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Simulating medium-term effects of cropping system diversification on soil fertility and crop productivity in southern Africa

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ABSTRACT

Diversification of cropping is perceived as a strategy to simultaneously achieve high productivity and maintain environmental sustainability. In southern Africa, however, due to a lack of medium to long-term field trials, there is missing quantitative information. Utilising the capability of agro-ecosystem models to quantify the interactions of crop productivity with management and environmental variables, the APSIM model was evaluated against six and an eight-year field trial datasets comprised of different crop rotations and fertiliser rates under two contrasting agro-ecological conditions in South Africa (clay soil with a mean rainfall of 871 mm versus a sandy soil with a 570 mm rainfall). Model output was compared to observed grain yield, aboveground dry matter, soil organic carbon (SOC), and mineral nitrogen (N_{min}) dynamics. APSIM was able to reproduce the observed grain yield dynamics fairly well as indicated by a Wilmott index of agreement of 0.90. Prediction accuracy, as indicated by the absolute model error across all crops, however, only reached 39%. Simulated N_{min} and SOC dynamics showed similar patterns to the observations.

Subsequently, the model was applied in a ten-year simulation experiment with rotation treatments (14 rotations, respectively intercropping systems, including a maize monoculture control), fertiliser levels (zero and 70 kg N ha^{-1}), and residue management (retained and removed) for the two sites. For low input systems, such as smallholder farms, residue management and legume integration are of the utmost importance to maintain SOC and more pronounced Nmin levels, which, for the sandy soil, resulted in an average maize yield increase of up to 1000 kg ha^{-1}. Maize monoculture treatments with residues removed reduced SOC moderately by 0.04–0.08 %, while yields declined strongly (> 1000 kg ha^{-1}) over the simulated period of ten years. In commercial, fertilised cropping systems, allocating land to cultivate crops other than maize reduced the simulated total yield performance. This diversification disadvantage has to be considered against the benefits of increased SOC and yields in the medium-term, i.e. a period of ten years. For the commercial systems, maize intercropped with delayed sown oats or cowpea appeared promising.

1. Introduction

Food insecurity and poverty remain major challenges in Africa, where the population is projected to double by 2050 as compared to 2010 (United Nations, 2019). Alongside increased food production demands this development places a burden on limited natural resources. This is especially true for southern Africa, where natural resources for agriculture are fragile and prone to degradation, such as soil organic matter depletion, soil erosion, acidification and nutrient mining (Lal and Stewart, 2010; Swanepoel et al., 2016). The Sustainable Development Goals (SDGs), as adopted by all the United Nations (UN) member states in 2015, aim to find solutions to these environmental problems, and simultaneously improve livelihoods. Sustainable and productive agricultural practices could reduce poverty, improve

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nutrition and contribute towards food security (United Nations, 2018).

Intensive, commercial agriculture depends on high external inputs to maximise productivity and increase food production. However, such agricultural intensification comes with its own challenges, such as negative environmental impacts, contributions to global warming through greenhouse gases emissions (Garnett et al., 2013; Tilman et al., 2011), reduction of soil quality through erosion, and loss of soil organic matter (specific for southern Africa: Swanepoel et al., 2016; van der Laan et al., 2017). Furthermore, these high input approaches are not attainable for many smallholder farmers, who often do not have access to the associated inputs. Southern Africa has a dual agricultural economy, consisting of commercial and smallholder farming systems. For instance, in South Africa small-scale farming alone supports around 13 million people, linked to four million farms (~30 % of arable land) according to Mkuhlani et al. (2019). However, in 2015 around 95 % of the maize produced in South Africa came from commercial farms (Greyling and Pardey, 2019).

Maize is the most important crop in the region for both commercial and subsistence systems (FAOSTAT, 2019), as it is a productive crop, provides large amounts of calories, and is relatively robust against pests. Also, due to market prices and demand, the inclusion of maize in a cropping system tends to be most profitable (Swanepoel et al., 2018a). However, it is argued that more complex rotations are better equipped to achieve long-lasting soil fertility, and reduce the risk of complete failures by increasing the number of crops planted in a given year (Davis et al., 2012; Shiferaw et al., 2014).

Selecting an appropriate cropping system for a particular site requires sound empirical site-specific data on the interactions between management and environment. Typically, such data is generated by field trials. In particular, medium-term, defined as 6–10 years, and long-term, defined as 11–20 years, field trials are required to understand the effect of cropping system on slowly changing variables, such as soil organic carbon (SOC) and medium to long-term yield trends driven by management, as variable seasonal rainfall can strongly modify temporal patterns. Yet, in a recent study on conservation agriculture in South Africa it was found that 78% of field trials lasted less than five years (Swanepoel et al., 2018b). The few existing long-term trials only cover some specific topics, such as the fertiliser trial at the University of Pretoria (1939-present), the sugarcane trial at Mt. Edgecombe (1939-present), or the wheat/ burning trial at Bethlehem (1933-present). Equally, medium-term field trials are lacking. Unfortunately, for many of the medium- to long-term trials, rigorous records of management practices (such as fertiliser or biocide use) or trial monitoring variables (such as yield or soil analysis data) are limited, often due to institutional constraints and lack of funding. Such poor record-keeping tends to limit knowledge gains and data sharing alike (Swanepoel et al., 2018b).

In situations of scarce field data, Whitbread et al. (2010) suggested that process-based crop modelling might be a suitable option to support the identification of best site-specific cropping systems, given its capability to carry out millions of virtual experiments within days. Indeed, crop modelling has become a popular method with which to explore the effect of planting dates, cultivar choice, intercropping options, and nutrient limitations on crop yields in southern Africa (for instance, Chimonyo et al., 2016; Hoffmann et al., 2018b; Rurinda et al., 2015; Rötter and van Keulen, 1997). However, most of these studies are limited to a single season, and only few studies investigated seasonal carry-over effects (Masikati et al., 2014; Ncube et al., 2009; Robertson et al., 2005). Still, these medium-term simulation studies are restricted to a maximum of two years of field trial data for calibration and testing, therefore limiting their usefulness and applicability in the region so far.

With the potential usefulness of agro-ecosystem modelling in mind, this study evaluated a process-based crop simulation model, the Agricultural Production Systems sIMulator (APSIM) (Holzworth et al., 2014), against data from six- and eight-year trials in maize producing areas of South Africa (Swanepoel et al., 2018a), and, secondly, applied the model to explore the effects of different cropping systems along a diversification gradient at two sites with contrasting environmental conditions. The study examined the effects of a simple maize monoculture in comparison to varying different (complex) cropping arrangements (rotations and intercropping). Varying crop residue and fertiliser applications were also assessed in terms of yield trends, production risk and average crop productivity, as well as soil fertility over a period of ten years, which we considered as medium-term.

2. Material & methods

The agro-ecosystem model APSIM version 7.7 (Holzworth et al., 2014) was applied as a key tool. Hence, a quick overview about its main features is provided: plant development and growth, as affected by temperature, radiation, and water and nutrient supply, are simulated on a daily time-step, also calculating nitrogen (N) and water dynamics (Probert et al., 1998). Organic matter turnover is simulated based on the concept of dividing it in three pools, FOM (fresh organic matter), FBIOM (fast decomposing pool), and FINERT (hardly decomposing pool). For water dynamics, the standard tipping bucket module in APSIM, called SOILWAT, is utilised. Potential evapotranspiration is simulated using a modified Priestley-Taylor approach (Priestley and Taylor, 1972). Runoff is calculated using the USDA runoff curve number approach linking empirical rainfall intensity and texture. A wide range of crops can be modelled in APSIM. Of relevance for this study are maize (*Zea mays*) (Carberry and Albrecht, 1991), pearl millet (*Pennisetum glaucum*) (van Oosterom et al., 2001), sunflower (*Helianthus annuus* L.) (Chapman et al., 1993), oats (*Avena sativa*), and the legumes soybean (*Glycine max*) and cowpea (*Vigna unguiculata*) (Robertson et al., 2002). While APSIM has been applied globally, many studies since the early 1990s have been conducted for these crops in sub-Saharan Africa (Keating and Thorburn, 2018); for a specific overview on crop modelling in southern Africa see Whitbread et al. (2010); for cowpea (Ncube et al., 2009; Sennhenn et al., 2017), soybean (Mabapa et al., 2010), pearl millet (Akponikpè et al., 2010), and maize (Rurinda et al., 2015). The model has not only been applied for monocultures in southern Africa, but also for intercropping (Chimonyo et al., 2016), and for investigating residue management effects in rotations (Masikati et al., 2014; Ncube et al., 2009; Robertson et al., 2005).

2.1. Evaluation of model performance

2.1.1. Field trial data for evaluation

To calibrate and evaluate the APSIM model, we used data from two medium-term field trials, Buffelsvlei and Zeekoegat, located in the key maize growing regions of South Africa. More detailed information on both trials can be found in Swanepoel et al. (2018a). Here, we summarise the key information:

Buffelsvlei (26°29'42“S, 26°36'07”E, altitude: 1390 m a.s.l.) hosted an eight year on-farm trial (2009–2016) following continuous cropping at the site in the North West Province. This site has a sandy soil, is situated in the arid steppe region, and received an annual rainfall of 570 mm year^{-1} over the trial period, with average maximum and minimum temperatures of 26.2 °C and 9.6 °C, respectively. Zeekoegat (25°36'55“S, 28°18'56”E, altitude: 1168 m a.s.l.) hosted a six year on-station trial (2007-2013), at the Zeekoegat Experimental Farm, Gauteng Province. This site was fallow prior to the trial. It has a clay soil, is situated in a warm temperate region, and received annual rainfall of 871 mm year^{-1} over the trial period with average maximum and minimum temperatures of 27.0 °C and 10.7 °C, respectively. For both sites, most of the precipitation (on average > 80 % of annual amount) occurred during the summer cropping season (November to April). Rainfall is highly variable between and within seasons, and consequently greatly affects dryland crop production.

