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Design of a Soil-based Climate-Smartness Index (SCSI) using the trend and variability of yields and soil organic carbon

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ABSTRACT

Climate-Smart Agriculture (CSA) has had an increasing role in the agricultural policy arena, as it aims to address climate change mitigation, adaptation and food security goals in an integrated way. In regions where agriculture has been constrained because of soil degradation and climate change, CSA aims to implement soil-based strategies that restore soil function and increase carbon storage. The extent to which such strategies succeed in achieving mitigation, adaptation and productivity goals is referred to as climate-smartness. The co-evolution of yield and Soil Organic Carbon (SOC) over the years presents a proxy for the trade-off between productivity, soil fertility and carbon sequestration. Yield and SOC are widely monitored, analysed and used to inform CSA planning. Yet their analysis is often conducted separately and for a small number of years, which neglects long-term soil fertility dynamics and their impact on crops. Given the absence of integrated climate-smartness metrics to capture the trade-offs and synergies between SOC and yield, we present a soil-based Climate-Smartness Index (SCSI). The SCSI is computed using normalized indicators of trend and variability of annual changes on yield and SOC data. The SCSI was calculated for a set of published experiments that compared Conservation Agriculture (CA) practices with conventional management. The CA treatments scored higher SCSI during the first 5 years of evaluation as compared to conventional management. Analysis of the temporal dynamics of climate-smartness indicated that minimum SCSI values typically occurred before 5 years after the start of the experiment, indicating potential trade-offs between SOC and yield. Conversely, SCSI values peaked between 5 and 10 years. After 20 years, the SCSI tended towards zero, as substantial changes in either SOC or yield are no longer evidenced. The SCSI can be calculated for annual crops under any soil management and at different time periods, providing a consistent metric for climate-smartness across both practices and time.

1. Introduction

Climate-Smart Agriculture (CSA) is a concept that responds to the multifaceted objectives for agriculture within the context of climate change and food insecurity (Lipper and Zilberman, 2018). The principles of CSA aim for the achievement of three general objectives: 1) sustainable increase in agricultural productivity, 2) build climate resilience, and 3) reduction the Greenhouse Gas (GHG) emissions from agricultural activities (FAO, 2013). Each CSA objective represents the general vision of productivity, adaptation, and mitigation in agriculture; however, such objectives are interpreted according to the context, and their trade-offs and synergies are a core component of the CSA approach.

In the case of cropping systems, the soils play a transversal role in the achievement of CSA objectives. Soil conditions largely determine crop productivity; loss of fertility or the accumulation of pollutants in the soil can reduce the yields even under favourable climate conditions. Besides, the degradation of soil affects the adaptative capacity of farmers due to the reduction of soil functioning relevant for climate resilience, such as like physical stability, water dynamics, or nutrient recycling (Chappell et al., 2019; Lankoski et al., 2018; Webb et al., 2017). Finally, the

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agricultural soils are the principal source of nitrous oxide (N_2O), while alternatively have important CO_2 sequestration potential (Smith et al., 2008; Paustian et al., 2016).

Given the role of agricultural soils in climate change, CSA widely promotes soil-oriented strategies. Practices such as minimal soil disturbance and permanent soil organic cover, which characterise conservation agriculture (CA), increase soil water retention during droughts and heatwaves (Delgado et al., 2011; Kang et al., 2009) and reduce erosion and nutrients leaching during heavy rainfall events (Kaye and Quemada, 2017). Moreover, practices like the use of organic fertilizers or crop residue retention enhance the SOC content. A SOC increase may, in turn, increase water retention and Cation Exchange Capacity (Zingore et al., 2011) and contribute to mitigation goals in the long-term as more stable fractions of SOC are sequestered. Such changes in SOC may indicate the potential availability of C and N sources for plants and microorganisms, as well as an increased capacity for water retention, among others SOC-associated soil quality parameters. (Manns et al., 2016).

The impact of sustainable soil practices can be expected to translate into improved productivity and resilience, especially during climate-related events (Kaczan et al., 2013; Thierfelder et al., 2017). SOC and yields are both affected by a broad range of agro-environmental factors, including climate, land-use history, or initial soil conditions. These factors confound the relationship between yields and soil organic carbon, even conditioning their temporal response in cropping systems under good soil management conditions (Hijbeek et al., 2017; Oldfield et al., 2019). For instance, practices focused on increasing soil organic matter may carry yield penalties in the short term (Corbeels et al., 2020). However, the expected benefits in terms of productivity and adaptation would be evidenced in the middle to long-term after a cumulative effect of continuous organic matter incorporation (Prestele and Verburg, 2019; Thornton et al., 2018). Accordingly, the synergies between the SOC increasing, the soil improvement, and the enhancement of yield, could be used as an indicator of the climate-smartness in cropping systems.

