Clean Technologies and Environmental Policy
https://doi.org/10.1007/s10098-022-02272-7

ORIGINAL PAPER

Integrating a crop model with a greenhouse gas calculator to identify low carbon agricultural intensification options for smallholder farmers in rural South Africa

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Received: 8 April 2021 / Accepted: 10 January 2022

Abstract
Models that enable the estimation of crop yields and greenhouse gas (GHG) emissions concurrently are still lacking. This study develops a biophysical modelling framework encompassing a farm typology, a crop model, and a farm-focused GHG calculator to assess productivity (crop yield) and GHG emissions of crop management practices concurrently. Using this modelling framework, the study developed cropping system scenarios based on the concept of conservation agriculture (CA) to identify and design cropping systems that deliver ecological intensification for different farm types. All farm types were found to be net sources of GHG with cropping system inefficiency across all farm types. However, the integration of CA-based practices independently and in combination into farm-type maize-based cropping systems showed significant potential in improving crop yields and lowering GHG emissions across all farm types. CA-based practices in combination were more efficient and able to deliver ecological intensification with high productivity and ecosystem services which contribute to climate change regulation. This study concludes that the modelling approach identified intensification options that maintain or increase crop yields while reducing GHG emissions at the farm level. This can guide policy simulations and scenario analysis to tailor interventions for farm-type sustainability.

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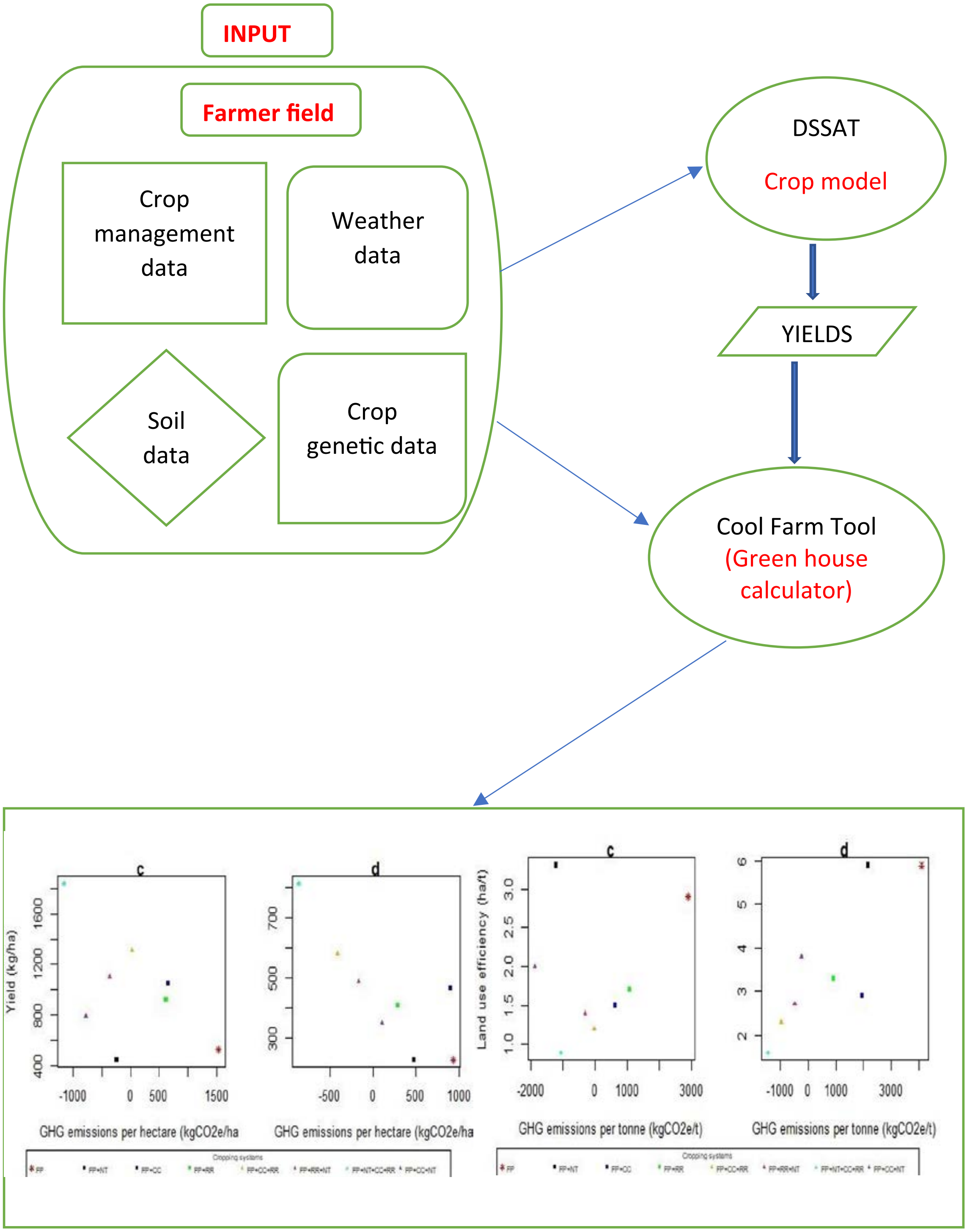
Published online: 22 January 2022

Graphical abstract



Keywords Conservation agriculture · Crop yields · Greenhouse gas emissions · Smallholder agriculture · Ecological intensification

Abbreviations

CA	Conservation agriculture
CC	Cover cropping
CFT	Cool farm tool

DSSAT	Decision support system for agrotechnology transfer
EF	Emission factors
FP	Farmer practice
GHG	Greenhouse gas
GREET	Greenhouse gases, regulated emissions, and energy use in transportation
N	Nitrogen
NT	No till
RMSE	Root mean square of error
RT	Residue retention

Introduction

Issues of agricultural intensification and environmental sustainability have become highly topical because of food insecurity and climate change impacts in sub-Saharan Africa (SSA) (Rockstrom et al. 2017). Sustainable and ecological intensification have been identified as viable means to increase food production and ensure environmental sustainability in smallholder farming systems in SSA (Pretty et al. 2018; Syampungani et al. 2021). At the same time, there is a growing global consensus that agricultural intensification should evolve in parallel with environmental sustainability (Gil et al. 2019), which must involve reducing emissions of greenhouse gases (GHG) from agriculture (Hunter et al. 2017). GHG emissions in smallholder farming systems in SSA are significantly high as smallholders are responsible for contributing up to 32% of agricultural-related GHG emissions (Descheemaeker et al. 2016). Reversing or simply slowing down current trends of agriculture-driven GHG emissions will require transdisciplinary approaches such as efficient agricultural intensification pathways, increasing resource use efficiency, and changing current agricultural techniques to enhance soil carbon sequestration efforts (Wollenberg et al. 2016). However, it remains unclear how intensification options may affect whole-farm GHGs balances in SSA (Jin et al. 2017).

Conservation agriculture (CA) a land management concept compromising of minimum soil disturbance, retention of crop residues, and crop diversification, has been identified as a key route to deliver both intensification and mitigation in smallholder cropping systems (Kassam et al. 2019). However, considerable debate whether CA is the best approach to intensify smallholder farming systems, and on whether CA can simultaneously address yield gaps, adaptation and mitigation challenges in smallholder agriculture exist (Giller et al. 2015). Several studies have shown that smallholder farmers rarely implement the full CA package and question the suitability of CA in the smallholder context in SSA (Bouwman et al. 2021). Few studies have focused on the contribution of the different CA components to reducing GHG emissions. Most have focused on closing yield gaps and adapting to climate change (Thierfelder et al. 2018).

Data quantifying existing GHG emissions from smallholder production systems is limited and only available for a handful of crops resulting in a huge data gap (Musafiri et al. 2020). Quantification of GHG emissions must be considered in farming system design if smallholders are to achieve the goals of improving agricultural productivity and environmental sustainability (Hunter et al. 2017). Most GHG emission studies, so far, highlight the emission reduction potential of farming practices, without concurrently paying attention to yield and livelihood impacts for smallholders (Rosenstock et al. 2013). Quantification of GHG emissions only is not helpful from a development perspective, if yield benefits of those options are ignored, because crop productivity and yield are inextricably linked to food security of smallholder farmers in SSA (Linquist et al. 2012). It is therefore important to develop an integrated framework that can assess the impacts of crop management practices on both crop yields and GHG emissions simultaneously when designing sustainable cropping systems for smallholder farming systems.

