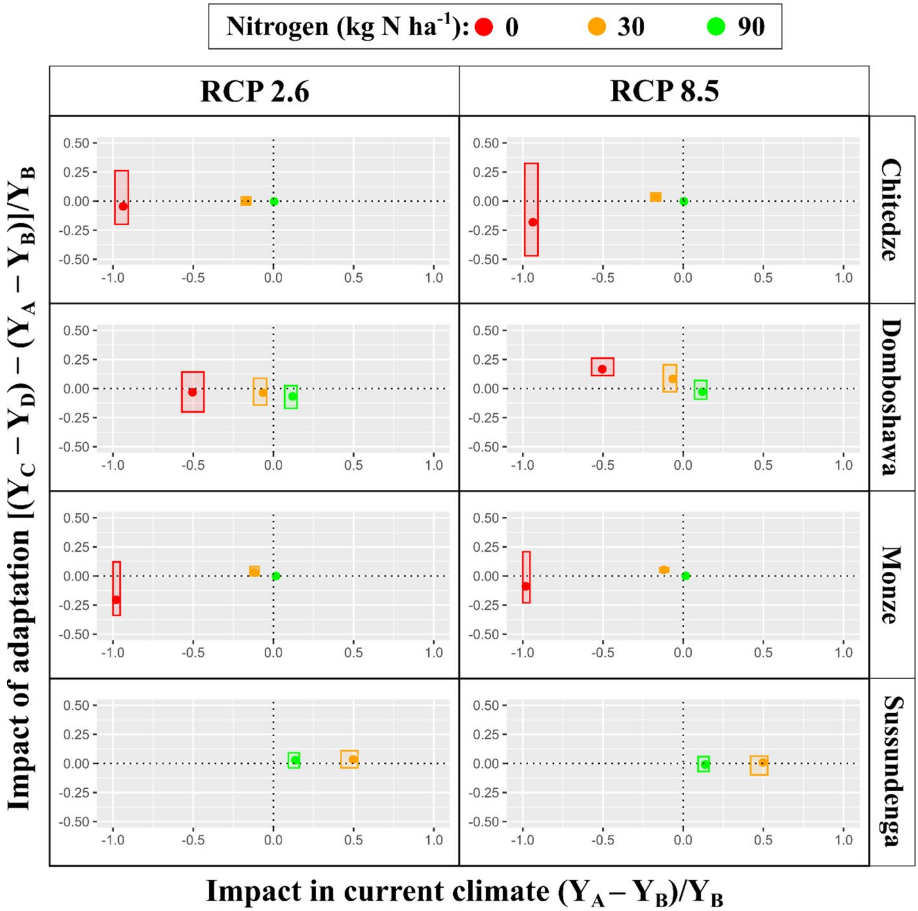

Fig. 6 The impact of NT management versus conventional tillage practice (CP) for three levels of nitrogen fertilization on the mean maize grain yield in the current climate (2011–2020) and their impact of adaptation potential. The boundaries of each box show the 25 th and 75 th percentile values of the mean yield change of each adaptation option across all the 17 GCMs. Y_A is the maize grain yield of NT in the current climate, Y_B is the yield of CP in the current climate, Y_C is yield of NT in future climate (2051–2060) and Y_D is the yield of CP in the future climate

was more pronounced under RCP8.5 than RCP2.6. However, in some scenarios simulated productivity decreases were close to zero, especially when initial productivity was low (i.e. without N fertilizer). In simulation runs without N fertilization at Domboshawa, grain yields were even predicted to increase slightly, though simulated aboveground biomass decreased.

a. Impact of climate change

At Chitedze, the average predicted maize grain yield decline by 2051–2060 was relatively small (< 7%) for all scenarios, except for the scenario with 90 kg N ha^{-1} under RCP8.5 that gave rise to a yield decrease of 18% for both CP and NT. At Domboshawa, predicted grain yield decline under RCP2.6 was small to zero, or even slightly positive both for CP and

NT. Under RCP8.5, a yield decline of around 20% was predicted in the scenario with 90 kg N ha^{-1}, both under NT and CP. At Monze, predicted yield decline under RCP2.6 with N fertilization was around 4 to 8%, but increased to about 14% and 21% under RCP8.5, for respectively 30 and 90 kg N ha^{-1}. At Sussundenga, predicted yield decline by 2051–2060 was small for all scenarios, i.e. between 2 and 6%.

b. Adaptation potential to future climate

The average adaptation potential of NT across the N fertilization rates at the four sites was mostly small to zero, and not significant (25–75% quantile values include zero, Fig. 6). Only at Domboshawa in a situation without the use of mineral N fertilizer, NT management is simulated to reduce the impact of future warmer climate. However, there were no management options with current impact that contribute toward reducing climate change impacts (upper right quadrant of Fig. 6). Hence, our simulation results indicate that in general maize grain yield responses to NT are not higher in the future than in the current climate, so NT management is not expected to mitigate the climate change impacts at the study sites.

4 Discussion

4.1 Crop management and crop productivity

The APSIM simulation results showed that N fertilizer use is crucial to maize yields at all four study sites regardless of the (no)tillage system (Fig. 5). Yield responses to N fertilizer differed however among the study sites. Diverse factors determine crop responsiveness to N fertilizer, including rainfall regime, soil type and its physical and chemical properties, and the history of soil fertility management defining residual soil fertility (Roobroeck et al. 2021). These factors are to a certain extent included in the APSIM model simulations (see Sect. 2.2). Although we only focus on N, the maize responses to N fertilizer applications in the model simulations at the four sites suggest that N is a major limiting nutrient under the pedoclimatic conditions of the sites of our study and that its input is needed for meaningful crop production to occur. Nitrogen stress on maize productivity has been reported in several experimental studies in the sub-humid zones of southern Africa (Chikowo et al. 2004; Pasley et al. 2020; Gotosa et al. 2021; Kafesu et al. 2018). These findings suggest that investments in annual N fertilizer application are essential in the study regions; highest N use efficiency is attained in combination with manure application, particularly on soils with low organic matter content and limited natural N supply (Zingore et al. 2008). Yet, fertilizer use by farmers generally remains low in sub-Saharan Africa, about 20 kg ha^{-1} (Chianu et al. 2012). The highly variable crop responses to fertilizer on the one hand, and the high fertilizer prices relative to agricultural commodity prices on the other hand, pose major threats to fertilizer investments by farmers and governments (Kihara et al. 2016). Moreover, other factors, including the general lack of market information about the availability and cost of fertilizer, the inability of many farmers to raise the resources needed to purchase fertilizer, and the lack of knowledge on the part of many farmers about how to use fertilizer efficiently may further aggravate the low use.

