Modelling long-term yield and soil organic matter dynamics in a maize cropping system

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ABSTRACT

Long-term cropping system experiments are one of the most reliable sources of information for informing sustainable agriculture and predicting future trends. When combined with crop modelling, expansion of findings on optimised management approaches is possible. In this study, results from a South African semi-arid region long-term (66 years) maize (*Zea mays* L.) trial are presented and combined with crop modelling to identify the impacts of fertilisation and residue management on yield and soil organic matter (SOM) levels. Simulated and observed results generally agreed well in calibration and testing exercises with APSIM. For the fertilised treatment, residue retention led to a 41% increase in average yield over the long term, and for unfertilised treatment the average yield increase was even higher at 59%. The greatest SOM decline of 46% was observed for the unfertilised plus residue removal treatment (over 66 years and considering a 60 cm soil depth). Fertilising and retaining residue reduced the SOM decline to 18%. Using only fertiliser without residue retention did not lead to a declining yield trend over the long-term for this soil. The study indicated that the APSIM model can be used to explore the ecological intensification of maize production in sub-Saharan Africa. Further attention is recommended, however, on testing the simulation of subsoil SOM dynamics. The results of this study give insight into soil fertility in low-input maize production systems and quantify the benefits of N fertiliser and residue retention guided by long-term measured data.

Key words: long-term experiment, APSIM, soil organic carbon, nitrogen.

1. INTRODUCTION

Soil organic matter (SOM) is the most important carbon (C) reservoir in agroecosystems, and long-term agricultural management practices can have significant impacts on the global soil C cycle (Luo et al. 2010a). Agricultural soil C accumulation or decline is mainly determined by the balance between soil C inputs from crop residue or organic amendments generating the formation of new SOM, and outputs due to cultivation-driven decomposition of SOM, and losses via erosion (Vallis et al. 1996, Kuzyakov and Domanski 2000). Soil organic matter is often used as an indicator of soil quality due to its beneficial influence on soil physical, chemical and biological properties (Herrick 2000, Mills and Fey 2003, Aziz et al. 2013). It can be strongly influenced by management practices such as fertilization, retaining or removal of crop residue, and tillage practices (Dominy and Haynes 2002, Cates et al. 2016, Swanepoel et al. 2016, Swanepoel et al. 2018), as well as environmental factors such as soil texture, soil temperature and water content, and microbial population composition and activity (Jiang et al. 2014). The loss of SOM in cropping systems is one of the key factors contributing to agriculturally induced soil degradation (Luo et al.

2010a) . A review of soil organic carbon (SOC) in cultivated soils in southern Africa reported a 25 – 53% SOM decline for different precipitation zones, with an average of 46% (Swanepoel et al. 2016). Since quantity, quality and dynamics of SOM can be an indicator of human impacts on a wide range of ecosystem functions (Tiessen et al. 1994), these metrics can be used to identify mechanisms to improve soil health and its sustainable use as a natural resource (Lal 2004).

Over many areas of sustainability research and policy making, SOM has become an increasingly important consideration (Manlay et al. 2007). Changes in SOC stocks cannot be determined in short-term experiments, as this is a slow process that can only be reliably determined in medium or long-term experiments (Hoffmann et al. 2020). Datasets from long-term trials can also be important in developing and evaluating crop models to study the effect of various management practices on yield and soil quality. The interactions between a changing climate and soil and management practices can further be explored with models in a way that field trials alone cannot do (Archontoulis et al. 2014, Hoffmann et al. 2020). Research efficiency can also be increased by models through their ability to analyse system performance at different locations and for varying climatic conditions (Keating et al. 1999).

A range of models with different levels of complexities have been designed to simulate yield, evapotranspiration and SOM dynamics in maize cropping systems (Liu et al. 2011; Falconnier et al. 2020). The most popular and widely used process-based crop growth simulation models include the APSIM (Agricultural Production Systems Simulator) (Keating et al. 2003), STICS (Simulateur mulTIdisciplinaire pour les Cultures Standard) (Brisson et al. 2003) and DSSAT (Decision Support System for Agrotechnology Transfer) (Jones et al. 2003) cropping systems models. Falconnier et al. (2020) evaluated the performance of 25 crop models in simulating low-input African maize production systems, observing that models were less accurate for low input conditions and below yield potential simulations, highlighting the importance of calibration to improve accuracy. If such models can predict yield and SOM responses using measured data from long-term experiments, then they can be applied more confidently in simulations to provide credible yield and SOM predictions for various site-specific conditions. Application of crop models is increasing worldwide for exploring options and solutions for food security, climate change adaptation and mitigation, as well as sustainable production systems (Holzworth et al. 2014, Hoffmann et al. 2020).

Due to a limited number of long-term experiments, there have been only a few attempts made to study changes in soil quality in response to long-term management practices (Debreczeni and Körschens 2003, Grahmann et al. 2020). Nonetheless, these experiments have been instrumental in identifying beneficial management practices that are able to produce profitable crop yield whilst maintaining soil quality at acceptable levels (Liu et al. 2011). An evaluation of DSSAT-CSM on a long-term (14 years) maize-wheat rotation experiment in north-western China found that there is great potential for using these crop models to assess the impacts of various practices on yield, and soil C and N dynamics (Li et al. 2015). The APSIM model has been reported to reasonably simulate long-term crop yield and SOM dynamics in studies in Australia (O'leary et al. 2016), Niger (Akponikpè et al. 2010), Kenya (Micheni et al. 2004), and South Africa (Hoffmann et al. 2020), and further studies of this nature in different agro-ecological zones can enhance understanding of the ability of the model to make accurate long-term predictions.

In this study, the accuracy of the APSIM model to simulate maize growth, yield, and SOM in a South African semi-arid region over the long-term was assessed. An evaluation was done using the calibrated model to assess combinations of fertilization and residue retention on long-term yield and SOM dynamics. It is envisaged that the findings can be useful to inform higher maize productivity and inform enhance C sequestration in southern African cropping systems.