Simulation models are useful tools to explore and would significantly increase our understanding of the impacts of the proposed interventions and help target those interventions which improve productivity and environmental sustainability, using fewer resources and time than field experimentation (Masikati et al. 2017). Crop simulation models can be used to estimate crop yields (Holzworth et al. 2015) and can be used for strategic, tactical, or operational decision support in on-farm crop management (Webber et al. 2014). However, crop models are unable to simulate GHG emission consequences of different cropping systems. GHGs calculators use simple accounting approaches based on a mix of emission factors and empirical models to calculate GHG emissions with minimal input data (Hillier et al. 2011). A wide range of calculators hase been developed to assess the greenhouse gas (GHG) emissions of agricultural products (Sykes et al. 2017). However, these calculators often fail in their ability to consider any changes in agricultural management practices to estimate crop yield improvements (Peter et al. 2017). This is because the yield estimation of a particular cropping system may not adequately reflect the yield estimate for a new cropping system. As a result, the predictions of GHG emissions by these calculators are characterized by a high level of uncertainty which also emanates from the lack of data in SSA, and calculators may fail in their ability to detect mitigation options along the production chain (Richards et al. 2016).

Therefore, developing approaches that integrate crop models and GHGs calculators and are capable of incorporating relevant controls to predict crop yield and greenhouse emissions across a range of scales could better inform the selection of agricultural intensification options, which seek to address the joint yield gap and mitigation challenges in smallholder agriculture. Integrated modelling has been used to model interactions of agricultural systems at various scales. For example, McNider et al. (2015) coupled the Decision Support System for Agrotechnology (DSSAT) with a hydrologic model to examine the benefits of irrigation, cost of irrigation, and the impact of irrigation water extraction on surface water resources. In another study, Kadiyala et al. (2015) integrated a crop simulation model DSSAT and the geographical information system (GIS) to assist in agronomic decision-making. Whilst there are many of these studies on the integrated assessment modelling in agricultural systems few have attempted to evaluate agricultural productivity and GHG emissions in agricultural systems. For example, Anderson et al. (2018) integrated DSSAT with Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) model to assess the environmental impacts of biofuel production in the United States of America (USA). In another study in China, Tian et al. (2021) integrated DSSAT with the DeNitrification-DeComposition (DNDC) model to assess food-water-GHG emissions trade-offs to offer a viable solution for policymakers and stakeholders. While these kinds of assessments and tests performed well in developed countries, they have largely been missing in SSA, especially in smallholder agricultural systems which are diverse, thus presenting a large research gap. Hence, in this study, a biophysical modelling framework that combines a crop simulation model and a farm-focused GHG calculator is proposed to explore and assess the productivity (yield) and sustainability (GHG mitigation) potential of current and redesigned cropping systems in heterogeneous smallholder farming systems and communities in South Africa.

The study used the concept of CA as a guide to remodelling cropping systems to deliver ecological intensification in smallholder cropping systems. This article provides evidence that simulation models can be integrated to identify and design environmentally sustainable and productive cropping systems. The outcomes of the study are useful for understanding the role simulation models can play in farming system design which will serve as a reference for policymakers and stakeholders to identify and tailor effective CA packages and interventions for ecological intensification to suit farm type level needs to improve farm type sustainability.

Materials and methods

Study area and data on farm typologies and cropping systems attributes

The data for this study was obtained from Ha Lambani, Limpopo and Amathole, Eastern Cape, South Africa. The study sites were selected because they typify smallholder farming areas that are less developed and less-resourced and that can, in similar forms, be encountered in other villages and districts in the Eastern Cape and Limpopo provinces of South Africa. The farm typologies and related cropping system attribute data used in this study come from Rusere et al. (2019) and Mkuhlani et al. (2020) and are based on a survey of representative smallholder farms, in consultation with local experts in the two study regions. In the surveys, smallholder farms and farmers which fitted in the typologies developed by Rusere et al. (2019) and Mkuhlani et al. (2020) were identified through snowball sampling. The farmers who fitted in these farm types were interviewed through a semi-structured interview schedule. The data collected during the field surveys included farm size, types of crops grown, planting dates, tillage practices, planting patterns, fertiliser types and amounts, irrigation, harvesting dates, crop residue management practices, and farm power sources. A more detailed description of the survey is found in Rusere et al. (2019) and Mkuhlani et al. (2020). The data was analysed, and this resulted in the development of a prototype cropping systems for the farm types in study locations defined in Tables 1 and 2. The farm-type cropping systems were validated through focus group discussions with the local agricultural experts (mainly agricultural extension officers) in the study areas.

Table 1 Description of the cropping system patterns and agronomic practices in different farm types in Ha Lambani, Limpopo, South Africa

Farm type	Crop	Power source	Tillage	Fertilizer type and application rate	Crop residue management
Cereal and livestock	Maize	Draught power	Ox drawn ploughing	Cattle manure @ 5000 kgha^{-1} Compound fertiliser 2:3:2@ 50 kgha^{-1} Ammonium Nitrate (AN) @ 50 kgha^{-1}	Removed to feed livestock
Horticulture	Maize	Tractor	Ploughing and disking	Cattle manure @ 5000 kgha^{-1} Compound fertiliser 2:3:2 @ 250 kgha^{-1} Ammonium Nitrate (AN) @ 150 kgha^{-1}	Ploughed in
Off farm income	Maize	Draught power	Ox drawn ploughing	Cattle manure@ 2000 kgha^{-1}	Left in the field

Table 2 Description of the cropping system patterns and agronomic practices in different farm types in Amathole, Eastern Cape, South Africa

Farm type	Crop	Power source	Tillage	Fertilizer type and application rate	Crop residue management
Cereal and livestock	Maize	Draught power	Ox drawn ploughing	Cattle manure @ 5000 kgha^{-1} Compound fertiliser 2:3:2@ 50 kgha^{-1} Ammonium Nitrate (AN) @ 50 kgha^{-1}	Removed to feed livestock
Horticulture	Maize	Tractor	Ploughing and disking	Cattle manure @ 5000 kgha^{-1} Compound fertiliser 2:3:2 @ 250 kgha^{-1} Ammonium Nitrate (AN) @ 100 kgha^{-1}	Ploughed in
Cooperative	Maize	Tractor	Ploughing and disking	Cattle manure@ 2000 kgha^{-1} Compound fertiliser 2:3:2 @ 150 kgha^{-1} Ammonium Nitrate (AN) @ 50 kgha^{-1}	Left untreated in heaps and pits to make compost
Social welfare dependent and struggling subsistence	Maize		Hoeing	Cattle manure@ 2000 kgha^{-1}Compost @ 250 kgha^{-1}	Left untreated in heaps and pits to make compost

Models used and their description

DSSAT model

The Decision Support System for Agrotechnology Transfer (DSSAT v4.7) is a comprehensive framework of more than 28 biophysical models (Hoogenboom et al. 2019). The main structure of DSSAT is designed as a matrix of simulation treatments that select crop and soil models to describe the changes in plant and soil variables that occur in a specific field in response to weather and management. A detailed description of DSSAT and how it functions are given by Jones et al. (2003) and Hoogenboom et al. (2019). DSSAT simulates crop growth and yield as a function of many input parameters such as physiological crop parameters, climate, soil and management conditions. DSSAT extensive use as a tool to compare different crop management practices under diverse soil, and climate conditions (Webber et al. 2014), its experimented capacity to integrate with other models in the past (Anderson et al. 2018), and previous performance of the DSSAT in simulating maize yield under conservation agriculture (Corbeels et al. 2016), makes it suitable for our application.

The cool farm tool

The Cool Farm Tool (CFT) (Hillier et al. 2011) is a GHG calculation model that consists of several modules that integrate several globally determined empirical models into a GHG calculator (Hillier et al. 2011). The modules consist of a generic set of empirical models that are used to estimate GHG emissions based on a mix of IPCC Tier 1, Tier 2, and simple Tier 3 approaches. Due to the complexity of the CFT model and its many sub-models, on how the IPCC Tier 1, Tier 2 and Tier 3 methods are used and in which modules and on how the sub-models calculate GHG emissions are found in detail in Hillier et al. (2011). The model recognises context-specific factors that influence GHG emissions such as pedo-climatic characteristics, production inputs and other management practices at the farm level. The tool also has strong farm-scale focus and was identified as the highest-ranking tool that is available in the public domain (Whittaker et al. 2013). The tool has also been applied in several studies that range from model comparisons (Colomb et al. 2013) to product assessments (Aryal et al. 2015) and investigations of mitigation strategies at the global scale (Hillier et al. 2011). The CFT allows us to assess the performance of a cropping systems at the farm level both in terms of land-use efficiency and efficiency per unit of product. Its detailed crop submodule, which can account for land-use changes, fertiliser applications, and management changes such as tillage or cover cropping, fits the study ambition of integration with a management-sensitive crop model.