Our APSIM simulations also revealed that yield responses to N fertilizer were generally larger for NT than for CP, which was largely due to the higher N constraint under NT as a result of simulated immobilization of mineral N into soil organic matter. In experiments, it has been observed that the application of crop residues with a wide C: N ratio, such as maize residues, leads to a substantial temporary net N immobilization by soil microbes (Handayanto et al. 1997; Corbeels et al. 2000; Gentile et al. 2008, 2011), and may reduce (early) crop growth and subsequent grain yield, especially in situations where soils are N constrained (Mupangwa et al. 2020; Kitonyo et al. 2018). In APSIM, retention of crop residues with a high C: N ratio results in the simulation of immobilization of soil mineral N that may cause N stress to crop growth. The model assumes that the soil organic matter pools have C: N ratios that are unchanging through time. The input of residues with the formation of soil organic matter thus creates a demand for N that has to be met by drawing on the soil mineral N (Probert et al. 1998). On the other hand, immobilization of mineral N may also lead to reduced N leaching losses, depending on soil texture and rainfall regime (Gentile et al. 2009). Thus, strong interactions between rainfall, soil type and mineral N availability control to a large extent the effects of the retention of crop residues (and thus NT) on maize yield in low-input cropping systems of the sub-humid tropics (Corbeels et al. 2000).

As a result, simulated maize yields were generally lower for NT than CP when N fertilizer input was small. This corroborates with results from Lundy et al. (2015); their global meta-analysis highlighted the importance of N fertilization in counteracting yield decline in no-tillage systems in tropical/subtropical regions. The findings support the call that strategies for using NT in sub-Saharan Africa must integrate and promote good agriculture practices including improved nutrient management to increase the likelihood of benefits from NT for smallholder farmers (Sommer et al. 2014; Vanlauwe et al. 2014).

On the other hand, higher crop yields in NT compared to CP, as simulated for the Sussundenga site in Mozambique, can be attributed to soil moisture conservation through reduced soil evaporation and runoff, as a result of crop residue mulching (Thierfelder and Wall 2010). Several experiments in southern Africa demonstrated higher crop yields in NT systems compared to CP systems, because crops better resisted drought stresses (Thierfelder et al. 2015; Steward et al. 2019; Komarek et al. 2021). This is particular the case in dryer climates or in climates where dry spells regularly occur, or when droughts occur around anthesis. More generally, meta-analyses found that relative maize yield performance of NT improves with lower seasonal rainfall (Rusinamhodzi et al. 2011; Corbeels et al. 2020; Steward et al. 2018). To account for the effect of crop residue mulching on soil moisture dynamics, potential first-stage evaporation rate is reduced in the SURFACEOM module of APSIM as a function of the amount of surface crop residues by a negative exponential relationship following Adams et al. (1976), and the runoff curve number is reduced as a function of residue cover (Littleboy et al. 1992).

4.2 Climate change and crop productivity

Although the climate change projections were characterized by large uncertainty among GCMs without clear consistency between them across sites, there was a clear trend of increasing temperatures. Seasonal temperatures were projected to increase by about 2.0 °C in 2060 under RCP8.5 in the four study sites (Fig. 3). On the other hand, projected seasonal rainfall over the 2021–2060 period did not show trends of change at any site, though high variability was projected (Fig. 4). Herewith, it is interesting to note that weather observations from 1950 to 2000 in the region were found to have a strong increasing temperature trend, particularly in the period after 1970, but a nonsignificant downward trend for annual rainfall (Wolski et al. 2020).

Therfore, the predicted decline of maize productivity at the four sites (Fig. 5) was primarily caused by simulated effects of rising temperatures. In APSIM, higher temperature shortens the length of the crop development stages (thereby reducing the effective period during which biomass builds up before grain filling can take place) and reduces photosynthesis with direct effects on biomass production, but also influences grain number development and grain filling, when temperature exceeds critical values (see Sect. 2.2). These simulated temperature effects on maize development and growth also explain the higher reductions in maize productivity under the RCP8.5 scenario than the RCP2.6 scenario (Fig. 5). In our study, we also found that even when grain yield was zero, some biomass yield was simulated, indicating that by the time of flowering there were however not enough assimilates in the plant to allocate to grain formation (Gonzalez-Dugo et al. 2010), and heat stress resulted in kernel abortion (Niu et al. 2021).

In line with earlier modelling results for maize cropping systems in sub-Saharan Africa (e.g. Falconnier et al. 2020), our study found a strong interaction between N fertilizer input and the effects of climate change. With no N fertilizer input, the model simulations predicted minimal to no impact on maize yield for the projected future climate, i.e. rising temperatures (Fig. 5), indicating that N limitation made temperature stresses to crop growth less prominent. On the other hand, with increased N fertilization (and higher yields) maize was increasingly n egatively impacted by rising temperatures; our modeling predicted a decline in maize grain yields of up to about 20% by 2060. The main lesson here is that that farmers in the process of intensifying maize production through higher fertilizer use will face a larger impact of climate change. The larger yield variability may exacerbate the current risk of unfavourable benefit-cost ratio for mineral fertilizer application (Falconnier et al. 2023).

These values are relatively high, but in line with values for southern Africa reported by Waha et al. (2013). These authors also found that the effect of reduced seasonal rainfall is less strong than the effect of increasing temperatures in the sub-humid parts of southern Africa. This is because on average the growing season is long and wet enough for the cultivation of maize. On the other hand, the region is highly vulnerable to temperature increase since current seasonal temperatures are already at the higher end of the optimum temperature range (21–26 °C) for maize productivity. Higher temperatures may, however, increase the frequency and intensity of soil drought due to the forcing effect on evapotranspiration.