2. MATERIALS AND METHODS

2.1 Experimental site

The long-term experiment is located at the University of Pretoria's Hillcrest Campus Experimental Farm (29.70303°S, 31.0447°E, 1 372 m above sea level). The soil was classified as a sandy loam of the Hutton form and belong to the Suurberkom Family (Soil Classification and Working Group, 1991) [Acrisol according to Food and Agriculture Organization of the United Nations World Reference Base (WRB), WRB (2014)]. The long-term average annual rainfall for Pretoria is 670 mm, which is mostly received in summer, with about 80% falling between October and March. The average annual potential evapotranspiration (PET) is approximately 2 000 mm, which gives the site an aridity index of 0.3 – 0.35 (Rethman et al. 2007).

2.2 Long-term experiment details

2.2.1 Experimental design

The experiment was laid out according to a randomized complete block design with five factors at two levels each. The treatments included those that originally received supplementary irrigation (W_1), zero irrigation (W_0, relying solely on rainfall), and combinations of nitrogen (N), phosphorus (P), potassium (K), and manure (M), resulting in a total of 32 treatments with four replications leading to the experiment having 128 plots (Nel et al. 1996). The gross plot size is 8.3 × 6.3 m (52.3 m^2) and the net size is 7.5 × 4.9 m (36.8 m^2).

2.2.2 Agronomic management

The original intention was to ensure a minimum of 450 mm of water (rainfall + irrigation) was received by the W_1 treatments in the maize growing season, while the W_0 treatments would be purely rain-fed. Since 1990, however, irrigation applications were reduced and W_1 treatments received supplementary irrigation only when no rain was received over a period of two weeks. The historical fertiliser application for the different treatments has changed over time (Table 1) in response to soil analysis results. Nitrogen was initially applied as ammonium sulphate ($(NH_4)_2SO_4$) and later in the form of ammonium nitrate (NH_4NO_3) (Belay et al. 2002), but in recent years it has been applied in the form of limestone ammonium nitrate (LAN). Phosphorus has been applied in the form of superphosphate ($Ca(H_2PO_4)_2$) and potassium (K) as potassium chloride (KCl). The application of P was discontinued in 1984 as levels on some plots had built up to above 200 mg P kg^{-1} (Bray II) (Nel et al. 1996). As the APSIM model capabilities to simulate P and K deficiency effects on yield is not very advanced, only two fertiliser treatments were selected for the purpose of the study, the treatment receiving zero fertiliser (control) and the treatment receiving complete NPK applications.

Table 1. Nitrogen (N), phosphorus (P) and potassium (K) applied per treatment to the different treatment combinations between 1939 and 2017 (Nel et al. 1996, Belay and Wehner 2002).

Season	N	P	K
		$kg\ ha^{-1}$	
1939/40 –1966/67	43	34	32
1967/68 – 1972/73	85	68	63
1973/74 –1983/84	205	100	100
1984/85	205	0	100
1985/86 – 2004/05	125 + 125*	0	80 + 100*
2005/06 – 2011/12	100 + 50*	0	80
2012/13 – 2017	100	0	80

*Applied as a split at planting and top dressing after six weeks on N and NPK treatments

Five different maize cultivars have been planted since the inception of the trial (Table 2). The plant population was 18 000 plants per ha^{-1} (1939 – 1957), 36 000 plants per ha^{-1} (1958 – 1984) and 55 000 plants per ha^{-1} (1985 – present). From 1939 maize was grown in summer in rotation with field pea (Pisum sativum L.) as a cover crop in winter until 1999. At harvest, field pea residue was incorporated into the soil up until 1983, and since then residue was removed because of residual N effects (Nel et al. 1996). Standard pest, disease and weed control measures were applied, but it is acknowledged that unexpected issues could have reduced yield in some seasons. Harvesting was done by hand, and the maize stover was removed from the plots (Nel et al. 1996).

Table 2. Maize cultivars planted since 1939 at the University of Pretoria, Hillcrest Experimental Farm long-term maize trial.

Cultivar	Period planted
Pretoria Potchefstroom Pearl	1939 – 1971
R200	1972-1984
Pioneer 6431	1985 – 2010 (except 2006)
Pioneer PHB 32W7	2006
DKC 7374 BR	2011– present

2.2.3 Measured data

Maize trial data from the control and NPK treatments during 1990 – 2017 was acquired from the trial records and published literature (Nel et al. 1996, Belay et al 2002a) since poor data handling and record keeping led to gaps and unavailability of data in seasons before 1990. This was, however, different to SOM, as fewer data points for SOM were available due to it not being a standard variable analysed as part of the trial. Certain publications, however, sporadically reported SOC or total carbon (C) content (Nel et al. 1996, Belay et al. 2002b, Bello 2008), but these values were not always reported for the exact same depth intervals. Data for SOC in 1998, 2006, 2013 and 2017 could be used to compare with model estimates. The factor of 1.72 (Stevenson and Cole 1999) was used to convert percentage SOC to percentage SOM.

2.3 Description of APSIM

The APSIM model has been extensively used to evaluate the productivity, nutrient cycling and environmental impacts of cropping systems as influenced by soil, weather and management interventions (Keating et al. 2003, Luo et al. 2011). APSIM requires daily weather data (solar radiation, maximum and minimum temperature, and rainfall), and information on soil properties. A range of diverse management practices relating to planting, tillage, fertilization, irrigation and residue management can be specified due to the versatile nature of the model.

APSIM modules

In APSIM, the 'MAIZE' module simulates maize response to weather conditions and soil water and N levels on a daily time step (Keating et al. 2003). Biomass accumulation is estimated from the minimum of two potential biomass increment values, one determined by light (radiation limited growth) and the other determined by soil water availability (water limited growth). From emergence to flowering, C and N allocation priority is towards canopy development, and from flowering to physiological maturity allocation priority goes to the grain (Archontoulis et al. 2014).

The 'SOILWAT2' module simulates the processes that take place in the soil profile, including water infiltration and drainage, evapotranspiration, runoff, temperature, nutrient cycling and solute movement (Keating et al. 2003, Holzworth et al. 2014). This module is interfaced with the 'RESIDUE2' and 'MAIZE' modules to enable the simulation of the soil water balance in response to changes in surface residue and crop cover.

The 'RESIDUE2' module deals with residue cover and incorporation following cultivation, residue decomposition, and transfers of C and N from residue to the soil (Probert et al. 1998). All aboveground material is classified as residue and can be burnt or incorporated into the soil as fresh organic matter (FOM). When new residue is added, new values are calculated to describe the total available mass of residue present and C:N ratios. Decomposition of residue is controlled by, among other factors, a crop species-specific decomposition rate and soil contact fraction factor of the residue. The crop-specific decomposition rate is influenced by residue C:N ratio, soil temperature and soil moisture. The effect of surface residue on reducing soil evaporation are simulated.