Intensification pathway scenario analysis

The cropping system for each farm type described in Tables 1 and 2 defines the baseline scenario and is referred to as the current farmer practice (FP). The CA principles of no till (NT), crop residue retention (RT), and cover cropping (CC) were considered as the varying management scenarios under investigation, given their potential to deliver ecological intensification in smallholder cropping systems in the different farm types. Their productivity, GHG emission, or sequestration potential was quantified to determine their suitability in redesigning those smallholder cropping systems deliver ecological intensification. The scenarios were as follows, scenario 1, considers the adoption of minimum soil disturbance through no till (FP + NT). Scenario 2 (S2), considers the adoption of crop residue retention only in cropping fields (FP + RT). Scenario 3 (S3), considers the adoption of cover crops only (FP + CC). Scenario 4 (S4), considers the adoption of cover crops and minimum soil disturbance through no till (FP + CC + NT). Scenario 5 (S5), considers the adoption of residue retention and minimum soil disturbance through no till (FP + RT + NT). Scenario 6 (S6), considers the adoption of residue retention and residue retention and cover cropping no till (FP + CC + RT). Scenario (S7), considers the adoption of the full CA package of residue retention, cover cropping and no till to the current farmer practice (FP + CC + NT + RT). Additional information on the scenarios simulated is provided in the supplementary material Table 6.

Modelling framework

Our central hypothesis was that coupling the Cool Farm Tool (CFT) with crop yield data from the Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al. 2019), can help identify and package together individually proven ecological intensification farming practices which can simultaneously support both productivity and environmental sustainability in smallholder cropping systems. The two stand-alone models, DSSAT and CFT are run separately but in coordination, as crop yield output from DSSAT is used as input data in the CFT (Fig. 1). DSSAT predicts crop yield under different cropping systems and agroecological conditions. The yield outputs from DSSAT are fed into CFT. CFT uses yield data to predict soil and atmospheric carbon dynamics under different regimes. Maize, a common crop in all farm types was used to illustrate the utility of the modellling framework. The impact of agroecological practices of CA individually and in combination for both crop yield improvement and GHG emissions were explored at the farm scale. This allowed us to identify management practices that enhance productivity

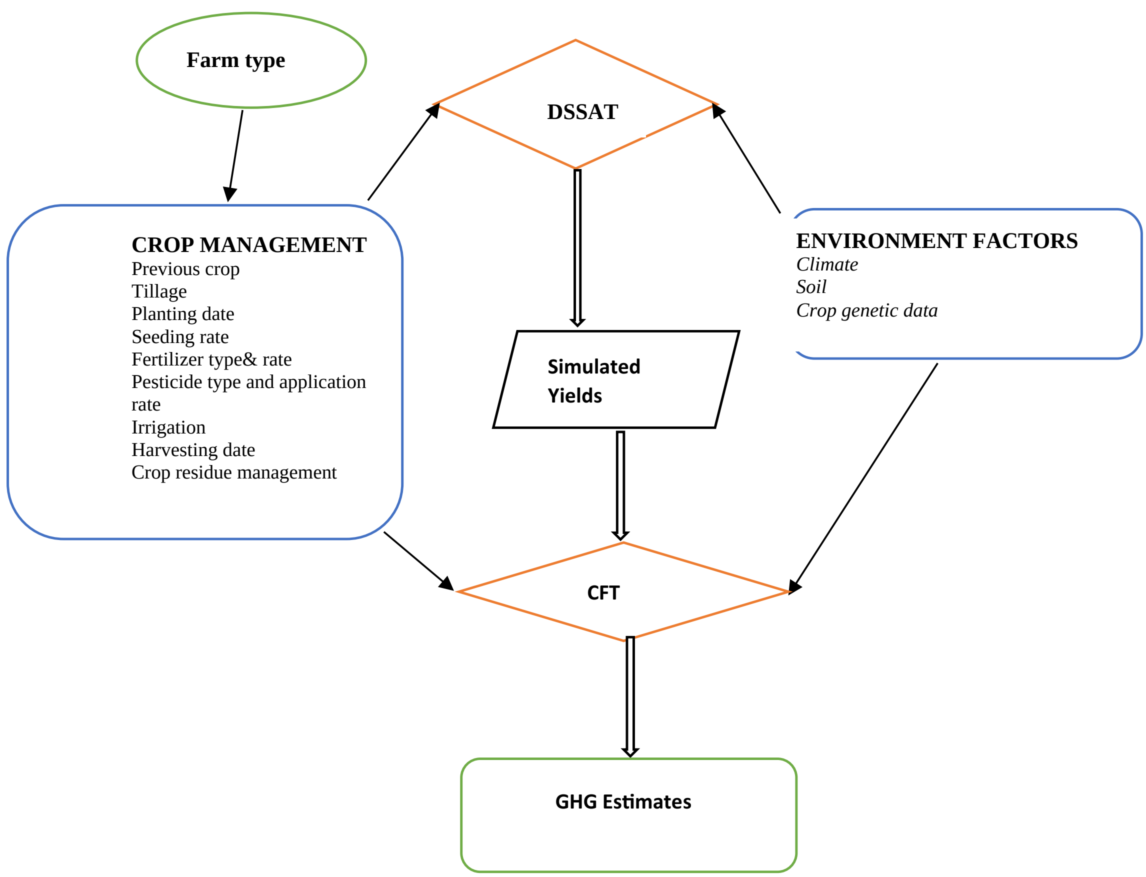


Fig. 1 A conceptual flow diagram of the biophysical modelling approach used to investigate crop yields and GHG emissions in maize-based cropping systems in different farm types in rural South Africa

and environmental sustainability in smallholder cropping systems.

Modelling crop yields with DSSAT at the farm level

DSSAT model input data

DSSAT requires at least four sets of data encompassing crop, crop management, soil and daily weather to simulate crop yields.

Daily weather data The minimum weather input requirements for the model include daily maximum and minimum temperatures (^{o}C), rainfall (mm), and solar radiation (MJm^{-2}d^{-1}). Those variables were obtained from the South African Weather Service (SAWS) for the period 2000–2015 for both Ha Lambani and Amathole.

Soil profile data Soil data describing soil texture, organic matter content, mineral and nutrient, and soil water dynamics is also required to run DSSAT. This data was not readily available for the different farm types and was obtained from previous studies done in the study area. Soil characteristics data were extracted from the International Soil Reference and Information Centre (ISRIC) global soil database (Poggio et al. 2021). Additional data on soil physical and chemical properties were derived from Choruma et al.(2021) and Choruma et al. (2019) for Amathole, Eastern Cape, and from Mzezewa et al. (2011) and Mzezewa and van Rensburg (2011) for Ha Lambani, Limpopo. Tables 3 and 4 below summarises the soil characteristics data for the two locations used in this study.

Crop management data The model requires information on tillage systems, planting dates, planting density, planting depth and row spacing, type of fertilizer applied, amount and frequency of fertilizer application, irrigation amount and frequency, and harvesting dates. The data are summarised in Tables 1 and 2 with detailed information in supplementary material Tables 2 and 3.

Crop data Effective calibration of the DSSAT model would include evaluation of the model's ability to simulate phenological aspects such as emergence, silking and maturity dates for each crop and season and location. The data were collected from farmers during household surveys and focus group discussions. In cases where such data was of poor quality, relevant literature such as Ncube et al. (2016), Zinyengere et al. (2014) and Zinyengere et al. (2015) were used in this study.