Despite the fact that the average seasonal rainfall at all four study sites (750–1100 mm, Table 1) is sufficient for maize cultivation, maize productivity in sub-humid southern Africa is increasingly affected by the occurrence of dry spells (e.g. Rurinda et al. 2013). Prolonged dry spells or droughts in the region are often related to the occurrence of El Niño events in the tropical Pacific (Funk et al. 2018). The projections of the intra-season daily rainfall patterns (and dry spells) in the region, and their possible changes at local scale, remain however uncertain in most GCMs, including many characteristics of the future El Niño–Southern Oscillation cycles (Fredriksen et al. 2020). In APSIM, the occurrence of water stress to crop growth as a result of dry spells is to a large extent governed by the water holding capacity of the soils (largely determined by soil texture and soil depth); high water holding capacity potentially represents an important buffer for grain yield production when droughts occur.

Soils in our study sites had relatively high capacities to store soil water and thus cope with periodic water stresses (Table 1). Finally, it is important to note that crop sensitivity to high temperatures is aggravated in drought conditions, as demonstrated by Lobell et al. (2011) who analyzed more than 20,000 historical maize trials in southern and eastern Africa. The mechanisms of the interactive effects of heat and drought stresses, which are particularly strong when they occur at the reproductive stages of maize development, are however not fully incorporated in APSIM.

4.3 Conservation agriculture as a climate change adaptation option

Whilst NT has increasingly been endorsed as a ‘climate-smart’ practice that can contribute to adaptation and resilience to climate change (Kassam et al. 2019; Komarek et al. 2021), our APSIM modelling results do not support this (Fig. 6). This is partly due to the fact that climate resilience of NT is largely caused by its positive effects on soil moisture conservation during dry years or years with dry spells (e.g. Thierfelder et al. 2017), whilst in our study seasonal rainfall was not projected to change over time (Fig. 4).

APSIM incorporates the effects of crop residue mulching on the soil water balance, which partly explains the good reproduction of observed maize yields under NT (Fig. 1), and, for example, the higher simulated maize yields under NT compared to CP in Sussendenga (Fig. 5). However, the practice of NT may have other beneficial effects on crop water productivity that are realized in the long term, but were not simulated in our study since the model was reinitialized for each year in the scenario simulations. Importantly, NT is known to improve soil organic carbon and soil structural stability in the long term that are also expected to contribute to enhanced climate resilience of cultivated crops under CA (Thierfelder et al. 2017). Besides, mulching may have positive effects on root growth and water and nutrient uptake under heat stress (Acharya and Sharma 1994), which are not incorporated in APSIM. Finally, full CA (NT +rotation) with crop diversification has been reported to enhance maize yields (e.g. Thierfelder and Mhlanga 2022), and may increase the resilience of maized-based cropping systems to climate change (Rusinamhodzi et al. 2012).

Our simulation results suggest that sustainable intensification with increased nutrient inputs could drastically increase maize production and improve household food availability, but with increased vulnerability to climate change. Given the trends of increased temperatures, agronomic adaptation strategies need to be combined with genotypes that have higher thermal time requirement (Zabel et al. 2021) and are tolerant to heat stress to maximize resilience under negative climatic conditions (Cairns et al. 2013a, b). However, if drought stress is increasing, there may be little opportunity to adopt longer duration maize varieties.

Despite the widespread availability and on-going breeding efforts for better adapted maize varieties (Cairns et al. 2013b), the widespread adoption and continued use among smallholder farmers remains low, although variations exist among countries from as low as 9% to as high as 61% (Fisher et al. 2015). Some of the reasons for low adoption are high prices, inadequate information, perceived variety attributes(Fisher et al. 2015). And access to government subsidies on agricultural inputs has been reported as a major driver of adoption e.g., in Malawi (Katengeza et al. 2018).

4.4 Predicting the unknown - uncertainties

Several uncertainties were identified in this study, as already highlighted above. Most importantly, the model projections reported in this paper were done with high uncertainties. The sources of uncertainty in model outputs are manifold, both from climate and crop models. Future climate is generated by GCMs using a quite coarse resolution with weaknesses related to the simulation of various feedback mechanisms involving water vapor and warming, clouds and radiation (Notz 2015). As a result, GCMs may generate different climatic conditions under similar circumstances due to the way certain processes and feedbacks are modeled. The absence of an obvious choice among the different GCMs underscores this, yet temperature signals were robust across sites in our study. On the other hand, studies with multi-crop model ensembles have shown the wide range of model responses to climate change, associated with the inadequacies of the crop models, and further work is needed to address this (Jägermeyr et al. 2021). First, crop models such as APSIM, do not consider the combined effects of heat and water stresses on crop growth. Temperature effects are either worsened or moderated by the soil water status such that below-optimum precipitation in combination with high temperatures increases the negative effects on grain production (Christopher et al. 2016). For example, in the absence of sufficient soil moisture but with high temperatures, plants initiate early flowering which often leads to low grain yield due to low assimilates associated with low biomass (Jagadish et al. 2016). Overall, improved simulation of responses to (extreme) temperatures are a key step to improved crop yield projections under rising temperature and climate change (Jin et al. 2017; Wang et al. 2015). Second, although crop models as shown in this study can simulate crop productivity with good accuracy once they are calibrated, the mechanisms of soil N cycling and crop responses to it, are still poorly represented in crop models and their output highly uncertain. Whilst the SOILN module in APSIM is based on conceptual soil organic matter pools that are not measurable, the next generation of crop models need a more mechanistic representation of soil microbial activities and N transformations (Huang et al. 2021).

Despite these uncertainties, it is clear from our analyses that in constrained environments characterized by low inputs and high temperatures clear differences were observed in maize yields and the models are useful to provide guidelines for fine-tuning technologies including identifying optimum N and crop residue mulch application, and possibly resolving potential tradeoffs (Rusinamhodzi et al. 2015).