At Buffelsvlei, the experiment followed a randomised complete block design with four replicates, comparing maize conventional tillage with five cropping systems under reduced tillage: i) maize monoculture, ii) maize/sunflower rotation, iii) maize/cowpea rotation, iv) maize/sunflower/pearl millet rotation, and v) maize/cowpea/pearl millet rotation. To have each crop represented every year, additional plots were added in each system, for example, the maize/sunflower rotation was mirrored by a sunflower/maize rotation. Crop management followed standard farming practices in the area: planting main crops took place from November to December, followed by legumes a few weeks later, depending on the soil water status. Fertiliser rate was determined according to annual soil analyses and ranged for N between 10 and 107 kg N ha^{-1} $year^{-1}$ (in maize: 35–107 kg N ha^{-1} $year^{-1}$, legumes 10–25 kg N ha^{-1} $year^{-1}$, sunflower 17–97 kg N ha^{-1} $year^{-1}$, millet 13 97 kg N ha^{-1} $year^{-1}$). Additionally, phosphorous (8-20 kg ha^{-1} $year^{-1}$) and potassium (4–11 kg ha^{-1} $year^{-1}$ one exception in 2008/09 sunflower received no potassium) were applied annually to each crop. The cultivar planted was the same each year. In a few cases, a certain cultivar was no longer available and was replaced by a similar one (Suppl. Material Table S1). At the start of the season, residues were flattened and slashed when still standing (like maize and pearl millet), and furrows were made for planting in the no-till treatments. In the conventional comparison, residues were incorporated into the soil, while crop remnants remained on the soil surface in reduced tillage treatments.

At Zeekoegat, the experiment followed a randomised complete block design with three replicates. Twelve treatments were implemented, consisting of a combination of six rotations and two fertiliser levels (low and standard fertiliser) and two tillage levels (reduced tillage and conventional ploughing). The rotations, respectively intercropping systems, were: i) maize monoculture, ii) maize/ cowpea rotation, iii) maize/soybean rotation, iv) maize/cowpea intercropping, v) maize/ oat intercropping and vi) maize/vetch intercropping. The maize/vetch treatments were excluded as vetch has not yet been parameterised in APSIM. Furthermore, the reduced till treatments at Zeekoegat resulted in complex effects on soil physical properties, which cannot currently be captured in the model, and were subsequently excluded (see Section 2.1.2 for a detailed explanation). Management followed standard agronomic practices for the region: Planting took place from November to December, following the first significant rain of at least 20 mm within three to six days. The same cultivars common to the region were planted each year (Suppl. Material Table S1). Standard fertiliser treatments received N between 67 and 72 kg N ha^{-1} $year^{-1}$ (in maize: 67–72 kg N ha^{-1} $year^{-1}$, legumes 0 N ha^{-1} $year^{-1}$, oats 28–46 kg N ha^{-1} $year^{-1}$). Additionally, phosphorous (5–20 kg N ha^{-1} $year^{-1}$) was applied annually. Potassium was given only in the first year (8-12 kg ha^{-1} year-1) due to the high potassium content of the soil. The low fertiliser treatments received half of the standard dose. At harvest, grains were removed, but the residues were left in the field (only a sample was removed to determine aboveground dry matter). Bulky residues were slashed to ease subsequent farming practices such as ploughing and drawing furrows, to avoid crop residues being drawn across the trial. Conventional plots were cultivated to 300 mm soil depth with a mouldboard plough, followed by a disk harrow or four-tine implement to create furrows for planting.

Data collected from the two sites included grain yield, aboveground total dry matter and SOC. At Zeekoegat, N_{min} samples were taken before sowing.

2.1.2. Model setup and calibration

The following steps were conducted to set up the calibration of APSIM: weather data (nearby weather stations, Buffelsvallei (26.49487^{0}S 26.60200^{0}E), and Roodeplaat (25.60398^{0}S 28.35429^{0}E) were used for Buffelsvlei and Zeekoegat, respectively (ARC-SCW, 2015), which included daily maximum and minimum temperatures, solar radiation and precipitation for the trial period. The soils at Zeekoegat and at Buffelsvlei were parameterised as follows: Soil organic carbon and pH (H_2O) were measured to a depth of 60 cm for Zeekoegat and to a depth of 30 cm for Buffelsvlei at the start of the trial at each site (Table 1). In the layers below the sample depth, SOC was assumed to half every thirty centimetres as suggested by Dalgliesh et al. (2016) and pH was kept constant. At Zeekoegat volumetric soil water content was calculated after extended dry periods and after wet periods from gravimetric soil water measurements in the field. The results were used for crop lower limit (CLL), also known as soil moisture content at wilting point, and drained upper limit (DUL), also known as field capacity, respectively. Soil bulk density (BD) at Zeekoegat was measured for the whole profile. At Buffelsvlei CLL, DUL and BD were estimated using pedo-transfer functions as described by Saxton and Rawls (2006) with measured SOC (0–30 cm, with deeper values halved as described above) and soil texture values (0–60 cm, with deeper values assumed to be the same as above) as input (Table 1). Saturation at both sites was determined using the approach by Dalgliesh and Foale (1998).

Apart from this general setup, further input data necessary for model calibration was obtained by visually matching simulation results for yield, dry matter and N_{min} against observed ones from the following treatments (Fig. 1a & b, Supplementary material: Fig. 1): at Buffelsvlei: maize/cowpea and pearl millet/sunflower/maize, and at Zeekoegat N_{min} maize/cowpea rotation and intercropped low fertiliser, maize/oat intercropped low fertiliser and maize/soybean intercropped low fertiliser. The treatments were chosen because they contained all crops and systems. At Zeekoegat, the low fertiliser treatments were chosen on the basis that they could provide deeper insight into the mineralisation of the organic matter.

In addition, the calibrated values had to be within ranges suggested by the literature (Dalgliesh et al., 2016; Hoffmann et al., 2017; Whitbread et al., 2017). This included the KL value, which describes the fraction of water a plant can take up per day from a specific layer (Suppl. Material Table S2). The runoff curve number was set according to soil texture for Zeekoegat to 85 and for Buffelsvlei to 63. Similarly, the SWCON for saturated water flow to 0.3 for Zeekoegat and 0.7 for Buffelsvlei, and Diffcon and Diffslope for unsaturated soil water conditions to 40 and 16 for Zeekoegat and 250 and 22 for Buffelsvlei, respectively. The first and second evaporation terms, Con and U, used in the adjusted Priestly-Taylor approach of APSIM, was set to 6 and 3.5 for the summer and 4 and 2 for the winter period at Zeekoegat, and 4 and 2 for both periods at Buffelsvlei. Rooting extent, as represented by the XF factor, also called the hospitality factor for root growth for each layer, was estimated based on expert knowledge (Suppl. Material Table S3). The two soil organic fractions, which need to be determined in APSIM, are FBIOM and FINERT, which were set within ranges reported in the literature (Suppl. Material Table S4) (Dalgliesh et al., 2016; Hoffmann et al., 2018a). Initial surface organic matter was estimated as 1000 kg ha^{-1} of maize at Buffelsvlei and 8000 kg ha^{-1} of grass at Zeekoegat reflecting the land use/cultivation history of the two sites. Initial soil water at both sites, and N_{min} at Buffelsvlei, was not available, and consequently determined by inverse modelling using the calibrated treatments. As stated above, the treatments for calibration were purposefully chosen to include all crops/ cultivars used in the rotation. As no information was available on cultivar traits (including phenology, apart from recalled harvest dates) from the trials, such aspects were only slightly adapted for a maize cultivar based on an existing APSIM cultivar. For the other crop cultivars no changes were made to the APSIM default cultivar parameters, since harvest dates were just recalled and APSIM had already been evaluated for most of the cultivars in southern Africa. All information is presented in Table S1 (Suppl. Material).

A key challenge for the simulations was to capture the growth dynamics at Zeekoegat, where two high yielding years were followed by a number of low yielding years (Fig. 1b). This could not be explained by the rainfall pattern or biotic stress events. Deeper investigation into the matter showed a development of compaction in the subsoil, which may have limited the root growth to 30 cm. Hence, maximum rooting depth was reduced from 75 cm to 30 cm after the second season by setting the XF factor from 1 to 0 in the layers below 30 cm.

Table 1
Soil properties (bulk density (BD), crop lower limit (CLL), drained upper limit (DUL), saturation (SAT), pH and total soil organic carbon (SOC) used for soil parameterisation in APSIM.

Name	Layer No	Thickness (mm)	BD (g cm^{-3})	CLL (mm mm^{-1})	DUL (mm mm^{-1})	SAT (mm mm^{-1})	pH H_2O	SOC (%)
Zeekoegat	1	100	1.467	0.142	0.359	0.416	6.00	1.65
Zeekoegat	2	120	1.467	0.142	0.359	0.416	5.90	1.61
Zeekoegat	3	80	1.435	0.142	0.359	0.428	5.90	1.34
Zeekoegat	4	80	1.338	0.187	0.369	0.465	5.90	0.65
Zeekoegat	5	140	1.338	0.187	0.369	0.465	5.90	0.39
Zeekoegat	6	230	1.285	0.176	0.377	0.485	5.90	0.13
Buffelsvlei	1	150	1.600	0.099	0.154	0.326	5.99	0.61
Buffelsvlei	2	150	1.600	0.098	0.152	0.326	5.03	0.57
Buffelsvlei	3	300	1.610	0.135	0.201	0.322	4.88	0.53
Buffelsvlei	4	300	1.620	0.133	0.198	0.319	4.88	0.52
Buffelsvlei	5	200	1.620	0.133	0.198	0.319	4.88	0.26
Buffelsvlei	6	200	1.630	0.131	0.196	0.315	4.88	0.26
Buffelsvlei	7	200	1.630	0.131	0.196	0.315	4.88	0.13
Buffelsvlei	8	300	1.630	0.131	0.196	0.315	4.88	0.13