The 'SOIL_N' module describes SOM dynamics in terms of soil C and N cycling. Soil organic matter exists in three different pools, the fast decomposing (BIOM), an intermediate (HUM), and a stable (INERT) pool. Fresh organic matter from roots and residue from the previous crop that have recently been incorporated by tillage forms a separate pool (FOM) (Keating et al. 2003, Holzworth et al. 2014). The INERT pool is stable and not susceptible to decomposition and this prevents the total decomposition of SOM in deeper layers in APSIM.

2.4 APSIM calibration datasets

Maize cultivar parameterization

The maize cultivar was calibrated using a specially collected growth analysis dataset for the 2016 – 2017 season. Planting was done on 11 November 2016 and fertilization was done as described previously (Table 1). Maize aboveground dry matter accumulation and leaf area index (LAI) was routinely monitored by taking measurements in the control (no fertilization) and NPK treatments every two weeks. Four plants were harvested per plot and samples were oven dried at 72˚C until a constant mass was reached to determine dry matter. A Licor Li-3001 leaf area meter (LiCor Inc., Nebraska, USA) was used for leaf area determination.

These data were used to calibrate cultivar DKC 7374 BR, building on parameters of the existing cultivar DKC 6018 110 in APSIM. Adjusted parameters are presented in Table 3. Calibration was done using the NPK treatment and the control treatment data were used for evaluation.

Table 3. APSIM calibrated values for new cultivar DKC 7374 BR, modified from cultivar DKC 6018 110, and used in the long-term maize trial simulation

APSIM parameter code	Description	Calibrated value
head_grain_no_max	Total grain number	500
grain_gth_rate	Grain growth rate	6.5 (mg grain^{-1} day^{-1})
tt_emerg_to_endjuv	Thermal time - Emergence to end of juvenile	290 (°Cd)
est_days_endjuv_to f_ini	Number of days - End of juv. to floral initiation	25
tt_endjuv_to_init	Thermal time - End of juv. to floral initiation	0.0 (ºCd)
photoperiod_crit1	Photoperiod factor	12.5 (hours)
photoperiod_crit2	Photoperiod factor	24.0 (hours)
photoperiod_slope	Photoperiod factor	10.0 (ºC/hour)
tt_flower_to_maturity	Thermal time - Flowering to Maturity	800 (°Cd)
tt_flag_to_flower	Thermal time - Flag leaf to Flowering	10 (ºCd)
tt_flower_to_start_ grain	Thermal time - Flower to start of grain	300 (ºCd)
tt_maturity_to_ripe	Thermal time - Maturity to ripe	1 (ºCd)

2.5. Long-term simulation parameterisation

Although the long-term trial started in 1939, the model was applied to simulate long-term maize yield and soil organic matter content from 1950 – 2017, due to unavailability of measured weather data for 1939 – 1949. The model was parameterised to reflect as closely as possible how the trial was managed over the 66 years. Tillage was done every year on 1 October to a depth of 0.3 m using a disc plough and 70% of the residue present was assumed to be incorporated. The planting window was 1 October to 1 January every year, and sowing was done when a total of over 20 mm of rain occurred within five consecutive days. No sowing was allowed after 1 January as the growing season would then be too short. The parameterized maize cultivar (DKC 7374 BR) was used for the simulation at a planting density of 5 plants m^{-2}. Only N additions were considered in the model, and P and K were assumed to be non-limiting factors for maize yield. Supplementary irrigation was added based on rainfall, with 15 mm irrigation being applied if rainfall over the previous 15 days was less than 5 mm. At harvesting, 80% of the maize residue was assumed to be removed every season.

In the simulation, field pea was planted every year as a winter cover crop from 1950 up until 1999 when it was discontinued. For the years when field pea was planted, tillage was also simulated every year on 15 May to a depth of 0.3 m using a disc plough. The planting window was 15 May to 15 June. The field pea cultivar 'Dingxi' was used for the simulation at a planting density of 10 plants m^{-2}. No N fertilization was applied to field pea. Supplementary irrigation was simulated based on rainfall, with 15 mm irrigation being applied if rainfall over the previous 15 days was less than 5 mm. At harvesting, all of the field pea residue was incorporated into the soil every season from 1950 up until season 1983, after which all residue was removed after harvest (Nel et al. 1996).

Soil data

Initial soil condition data dating back to 1950 were not available from trial records. To initialise the model, therefore, soil samples from an adjacent, undisturbed site were taken in 2017 for analysis. The samples were taken at 0 – 0.05 m, 0.05 – 0.1 m, 0.1 – 0.3 m and 0.3 – 0.6 m depth (Table 4). Soil chemical analyses were done to determine soil pH (H_2O) and organic carbon (C) (Walkley-Black method). The remaining soil physical properties needed were estimated from soil texture using pedotransfer functions programmed into the SPAW (Soil-Plant-Air-Water) computer programme developed by K. E. Saxton (USDA/ARS) and based on Saxton et al. (1986).

Table 4 Soil organic carbon (SOC), bulk density (BD), volumetric water content at saturation (SAT), drained upper limit (DUL), and lower limit at 15 metric bar pressure (LL15) and soil pH for the long-term maize trial.

Soil Layer (m)	SOC (%)	BD (Mg m^{-3})	SAT (m^3 m^{-3})	DUL (m^3 m^{-3})	LL15 (m^3 m^{-3})	pH H_2O)
0.00 – 0.10	1.6	1.48	0.43	0.24	0.16	6.0
0.10 – 0.30	0.7	1.48	0.43	0.29	0.20	6.0
0.30 – 0.60	0.5	1.46	0.43	0.33	0.23	6.0
0.60 – 0.90	0.4	1.46	0.43	0.33	0.23	6.0
0.90 – 1.20	0.4	1.46	0.43	0.33	0.23	6.0

Weather data

Hatfield daily maximum and minimum temperature and rainfall data from 1950 – 1983 was obtained from a database developed by the School of Bio-resources Engineering and Environmental Hydrology at the University of KwaZulu Natal using the South African Atlas of Climatology and Agro Hydrology (Van Heerden et al. 2009). An on-site automatic weather station provided data from 1984 – 2000, and data for 2001 – 2017 were obtained from the South African Weather Service (SAWS). Solar radiation for the whole period was generated using the method of Bristow and Campbell (1984). The equation estimates solar radiation as a function of the difference between the minimum and maximum temperatures, and estimations of the sun's position relative to the point of interest on the earth's surface calculated by the day of year, latitude and elevation. The annual average ambient temperature (TAV) and annual amplitude in monthly temperature (AMP) were calculated using the long-term daily minimum and maximum temperatures using the 'tav_amp' software provided by the APSIM platform.