5 Conclusions

The objective of the study was to assess the potential of NT (no-tillage and mulching) and N fertilizer management to mitigate the negative effects of future climate change on continuous mono-cropped maize in the sub-humid regions of southern Africa. Results showed that proper targeting is important as shown by different crop performance in the (no)tillage and N fertilizer application combinations across the four study sites considered. The presence of maize crop residues with wide C: N ratio demands higher N input to maintain the same yield levels as in CP if rainfall is abundant. This means that NT requires higher N fertilizer inputs to offset the negative effects of N immobilization compared to CP systems. Generally, results suggested that NT management (no-tillage and mulching) is not more beneficial in the future than in the current climate, and there is no evidence to support its ability to mitigate the climate change impacts at the study sites, because they are principally exerted through increased temperatures. Sources of uncertainty in model outputs are, however, manifold, both from climate and crop models, and improvements in these areas are needed. Improved crop management practices such a NT need to be combined with improved crop genotypes that are tolerant to multiple stresses such as drought and heat to maximize resilience under future climatic conditions.

Acknowledgements The study was financially supported by the Twin-Postdoc Program between the French Agricultural Research Centre for International Development (CIRAD) and the CGIAR Research Programs on Climate Change, Agriculture and Food Security (CCAFS), and on Maize (CRP MAIZE; www.maize.org), as part of the Agriculture Model Intercomparison and Improvement Project (AgMIP). Other funders that previously supported the establishment of on-station trials, namely Bundesministerium für wirtschaftliche Zumsammenarbeit und Entwicklung/Gesellschaft für International Zusammenarbeit GmbH (BMZ/GIZ Grants No 2003.7860.4 −002.00 and 13.22.44.5–002.00), Germany, International Fund for Agriculture Development (IFAD, Grants No 898 and 1309), United States Agency for International Development (USAID)- funded Feed the Future projects such as the Sustainable Intensification in Maize-Legume Systems in Eastern Province of Zambia (SIMLEZA, Grant No EEM-G-00–04–00013) and Africa Research in Sustainable Intensification for the Next Generation (Africa RISING, AID-BFS-G-11–00002) are gratefully acknowledged.

Authors' contribution Leonard Rusinamhodzi: Data curation, Model Calibration, Data analysis, Writing original draft. David Berre: Data visualization, Writing- review and editing. Christian Thierfelder: Data curation, Writing- review and editing. Santiago-Lopez Ridaura: Conceptualization, Writing- review and editing. Marc Corbeels: Conceptualization, Writing- review and editing. All authors reviewed the results and approved the final version of the manuscript.

Funding Open access funding provided by CIRAD.

Data availability The datasets (crop and climate) used for calibrating the APSIM model during the study are available from the corresponding author upon reasonable because they contain geo-location information. The soil data is already included in the manuscript.

Declarations

Competing interests The authors declare that they have no known competing financial or non-financial interests or relationships that could have appeared to influence the work reported in this paper.

References

Acharya CL, Sharma PD (1994) Tillage and mulch effects on soil physical environment, root growth, nutrient uptake and yield of maize and wheat on an Alfisol in north-west India. Soil Tillage Res 32(4):291–302. https://doi.org/10.1016/0167-1987(94)00425-E

Adams JE, Arkin GF, Ritchie JT (1976) Influence of row spacing and straw mulch on first stage drying. Soil Sci Soc Am 40:436–442

Cairns J, Hellin J, Sonder K, Araus J, MacRobert J, Thierfelder C, Prasanna BM (2013a) Adapting maize production to climate change in sub-Saharan Africa. Food Secur 5(3):345–360. https://doi.org/10.1007/s12571-013-0256-x

Cairns JE, Crossa J, Zaidi PH, Grudloyma P, Sanchez C, Araus JL, Thaitad S, Makumbi D, Magorokosho C, Bänziger M, Menkir A, Hearne S, Atlin GN (2013b) Identification of drought, heat, and combined drought and heat tolerant donors in maize. Crop Sci 53(4):1335–1346. https://doi.org/10.2135/cropsci2012.09.0545

Carberry PS, Muchow RC, McCown RL (1989) Testing the CERES-Maize simulation model in a semi-arid tropical environment. Field Crops Res 20(4):297–315. https://doi.org/10.1016/0378-4290(89)90072-5

Challinor A, Wheeler T, Garforth C, Craufurd P, Kassam A (2007) Assessing the vulnerability of food crop systems in Africa to climate change. Clim Change 83(3):381–399 doi:DOI:. https://doi.org/10.1007/s10584-007-9249-0

Chianu JN, Chianu JN, Mairura F (2012) Mineral fertilizers in the farming systems of sub-Saharan Africa. A review. Agron Sustain Dev 32(2):545–566. https://doi.org/10.1007/s13593-011-0050-0

Chikowo R (2011) Climatic risk analysis in conservation agriculture in varied biophysical and Socio-economic settings of southern Africa. FAO, Rome, Italy

Chikowo R, Mapfumo P, Nyamugafata P, Giller KE (2004) Maize productivity and mineral N dynamics following different soil fertility management practices on a depleted sandy soil in Zimbabwe. Agric Ecosyst Environ 102(2):119–131. https://doi.org/10.1016/j.agee.2003.08.009

Christopher JT, Christopher MJ, Borrell AK, Fletcher S, Chenu K (2016) Stay-green traits to improve wheat adaptation in well-watered and water-limited environments. J Exp Bot 67(17):5159–5172. https://doi.org/10.1093/jxb/erw276

Cichota R, Vogeler I, Sharp J, Verburg K, Huth N, Holzworth D, Dalgliesh N, Snow V (2021) A protocol to build soil descriptions for APSIM simulations. MethodsX 8:101566. https://doi.org/10.1016/j.mex.2021.101566

Corbeels M, Hofman G, Van Cleemput O (2000) Nitrogen cycling associated with the decomposition of sunflower stalks and wheat straw in a vertisol. Plant Soil 218(1/2):71–82