Simulation of crop yields at the farm level

The study utilised soil data, crop management, grain, and above-ground biomass yield to parameterise and calibrate the DSSAT model for each of the different farm types at each location. The root mean square error (RMSE) approach was utilised to evaluate the DSSAT models' ability to simulate

Table 3 Soil data characteristics used to calibrate the DSSAT v4.7 model for Ha Lambani, Limpopo

	Soil profile Depth					
Soil characteristics	0–5 (cm)	5–15 (cm)	15–30 (cm)	30–60 (cm)	60–100 (cm)	100–200 (cm)
pH	6.8	6.8	6.9	7.2	7.2	7.1
Phosphorus (P) mg kg^{-1}	15.7	9.17	3.55	2.17	1.55	0.17
Potassium (K) mg kg^{-1}	264.3	325	163	159	163	59
Calcium (Ca) mg kg^{-1}	2700	1270	1212	879	212	97
Magnesium (Mg) mg kg^{-1}	712.4	809.8	599.8	539	261	189
Zinc (Zn) mg kg^{-1}	2.8	2.2	1.6	1.1	0.7	0.2
Manganese (Mn) mg kg^{-1}	30.4	27.3	19.9	17.7	8.3	4.1
Copper (Cu) mg kg^{-1}	5.7	5.1	4.3	3.8	2.2	0.7
Total nitrogen (N) mg kg-1	114	75	73	59	42	32
Organic carbon (%)	1.33	0.88	0.67	0.53	0.45	0.39
Clay (%)	26.7	26.8	31.9	36.4	34.5	33.8
Silt (%)	15.3	15.4	14.3	13.9	14.6	14.7
Sand (%)	58	57.8	53.8	49.7	50.9	51.5
Soil texture Sandy clay loam						
Organic matter (%) < 1.72						
Drainage good						

Table 4 Soil data characteristics used to calibrate the DSSAT v4.7 model for Amathole, Eastern Cape

Soil characteristics	0–5 (cm)	5–15 (cm)	15–30 (cm)	30–60 (cm)	60–100 (cm)	100–200 (cm)
pH	6.2	6.2	6.3	6.4	6.6	6.7
Phosphorus (P) mg kg^{-1}	51.07	55.85	42.67	36.47	12.76	7.46
Potassium (K) mg kg^{-1}	172.08	265.33	133.75	108.4	75.33	18.41
Calcium (Ca) mg kg^{-1}	2248.6	2303.6	1221.9	1003	912.34	250
Magnesium (Mg) mg kg^{-1}	503.83	515.83	460.42	349.8	224.6	194.56
Zinc (Zn) mg kg^{-1}	0.94	1.51	0.85	0.28	0.17	0.03
NO_3-N mg kg^{-1}	1.09	1.28	0.88	0.85	0.43	0.27
NH_4-N mg kg^{-1}	0.82	1.21	0.74	0.32	0.19	0.03
Total mineral nitrogen (N) mg kg−1	256	180	129	70	90	39
Soil organic carbon (%)	3.25	2.16	1.24	0.85	0.69	0.68
Clay (%)	24.7	25.3	30.4	32.9	33.3	32.4
Silt (%)	20.7	20.8	20	19.1	20	20.5
Sand (%)	54.6	53.9	49.6	48	46.7	47.1
Soil texture sandy clay loam						
Organic matter (%) < 1.72						
Drainage good						

the current cropping systems conditions. The RMSE compared farmer measured grain and biomass yields with model-simulated yields for the three growing seasons 2000/1 to 2002/3. The RMSE values were computed using the Eq. (1):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (Si - Mi)^2}{n}} \tag{1}$$

where n is the total number of data, S and M represent the simulated and measured values, respectively.

Calibration of DSSAT model undertaken in this study showed that the RMSE across all parameters, crops and locations were under 30%, with some even under 10% (Supplementary material Tables 4 and 5) This highlighted the calibrated model's ability to effectively simulate crop yields. The calibrated DSSAT model was used to simulate maize yields based on local parameterisation and farm type agronomic characteristics. Crop yields were simulated for each farm type cropping system for the 15 growing seasons running from 2000/01 to 2014/15. Depending on the scenario, crop yields for each scenario were simulated by resetting either the tillage component or the crop management aspect of either residue retention or cover cropping. DSSAT simulated for the same period potential yields for each of the 7 scenarios in each farm type at both locations. Farm type and scenario yield results were compared using a one-way analysis of variance (ANOVA). Differences between farm types and scenarios in farm types were performed using Fisher's least significant difference (LSD) when $P < 0.05$.

Assessing GHG emissions with the CFT at the farm level

CFT model input data

The CFT requires the following information to estimate GHG emissions from cropping systems (i) location, climate, soil parameters (soil moisture, drainage, pH, soil organic matter); (ii) material and energy inputs to farming, i.e. fertiliser and pesticide types and amounts and energy used on-farm and (iii) crop yields and harvested area.

Table 5 Simulated maize crop yields, GHGs emissions per hectare and per unit of crop yield in Ha Lambani, Limpopo

Farm type	Simulated average yields ($kgha^{-1}$)	Estimated GHG emissions per hectare ($kgCO_2eha^{-1}$)	Estimated GHG emissions per tonne crop yield ($kgCO_2et^{-1}$)
Cereal and livestock	865[a]	572[a]	660[a]
Horticulture	1039[a]	1012[b]	970[a]
Off farm income	458[b]	378[c]	830[a]
LSD	245	33	460
P value	0.00	0.00	0.085

Means with different letters in the same column are significantly different at $P < 0.05$

LSD, least significant difference

Data for characteristics of the study area Data for characteristics of the study area were obtained from Ubisi et al. (2017) for Ha Lambani and from Chari et al. (2018) for Amathole (Supplementary material Table 1).

Soil characteristics Majority of the soils in the Eastern Cape are associated with low organic matter content thus presenting challenges for agricultural production (Nebo et al. 2020). However, in Amathole District, in the Eastern Cape, the most predominant soils are Oak leaf (SCWG 1991) and classified as Haplic Cambisol according to the International Union of Soil Sciences working group. According to the Department of Agriculture, Forestry and Fisheries (DAFF 2011) the soils in the area are very deep and sandy which allows the farmers to exercise their farming practices, especially for both livestock and cropping activities. Other soil characteristics data was extracted from Choruma et al. (2021) and Choruma et al. (2019).

Majority of soils in Lambani were identified as suitable or ideal for crop production (Petja et al. 2010). Soils in Ha Lambani are classified as Hutton, Pinedene, Clovelly, Avalon, and Oakleaf according to the South African soil classification system (Francis and Botha 2012). According to Francis and Botha (2012), the average soil depth in Ha Lambani is 1035 mm with a clay content of up to 40%. The soils in the study area are slightly acidic to more alkaline. Thus, the soils are generally good and suitable for crop production. Additional soil characteristics data used in this study were extracted from Mzezewa et al. 2011 and Mzezewa and van Rensburg (2011).

Crop management Crop management information was obtained from the field surveys and farmer interviewers and is summarised in Tables 1 and 2 and more details are in the supplementary material. In our case, only cooperative farms, in Amathole and horticulture-based farms in the two study areas use tractor-drawn implements while all the other farm types rely on animal draught power for field operations. Although livestock is not carbon neutral, the CFT does not consider entries directly related to crop production, such as livestock. This is a limitation as most communal area growers use animal draft power. As such, animal draft power as a source of energy was not included in the calculation for these types of farms. Irrigation was not included as these farmers operate under dryland conditions. DSSAT simulated maize yields for each farm type were input into CFT.

Calculation of greenhouse gas emissions at the farm level

The above-mentioned data and crop yields from DSSAT were coupled into the CFT to calculate farm-type GHGs emissions of current farm practices (FP) to identify the emissions at the farm-type level. In the estimation of GHG emissions, a boundary was set to estimate emissions from the field only. Within the set boundaries crop, soil inputs applied, fuel, and energy and carbon and sequestration changes were used to estimate the GHG emissions for each cropping system scenario. The irrigation and transport module components of the CFT were not included in the calculation of GHG emissions. This is because in these study areas maize is grown under rainfed dryland conditions and transport was not included as were only interested in GHG emissions at the field level. Each farm type was run separately and the mean GHGs emissions were computed. The study accounted for GHG emissions related to crop management and did not account for processing or transport beyond the farm gate. Two metrics were determined for each agricultural season running from 2000/01 to 2014/15 namely, the quantity of greenhouse gases emitted per hectare and the quantity of greenhouse gases emitted per unit crop yield. The maize yields simulated under CA scenarios described above were input into CFT to estimate the GHG emissions or sequestration potential per hectare and per crop yield of the various cropping system scenarios for each farm type. GHGs emissions were compared among different farm types and scenarios results using one-way analysis of variance (ANOVA). Differences between farm types and between scenarios within farm types were explored using Fisher's least significant difference (LSD) when the ANOVA showed a significant difference between groups *($P < 0.05$).*

Land use efficiency

To assess the potential of cropping systems to ecologically intensify across farms, the land-use efficiency indicator was used. It estimates the amount of land required to produce a unit of crop yield. Instead of measuring tonnes produced per hectare, land use efficiency measures the number of hectares required to produce a tonne of the crop.