2.6 Testing model performance

The simulated and observed aboveground dry matter accumulation and LAI were compared and used to test how well the model estimates crop growth over the season.

Model evaluation in the long-term simulation was performed using long-term yield (1990 – 2017) and SOM (1950 – 2017) data for the control and NPK treatments. The aim of comparing simulated and measured values statistically when testing a model is to objectively determine what proportion of treatment error, excluding experimental error, is accounted for by the model (Yang et al. 2000). Model performance was evaluated using the reliability criteria recommended by De Jager (1994). The mean absolute error (MAE) is used to determine average errors, root mean square error (RMSE) summarises overall error, and Wilmot's index of agreement (D) is used to indicate the relative size of the differences. Statistical criteria for an accurate simulation are D values above 0.80, and MAE below 20%. RMSE depends on the data and units used for analysis. High values of RMSE indicate poor model performance.

2.7 Long-term management scenarios

Management scenarios were selected based on quantifying the effects of practices that are practically achievable in the fields of maize farmers with limited resources in sub-Saharan Africa. Combinations of fertiliser and residue management techniques were tested over the long term (1950 – 2017), and the impact on yield and SOM levels were assessed. These scenarios represent a combination of treatments that were either fertilised (F1) or unfertilised (F0), and residue retained (R1) or removed (R0). Fertiliser application for the F1 scenarios was set at 100 kg N ha^{-1} at planting for the entire simulation after an iterative process running the model to determine at what rate N is generally non-limiting. For the R1 scenario all residue was retained at harvest, while for R0, 80% of residue was removed.

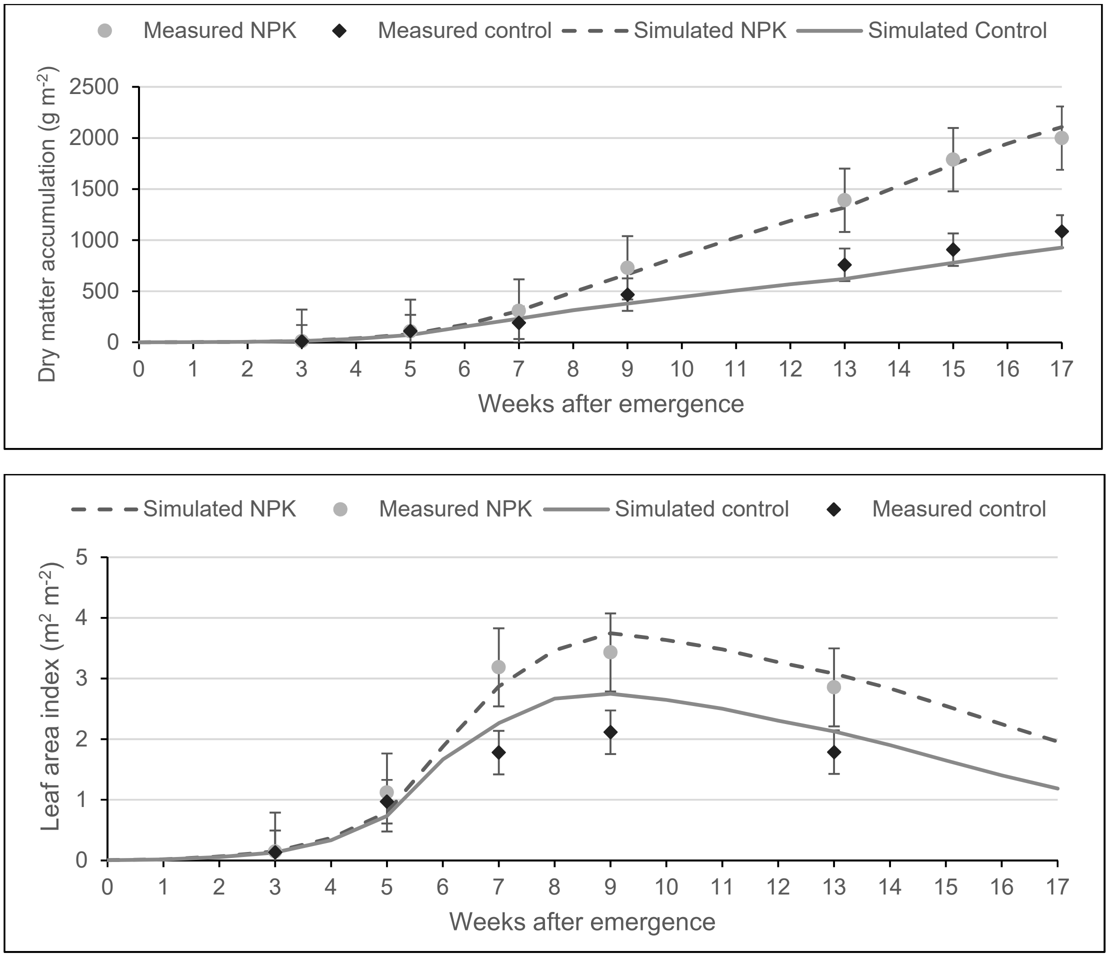

Figure 1. Measured and simulated aboveground dry matter accumulation and leaf area index for the NPK and control treatments in the 2016 – 2017 growing season.

3. RESULTS

3.1 Maize cultivar calibration

Aboveground dry matter and LAI were well simulated for the 2016 – 2017 growing season for the NPK treatment used for calibration, as well as the control treatment used for testing. Accurate estimation of aboveground dry matter was indicated by RMSE values of 649 kg ha^{-1} and 1 092 kg ha^{-1}, MAE values of 5% and 17%, and D values of 1 and 0.98 for the NPK and control treatments, respectively. Simulated and observed LAI compared well for the NPK treatment (RMSE = 0.31, D = 0.99, MAE =

11%), but for the control, LAI was generally overestimated (RMSE = 0.45 m^2 m^{-2}, D = 0.95, MAE = 25%). Dry matter accumulation was similar for both treatments in the first five weeks despite the control treatment being unfertilised. This could be a result of newly mineralized N over the winter period supporting early growth in the control, which was also predicted by the model.