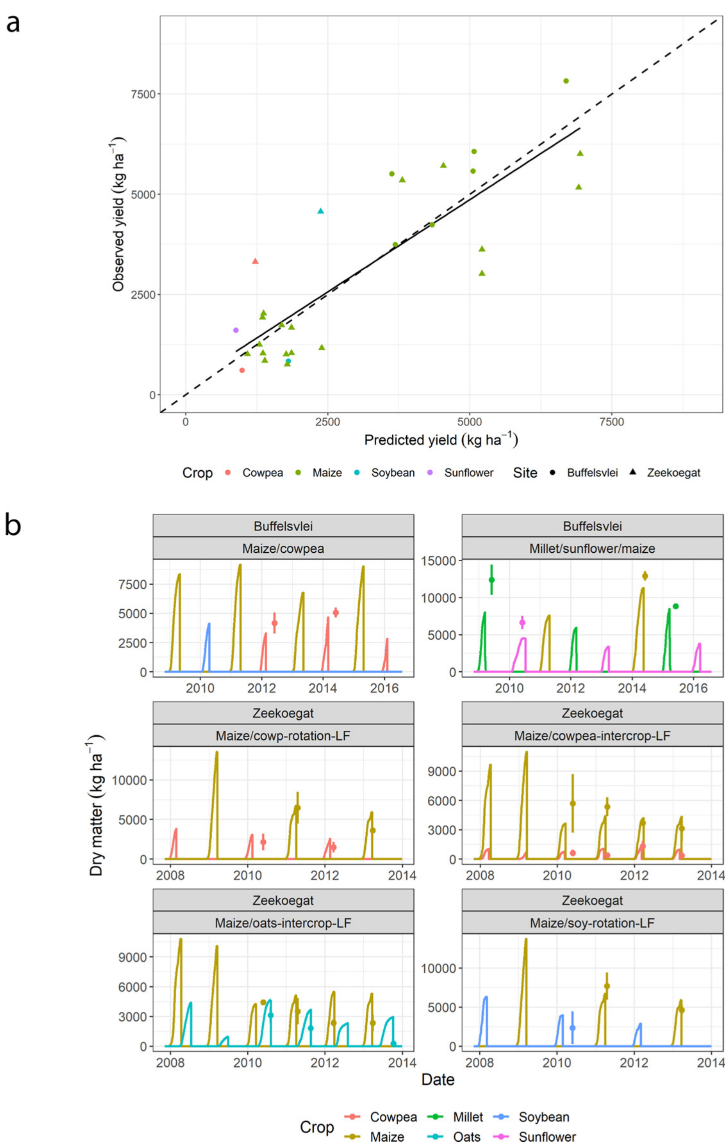

Fig. 1. (a) Observed versus predicted yield across each year, site and treatment for the calibration exercise. Marker colour indicates crop types and marker shape indicates site, the dashed line is the 1:1 line, and the straight line is the regression line across all data points (n = 29). (b) Observed versus predicted dry matter for Zeekoegat and Buffelsvlei over the project period for the calibration exercise. The solid line indicates predicted results. Markers indicate mean observed values (n = 28). Bars indicate standard deviation for observed values. Title of each facet gives site, crops, cropping system (rotation or intercropping) and fertiliser level, which was, in the case of the calibration, always low fertiliser (LF). Note that crop measurements were not available for all seasons.

2.1.3. Statistical analysis of model performance

All treatments not used for calibration were used to evaluate model performance in terms of dry matter and grain yield independently. As in other studies (Archontoulis et al., 2014; Hoffmann et al., 2018a), a range of statistical indicators was applied to describe model accuracy and robustness: root mean square error (RMSE), and its normalisation (nRMSE 0–1, the closer to zero the better), model efficiency (EF indefinte-1, the closer to one the better), the Willmott index of agreement

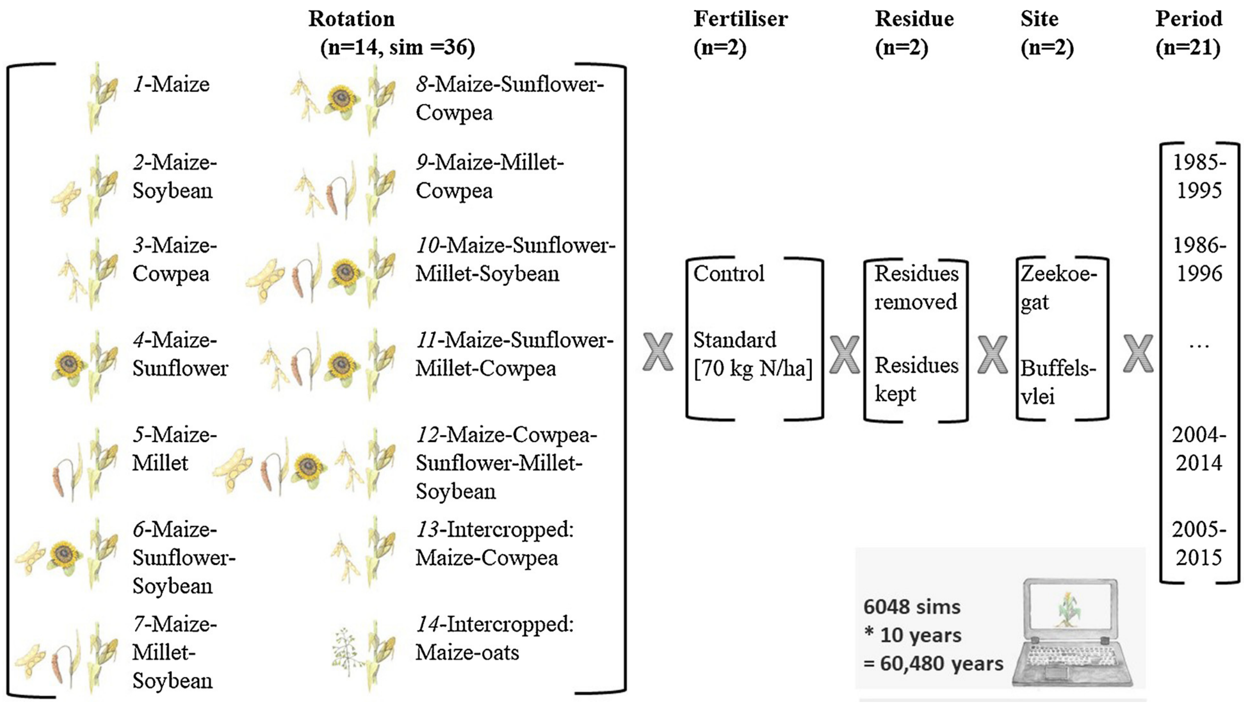

Fig. 2. Overview of the different factors taken into account for the simulation experiment. This constitutes the overall cropping system; rotation, fertiliser, residue management, plus the environment characterised by site and simulation period; in brackets, the number of levels. For rotations with a temporal sequence of crops, simulations were conducted with each crop as the starting crop; resulting in, for instance with a rotation including five crops, five different independent simulations.

(IA 0–1, the closer to one the better), and adjusted r regression analysis (the closer to one the better). All data analyses were done using R software (R Core Team, 2016) and the goodness-of-fit function from the package 'ZeBook' (Wallach et al., 2019) for statistical evaluation of grain yields and dry matter across all crops and each crop individually. Taking the high uncertainty of N_{min} data and the non-responsiveness of SOC towards treatment effects into account, we simply inspected results visually by plotting simulated and observed values over time to see whether the model results capture resource dynamics.

2.2. Simulation experiment

2.2.1. Model setup

For the simulation experiment, three treatments were chosen that constituted the cropping system diversification in the study: rotation, fertiliser and residue management (Fig. 2). Simulations were done for two sites and 21 different historical climate conditions.

Rotation is defined in a wider sense: including intercropping and monoculture systems. In total, 14 different rotations were chosen, reflecting the aim of using the model within the evaluated ranges of crop types, residue management and fertiliser treatments. Rotations ranged from standard maize monocultures to highly complex rotations with five crops in a sequence. For the sake of having maize yield data in each year, rotation simulations were conducted with varying crop sequences, having each crop as the first as part of a rotation cycle. For instance, a rotation with five crops in a sequence resulted in five simulations for it. Fertiliser management levels for the crops maize, millet and sunflower were controlled without any N applications (zero); and standard fertilisation, which consisted of 70 kg N ha^{-1} split into two equal doses - at sowing and 35 days after sowing. Legume crops (cowpea, soybean) did not receive N fertiliser. Oats intercropped with maize did not receive additional fertiliser on top of what was already applied to the maize crop. Two levels of residue management were introduced: one where all residues were removed, and one where all residues remained in the field. Initial surface organic matter was set to 0 kg ha^{-1}.

Site and soil set-up was as in the evaluation dataset for Zeekoegat and Buffelsvlei. For Zeekoegat, the rooting depth was restricted to 30 cm, which was found to realistic based on the assumption that previous cropping took place with no fallow period. This reflects that compaction is a common problem in South African clay soils (Bennie and Krynauw, 1985; Kayombo and Lal, 1993). According to Smith et al. (1997), soils in plantations with between 50 and 70 % clay underwent the greatest increase in compaction as measured by the compression index.

Initial N_{min} was 35 kg N ha^{-1} for 0–90 cm and initial water set to field capacity. This remained the same for all simulations.

To disentangle the medium-term effects from the seasonal variation in climate, we ran this simulation setup for 21 historical periods: 1985⁻1995, 1986⁻1996 and so forth until 2005-2015. Using this method, 21 replicates of a ten-year period were produced, capturing the carry-over effects as part of a longer simulation period of 10 years. By having 21 climate variations for each cropping year (from cropping year one to cropping year ten) the effect of the seasonal specific climate on medium-term patterns of yield dynamics was minimised. This helped to isolate the medium-term management effects.

There were no on-site climate records for the medium-term periods (defined by a period of up to 10 years) investigated. Thus, we used the NASA power larc dataset (NASA, 2017). We trained this dataset against the on-site data for the available dates using simple linear regression - for details, see Suppl. Material Fig. S2). Derived relationships were used to generate medium-term weather records. This data source has been widely used (van Wart et al., 2015), including for South Africa-based studies (Moeletsi and Walker, 2012; Rapholo et al., 2019). For temperature and solar radiation, we found an excellent fit, but the observed extreme rainfall events at Zeekoegat were not captured.

Besides these changes, all management options were kept constant reflecting standard management practices in the region as applied in the experiments.