Corbeels M, Cardinael R, Naudin K, Guibert H, Torquebiau E (2019) The 4 per 1000 goal and soil carbon storage under agroforestry and conservation agriculture systems in sub-Saharan Africa. Soil Tillage Res 188:16–26. https://doi.org/10.1016/j.still.2018.02.015

Corbeels M, Naudin K, Whitbread AM, Kühne R, Letourmy P (2020) Limits of conservation agriculture to overcome low crop yields in sub-Saharan Africa. Nat Food 1(7):447–454. https://doi.org/10.1038/s43016-020-0114-x

Derpsch R, Friedrich T, Kassam A, Hongwen L (2010) Current status of adoption of no-till farming in the world and some of its main benefits. Int J Agric Biol Eng 3(1):1–25

Dixon J, Gulliver A, Gibbon D, Hall M (2001) Farming systems and poverty: improving farmers' livelihoods in a changing world. FAO and World Bank, Rome and Washington D.C

Durand J-L, Delusca K, Boote K, Lizaso J, Manderscheid R, Weigel HJ, Ruane AC, Rosenzweig C, Jones J, Ahuja L, Anapalli S, Basso B, Baron C, Bertuzzi P, Biernath C, Deryng D, Ewert F, Gaiser T, Gayler S, Heinlein F, Kersebaum KC, Kim S-H, Müller C, Nendel C, Olioso A, Priesack E, Villegas JR, Ripoche D, Rötter RP, Seidel SI, Srivastava A, Tao F, Timlin D, Twine T, Wang E, Webber H, Zhao Z (2018) How accurately do maize crop models simulate the interactions of atmospheric CO2 concentration levels with limited water supply on water use and yield? Eur J Agron 100:67–75. https://doi.org/10.1016/j.eja.2017.01.002

Falconnier GN, Corbeels M, Boote KJ, Affholder F, Adam M, MacCarthy DS, Ruane AC, Nendel C, Whitbread AM, Justes E, Ahuja LR, Akinseye FM, Alou IN, Amouzou KA, Anapalli SS, Baron C, Basso B, Baudron F, Bertuzzi P, Challinor AJ, Chen Y, Deryng D, Elsayed ML, Faye B, Gaiser T, Galdos M, Gayler S, Gerardeaux E, Giner M, Grant B, Hoogenboom G, Ibrahim ES, Kamali B, Kersebaum KC, Kim SH, van der Laan M, Leroux L, Lizaso JI, Maestrini B, Meier EA, Mequanint F, Ndoli A, Porter CH, Priesack E, Ripoche D, Sida TS, Singh U, Smith WN, Srivastava A, Sinha S, Tao F, Thorburn PJ, Timlin D, Traore B, Twine T, Webber H (2020) Modelling climate change impacts on maize yields under low nitrogen input conditions in sub-Saharan Africa. Glob Chang Biol 26(10):5942–5964. https://doi.org/10.1111/gcb.15261

Falconnier GN, Cardinael R, Corbeels M, Baudron F, Chivenge P, Couëdel A, Ripoche A, Affholder F, Naudin K, Benaillon E, Rusinamhodzi L, Leroux L, Vanlauwe B, Giller KE (2023) The input reduction principle of agroecology is wrong when it comes to mineral fertilizer use in sub-Saharan Africa. Outlook Agric 52(3):311–326. https://doi.org/10.1177/00307270231199795

Fisher M, Abate T, Lunduka RW, Asnake W, Alemayehu Y, Madulu RB (2015) Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: determinants of adoption in Eastern and Southern Africa. Clim Change 133(2):283–299. https://doi.org/10.1007/s10584-015-1459-2

Franzluebbers AJ (2010) Achieving soil organic carbon sequestration with conservation agricultural systems in the southeastern united States. Soil Sci Soc Am J 74(2):347–357. https://doi.org/10.2136/sssaj2009.0079

Fredriksen HB, Berner J, Subramanian AC, Capotondi A (2020) How does El Niño–Southern Oscillation change under global warming—A first look at CMIP6. Geophys Res Lett 47(22). https://doi.org/10.1029/2020gl090640

Funk C, Harrison L, Shukla S, Pomposi C, Galu G, Korecha D, Husak G, Magadzire T, Davenport F, Hillbruner C, Eilerts G, Zaitchik B, Verdin J (2018) Examining the role of unusually warm Indo-Pacific sea-surface temperatures in recent African droughts. Q J R Meteorol Soc 144(S1):360–383. https://doi.org/10.1002/qj.3266

Gentile R, Vanlauwe B, Chivenge P, Six J (2008) Interactive effects from combining fertilizer and organic residue inputs on nitrogen transformations. Soil Biol Biochem 40(9):2375–2384

Gentile R, Vanlauwe B, van Kessel C, Six J (2009) Managing N availability and losses by combining fertilizer-N with different quality residues in Kenya. Agric Ecosyst Environ 131(3):308–314. https://doi.org/10.1016/j.agee.2009.02.003

Gentile R, Vanlauwe B, Chivenge P, Six J (2011) Trade-offs between the short- and long-term effects of residue quality on soil C and N dynamics. Plant Soil 338(1):159–169

Giller KE, Corbeels M, Nyamangara J, Triomphe B, Affholder F, Scopel E, Tittonell P (2011) A research agenda to explore the role of conservation agriculture in African smallholder farming systems. Field Crops Res 124(3):468–472. https://doi.org/10.1016/j.fcr.2011.04.010

Gonzalez-Dugo V, Durand J-L, Gastal F (2010) Water deficit and nitrogen nutrition of crops. A review. Agron Sustain Dev 30(3):529–544. https://doi.org/10.1051/agro/2009059

Gotosa J, Kodzwa J, Gwenzi W, Nyamangara J (2021) Maize nitrogen uptake and productivity under reduced and conventional tillage. Nutr Cycl Agrosyst 119(1):23–36. https://doi.org/10.1007/s10705-020-10104-7

Handayanto E, Giller KE, Cadisch G (1997) Regulating N release from legume tree prunings by mixing residues of different quality. Soil Biol Biochem 29(9–10):1417–1426. https://doi.org/10.1016/S0038-0717(97)00047-3