Results and discussion

Current yields and GHG emissions in different farm types and locations

Maize-based cropping systems from the different farm types in Amathole and Ha Lambani were compared to provide a baseline for exploration of alternatives that concurrently lead to higher crop yields per unit area and lower GHG emissions. The simulated maize crop yields using the suite of farming practices described in Sect. 3 varied significantly in different farm types ($P < 0.05$) and were low in all farm types ranging from 0.2 to 1.1 tha^{-1} and 0.4 to 1 t ha^{-1} in Amathole and Ha Lambani, respectively (Tables 5 and 6).

Table 6 Simulated maize crop yields, GHGs emissions per hactare and per unit of crop yield in Amathole, Eastern Cape

Farm type	Simulated average yields (kgha^{-1})	Estimated GHG emissions per hectare (kgCO$_2$eha^1)	Estimated GHG emissions per tonne crop yield (kgCO$_2$et^{-1})
Cereal and livestock	796^a	350^a	440^a
Horticulture	1122^a	712^b	630^b
Cooperative	528^b	1538^c	2910^c
Social welfare and struggling subsistence	228^d	932^b	4090^d
LSD	258	241	110
P value	0.00	0.00	0.00

Means with different letters in the same column are significantly different at $P<0.05$

LSD, least significant difference

The simulated yields indicate that there is an opportunity to improve agricultural productivity through intensifying cropping systems on the current agricultural land. Maize yields simulated using farming practices described above were estimated to have a positive (undesirable) GHG emissions, both based on per hectare and per unit grain yield produced (Tables 5 and 6). The estimated GHG emissions per unit crop yield were high and varied significantly ($P<0.05$) across all farm types. The magnitude of GHG emission per unit crop yield ranged from 440 to 4 090 kgCO$_2$e t^{-1} and from 660 to 970 kgCO$_2$e t^{-1} across farms in Amathole and Ha Lambani, respectively. In Amathole, cooperative farms and the struggling subsistence and social welfare dependent farms were estimated to have the highest emissions per hectare of 1538 kgCO$_2$e ha^{-1} and 932 kg CO$_2$e ha$^{-1,}$ respectively. In Amathole, cereal and livestock farms were estimated to have the lowest emissions per hectare of 351 kgCO$_2$e ha^{-1} while in Ha Lambani the off-farm income-dependent farms were estimated to have the lowest emissions per hectare of 378 kgCO$_2$e ha^{-1}. However, in Amathole and Ha Lambani the estimated GHG emissions per unit crop yield showed that cereal and livestock farms have the lowest GHG emissions per unit crop yield of 660 kgCO$_2$et^{-1} and 440 kgCO$_2$et$^{-1,}$ respectively.

These results are generally similar and within range to those of other low input smallholder systems in SSA found by Ortiz-Gonzalo et al. (2017). The heterogeneity in crop management resulted in variation of these emissions among farm types. Fertilisation, tillage and crop residue management were the major emission hotspots that contributed to the magnitude of the emissions. In Amathole, the social welfare and struggling subsistence farms and the cooperative farms poor residue management contributed significantly to the high GHG emissions per unit area. In these farms crop residues are usually left in heaps or pits for composting thus, the decomposition of crop residue contributes significantly to GHG emissions. In cooperative and horticulture-based farms, tillage, fertiliser use, and fossil fuel energy mostly contributed to the high GHG emissions. In these farms, the use of inorganic fertilisers is relatively high when compared to the other farm types. In addition, machinery-drawn implements associated with the burning of fossil fuels contributed significantly to high the GHG emissions whilst the ploughing in of crop residue in horticulture creates favourable conditions for organic matter oxidation and mineralisation, resulting in soil carbon loss and further contributing to GHG emissions.

The lowest crop yields per hectare and the highest GHG emissions per unit area observed in social welfare and struggling subsistence confirm the inefficiency of the production process despite having low inorganic N application rates and no use of fossil fuels which are the major drivers for GHG emissions in cropping systems are. These results are in agreement with Bellarby et al. (2014) who found out that smallholder farms with exceptionally low yields in Kenya had very high GHG emissions per tonne of maize. In these farms, poor management of crop residue contributes significantly to the estimated high GHG emissions thus contributing significantly to the inefficiency of the cropping system. The low greenhouse gas emission per unit crop yield observed in cereal and livestock-based farms maize-based cropping systems emanates from the fact that in these farms crop residues are exported to feed livestock hence crop residues do not contribute significantly to GHG emissions in such maize-based cropping systems hence these systems are comparatively more efficient when compared to cropping systems in other farm types.

Our results reveal that even farms (horticulture and cooperative-based farms) that are well resource endowed, i.e. farms with high N application rates compared to the other farm types (although limited), there are still experiencing low yields and high GHG emissions in their maize-based cropping systems. This means the currently available resources in these production systems are being used inefficiently, as evidenced by low yields and high GHG emissions. There is, however, a risk that in such smallholder farming systems agriculture intensification based on high external input use may further lead agricultural to an increase of GHG emissions leading to further environmental degradation, amplified climate change, and overall unsustainable development of SSA agricultural systems. This current relationship of low crop yields and high GHG emissions in smallholder farms can be reversed by using eco-efficient intensification solutions such as ecological intensification that utilise ecological processes to improve the efficiency of the limited external input resources, productivity (yield) and ensure reduced GHG emissions.

The impact of conservation agriculture practices on yield and GHG emission

CA is being promoted as an agroecological approach to deliver both sustainable and ecological intensification in smallholder cropping systems. The study opted to redesign the cropping systems with CA to deliver ecological intensification because of limited access, affordability and minimal inorganic fertiliser use, which is way below the recommended fertiliser application rates of the study areas. Figures 2 and 3 show yield per hectare on the y-axis and GHG emissions per hectare on the x-axis of the various crop management scenarios. They illustrate on the right-hand side crop management scenarios that are positive emitters of GHG (undesirable cropping scenarios) while on the left-hand side crop management scenarios that are negative emitters of GHG (desirable cropping scenarios). A combination of high yield and negative emissions, "desired crop management scenarios" would be on the top left and a combination of low yield and high emissions, "undesired crop management scenarios" would be on the bottom right. The trend building up from Figs. 2 and 3 show farmer practices (FP) on the bottom right (undesired) and the full CA package (FP + NT + CC + RR) on the top left (desired), illustrating concurrent yield and GHG emission improvement from integrating CA practices to the farmer practices.

More specifically, our simulations (Figs. 2 and 3) show that integrating conservation agricultural practices of no till (NT), residue retention (RR), and crop diversification and associations through rotations, intercropping, or cover cropping (CC) to the current farmer practice (FP) alone or in combination significantly impacts both crop yield and GHG emissions in cropping systems. Simulations showed that integration of residue retention (FP + RR) and cover cropping (FP + CC) to the current farmer practice (FP) alone significantly improved crop yields ($P < 0.05$) while the no till (FP + NT) practice resulted in lower yields when compared to the current farmer practice across all farm types and locations. The result for the no till (FP + NT) practice is in agreement with Rodenburg et al. (2020) who observed that crop yields were generally lower in no till systems. However, the results for the integration of cover crops (FP + CC) practice are in agreement with Mupangwa et al. (2017) observed that legume cover crops improved maize grain yield and the maize crop benefitted from the residual soil fertility contributed by legume cover crops. With regards to residue retention our results concur with Rusinamhodzi et al. (2015) who observed yield gains in maize cropping systems of smallholder farmers with different resource endowments. With regards to GHG emissions, our estimates show that integrating the no till (FP + NT) practice and cover cropping (FP + CC) significantly lowers GHG emissions and results are in agreement with Rutkowska et al. (2018) who observed that CO_2 emissions were significantly lower in no till systems compared to conventional tillage systems. A similar trend of lowering of GHG emissions was also observed with the integration of cover crops in cropping systems by Schipanski et al. (2014). However, the residue retention practice (FP + RR) significantly contributed to increased GHG emissions when compared to current farmer practices. These results are in agreement with Pugesgaard et al. (2017) who found crop residues to significantly stimulate GHG emissions in cropping systems with restricted access to fertilizers or manure.