2.2.2. Analysis of simulation experiment

We compared the effect of rotation, fertiliser and residue management for the two sites with regard to the following seven indicators (four for crop productivity and three for soil fertility):

(i) Grain yield per crop (kg ha^{-1}): average yield of each crop and summed up for each rotation, fertiliser and residue management practice. To account for the effect of rotations with several crops in reality, farmers would have to sacrifice maize areas to enable a fair comparison. The yield per hectare was divided by the number of crops per sequence. For instance, for a rotation with four crops, yield for each crop is simulated as kg per hectare and was consequently multiplied by 0.25 to capture the notion that only one fourth of the land would be dedicated to this specific crop. Special attention was given to whether simulated yields were above a 1000 kg ha^{-1} threshold. Yields below are considered too low to ensure the economic survival of the farm in the long-term.

(ii) Straw yield (kg ha^{-1}): the same approach was followed as for grain yield above.

(iii) Yield trends (%): the relative change between the maize yield in the final year and the maize yield in the first year was calculated by averaging values across the 21 periods. The difference may be a result of the previous 10 years of cropping. Season-specific weather conditions were cancelled out by taking the average difference across 21 ten-year periods. Maize was chosen as it is the key staple crop - maize monocultures are often found as the 'default' cropping system in the region.

(iv) Total yield (kg ha^{-1}) in the worst (lowest) rainfall season as indicator for production risk: total grain yield as a sum of the individual crop yields was calculated for the season 2006/07. This season was chosen because of the lowest seasonal rainfall across all available seasons (October to April): At Buffelsvlei it was 298 mm and at Zeekoegat it was 722 mm.

(v & vi) Soil organic carbon (SOC) and total N (both in %): for the top 30 cm: the mean and the standard deviation of the simulated SOC value was used from Julian day 240 of the final year (a day at which most crops had been harvested).

(vii) Soil N_{min} (kg ha^{-1}): The average simulated N_{min} (nitrate + ammonium) for the top 30 cm for the final year of the simulation.

3. Results

3.1. Model evaluation

Overall, the dynamics of yields over the seasons and sites were captured well (Table 2), as indicated by an IA of 0.90 and model efficiency of 0.66 (Fig. 3) across all crops. The nRMSE and nRMAE for maize yields, which constitutes more than 60 % of all data points, were 0.33 and 0.27, respectively. When all crops were taken into account, the nRMSE and nRMAE were slightly higher at 0.39 and 0.31, respectively. Sunflower yield was predicted with a RMSE of 480 kg ha^{-1} against a generally low level of simulated yields mean (1119 kg ha^{-1}). The observed yields were low (1202 kg ha^{-1}) and were within a narrow range (minimum of 1046 kg ha^{-1} and a maximum of 1859 kg ha^{-1}). At Zeekoegat, cowpea and soybean yields were underestimated by the model, while cowpea was overestimated. However, the overall observation number was rather small (n = 4).

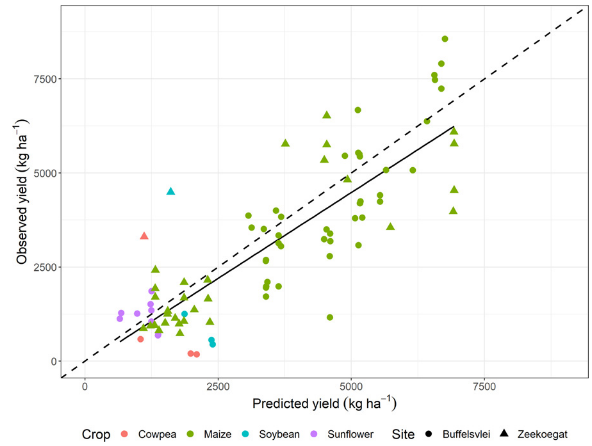

Fig. 3. Observed versus predicted yield across each year, site and treatment. Colour represents crop, and shape represents site. The dashed line is the 1:1 line and the straight line the regression across all data points.

Total above-ground dry matter was simulated slightly less accurately than grain yield, as indicated by the respective IA of 0.85 for all crops and 0.82 for maize only. The high dry matter potential of millet was reflected by the model, which simulated observed dry matter of around 9000 kg ha^{-1}. Cowpea, millet and sunflower dry matter were simulated with a similar level of accuracy of 0.33 to 0.40 nRMSE. Dry matter of oats was strongly overestimated, in particular in the season 2012/13 and 2013/14, where observed values were only 277, respectively 150 kg ha^{-1} (Fig. 4b). It should, however, be noted that for total dry matter much fewer data points were available than for grain yield (56 for all crops, 31 for maize only) (Table 2). At Zeekoegat, the simulated results matched the observed difference between maize and the companion crop well (Fig. 4a); and at Buffelsvlei model results correctly distinguished between high and low production years (Fig. 4b).

At Zeekoegat, N_{min} was also measured, which showed high N_{min} content at the beginning of the trial after a fallow period and a sharp decline thereafter (Fig. 5). There was a good match for sole maize-HF and the intercrops, but for the rotation treatment, the simulated Nmin content underestimated the measured values in the year 2010 (following a maize crop).

The model did not suggest significant changes for SOC at both sites over time. At Buffelsvlei, field-based variation from year to year was observed, which the model was not able to capture (Fig. 6a). Differences between observed and simulated values were, however, small in

Table 2
Statistical performance of the model for grain yield and dry matter (DM). For variables with n = 1 no statistical analysis is presented.

Var.	Crops	N	Mean obs kg ha^{-1}	Mean pred kg ha^{-1}	RMSE kg ha^{-1}	Rel. RMSE	MAE kg ha^{-1}	Rel. RMAE	EF inf-1	IA 0-1	Adj. r2
Yield	all	89	3118	3505	1207	0.39	978	0.31	0.66	0.9	0.7
Yield	maize	72	3552	3991	1178	0.33	965	0.27	0.65	0.9	0.7
Yield	soybean	4	1686	2065	1990	1.18	1821	1.08	−0.46	0	0.67
Yield	sunflower	9	1202	1119	480	0.4	432	0.36	−0.88	0.15	−0.11
Yield	cowpea	4	1066	1562	1728	1.62	1594	1.5	−0.76	0.04	0.11
DM	all	56	4992	5593	2346	0.47	1987	0.4	0.59	0.85	0.63
DM	maize	31	5728	6649	2525	0.44	2147	0.37	0.54	0.82	0.65
DM	soybean	1	913	3316							
DM	sunflower	7	5516	4596	2229	0.4	2090	0.38	−0.49	0.25	−0.05
DM	cowpea	10	2829	3000	908	0.32	768	0.27	0.88	0.96	0.91
DM	millet	3	9992	8953	3315	0.33	3148	0.32	−1.58	0	0.79
DM	oats	4	1040	3682	2679	2.58	2642	2.54	−8.62	0.45	0.62

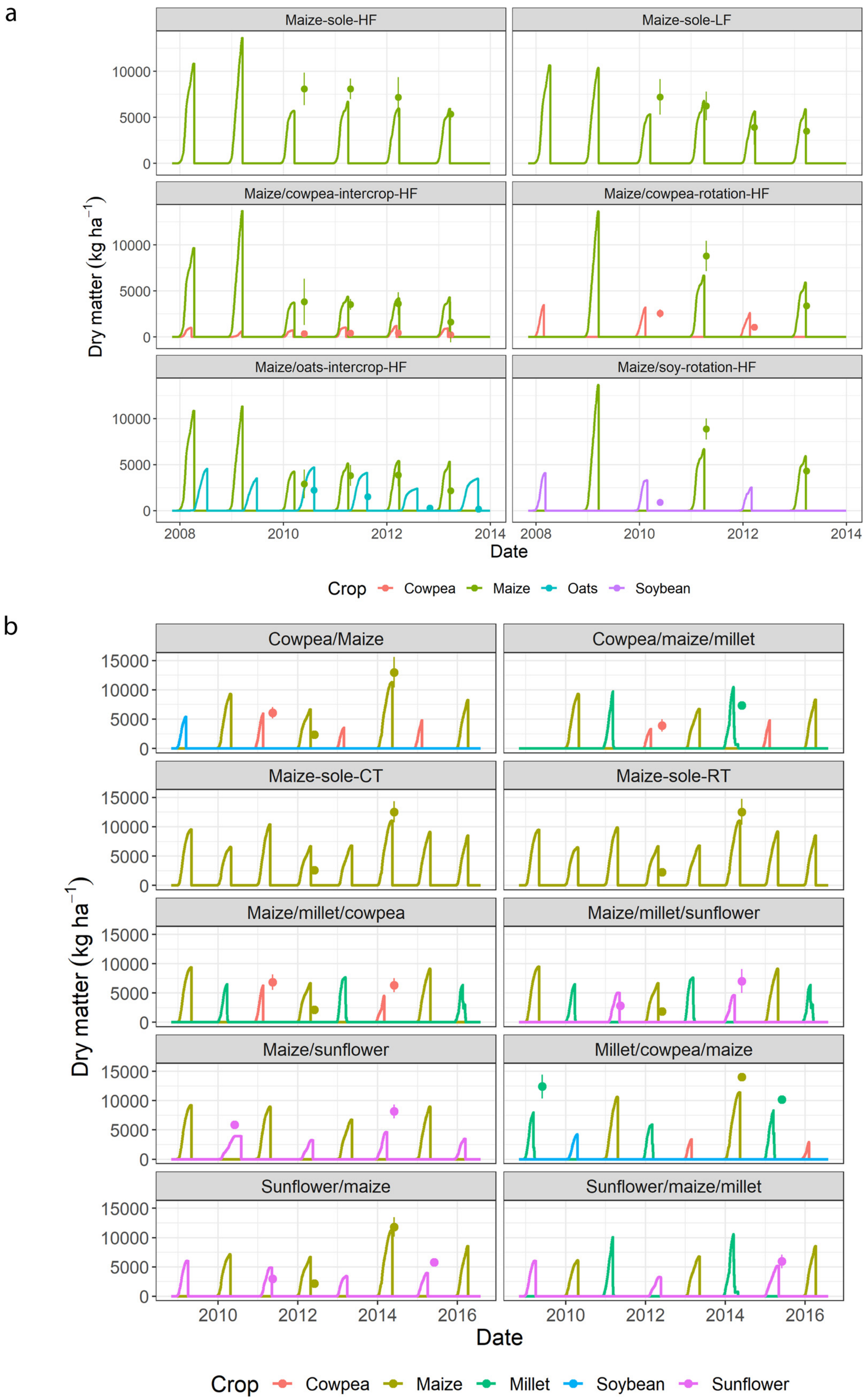

Fig. 4. (a) Dry matter production for Zeekoegat over the study period. Lines represent predicted results, points indicate mean observed values, and bars indicate standard deviation for observed values. The title of each facet describes crops, cropping system (sole monoculture, rotation or intercropping), and fertiliser level (high fertiliser (HF) and low fertiliser (LF)). (b) Dry matter production for Buffelsvlei over the study period. Lines represent the predicted results, points indicate the mean observed values, and bars indicate standard deviation for observed values. Titles of each facet lists the crops in the rotation sequence. Tillage systems for Buffelsvlei: conventional tillage (CT) and reduced tillage (RT) are included as well.