3.2 Long-term yield simulations

Simulated and observed yield from 1990 – 2017 were higher in the fertilised NPK treatment than the control, clearly demonstrating the benefit of N fertilization. Initially, yield was over-estimated by the model in the NPK treatment in most seasons from 1990 – 2001, but this improved in later years (Figure 2). In general, the control yield was well-estimated, and the estimations also improved after 2011. The N-limited growth was therefore well estimated by APSIM. In some seasons, for example in 1993, measuredyield with a high standard deviation were obtained between replicates, with the reason for this not being clear. A crop failure was also reported in 2005 – 2006 season due to bird damage, and resulted in a replant in January 2006 (Bello 2008). Such incidents would have also contributed to mismatches between simulated and observed yield.

Statistically, there was a better agreement (D = 0.97 and 0.87) between simulated and observed values. The RMSE (835 and 688 kg ha^{-1}, respectively) was relatively high, but was in the same order as those obtained by previous long-term maize modelling studies (Sadler et al. 2000, Ma et al. 2007, Liu et al. 2011).

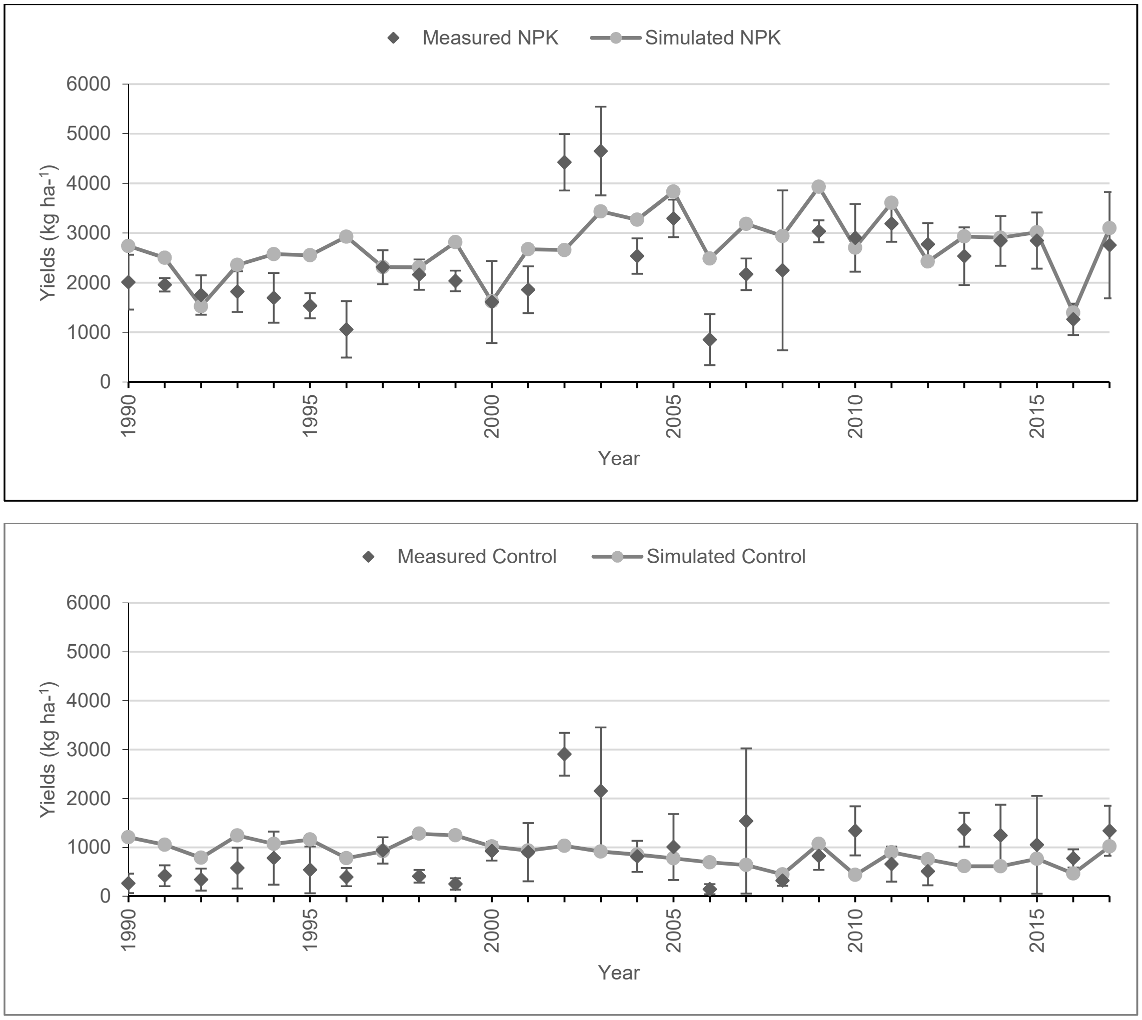

Figure 2. Measured and simulated maize grain yields for the NPK and control treatments from 1990 to 2017

3.3 Long-term fertilization effects on SOM

More long-term SOM decomposition was observed in the unfertilised control than the NPK treatment (Figure 3). Similar results were reported by Luo et al. (2011), where there was a continuous C decline in unfertilised wheat, but N fertilization slowed the decline. This demonstrates the beneficial effects of fertilization and improved crop biomass production on SOM levels. Higher organic residue returns in the fertilised plots trial were reported by Belay (2002a) for this trial, and it was also highlighted that the organic crop residue was mineralized at faster rates due to inorganic N applications enhancing the decomposition process. The SOM content in the top 0.2 m declined from an initial estimated 1.97% in 1950 to 0.83% in 2017 for the simulated and 0.84% for the measured control treatment. For the NPK treatment, SOM content declined from 1.97% in 1950 to 1.07% and 0.94% for the simulated and observed treatments, respectively. Soil organic matter still did not appear to have reached a new equilibrium in the top layer even after 66 years as indicated by both simulated and observed data.