Our results showed that when CA practices are used in combination for example when residue retention and cover cropping (FP + CC + RR), or when residue retention and no till (FP + RR + NT) or when cover cropping and no till and (FP + CC + NT) are combined and included in the current farming practices, crop yields are significantly improved ($P < 0.05$) across all farm types and GHG emissions are significantly lowered. Beyond understanding the impact offered by the integration of single CA practices, our results confirm that when CA practices are used in combination, crop yields are significantly improved and GHG gas emissions are significantly lowered when compared to when CA practices are used alone. For example, when no till is integrated with residue retention (FP + RR + NT) or when integrated with cover crops (FP + CC + NT) significant yield gains and GHG emissions are lowered when compared to FP + NT. A similar trend was observed for the following cropping scenarios FP + RR + NT and FP + CC + RR when compared to FP + RR and when FP + CC + NT and FP + CC + RR are compared to FP + CC cropping scenarios. Ultimately, the full CA package (FP + NT + CC + RR) showed to be the most desired cropping scenario (found on the top left of Figs. 2 and 3) as it showed significant potential to improve crop yields ($P < 0.05$) and lower GHG emissions ($P < 0.05$) in all farm types across the locations. These results are in agreement with other studies on smallholder farms that have focussed on the effects of CA on maize yield (Thierfelder et al. 2015). As regards GHG emissions, these findings add to previous studies by Thierfelder et al. (2017), showing that using a combination of CA practices may help sequester

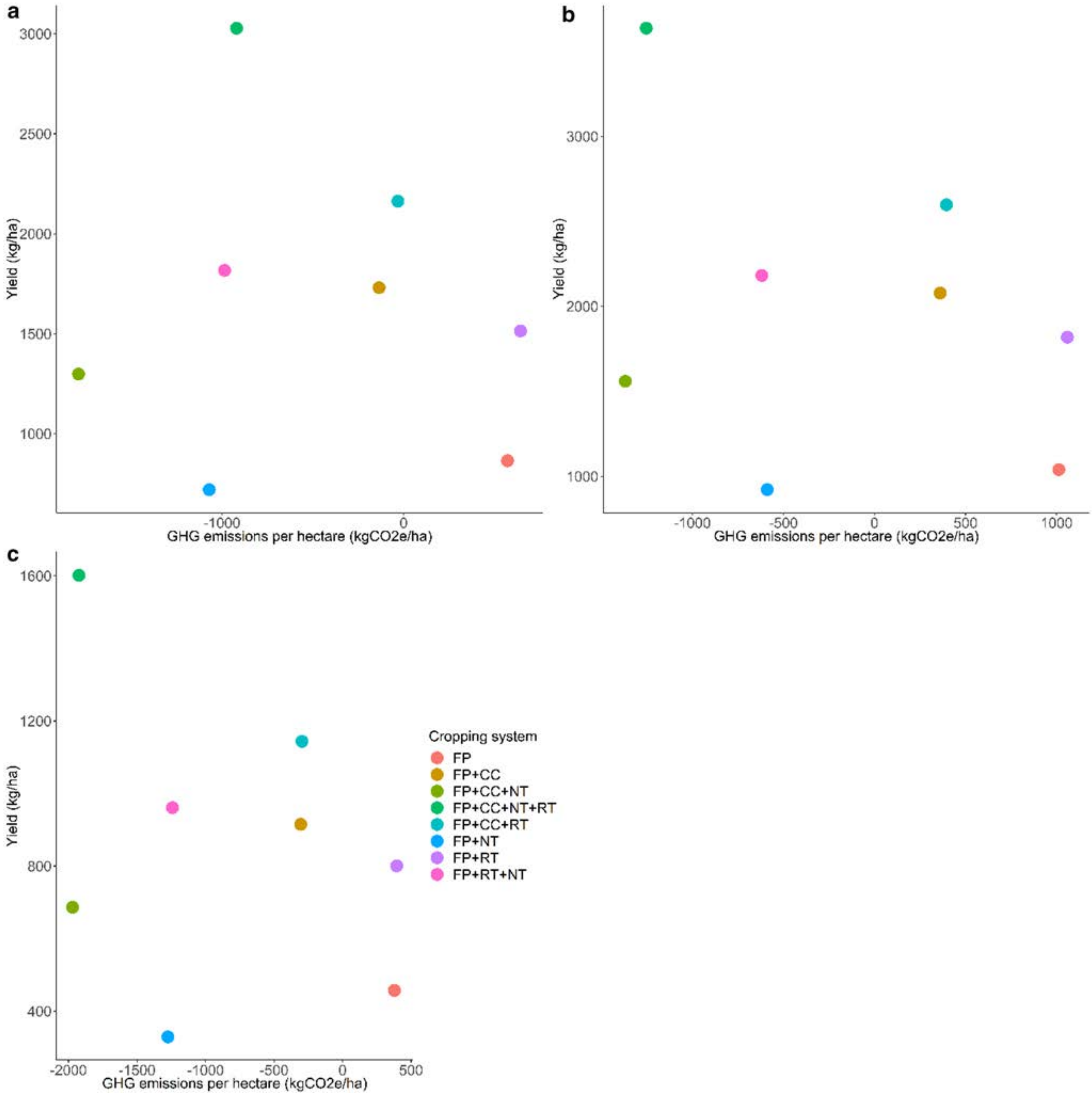


Fig. 2 Modelled impact of different crop management scenarios on maize crop yields and GHG emission per hectare in Ha Lambani: **a** cereal & livestock farms, **b** horticulture farms and **c** off farm income-based farms

carbon in the soil and significantly increase soil carbon content.

Impact of conservation agricultural practices on land use efficiency per unit yield and GHG emissions per unit yield

Figures 4 and 5 show land-use efficiency per tonne produced on the y-axis and GHG emissions per tonne on the x-axis of the various crop management scenarios. They illustrate on the right-hand side crop management scenarios that are positive emitters of GHG per tonne produced (undesirable crop management scenarios) while on the left-hand side are crop management scenarios that are negative emitters of GHG per tonne produced (desirable crop management scenarios). A combination of high land-use efficiency and negative GHG emissions per tonne produced would be on the bottom left (desired crop management scenarios) and a combination of