Climate-smartness, defined as the extent to which the productivity, resilience, and mitigation objectives of climate-smart agriculture (CSA) are synergistic, can be strongly context-dependent for soil-oriented strategies. Thus, climate-smartness is a joint property of both land management and the response of the cropping system to that management. Measuring climate-smartness, therefore, implies the combination of multiple measurements into CSA indicators for specific management-by-environment situations in particular cropping systems. These indicators offer a useful way of understanding the trade-offs and synergies between different objectives within a given agricultural system over time (e.g. Arenas-Calle et al., 2019; Hammond et al., 2017; Manda et al., 2019).

The last five years have seen considerable progress in the development of climate-smartness assessment methods. Many of these methods rely on the use of participatory approaches (e.g. Birnholz et al., 2017; Manda et al., 2019; Mwongera et al., 2017; Wassmann et al., 2019), or the use of climate model results and expert opinion (De Nijs et al., 2014), while others use household-level data (e.g. Hammond et al., 2017) to measure climate-smartness of specific households. These approaches, however, while broadly applicable, lack the replicability and comparability required to measure climate smartness across sites and years. There is a lack of integrated measures that can provide an overall quantification of climate-smartness (Lankoski et al., 2018; Rosenstock et al., 2016; Thornton et al., 2018), particularly for comparative assessments over space and time. Indeed, questions about how the climate smartness of an agricultural system changes over time have been subject to little empirical analysis.

One area of progress is the climate-smartness index, and associated methodological framework, of Arenas-Calle et al. (2019). The index is used to represent the extent of synergy between productivity, emissions, and adaptation around water use. The index, however, is applied to single seasons at a time and takes no account of longer-term issues such as evolving soil carbon stocks. Here, the approach of Arenas-Calle et al. (2019) was extended to develop a new index of climate-smartness for cropping systems under soil-oriented climate-smart practices. The Soil-based Climate-Smartness Index (SCSI) was built using normalized indicators of trend and variability of temporal changes on yield and SOC data. The SCSI is evaluated using data from published studies of controlled trials of soil management practices, for which SCSI is calculated at different periods. The SCSI results and the considerations in the use of SCSI to measure climate-smartness are discussed.

2. Materials and methods

2.1. *Design of the Soil-based Climate-Smartness Index (SCSI)*

Soil-based strategies can improve the productivity within the attainable thresholds and sustain this productivity over time. A soil-based index of climate smartness therefore needs to account for the way in which SOC and yield evolve over time, both in terms of long-term trends and short-term variability. High (low) climate-smartness is associated with steadily increasing (decreasing) yields and SOC. The index also needs to describe the trade-off whereby increasing yields may be associated with decreasing SOC and vice-versa.

To provide a quantitative measure of climate-smartness in cropping systems, a Soil-based Climate-Smartness Index (SCSI) is proposed (Fig. 1). The SCSI is based on the trend and variability of the changes in Yield and Soil Organic Carbon (SOC) data in temporal series (See Table 1). For the SCSI design, 3 steps were followed. First, the trend and variability of annual yield and SOC changes were calculated and normalized. Second, the normalized indicators of variability and trend were aggregated to create normalized indices of SOC and Yield. Finally, yield and SOC normalized indices were aggregated to build the SCSI.

2.1.1. *Step. 1 Variability and trend of yield and SOC indicators*

Yield and SOC were selected as indicators to represent the climate-smartness in crops under soil-oriented practices. The selection is grounded by literature related with CSA indicators (FAO, 2013; Mwongera et al., 2015; World Bank, 2016), climate-smartness assessments of soil-related practices on cropping systems (Bai et al., 2019; Birnholz et al., 2017; Notenbaert et al., 2017) and studies of soil-based indices (Cardoso et al., 2013; Pulido Moncada et al., 2014; Raiesi and Kabiri, 2016; Six et al., 2000, among others).