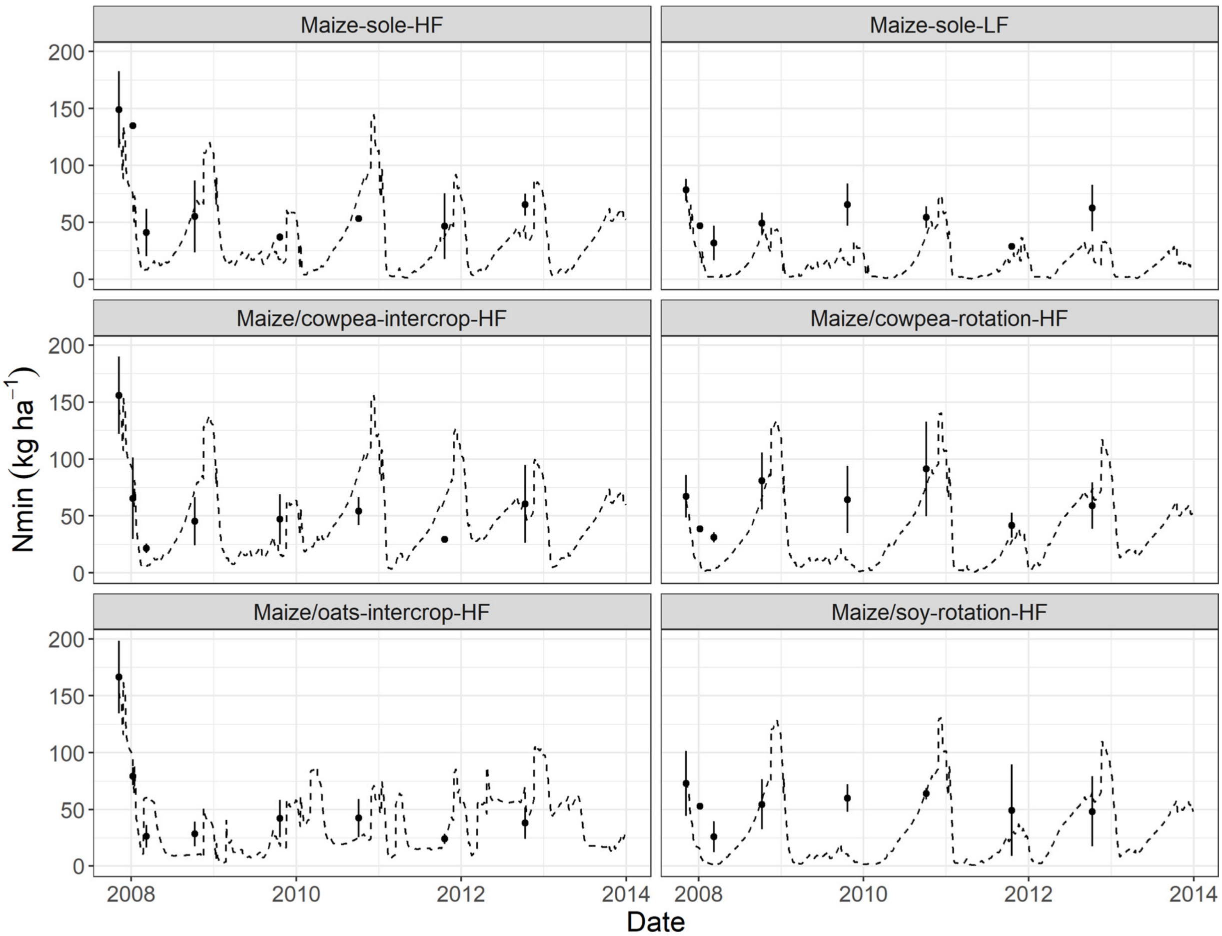

Fig. 5. Inorganic nitrogen content (kg ha^{-1}) in the top layer (0–30 cm) for Zeekoegat over the project period. Dashed lines are predicted results, markers indicate mean observed values, bars indicate standard deviations for observed values. Titles of each facet indicated the crop, cropping system (sole monoculture, rotation or intercropping) and fertiliser level (high fertiliser (HF) and low fertiliser (LF)).

absolute terms, *i.e.* just 0.1 to 0.15 %. At Zeekoegat, simulated results were within the measured error ranges (Fig. 6b).

3.2. Simulation experiment

The simulated results indicated that the highest average grain yields were achieved for fertilised treatments at both sites, where maize was planted every year: maize monoculture and maize intercropped with cowpea, and oats, respectively (Fig. 7a). At Buffelsvlei, maximum yields in the range of 4000 to 5000 kg ha^{-1} were attained when residues remained in the field. At Zeekoegat, maximum yields of around 3000 kg ha^{-1} were similar regardless of whether residues remained or were removed from the field. For the other treatments, the contribution of maize towards the total grain yield was diminished due to the smaller share of maize in the cropping area. The other crops, however, could not compensate for the reduction in crop production due to the decrease in area cultivated with maize. When no fertiliser was applied, the choice of rotation had a distinguished effect. Here, the rotation, which included legumes, namely cowpea and soybean, performed best. Unfertilised maize monoculture, or maize in combination with non-leguminous crops, led to the lowest yields of less than 1000 kg ha^{-1}.

For straw production a different pattern emerged (Fig. 7b): the inclusion of pearl millet, which had a low harvest index (HI), resulted in high productivity, outperforming other crops.

When we investigated the yield trend of maize as the most important crop in the region it became clear that maize yields declined by 40 % for non-leguminous rotations under zero fertilisation and when residues were removed (Fig. 8). When residues remained in the field under no fertilisation, and legumes were included, strong yield increases could be identified up to 1000 kg ha^{-1} for Buffelsvlei and 500 kg ha^{-1} for Zeekoegat (Supplementary Material Fig. S3). When rotations were fertilised, however, only slight yield changes could be detected over time (in the range of 1–15 %). However, it is striking that the fertilised intercropped systems led to a declining yield trend of up to 15%. Maize monoculture and maize-millet rotation also showed a decrease in maize yields at Zeekoegat. For the remaining rotations, slight yield increases of up to 5 % were simulated.

Production risk, as indicated by the simulated total yield for the low rainfall season 2006/07, was relatively low as only the rotation maize-sunflower under zero fertiliser yielded less than 1000 kg ha^{-1} (Fig. 9). Moreover, the low yield of this crop sequence can be related to N limitations rather than to water supply. While the yields for unfertilised conditions in the worst year were in a similar range to the average total yields across years, substantial reductions of up to 2000 kg ha^{-1} were simulated for standard fertiliser treatments. Under these fertilised conditions, cropping systems that were dominated by maize (maize monoculture, and maize intercropped) led to the highest yield in the worst season at both sites, Buffelsvlei (around 3000 kg ha^{-1}) and at Zeekoegat (around 2000 kg ha^{-1}) (Fig. 7a).

The SOC concentration in the first 0–30 cm in the final year was below the initial content at Zeekoegat by 0.03% and for unfertilised residue removed, and 0.06% > for fertilised removed (Fig. 10), which resulted for the given bulk density in a loss of 1000 kg ha^{-1}, respectively > 2000 kg ha^{-1}. Over ten years, this would translate into an average annual loss of 100 kg ha^{-1}, respectively 200 kg ha^{-1}. At Buffelsvlei, SOC was mainly 0.01% (non-fertilised) to 0.03% (fertilised)