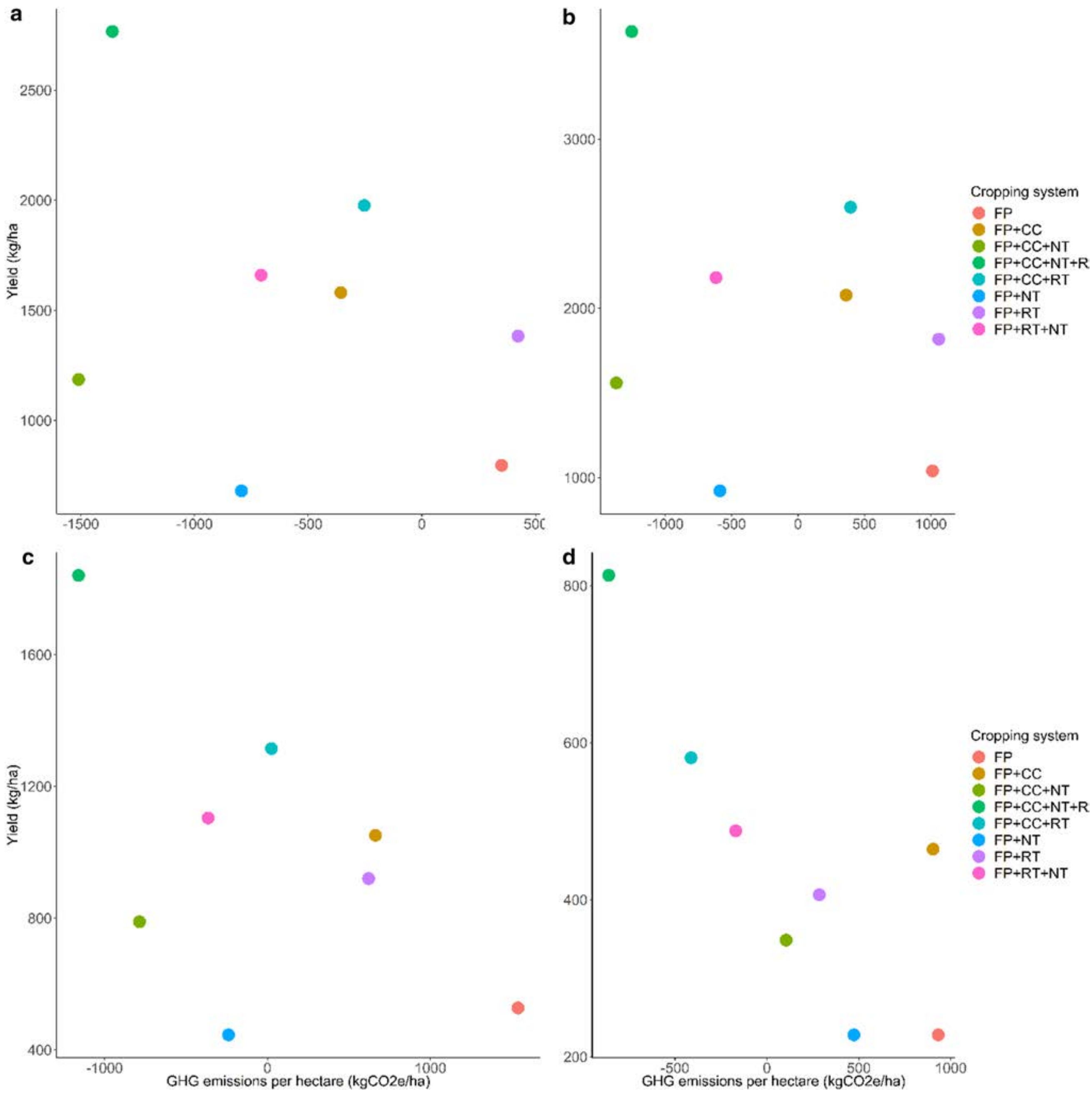


Fig. 3 Modelled impact of different crop management scenarios on maize crop yields and GHG emission per hectare in Amathole: **a** cereal & livestock farms, **b** horticulture farms, **c** cooperative farms, and **d** social welfare and struggling subsistence farms

low land-use efficiency and high GHG emissions per tonne produced, would be on the top right (undesired crop management scenario). The trend building up from Figs. 3 and 4 show farmer practices (FP) on the top right (undesired) and the full CA package (FP + NT + CC + RR) on the bottom left (desired), illustrating concurrent land-use efficiency and GHG emission (carbon sequestration) improvement from integrating CA practices to the farmer practices. More specifically, our results show that CA practices can contribute to reducing pressure on land and help deliver agricultural intensification with low GHG emissions per unit yield. Figures 4 and 5 show that the integration of cover crops (FP + CC) and the integration of residue retention (FP + RR) have the potential to produce a tonne of maize on a smaller land area as compared to the normal farmer practice (FP) across all farms and locations. Although FP + RR scenario maybe associated with crop yield gains and land-use efficiency, the increased GHG emissions and associated trade-offs for

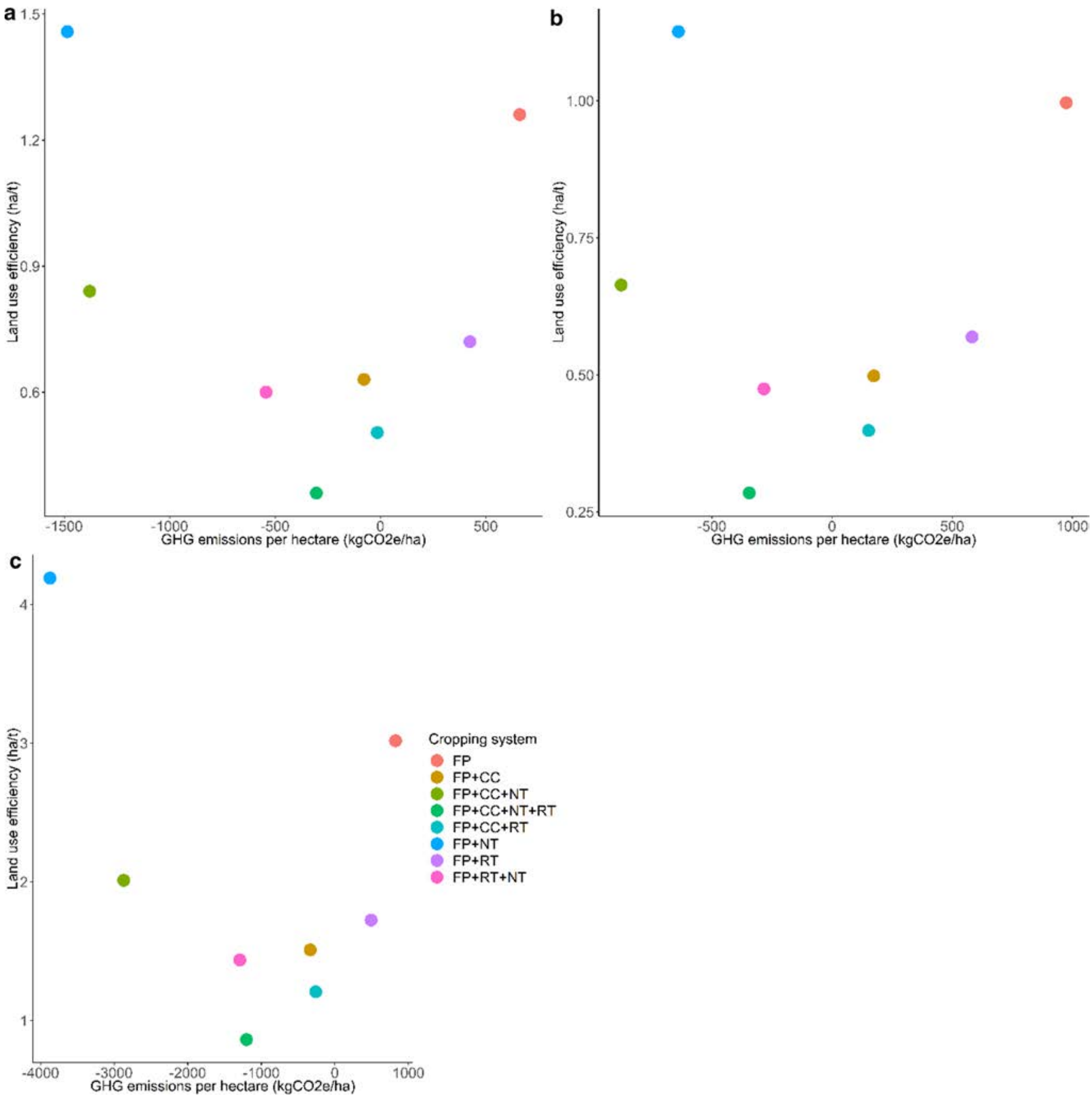


Fig. 4 The potential impact of different crop management scenarios on land use efficiency and GHG emissions per tonne of maize in Ha Lambani. **a** cereal and livestock-based farms, **b** horticulture-based farms; and **c** off-farm income-based farms

crop residue use as a livestock feed or as mulch for soil cover in cropping systems may make it an unsuitable cropping scenario to redesign smallholder cropping systems for ecological intensification in farms with livestock. However, the integration of no till (FP + NT) is expected to require a larger land area to produce a tonne of maize, compared to the normal farmer practice (FP) across all farms and locations making the practice unsuitable for agricultural intensification despite its potential in lowering GHG emissions in cropping systems.

Furthermore, our results (Figs. 4 and 5) show that using a combination of CA practices, for example, FP + RR + NT, FP + CC + NT, FP + CC + RR or FP + NT + CC + RR has the potential to significantly intensify maize cropping systems across farm types and location. Beyond understanding the impact offered by the integration of single CA practices our results confirm that when CA practices are used in