Hawkins E, Osborne TM, Ho CK, Challinor AJ (2013) Calibration and bias correction of climate projections for crop modelling: an idealised case study over Europe. Agric for Meteorol 170:19–31. https://doi.org/10.1016/j.agrformet.2012.04.007

Holzworth DP, Huth NI, deVoil PG, Zurcher EJ, Herrmann NI, McLean G, Chenu K, van Oosterom EJ, Snow V, Murphy C, Moore AD, Brown H, Whish JPM, Verrall S, Fainges J, Bell LW, Peake AS, Poulton PL, Hochman Z, Thorburn PJ, Gaydon DS, Dalgliesh NP, Rodriguez D, Cox H, Chapman S, Doherty A, Teixeira E, Sharp J, Cichota R, Vogeler I, Li FY, Wang E, Hammer GL, Robertson MJ, Dimes JP, Whitbread AM, Hunt J, van Rees H, McClelland T, Carberry PS, Hargreaves JNG, MacLeod N, McDonald C, Harsdorf J, Wedgwood S, Keating BA (2014) APSIM – Evolution towards a new generation of agricultural systems simulation. Environ Model Softw 62(0):327–350. https://doi.org/10.1016/j.envsoft.2014.07.009

Huang Y, Guenet B, Wang YL, Ciais P (2021) Global simulation and evaluation of soil organic matter and microbial carbon and nitrogen stocks using the microbial decomposition model ORCHIMIC v2.0. Global Biogeochem Cycles 35:e2020GB006836. https://doi.org/10.1029/2020GB006836

Jagadish SV, Bahuguna RN, Djanaguiraman M, Gamuyao R, Prasad PV, Craufurd PQ (2016) Implications of high temperature and elevated CO2 on flowering time in plants. Front Plant Sci 7:913. https://doi.org/10.3389/fpls.2016.00913

Jägermeyr J, Müller C, Ruane AC, Elliott J, Balkovič J, Castillo O, Faye B, Foster I, Folberth C, Franke JA, Fuchs K, Guarin JR, Heinke J, Hoogenboom G, Iizumi T, Jain AK, Kelly D, Khabarov N, Lange S, Lin T-S et al (2021) Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. Nat Food 2:873–885. https://doi.org/10.1038/s43016-021-00400-y

Jin Z, Zhuang Q, Wang J, Archontoulis SV, Zobel Z, Kotamarthi VR (2017) The combined and separate impacts of climate extremes on the current and future US rainfed maize and soybean production under elevated CO2. Glob Change Biol 23:2687–2704. https://doi.org/10.1111/gcb.13617

Jones PG, Thornton PK (2000) MarkSim: software to generate daily weather data for Latin America and Africa. Agron J 92(3):445–453

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ, Ritchie JT (2003) The DSSAT cropping system model. Eur J Agron 18(3–4):235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Kafesu N, Chikowo R, Mazarura U, Gwenzi W, Snapp S, Zingore S (2018) Comparative fertilization effects on maize productivity under conservation and conventional tillage on sandy soils in a smallholder cropping system in Zimbabwe. Field Crops Res 218:106–114. https://doi.org/10.1016/j.fcr.2018.01.014

Kassam A, Friedrich T, Derpsch R (2019) Global spread of conservation agriculture. Int J Environ Stud 76(1):29–51. https://doi.org/10.1080/00207233.2018.1494927

Katengeza SP, Holden ST, Lunduka RW (2018) Adoption of drought tolerant maize varieties under rainfall stress in Malawi. J Agric Econ 70(1):198–214. https://doi.org/10.1111/1477-9552.12283

Keating BA, Carberry PS, Hammer GL, Probert ME, Robertson MJ, Holzworth D, Huth NI, Hargreaves JNG, Meinke H, Hochman Z, McLean G, Verburg K, Snow V, Dimes JP, Silburn M, Wang E, Brown S, Bristow KL, Asseng S, Chapman S, McCown RL, Freebairn DM, Smith CJ (2003) An overview of APSIM, a model designed for farming systems simulation. Eur J Agron 18(3–4):267–288. https://doi.org/10.1016/s1161-0301(02)00108-9

Kihara J, Nziguheba G, Zingore S, Coulibaly A, Esilaba A, Kabambe V, Njoroge S, Palm C, Huising J (2016) Understanding variability in crop response to fertilizer and amendments in sub-Saharan Africa. Agric Ecosyst Environ 229:1–12. https://doi.org/10.1016/j.agee.2016.05.012

Kitonyo OM, Sadras VO, Zhou Y, Denton MD (2018) Nitrogen fertilization modifies maize yield response to tillage and stubble in a sub-humid tropical environment. Field Crops Res 223:113–124. https://doi.org/10.1016/j.fcr.2018.03.024

Komarek AM, Kwon H, Haile B, Thierfelder C, Mutenje MJ, Azzarri C (2019) From plot to scale: ex-ante assessment of conservation agriculture in Zambia. Agric Syst 173:504–518. https://doi.org/10.1016/j.agsy.2019.04.001

Komarek AM, Thierfelder C, Steward PR (2021) Conservation agriculture improves adaptive capacity of cropping systems to climate stress in Malawi. Agric Syst 190:103117. https://doi.org/10.1016/j.agsy.2021.103117

Köppen W (2020) Die klimate der Erde: Grundriss der Klimakunde. De Gruyter Doi. https://doi.org/10.1515/9783111491530

Littleboy M, Silburn DM, Freebairn DM, Woodruff DR, Hammer GL (1992) Impact of soil erosion on production in cropping systems. II. Simulation of production and erosion risks for a wheat cropping system. Aust J Soil Res 30:775–88

Lobell DB (2014) Climate change adaptation in crop production: beware of illusions. Global FoodSecurity 3:72–76. https://doi.org/10.1016/j.gfs.2014.05.002

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

Lobell DB, Bänziger M, Magorokosho C, Vivek B (2011) Nonlinear heat effects on African maize as evidenced by historical yield trials. Nat Clim Change 1(1):42–45. https://doi.org/10.1038/nclimate1043