Statistical criteria for a good simulation was met in both treatments for the top 0.2 m of the soil profile. The control treatment had statistical values D = 0.97 and MAE = 9.3%. For the NPK treatment, D = 0.96 and MAE = 9.52%, indicating a good simulation of SOM decline over the years in the top layer. The remaining layers were not statistically evaluated due to having only two data points from previous years beyond 0.2 m. For the 0.2 – 0.4 m and 0.4 – 0.6 m layers, the model estimated greater SOM decline than was observed for the measured data. In the case of the 0.4 – 0.6 m layer, measured data indicates that SOM increased for this layer. This is further addressed in the discussion.

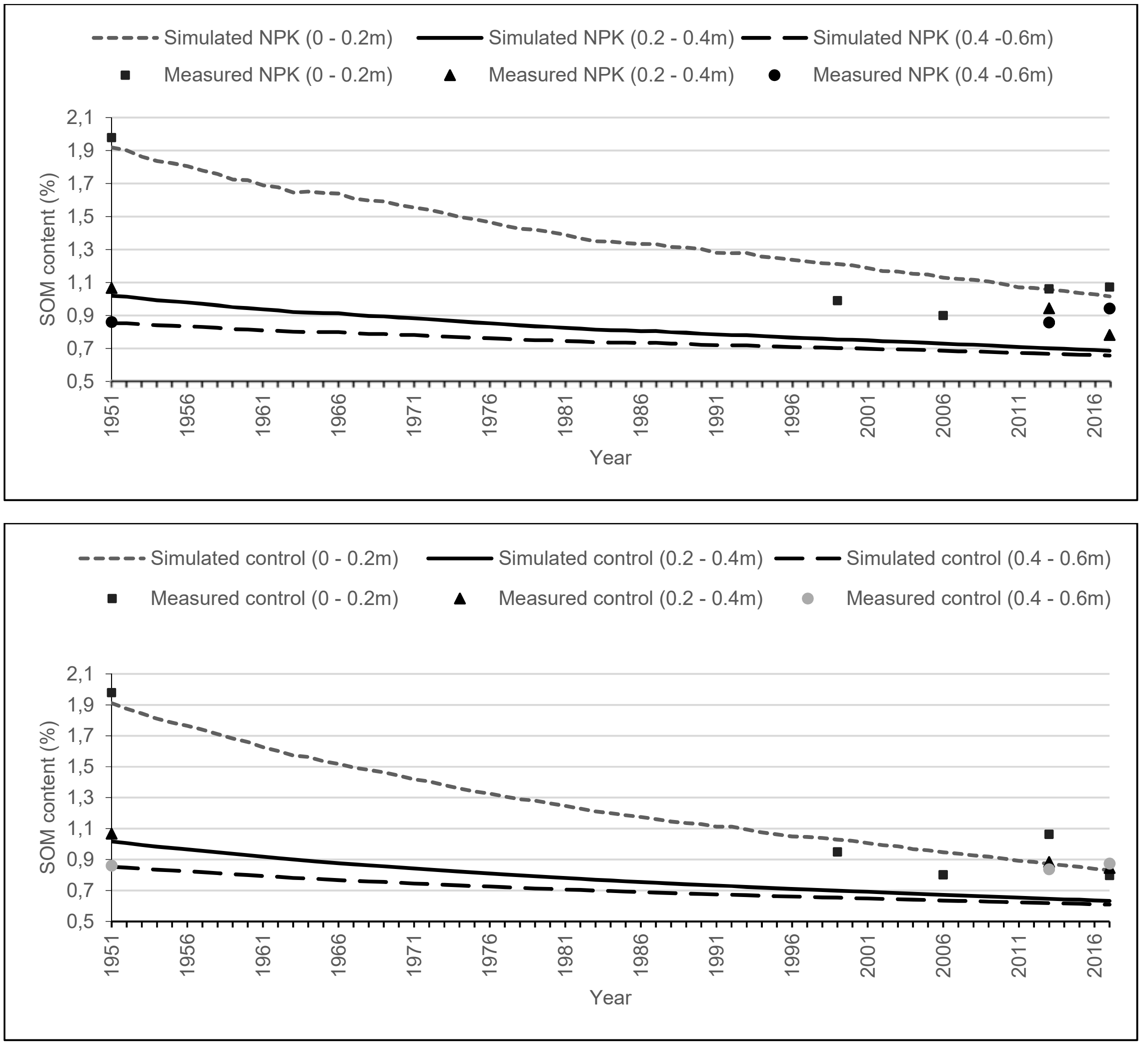

Figure 3. Measured and simulated soil organic matter content for the control and NPK treatments at different depths up to 0.6 m.

3.4 Long-term management scenario modelling

3.4.1 Simulating long-term crop residue management effects on yield

Retaining crop residue after harvest was estimated to be beneficial to yield as indicated by the comparisons in Figure 4. The NPK treatment (which included rotation with field pea from 1950 – 1999) had an average yield of 2 527 kg ha^{-1} over 66 years, whereas the simulated maize monoculture scenarios of fertilization plus residue retention (F1R1) and removal (F1R0) averaged 3 514 kg ha^{-1} and 2 490 kg ha^{-1},