Soil Organic Carbon is considered a “keystone” of soil condition and is commonly included in soil quality indices and carbon sequestration assessments (Bünemann et al., 2018; Calero et al., 2018; Hatfield et al., 2018; Muñoz-Rojas, 2018; Raiesi, 2017; Vasu et al., 2016). The widespread use of SOC as a soil health indicator is due to its strong correlation with Cation Exchange Capacity (CEC), water holding capacity (WHC), pH, biological activity and soil structure (Cardoso et al., 2013; Rabot et al., 2018). Such properties determine the soil aptitude for agriculture and an eventual increasing of SOC improves soil processes related to these properties. For instance, the CEC is low in sandy soils but may increase with the increment of organic negatively charged compounds present in Organic Matter (Ramos et al., 2018; Kaiser et al., 2008). Similarly, water availability can increase linearly with the increment on organic matter in soil (Lal et al., 2007; Rawls et al., 2003).

Likewise, crop yields are extensively used as an indicator of the climate impacts on agriculture (Hatfield et al., 2018) and climate-smartness assessments (Lee et al., 2014; Mwongera et al., 2017; Notenbaert et al., 2017; Shikuku et al., 2015; Shirsath et al., 2017), where the farmers and stakeholders identify the yields as a heavyweight indicator in the prioritization of CSA practices and food security. Moreover, its correlation with soil quality indices (Mukherjee and Lal, 2014; Obade and Lal, 2016., Vasu et al., 2016) shows its suitability to indicate the extent to which soil health are related with productivity benefits.

2.1.2. *Sustainable Yield (SYI) and SOC (SSOCI) Indices*

The variability of Yield and SOC were represented by the Sustainable

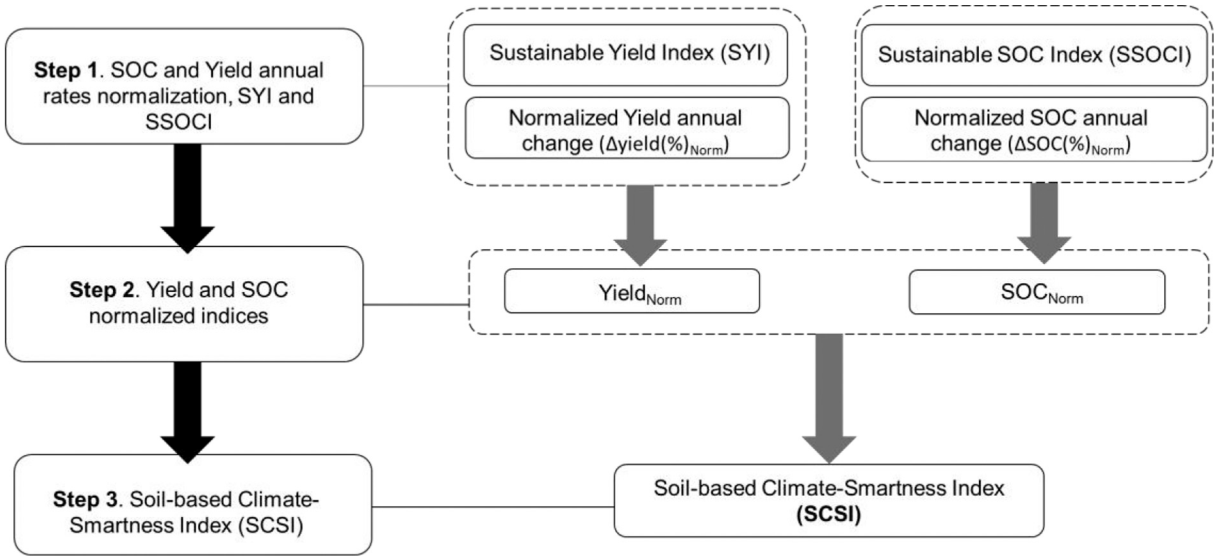

Fig. 1. Flowchart of steps to build the Soil based Climate-Smartness Index (SCSI).

Table 1
Characteristics of the studies used in this study.