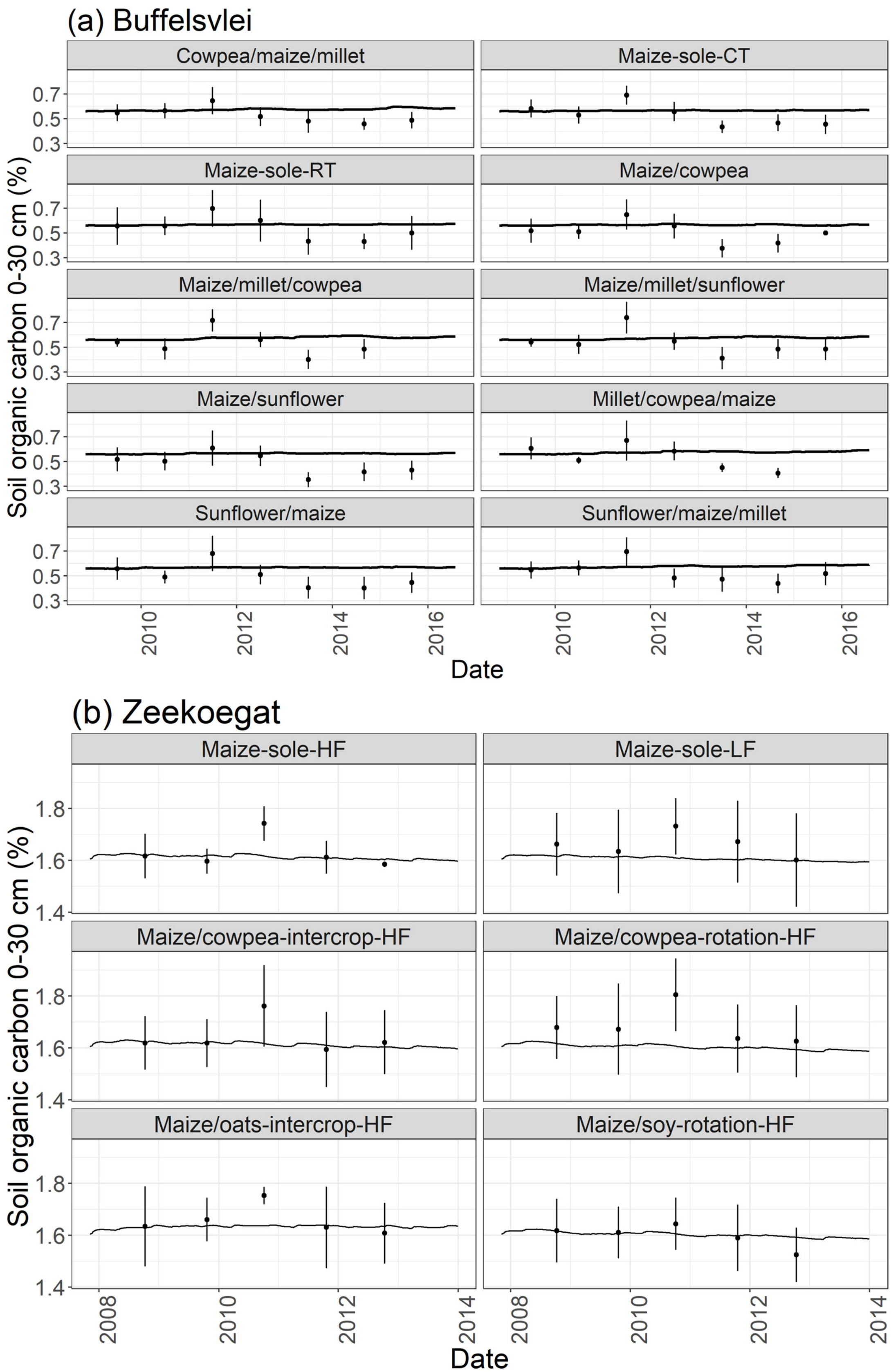

Fig. 6. a&b: Soil organic carbon content (%) in the top layer (0–30) for Buffelsvlei (a) and Zeekoegat (b) over the study period. Lines are predicted results. Points indicate mean observed values. Bars indicate standard deviations for observed values. The titles of each facet indicate the crop, cropping system (sole monoculture, rotation or intercropping) and fertiliser level (high fertiliser (HF) and low fertiliser (LF)).

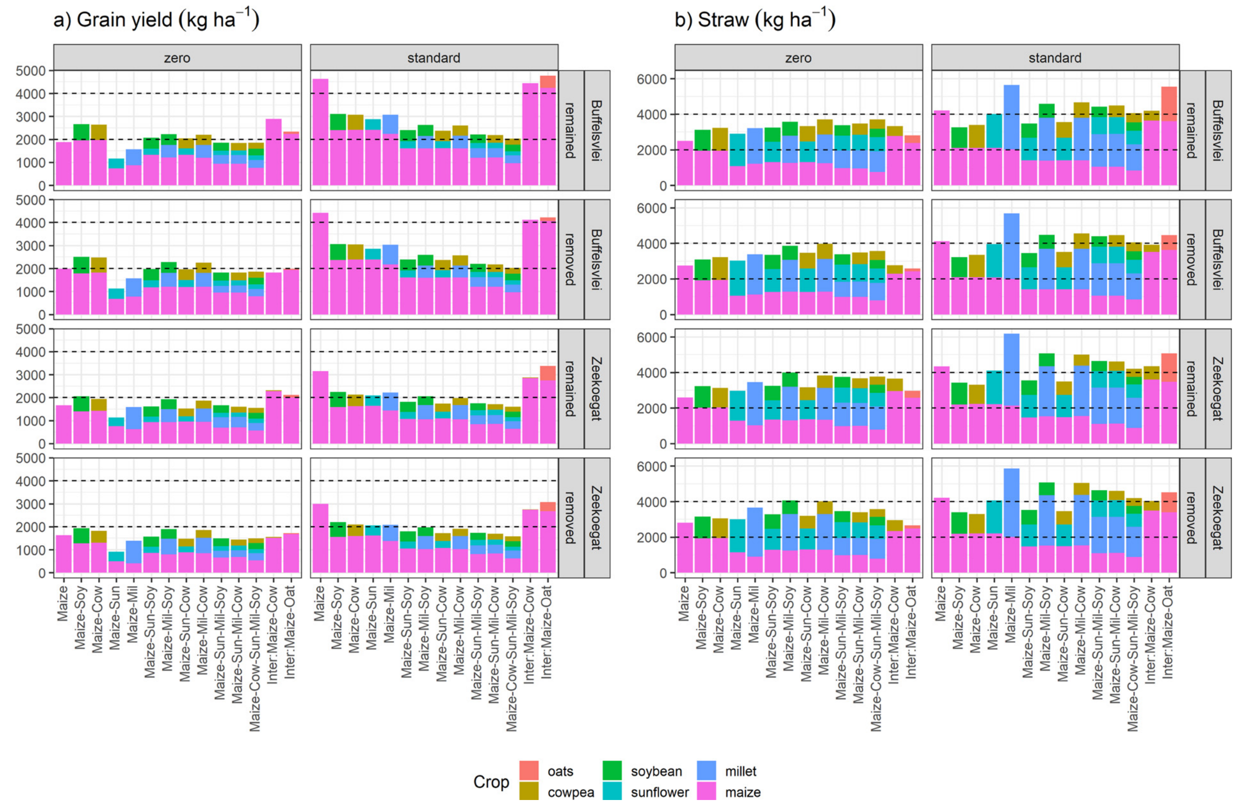

Fig. 7. a&b: Grain yields (a) and straw production (b) averaged over the 10 years for each simulated period for each rotation. Crop specific yields within the rotation are stacked. Vertical facets represent standard and zero fertiliser rates. Horizontal facets show the two sites and are nested in the residue management. Dashed lines are for better visualisation.

above initial conditions when residues remained in the field. An outlier was the intercropping treatment when fertilised and when residues remained. In this case, at both sites 0.09 to 0.10% (4,000–5,000 kg ha^{-1}) additional carbon was stored in the top soil. Total N followed the trend of simulated SOC (Suppl. Material Fig. S4). The C:N ratio remained almost constant, at 11.5–12 throughout the entire simulation period.

At Zeekoegat, there was a higher N_{min} content in the top 30 cm than at Buffelsvlei, reflecting the difference in SOC content at the two sites (Suppl. Material Fig. S5). Not surprisingly, N_{min} content was low when no fertiliser was applied. Residue management under this condition only had a marginal effect, *i.e.* had a slightly higher N_{min} content when residues remained in the field.

4. Discussion

4.1. Model performance

Overall, the model captured the seasonal, site- and treatment-specific yield dynamics as indicated by the high IA of 0.90 (Table 2). It must be mentioned that the evaluation covered a wide range of yield values from below 1000 kg ha^{-1} up to almost 8000 kg ha^{-1} for the 89 data points (Fig. 3). For maize yields, the nRMSE of 0.33 and the nRMAE of 0.27 showed that the model was also in a fairly reasonable range in terms of accuracy – similar model accuracy was reported by Rurinda et al. (2015). For the other crops, relatively few data points were available. Therefore, evaluation results need to be interpreted with caution. For soybean and cowpea, a distinct difference depending on the site could be observed. At Zeekoegat yields were underestimated, while at Buffelsvlei yields were overestimated. This might be related to the parameterisation of the soil. At Zeekoegat, the effect of compaction on the ability of the legumes to take up water might be overestimated. At Buffelsvlei, the hydrological properties were parameterised based on a pedo-transfer function. Differences between crop types in their ability to extract soil water might not be captured compared to field based measurements such as using rain-out shelter (Dalgliesh and Foale, 1998).

Total dry matter was simulated less satisfactorily than grain yield (nRMSE 0.47, nRMAE 0.40), possibly due to fewer available data points (n = 56) than for grain yields. Nevertheless, it appears that the dynamics at the two sites were captured (Fig. 4a & b; Table 2). The poor performance of the simulated oat dry matter was striking, where the model consistently overestimated the observed values. The oat model has rarely been evaluated, especially for southern Africa and requires more attention. The observed values in the last two seasons appear very low, therefore potential biotic stresses might have reduced the growth. However, no records were available to verify this. On the contrary, the high production of millet observed in the field trials was reproduced by the model with no specific cultivar calibration. The N_{min} data was evaluated visually in terms of whether it broadly captured the dynamics (Fig. 4). Data was available at Zeekoegat only. It was striking that the model underestimated the observed N_{min} content in the rotation treatments for the season 2009/2010, where a legume was planted following a maize crop. In those cases, no N fertiliser was given to legumes at sowing. Secondly, mineralisation (data not shown) after the previous maize crop with a high C:N ratio was relatively weak. That led to the low simulated Nmin content. In the field trial, maize stalks were flattened and chopped into smaller pieces using a disk, which might have accelerated N-mineralisation and caused the higher observed N_{min} value. The tillage event employed in the model influenced simulated N mineralisation through distributing a defined fraction of the surface residues in the different soil organic carbon pools, thereby subjecting them to different mineralisation rates. However, this did not reproduce the accelerated mineralisation observed in the field trial data.