Lundy ME, Pittelkow CM, Linquist BA, Liang X, van Groenigen KJ, Lee J, Six J, Venterea RT, van Kessel C (2015) Nitrogen fertilization reduces yield declines following no-till adoption. Field Crops Res 183:204–210. https://doi.org/10.1016/j.fcr.2015.07.023

Morris M, Kelly VA, Kopicki RJ, Byerlee D (2007) Fertilizer use in African agriculture: lessons learned and good practice guidelines. https://doi.org/10.1596/978-0-8213-6880-0

Mupangwa W, Thierfelder C, Cheesman S, Nyagumbo I, Muoni T, Mhlanga B, Mwila M, Sida TS, Ngwira A (2020) Effects of maize residue and mineral nitrogen applications on maize yield in conservation-agriculture-based cropping systems of southern Africa. Renewable Agric Food Syst 35(3):322–335. https://doi.org/10.1017/S174217051900005X

Niu S, Du X, Wei D, Liu S, Tang Q, Bian D, Zhang Y, Cui Y, Gao Z (2021) Heat stress after pollination reduces kernel number in maize by insufficient assimilates. Front Genet 12:728166. https://doi.org/10.3389/fgene.2021.728166

Notz D (2015) How well must climate models agree with observations? Philos Trans Math Phys Eng Sci 373(2052). https://doi.org/10.1098/rsta.2014.0164

Pasley HR, Camberato JJ, Cairns JE, Zaman-Allah M, Das B, Vyn TJ (2020) Nitrogen rate impacts on tropical maize nitrogen use efficiency and soil nitrogen depletion in eastern and southern Africa. Nutr Cycl Agroecosyst 116(3):397–408. https://doi.org/10.1007/s10705-020-10049-x

Porter CH, Jones JW, Adiku S, Gijsman AJ, Gargiulo O, Naab JB (2010) Modeling organic carbon and carbon-mediated soil processes in DSSAT v4.5. Oper Res Int Journal 10(3):247–278. https://doi.org/10.1007/s12351-009-0059-1

Powlson DS, Stirling CM, Thierfelder C, White RP, Jat ML (2016) Does conservation agriculture deliver climate change mitigation through soil carbon sequestration in tropical agro-ecosystems? Agric Ecosyst Environ 220:164–174. https://doi.org/10.1016/j.agee.2016.01.005

Probert ME, Dimes JP, Keating BA, Dalal RC, Strong WM (1998) APSIM's water and nitrogen modules and simulation of the dynamics of water and nitrogen in fallow systems. Agric Syst 56(1):1–28. https://doi.org/10.1016/S0308-521X(97)00028-0

R Core Team (2021) R: A Language and environment for statistical computing 4.1.2 Edn. R Foundation for Statistical Computing, Vienna, Austria

Roobroeck D, Palm CA, Nziguheba G, Weil R, Vanlauwe B (2021) Assessing and Understanding non-responsiveness of maize and soybean to fertilizer applications in African smallholder farms. Agric Ecosyst Environ 305:107165. https://doi.org/10.1016/j.agee.2020.107165

Rurinda J, Mapfumo P, van Wijk MT, Mtambanengwe F, Rufino MC, Chikowo R, Giller KE (2013) Managing soil fertility to adapt to rainfall variability in smallholder cropping systems in Zimbabwe. Field Crops Res 154:211–225

Rusinamhodzi L, Corbeels M, Van Wijk MT, Rufino MC, Nyamangara J, Giller KE (2011) A meta-analysis of long-term effects of conservation agriculture on maize grain yield under rain-fed conditions. Agron Sustain Dev 31(4):657–673. https://doi.org/10.1007/s13593-011-0040-2

Rusinamhodzi L, Corbeels M, Nyamangara J, Giller KE (2012) Maize-grain legume intercropping is an attractive option for ecological intensification that reduces climatic risk for smallholder farmers in central Mozambique. Field Crops Res 136:12–22. https://doi.org/10.1016/j.fcr.2012.07.014

Rusinamhodzi L, Corbeels M, Zingore S, Nyamangara J, Giller KE (2013) Pushing the envelope? Maize production intensification and the role of cattle manure in recovery of degraded soils in smallholder farming areas of Zimbabwe. Field Crops Res 147(0):40–53. https://doi.org/10.1016/j.fcr.2013.03.014

Rusinamhodzi L, Wijk MTv, Corbeels M, Rufino MC, Giller KE (2015) Maize crop residue uses and trade-offs on smallholder crop-livestock farms in Zimbabwe: economic implications of intensification. Agric Ecosyst Environ 214:31–45. https://doi.org/10.1016/j.agee.2015.08.012

Searle SR, Speed FM, Milliken GA (2012) Population marginal means in the linear model: an alternative to least squares means. Am Stat 34(4):216–221. https://doi.org/10.1080/00031305.1980.10483031

Setimela P, Gasura E, Thierfelder C, Zaman-Allah M, Cairns JE, Boddupalli PM (2018) When the going gets tough: performance of stress tolerant maize during the 2015/16 (El Niño) and 2016/17 (La Niña) season in southern Africa. Agric Ecosyst Environ 268:79–89. https://doi.org/10.1016/j.agee.2018.09.006

Sommer R, Thierfelder C, Tittonell P, Hove L, Mureithi J, Mkomwa S (2014) Fertilizer use should not be a fourth principle to define conservation agriculture. Field Crops Res. https://doi.org/10.1016/j.fcr.2014.05.012

Steward PR, Dougill AJ, Thierfelder C, Pittelkow CM, Stringer LC, Kudzala M, Shackelford GE (2018) The adaptive capacity of maize-based conservation agriculture systems to climate stress in tropical and subtropical environments: A meta-regression of yields. Agric Ecosyst Environ 251:194–202. https://doi.org/10.1016/j.agee.2017.09.019

Steward PR, Thierfelder C, Dougill AJ, Ligowe I (2019) Conservation agriculture enhances resistance of maize to climate stress in a Malawian medium-term trial. Agric Ecosyst Environ 277:95–104. https://doi.org/10.1016/j.agee.2018.07.009