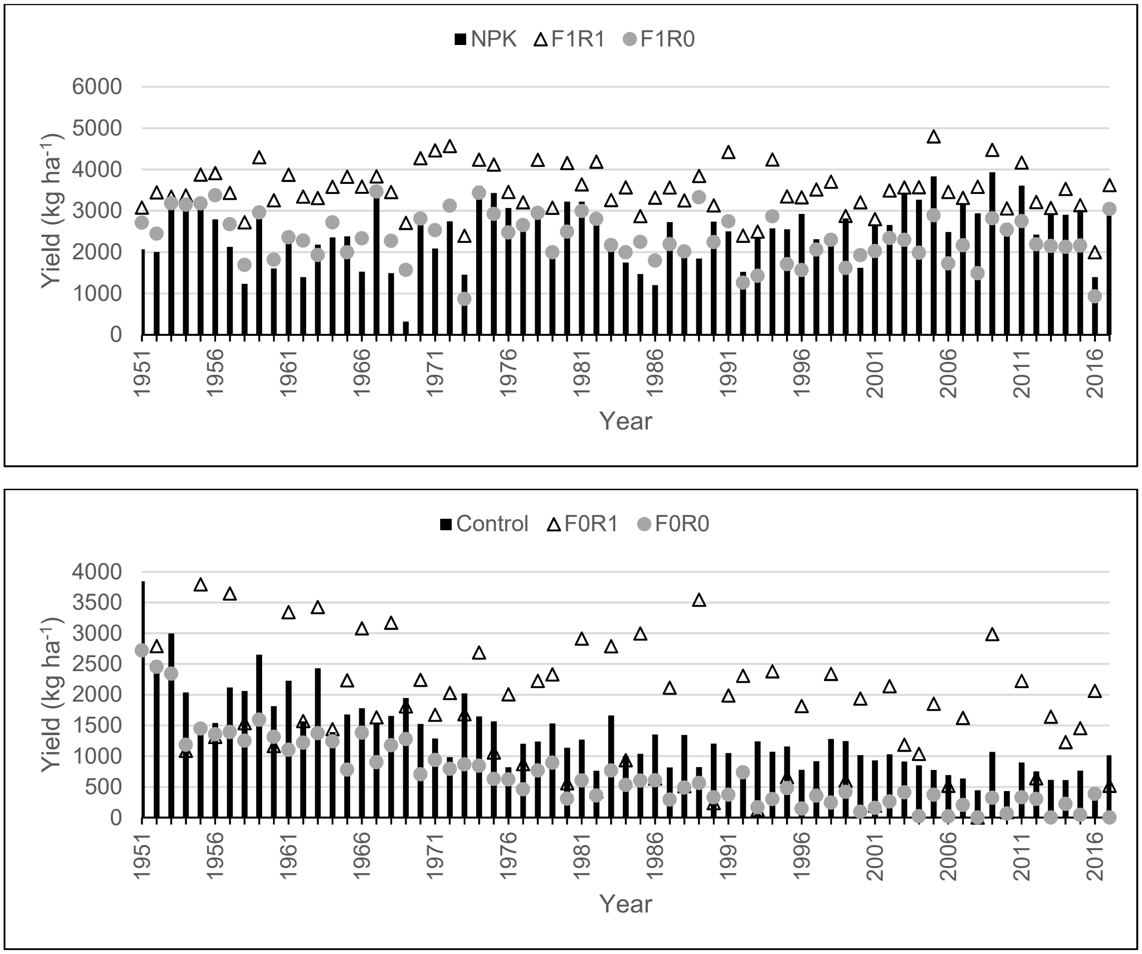

Figure 4. Seasonal yields comparison over a 66-year simulation period for the original treatments (NPK and control) and monoculture residue management scenarios (F1: fertilized, F0: unfertilized, R1: residues retained, R0: residues removed).

respectively. Residue retention therefore led to a 41% increase in average yield. In unfertilised treatments, the control averaged 1 326 kg ha^{-1}, which was 78% higher than the residue removal scenario (F0R0, 746 kg ha^{-1}), but 37% lower than the residue retention scenario (F0R1, 1 818 kg ha^{-1}). A 59% decrease in yield therefore occurred when residue was removed in unfertilised treatments. The differences in average yield indicate that retaining residue had a notable benefit on yield, more especially for the unfertilised crop. A declining yield trend was observed in simulated unfertilised treatments with and without residue retention due to the loss of SOM and soil fertility, with F0R0 showing the sharper decline. Crop failure was predicted in 2008, 2013 and 2017 for the F0R0 treatment.

3.4.2 Simulating long-term crop residue management effects on soil organic matter

Fertiliser application and residue retention was simulated to be beneficial in maintaining SOM levels in the soil profile (up to 1.2 m depth) (Figure 5). The F0R0 treatment showed the highest SOM loss, from 1.2% in 1950 to 0.65% in 2017 (46% loss over 66 years), while the F1R1 showed the smallest loss, declining to an estimated 0.98% SOM in 2017 (18% loss). Although the NPK treatment included a field pea rotation in winter from 1950 to 1999, with its residue retained until 1983, the SOM declined to 0.79% by 2017 (34% loss), lower than the F1R1 treatment. This was further indicated in unfertilised treatments, where the F0R1 scenario only had a slightly higher SOM in 2017 (0.74%) than the measured SOM in the control (0.70%), which also had field pea rotation. This indicates the beneficial effects of a winter legume cover crop in maize production, even over the longer term.

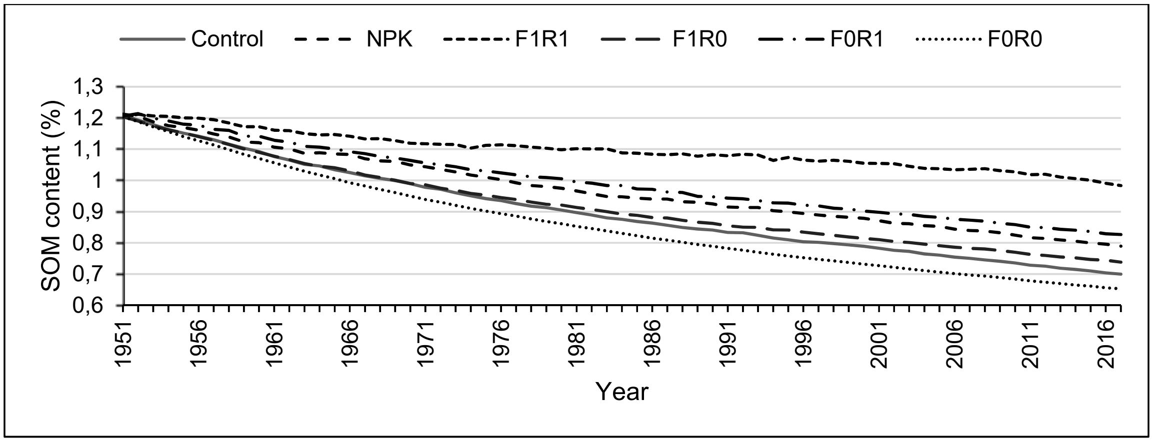

Figure 5. Seasonal simulated soil organic matter (SOM) (soil depth = 1.2 m) comparison over a 66-year simulation period for the original treatments (NPK and control) and monoculture residue management scenarios (F1: fertilized, F0: unfertilized, R1: residues retained, R0: residues removed).