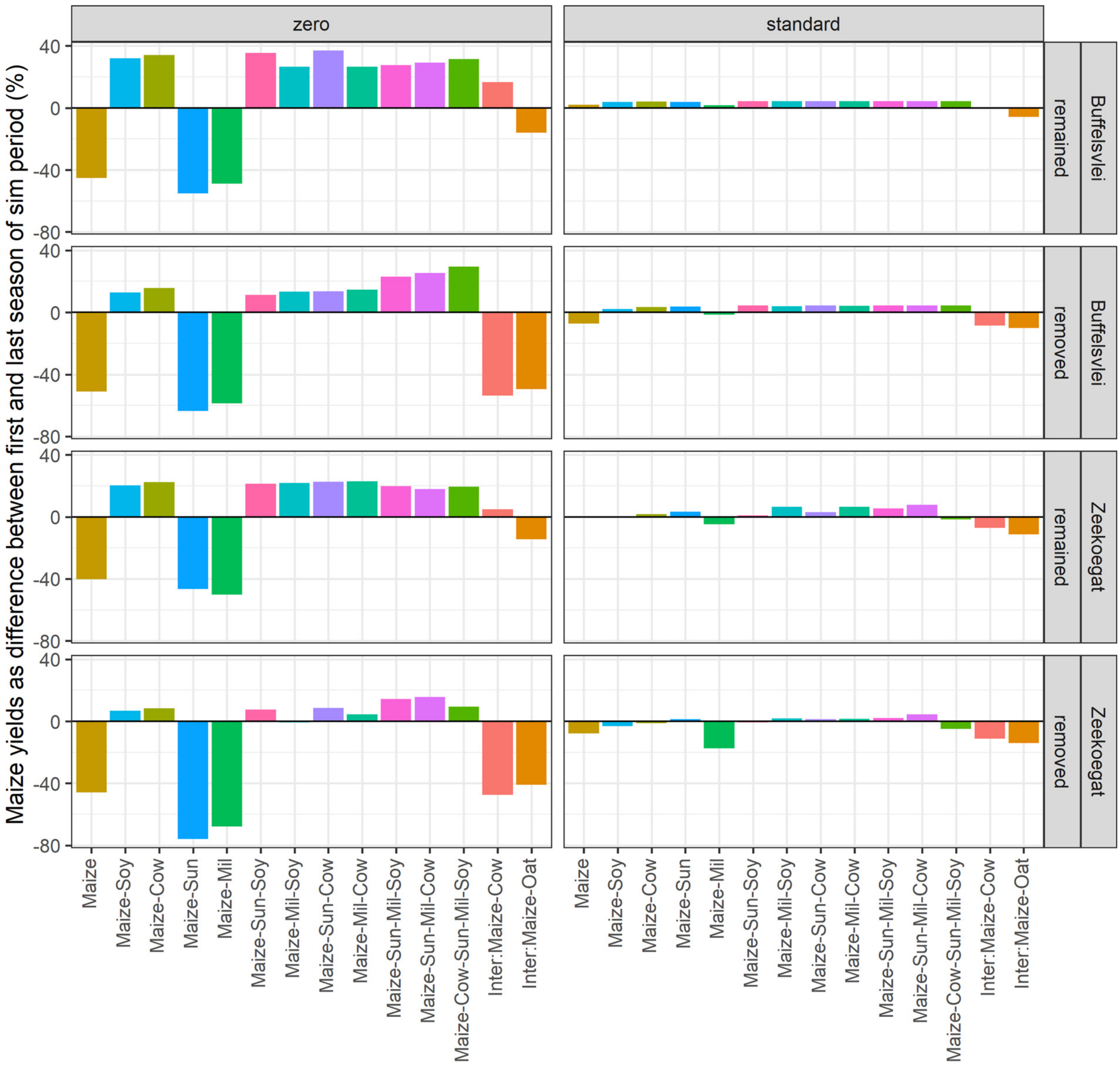

Fig. 8. The difference between maize yield in the last and the first year as percentage (indicator: yield trend). Vertical facets represent standard and zero fertiliser rates. Horizontal facets indicate the two sites the residue management.

Observed SOC showed stronger seasonal variability at Buffelsvlei than simulated SOC, however, errors were in the range 0.1–0.15 % only. At Zeekoegat, simulated results were in the range of the standard deviation. As is known from the literature (Luo et al., 2016), observed SOC often has large standard deviations due to the heterogeneity of soil. While crop models have been used to attempt to capture medium- and long-term SOC for other sites around the globe (e.g. Luo et al., 2016), we are not aware of a study that aimed to reproduce observed SOC dynamics using a crop model in southern Africa. Other crop model studies that investigated medium-term SOC dynamics in this region relied on simple sensitivity analyses, but did not test field data (Corbeels et al., 2016; Masikati et al., 2014).

To sum up, the evaluation demonstrated that the model was able to capture the dynamics of yields, dry matter and soil resources between sites and treatments. Interestingly, results were even better than for a crop rotation model inter-comparison in Europe (Kollas et al., 2015). However, the question remains, why it was not possible to achieve accuracy levels for maize- dominated cropping systems similar to those attained for intensive systems in the northern hemisphere? For instance, for maize dry matter in two year rotations in North-West Germany Hoffmann et al. (2018a) reported a nRMSE of 9 %, and in Iowa (USA) Archontoulis et al. (2014) found a RMSE of 7.7 % for grain yield. One obvious reason why such accuracy indicators are better in these high yielding systems is that relative RMSE values and similar indicators follow the observed yields in terms of performance, i.e. the higher the mean observed yield, the lower the nRMSE (Nendel et al., 2011).

However, other than this explanation, there are a number of other reasons why model accuracy was lower in this study: first, the complete plant phenology records were not available (observed harvest days in Figs. 3a&b and 1 b are estimated based on best recorded previous knowledge), neither was there any information on other cultivar-specific traits. Hence, we relied on cultivars that already existed in the data base. Although APSIM has been used frequently in southern Africa and cultivars from the data base are likely to be similar to the ones used in the field - here some uncertainty remains. Secondly, for Buffelsvlei the pedo-transfer functions for hydraulic soil properties were relied upon (Saxton and Rawls, 2006) as has been done in other studies (for instance: (Baudron et al., 2015; Hoffmann et al., 2018b)). However, it is known that soil parameterisation is a key challenge for achieving high

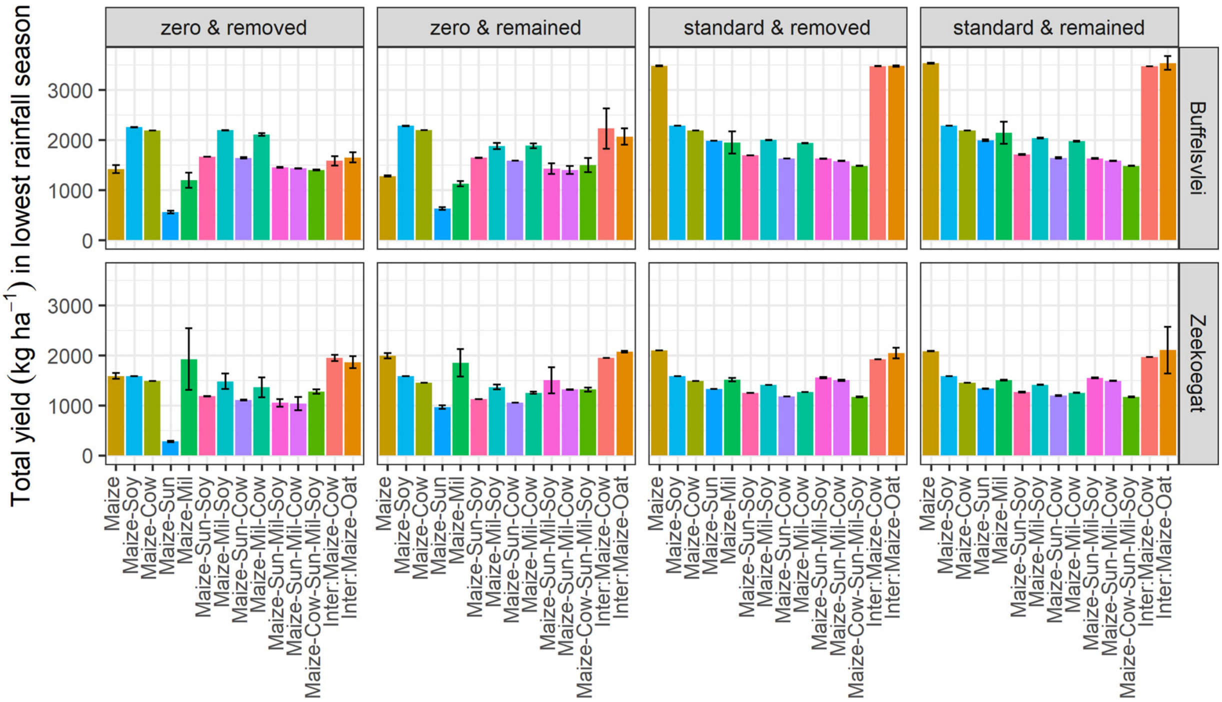

Fig. 9. Bar plot indicates average (plus standard deviation as error bars) total yield per rotation (x-axis) as affected by site (upper panel: Buffelsvlei; lower panel: Zeekoegat), residue management (removed vs remained) and fertiliser regime (zero vs standard) for the worst season – the season that received the lowest rainfall (2006/07).

model accuracy in predicting field results (Wallor et al., 2018), especially under water scarce conditions (Whitbread et al., 2017). Thirdly, the two studies mentioned by Hoffmann et al. (2018) and Archontoulis et al. (2014) included volumetric soil water and N_{min} data recorded with a high temporal frequency, which allowed decomposition patterns to be captured, and thereby achieve a highly accurate determination of SOC pools. Such data was not available for the model evaluation part of this study. Finally, weather station coverage is dense and on-site records are usually available in good quality for high yielding regions. On station weather records in southern Africa are scarce and one has to rely on derived weather data products as in this study.