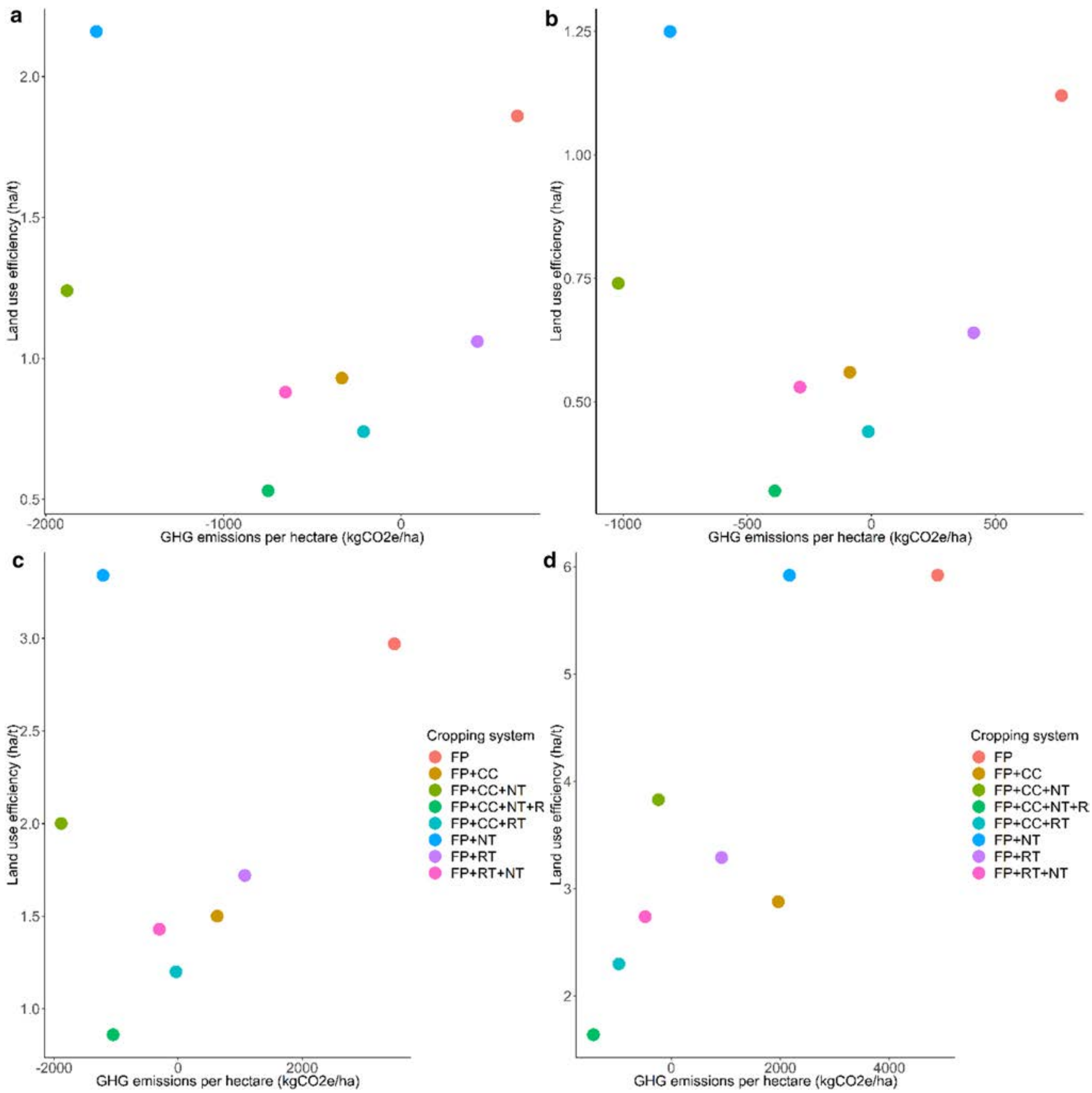


Fig. 5 The potential impact of different crop management scenarios on land use efficiency and GHG emissions per tonne of maize in Amathole. **a** cereal and livestock-based farms, **b** horticulture-based farms; **c** cooperative based farms and **d** social welfare and struggling subsistence farms

combination, land-use efficiency is significantly improved, and GHG emissions per unit crop yield are significantly lowered when compared to when CA practices are used alone. For example, when residue retention is integrated with no till residue (FP + RR + NT) or when integrated with cover crops (FP + CC + RR) land-use efficiency is significantly improved, and GHG emissions per unit yield are significantly lowered when compared to FP + RR. Ultimately, results showed that the full CA package of FP + NT + CC + RR has the potential to significantly improve land-use efficiency and GHG emissions per unit yield when compared to the farmer practice and other cropping scenario combinations across the farms and locations. Thus, our results agree with several authors such as Giller et al. (2015) and Jat et al. (2020) advocating for conservation agriculture as a pathway to low carbon agricultural intensification in sub-Saharan Africa.

Perspectives on the modelling framework

The study was based on crop management data from Ha Lambani and Amathole obtained through an expert-based farm typology. The number of farms surveyed for each farm type were small and this may have caused imperfect matching and bias of cropping systems attributes. However, the typologies were able to show the heterogeneity of the maize cropping systems in smallholder farming systems. This can, however, be improved by increasing the sample size of surveyed farm types. In this study, DSSAT was used to simulate crop yields from detailed farm management practices, allowing simulations to reflect detailed farm management strategies in cropping systems. DSSAT requires a large data set for correct parameterisation, calibration and validation procedures which were sometimes not available for the study areas. The study relied on secondary data from other sources for calibrations to improve the accuracy and reliability of our crop yield simulations. The CFT was the best able to calculate on-farm emissions using our data and it was best able to incorporate the different strategies for the different farm types. However, GHG calculators are usually fed with default emission factors (EF) and model parameters coming from developed countries as such GHG calculators may not be accurate when compared against field measurements and thus may not accurately estimate GHG emissions (Richards et al. 2016). However, it should be recognised that any positive or negative bias is of less importance when comparing samples from the same region with each other. Overall, the modelling framework allowed for the identification of practices that may improve crop yields and environmental sustainability through GHG efficient production systems.

Conclusion

Our research developed a biophysical modelling approach encompassing DSSAT a crop model and the CFT a farm-focused GHG calculator. Data from farm typologies were used to model the impacts of current farming practices and CA practices on crop yields and GHG emissions in maize-based cropping systems using this modelling approach. The stepwise assessment of CA practices alone or in combination also showed significant potential to deliver ecological intensification in circumstances where trade-offs associated with CA prevent the uptake of one of the three practices. Our analysis suggests that productivity and environmental sustainability may be improved through proper agronomic management (tillage, crop associations and proper crop residue management) even when fertiliser rates are not increased. Therefore, rather than agricultural intensification focusing on increasing the use of inorganic fertilisers and agrochemicals, the focus should be on improving the resource use efficiency of current resources in cropping systems.

The findings on the key drivers of sustainability in smallholder cropping systems will help agricultural scientists, policy-makers and other agricultural stakeholders to identify and tailor effective CA packages and interventions for ecological intensification to suite farm-type level need to improve farm type sustainability. Overall, the research provided an environmentally oriented indicator of cropping system efficiency in the form of GHGs emissions which has been lacking to capture farmers' initiatives towards mitigation and minimizing the negative impacts of their practices on the environment. In addition to the benefits stated above the integrated modelling framework presented in this study hold great potential to assess future agricultural systems in achieving these aims of the sustainable development goal (SDG) number 2 which aims to end hunger, achieve food security, and promote sustainable agriculture and the Paris Agreement which also aims to substantially reduce greenhouse gas emissions in an effort to limit global warming, thus enabling maximization of synergies and minimization of trade-offs in order to ensure policy coherence with the SDG number 2 and the Paris Agreement. The study recommends that future research on crop yield and GHG emission quantification tools to improve the accuracy of simulated crop yields and estimated GHG emissions. This may include field experiments to provide data for correct parameterisation, calibration and validation procedures.

Declaration

The authors declare that they have no financial or personal relationships which may have inappropriately influenced them in writing this article.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10098-022-02272-7.

Acknowledgements The authors are very grateful to Alliance for Collaboration for Climate and Earth System Sciences (ACCESS), South African Water Research Commission (WRC), African Climate Development Initiative (ACDI) and Natural Environment Research Council (NERC) (grant code: NE/N014472/1) for funding the work. The authors are indebted to the Department of Rural Development and Agrarian Reform (DRDAR), in the Eastern Cape province and Limpopo Department of Agriculture and Rural Development (LDARD), Risk and Vulnerability Science Centre within the Faculty of Science and Agriculture, at the University of Fort Hare and Institute for Rural Development (IRD), at the University of Venda for providing both technical and logistical support.

Funding This research was supported with funding from National Research Foundation (NRF), Water Research Commission

(WRC) [K5/2496/4], Alliance for Collaboration for Climate and Earth System Sciences (ACCESS) and African Climate Development Initiative (ACDI). Lynn Dicks was funded by the Natural Environment Research Council (NERC) (grant code: NE/N014472/1). Interpretation of the findings and conclusion drawn from the study were the responsibilities of the authors and not on any part of National Research Foundation (NRF), Alliance for Collaboration for Climate and Earth System Sciences (ACCESS), Water Research Commission (WRC), African Climate Development Initiative (ACDI) and Natural Environment Research Council (NERC).

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