Thierfelder C, Mhlanga B (2022) Short-term yield gains or long-term sustainability? – a synthesis of conservation agriculture long-term experiments in southern Africa. Agric Ecosyst Environ 326:107812. https://doi.org/10.1016/j.agee.2021.107812

Thierfelder C, Wall PC (2009) Effects of conservation agriculture techniques on infiltration and soil water content in Zambia and Zimbabwe. Soil Tillage Res 105(2):217–227

Thierfelder C, Wall PC (2010) Investigating conservation agriculture (CA) systems in Zambia and Zimbabwe to mitigate future effects of climate change. J Crop Improv 24(2):113–121. https://doi.org/10.1080/15427520903558484

Thierfelder C, Matemba-Mutasa R, Rusinamhodzi L (2015) Yield response of maize (Zea mays L.) to conservation agriculture cropping system in southern Africa. Soil Tillage Res 146, Part B:230–242. https://doi.org/10.1016/j.still.2014.10.015

Thierfelder C, Rusinamhodzi L, Setimela P, Walker F, Eash NS (2016) Conservation agriculture and drought-tolerant germplasm: reaping the benefits of climate-smart agriculture technologies in central Mozambique. Renewable Agric Food Syst 31(5):414–428

Thierfelder C, Chivenge P, Mupangwa W, Rosenstock TS, Lamanna C, Eyre JX (2017) How climate-smart is conservation agriculture (CA)? – its potential to deliver on adaptation, mitigation and productivity on smallholder farms in southern Africa. Food Secur 9(3):537–560. https://doi.org/10.1007/s12571-017-0665-3

Thierfelder C, Baudron F, Setimela P, Nyagumbo I, Mupangwa W, Mhlanga B, Lee N, Gérard B (2018) Complementary practices supporting conservation agriculture in southern Africa. A review. Agron Sustain Dev 38(2). https://doi.org/10.1007/s13593-018-0492-8

Tsubo M, Walker S, Ogindo HO (2005) A simulation model of cereal-legume intercropping systems for semi-arid regions: II. Model application. Field Crops Res 93(1):23–33. https://doi.org/10.1016/j.fcr.2004.09.003

van Wijk MT, Tittonell P, Rufino MC, Herrero M, Pacini C, Ridder Nd, Giller KE (2009) Identifying key entry-points for strategic management of smallholder farming systems in sub-Saharan Africa using the dynamic farm-scale simulation model NUANCES-FARMSIM. Agric Syst 102(1–3):89–101. https://doi.org/10.1016/j.agsy.2009.07.004

Vanlauwe B, Wendt J, Giller KE, Corbeels M, Gerard B, Nolte C (2014) A fourth principle is required to define conservation agriculture in sub-Saharan Africa: the appropriate use of fertilizer to enhance crop productivity. Field Crops Res 155(0):10–13. https://doi.org/10.1016/j.fcr.2013.10.002

Waha K, Müller C, Bondeau A, Dietrich JP, Kurukulasuriya P, Heinke J, Lotze-Campen H (2013) Adaptation to climate change through the choice of cropping system and sowing date in sub-Saharan Africa. Glob Environ Change 23(1):130–143. https://doi.org/10.1016/j.gloenvcha.2012.11.001

Wang Z, Qi Z, Xue L, Bukovsky M, Helmers MJ (2015) Modeling the impacts of climate change on nitrogen losses and crop yield in a subsurface drained field. Clim Change 129(1–2):323–335. https://doi.org/10.1007/s10584-015-1342-1

Wallach D, Makowski D (2006) Working with dynamic crop models: evaluating, analyzing, parameterizing, and applications. Elsevier, Amsterdam [etc.]

Whitbread AM, Robertson MJ, Carberry PS, Dimesd JP (2010) How farming systems simulation can aid the development of more sustainable smallholder farming systems in southern Africa. Eur J Agron 32:51–58

Wichkham H (2009) ggplot2: legant gaphisc for data analysis. Springer-Verlag, New York

Wilson DR, Muchow RC, Murgatroyd CJ (1995) Model analysis of temperature and solar radiation limitations to maize potential productivity in a cool climate. Field Crops Res 43(1):1–18. https://doi.org/10.1016/0378-4290(95)00037-Q

Wolski P, Lobell D, Stone D, Pinto I, Crespo O, Johnston P (2020) On the role of anthropogenic climate change in the emerging food crisis in southern Africa in the 2019–2020 growing season. Glob Chang Biol 26(5):2729–2730. https://doi.org/10.1111/gcb.15047

Zabel F, Muller C, Elliott J, Minoli S, Jagermeyr J, Schneider JM, Franke JA, Moyer E, Dury M, Francois L, Folberth C, Liu W, Pugh TAM, Olin S, Rabin SS, Mauser W, Hank T, Ruane AC, Asseng S (2021) Large potential for crop production adaptation depends on available future varieties. Glob Chang Biol 27(16):3870–3882. https://doi.org/10.1111/gcb.15649

Zingore S, Delve RJ, Nyamangara J, Giller KE (2008) Multiple benefits of manure: the key to maintenance of soil fertility and restoration of depleted sandy soils on African smallholder farms. Nutr Cycl Agrosyst 80(3):267–282

Authors and Affiliations

Leonard Rusinamhodzi[1] · **David Berre**[2] · **Christian Thierfelder**[3] · **Santiago-Lopez Ridaura**[4] · **Marc Corbeels**[2,5]

✉ Leonard Rusinamhodzi
L.Rusinamhodzi@cgiar.org; leonard.rusinamhodzi@gmail.com

1 International Institute of Tropical Agriculture (IITA), Accra, Ghana

2 CIRAD, UPR AIDA, Univ Montpellier, Avenue Agropolis, Montpellier F-34398, France

3 International Maize and Wheat Improvement Centre (CIMMYT), 12.5 Km Peg Mazowe Road, Harare, Zimbabwe

4 International Maize and Wheat Improvement Centre (CIMMYT), Apdo., Mexico, D.F Postal 6-641 06600, Mexico

5 International Institute of Tropical Agriculture (IITA), Kasarani, Duduville Campus, P.O. Box 30772-00100, Nairobi, Kenya