Reference	Country	Period (years)	Sampling depth (cm)	Soil Texture	Crop	CA practices
Agbede and Adekiya, 2013	Nigeria	3	60	Sandy Loam	Yam	MSD
Campbell et al., 2007	Canada	17	15	Loam	Wheat	MSD, CD
Chen et al., 2015	China	10	20	Silt loam texture	Winter-wheat + summer maize	OG
Datta et al., 2010	India	6	15	Loam	Wheat and Soybean	CD, OG
Dimassi et al., 2014	France	41	80	Silty loam to silty clay loam	Wheat and Maize	MSD, PSOC
Dou et al., 2014	United States	4	90	Silty loam	Sorghum	PSOC
Mohammad et al., 2012	Pakistan	6	60	loam to clay loam	Wheat	MSD, CD, PSOC
Rasmussen and Parton, 1994	The United States	56	60	Silt loam	Wheat	OG
Rothamsted Research, 2017	UK	145	23	Clay loam to silty clay loam	winter wheat	OG
Rothamsted Research, 2012	UK	145	23	Silty clay loam	Spring barley	OG
Sainju et al., 2002	The United States	5	20	Sandy loam	Tomato	PSOC
Wang et al., 2019	China	4	20	Clay loam	Wheat	CD, PSOC
Yadvinder-Singh et al., 2004	India	12	15	loamy sand	Rice	PSOC, OG

CA: Conservation Agriculture; MSD: Minimum Soil Disturbance; CD: Crop diversification; OG: Organic Fertilization; PSOC: Permanent Soil Organic Cover.

Yield Index (SYI) proposed by Singh et al. (1990). SYI was originally designed to apply to yield data but in this study, it was applied to detrended data of yield and SOC. For the case of SOC, we called the index the Sustainable SOC Index (SSOCI). The data were detrended by linear regression and then re-scaled by adding the average of raw data in order to avoid negative values. The use of detrended time series allowed us to focus on the fluctuations and identify the systematic trends in the variability of the data.

The index provides a measure of how sustainable the changes observed in the data are based on the relationship between standard deviation, average and maximum values (Eqs. 1 and 2). The indices take values between 0 and 1; when values tend to 0 indicate high fluctuations in the data, and the indices values that tend to 1 indicate low variability in the changes observed, indicating that such changes are constant across time.

$$SYI = \left(\overline{yield} - \sigma_{yield}\right) \Big/ yield_{max} \tag{1}$$

$$SSOCI = \left(\overline{SOC} - \sigma_{SOC}\right) \Big/ SOC_{max} \tag{2}$$

where SYI is the Sustainable Yield index and SSOCI is the Sustainable SOC index; $\overline{yield}$ and $\overline{SOC}$ is the mean of the detrended yield and SOC data; σ_{yield} and σ_{SOC} are the standard deviations of yield and SOC detrended data, and $yield_{max}$ and SOC_{max} are the maximum yields and SOC detrended values. Thus, time series with constant annual rates on for soil and yield or time series with no changes will result in high SYI and SSOCI, while time series with high dispersion in annual changes will result in low SYI and SSOCI.

Normalized Trend ($\Delta(\%)_{Norm}$).

The normalized trend was calculated first as the perceptual rate change of yield and SOC (Eqs. 3 and 4).

$$\Delta yield(\%) = \left\{\left[\left(Yield_f - yield_i\right)/\left(t_f - t_i\right)\right]/Yield_i\right\}*100 \tag{3}$$

$$\Delta SOC(\%) = \left\{\left[\left(SOC_f - SOC_i\right)/\left(t_f - t_i\right)\right]/SOC_i\right\}*100 \tag{4}$$

Where *Δyield(%)* and *ΔSOC(%)* are the annual rate of change of yield and SOC; $Yield_f$ and SOC_f are the yield and SOC in the last year of the time series; $Yield_i$ and SOC_i are the yield and SOC in the initial year of the experiment; and t_i and t_f are the initial and final year of the time series.

The percentage change rate was normalized by the min-max normalization method (Krajnc and Glavič, 2005; Pollesch and Dale, 2016). The normalization of yield and SOC trends was required to combine the trend with the sustainability indices (step 2) and then into one single yield-SOC index (step 3). For the normalization, 60% year^{-1} was the maximum reference value for annual yield changes. In the case of SOC, the maximum reference value used was 15% year^{-1}. The normalized values for yield and SOC were calculated as is shown in Eqs. 5 and 6.

$$\Delta yield(\%)_{Norm} = (\Delta yield(\%) - 0\%)/(60\% - 0\%) \tag{5}$$

$$\Delta SOC(\%)_{Norm} = (\Delta yield(\%) - 0\%)/(15\% - 0\%) \tag{6}$$

Finding suitable references values for annual changes in yield and SOC is a challenge due to the large range of climatic zones, agro-environmental contexts and type of disturbances present in agricultural lands. The maximum reference values for yield and SOC normalization were obtained from the review of a set of published experiments in peer-reviewed journals (Supplementary material 1). The yield and SOC data collected from those studies not only were used to select the reference values but also to assess the applicability of SCSI. 0% was assumed as the minimum reference value in both yield and SOC to conserve the negative sign in the cases of normalization of annual losses of yield or SOC.