4.2. The effects of a cropping system on soil fertility and crop productivity

The simulation exercises provided a systematic quantification of insights about the possible effects of rotation, fertiliser and residue management on soil fertility and crop productivity. While the model produced key results that were to be expected and reflect knowledge of the sites, the size of the effects depended strongly on site conditions, and the interactions between treatments. One obvious effect was that simulated yields, when fertilised, were higher at Buffelsvlei than at Zeekoegat due to rooting restrictions at Zeekoegat and the water limitations at the latter site (Fig. 7a). This corresponded to observations made by Swanepoel et al. (2018a). For low input systems, representative of the smallholder farms in the region (in this case the zero fertiliser treatments), residue management is of the utmost importance to maintain SOC levels. Unfertilised maize monocultures with residue removal led to SOC depletion (Fig. 10). The, simulated change, however, was within the error ranges of the model found in the evaluation section (Fig. 5). Furthermore, this specific treatment resulted in low amounts of N_{min} (Supplementary Material Fig. S5a & b) and strong declining yields as indicated by the maize yield difference of 1000 kg ha^{-1} (a decline of 40 %) between the first and last year of the simulation period. However, the effect was stronger at Buffelsvlei with its sandy soil and the associated low initial SOC in comparison to the high SOC clay soil at Zeekoegat, with higher N decomposition potential, and finally Nmin content (Fig. Supplementary Material S5). These results for the low input systems point to the general challenge of smallholder residue management. The produced residues can be fed to animals, sold and provide additional income or used to maintain soil fertility (Baudron et al., 2015). In this model setup, two extreme versions were applied either retaining 100 % of residues in the field, or removing 100 %. Optimising site-specific residue management based on fractioning the usage of residues following a farmer-defined priority list could be done or facilitated through a joint farmer-modeller session as known from Australia (Carberry et al., 2009; Whitbread et al., 2010).

For commercial farming, where fertilisation is standard, the situation might be different. Sacrificing land to grow crops other than maize reduced the simulated total performance in terms of grain yields (Fig. 7a), even in dry years (Fig. 9). Clearly, the simulation results pointed to the notion that rotation diversification may indeed come with short-term production losses when compared to the maize monoculture. Furthermore, it did not buffer climate-induced risk in dry years (Fig. 9). However, the model ignores pest and disease effects that could build up in monocultures and may therefore overestimate the production stability over longer time periods. Even in the simulation results, the threat of declining yields in monoculture maize was already identified for a ten-year time span (Fig. 8). When residues were removed, SOC declined in this treatment, resulting in degraded soil fertility (Fig. 10 and Suppl. Material Fig. S5). Intercropping systems were better able to maintain/improve soil fertility and also offered the opportunity of at least an equally high straw production rate compared with that of the maize monocultures. Hence, these intercropping systems seems beneficial as the commercial farming sector in South Africa is under increasing pressure to take environmental performance into account. This might result in a stronger focus on soil carbon sequestration and soil fertility management in the future (van der Laan et al., 2017).

Overall, the simulation experiment showed negative effects of the widely found maize monocultures in the region on medium-term targets, which are, at least, maintenance of soil fertility and stable yield trends (Figs. 8 & 10). This should be taken into account against short-

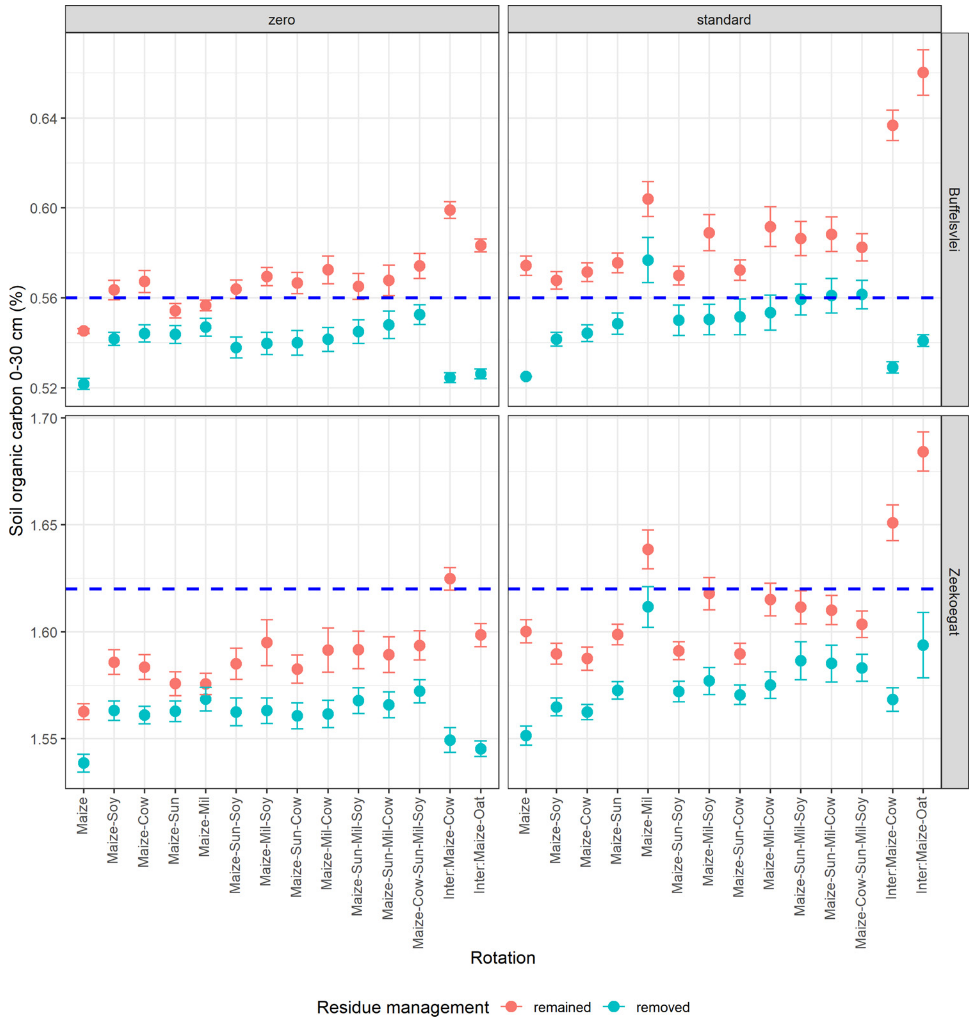

Fig. 10. Mean total soil organic carbon (%) at 0–30 cm depth (circles) and standard deviation (whiskers) in the final year across the simulation periods for each rotation (x-axis). Vertical facets represent standard and zero fertiliser rates. Horizontal facets indicate the two sites. The residue management is shown in colour (remained and removed). Blue dashed lines indicate the initial SOC content.

term high productivity of maize monoculture (Fig. 7). Considering the fact that the climate data used from NASA did not reproduce the observed high rainfall intensities (Supplementary Material Fig. S2), this study might underestimate the consequences of extreme conditions (increased runoff and/or drainage). Hence, positive mitigation of the negative impacts of extreme weather events by maintaining high organic matter levels in the soil and on the soil surface are potentially even more important than shown by the simulation results.

4.3. Further research needs

The choice of cropping system is a key decision taken by the farmer, regardless of spatial scale and input intensity (smallholder or commercial). Consequently, such choice should be based as much as possible on sound quantitative knowledge. Given the medium- to long-term perspective until effects on ecosystem services become apparent, a combined approach of field trials and simulation modelling appears promising (Rötter et al., 2018). For this purpose, more detailed field trials that monitor cultivar traits and soil resource dynamics in high temporal resolutions would be helpful – yet, this is costly and will require much time. In the meanwhile, however, crop model improvement can still take place with on-going trials, although such trials should also cover factors that models cannot currently capture well, such as weed competition, deficiency of phosphorus, pests and diseases, as well as changes in physical soil properties and surface residue properties as affected by management. In regard to tillage, Palmer et al. (2017) incorporated its impact into their study by modifying CLL, DUL and BD based on an ensemble of pedo-transfer functions. This was then used as APSIM input for reruns. The experiments used in this study for the evaluation were designed to compare the effect of reduced with conventional tillage (ploughing). However, the interaction between the heavy clay and reduced tillage at Zeekoegat, resulted in a complex change of soil physical structures, and ultimately yields, which were not monitored in sufficient detail to develop a robust model approach. The strong effects of soil compaction of widely found heavy clays of the region on crop growth and yield requires specific and renewed attention (Bennie and Krynauw, 1985; Kayombo and Lal, 1993; Smith et al., 1997). Finally, as shown in Fig. 5, the accelerated decomposition of the maize residues due to mechanical treatment was not well reproduced by the model, and will require more investigation.

The above discussed five factors (weed competition, deficiency of phosphorus, pests and diseases, dynamics of physical soil properties, and the effects of surface residues) of importance in many smallholder systems - also relevant for commercial farms - are either neglected or not even considered by most crop simulation models. Simple crop simulation experiments, as presented in this study and by others, such as Masikati et al. (2014); Corbeels et al. (2016) or Smith et al. (2016), provide useful insight when combined with expert knowledge, which in some cases can motivate targeted experiments with promising treatments that are designed to eliminate knowledge gaps.

5. Conclusions

This study provided the first-ever evaluation of continuously simulated output (i.e. the model was not reset after each season) from a crop model against field trial data over six and eight years in southern Africa. Model performance showed that APSIM was able to capture yield dynamics, although prediction accuracy needs improvement. More detailed measurements of soil variables might be needed. The simulation experiment suggests intercropping is a promising option for cropping system diversification. Simultaneously, it underlines the critical role of fertiliser and residue management when farmers diversify in maintaining soil fertility (SOC and Nmin levels), thereby stabilising yields in the medium-term. Overall, this study illustrates the usefulness of model applications for the design of suitable cropping systems in southern Africa addressing various dimensions of sustainability, such as improved environmental performance, and not only productivity.

Declaration of Competing Interest

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

CRediT authorship contribution statement

M.P. Hoffmann: Conceptualization, Validation, Funding acquisition, Formal analysis, Investigation, Visualization, Writing - original draft, Writing - review & editing. **C.M. Swanepoel:** Conceptualization, Data curation, Validation, Funding acquisition, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **W.C.D. Nelson:** Formal analysis, Investigation, Visualization, Writing - original draft, Writing - review & editing. **D.J. Beukes:** Data curation, Funding acquisition, Investigation, Writing - original draft, Writing - review & editing. **M. van der Laan:** Data curation, Funding acquisition, Investigation, Writing - original draft, Writing - review & editing. **J.N.G. Hargreaves:** Validation, Investigation, Writing - original draft, Writing - review & editing. **R.P. Rötter:** Conceptualization, Funding acquisition, Formal analysis, Investigation, Writing - original draft, Writing - review & editing.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.eja.2020.126089.

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