4. DISCUSSION

4.1 Maize growth and long-term yields can be well simulated using the APSIM model

The maize cultivar studied could be well-calibrated in the APSIM model. For the control, LAI was slightly overestimated from seven weeks after emergence to harvesting. Despite the slight over-estimation of LAI, yield from 1990 – 2017 was generally well estimated over the long-term for the zero-fertiliser treatment. Historical maize yield showed a high degree of seasonal variability across all treatments (Nel et al. 1996), and these variations were not always well represented by APSIM. The statistical analysis of yield simulations over the long-term did, however, met the statistical criteria, indicating good model performance. In some cases, variations between simulated and observed values could have been due to extreme, short-term duration environmental conditions such as very high temperatures and moisture stress at critical periods, hail damage, strong winds, attacks from pests (including birds) and diseases. These are factors that the model does not currently consider. A study by

Mangani et al. (2019) reported yield under-estimations in South African maize production using models accounting explicitly for extreme weather events when compared to existing models. A similar long-term maize simulation study conducted in Ontario, Canada also considered extreme short duration weather events, which are not considered by models such as APSIM the reason behind less accurate long-term maize simulations (Liu et al. 2011). Planting date is also known to influence maize yield (Saseendran et al. 2005, Soler et al. 2007), and in this study, the planting dates over the years were not always known exactly and had to be based on a management rule that initiated planting in a pre-defined planting window (Section 2.5). Planting date can also be affected by factors other than weather, for example, the availability of planting equipment, seed, fertiliser and labour. Finally, differences between simulated and observed yield may also have been due to higher yielding maize cultivars becoming available over time.

4.2 Residue retention and fertilization contributes to high long-term maize yields.

The high average yield of the NPK treatment compared to F1R0 monoculture scenario can be attributed to the NPK treatment having additional N sources, such as N fixation and field pea residue decomposition. Similarly, in the F0 treatments, the additional N benefits of the rotation were also indicated by the higher average yield in the control than F0R0. In the last 20 years, despite the discontinuation of the field pea in 1999, the control still records notable yield, whereas the F0R0 scenario recorded very low yield, and even crop failures in certain seasons due to low levels of plant available soil N. The benefits of retaining crop residue was clearly demonstrated in this study with both R1 scenario treatments in each fertiliser regime recording higher average yield than the original treatments and R0 scenarios. Beneficial effects associated with residue retention include conserving moisture by reducing evaporation, increasing soil fertility when residue is decomposed, reduction of erosion, preventing soil surface crusting, improving soil structure, and reducing soil acidification (Vallis et al. 1996, Hoffmann et al. 2020). The latter four are not represented in APSIM, so the advantages of residue retention may be under-estimated. Including these benefits in the commonly used crop models is recommended.

4.3 Residue retention and fertilizer application can maintain relatively high SOM content in long-term maize cropping systems.

Analysis of the APSIM model performance in simulating SOM indicated a good prediction for the top 0.2 m of the soil. In 2017, the higher SOM in the NPK than control treatment for the top 0.6 m can be attributed to higher C residue input because of fertilization increasing biomass production. In an experiment with barley (*Hordeum vulgare* L.) in England, Haynes and Naidu (1998) reported that fertilised plots had 15% higher SOM content than unfertilised treatments. A strong linear correlation between annual fertiliser applied and accumulation of SOM was also measured in the long-term continuous wheat experiment in Rothamstead, England (Edwards and Lofty 1982). In the APSIM model, the ‘conceptual pool’ approach is used to simulate SOC, and the decomposition rate of SOM varies between the pools. This comes with a huge uncertainty associated with estimation of decomposition rates for the different pools, which is something that cannot be directly measured. The ratio of total C to N in the different pools alters the decomposability of newly formed SOM. Decomposition of SOM also decreases with increasing soil depths due to C fixation on minerals and anaerobic limitations (Allison 2006, Schmidt et al. 2011). Kaur et al. (2008) reported that long-term use of inorganic fertilisers can significantly affect the distribution of SOM, noting that NPK fertiliser use is beneficial in maintaining the active C and N pools in the top layers of the soil surface (0 – 0.2 m depth), which helps to maintain the C associated nutrients in the rhizosphere increasing nutrient availability.

Based on the simulated long-term SOM trends from 1950 to 2017 for the control and NPK treatments, the initial decline was more rapid in the top 0.2 m compared to the 0.2 – 0.4 m and 0.4 – 0.6m soil layers in both treatments. A rapid loss of SOM after soil cultivation in cropping systems has been extensively reported in previous studies, with high initial SOM loss when natural vegetation is replaced with a cropping system (Dominy et al. 2002, Luo et al. 2010b, Swanepoel et al. 2016). This explains the R1 scenarios having the highest SOM content in 2017 because of long-term residue retention at harvest. Similar observations were made in the scenario simulation exercise with F1 scenarios having higher SOM than their unfertilised counterparts. The NPK treatment also had higher SOM than the F1R0 because of beneficial effects of field pea rotation until the discontinuation in 1983. In sub-Saharan Africa, livestock are often fed crop residue as fodder. Not feeding livestock with residue can reduce livestock production, but similar consequences can be observed in crop production when residue is removed through SOM decline and subsequent loss of soil fertility. Unfortunately, measured data was not available beyond 0.6 m for the trial. Studies to be better understand C dynamics beyond this depth are recommended.

5. CONCLUSIONS

Using a rare and valuable dataset, this study quantified the benefits of N fertiliser and residue retention in monoculture maize cultivation in a semi-arid environment over the long term. This is the first time that APSIM has been tested in southern Africa in this way to the best of our knowledge. APSIM was shown as a useful tool in simulating maize yield and SOM dynamics in this cropping system. The simulation of subsoil SOM dynamics, including ways to improve the estimation of the C:N ratios and decomposition rates of different fractions or pools, is recommended for future research. The model can further be applied to explore innovative ways beyond fertiliser and residue management to improve maize yield by smallholder farmers, as well as ways to maximise C sequestration to improve soil fertility and mitigate climate change.

Credit authorship contribution statement

Simphiwe Maseko: Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Visualization, Writing – review & editing. **Michael van der Laan:** Conceptualization, Funding acquisition, Supervision, Project administration, Methodology, Investigation, Writing – review & editing. **Diana Marais:** Methodology, historical data acquisition, Writing – review & editing. **Corrie Swanepoel:** Methodology, Data acquisition, Writing – review & editing.

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<u>Data availability statement</u>

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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