Yield reference values are consistent with those reported by Soussana et al. (2019) in their meta-analysis from 32 papers, where annual crop productivity ranged between 0 and 50% (approx.) after changes on soil management for several crops in Asia, Africa and Latin America. Regarding SOC, similar SOC annual rates were reviewed by West and Six, 2007, who reported a range between 0 and 8% SOC year^{-1} (approx.) at 0-30 cm in 67 global long-term agricultural experiments with a duration greater than 5 years located in Europe, Latin America and North America. Similarly, Soussana et al. (2019) reported a relative annual change in SOC (0–20 cm) between 0 and 14% year^{-1} in soils under changes in soil management. Finally, Poulton et al. (2018) reported an annual SOC change between −1 to 18% in 16 long-term experiments in the south-east United Kingdom.

The changes observed in SOC and yield differ in magnitude because of the spatial and temporal scale that both indicators respond to the variations in the cropping systems. By re-scaling these quantities separately, the min-max normalization method brings them onto the same scale (−1 to 1) and makes them comparable. Consequently, similar annual percentage changes on both indicators will result on different normalized values (e.g. +5% of SOC increasing will result in a normalized value 4 times bigger than the normalized value resulted from the same annual percentage change in yield).

2.1.3. Step 2. $Yield_{Norm}$ and SOC_{Norm}

With the indicators of variability and trend calculated for yield and SOC (from step 1), combined sub-indices were calculated by the aggregation of normalized variability and trend indicators (Eqs. 7 and 8). These indices contain information about the behaviour of yield and SOC in a single and non-dimensional metric.

$$\mathrm{YieldNorm} = SYI^{*}\Delta \mathrm{yield}(\%)_{\mathrm{Norm}} \tag{7}$$

$$\mathrm{SOCNorm} = SSOCI^{*}\Delta \mathrm{SOC}(\%)_{\mathrm{Norm}} \tag{8}$$

The higher and more stable the annual changes, the higher $\mathrm{Yield_{Norm}}$ and $\mathrm{SOC_{Norm}}$ will be. Where those annual changes are more irregular, YieldNorm and $\mathrm{SOC_{Norm}}$ will be lower. The same relationship applies for negative $\mathrm{Yield_{Norm}}$ and $\mathrm{SOC_{Norm}}$, where values close to −1 come from regular negative growth annual rates that become less negative if the negative rates become unsteady.

2.1.4. Step 3. Soil-based Climate-Smartness Index (SCSI)

The SCSI was built from the aggregation of $\mathrm{Yield_{Norm}}$ and $\mathrm{SOC_{Norm}}$ (Eq. 9). In the process, no weighting was assigned to $\mathrm{Yield_{Norm}}$ and $\mathrm{SOC_{Norm}}$. The decision to use this weighting method implies that the index will be an arithmetic average or counting of indicators (Greco et al., 2019). However, in the SCSI the use of min-max normalization method implicitly weighted the SOC and yield trends because of different reference values were used for each one (Mazziotta and Pareto, 2013).

$$SCSI = (Yield_{Norm} + SOC_{Norm})^{*}0.5 \tag{9}$$

A linear approach was selected to aggregate $\mathrm{Yield_{Norm}}$ and $\mathrm{SOC_{Norm}}$. This aggregation method is simpler than geometrical methods and is used when is seeking to represent a compensatory effect between indicators (Notenbaert et al., 2017). With this aggregation, the synergies and trade-offs between yield and SOC are clear: a good or bad performance of both indicators will lead to a clear climate-smartness or lack of climate-smartness respectively. On the other hand, the trade-off will be more or less climate-smart according to the predominant trend (e.g. slight positive trend on SOC and a loss on yield the first years might result in negative SCSI). Those situations occur since positive changes can not compensate an increasing negative trend.

The SCSI has a scale between −1 to 1. Values close to 1 indicate that yield and carbon increase at a constant rate, and values close to −1 refer to cases where both SOC and yield decrease constantly. The possible values of SCSI in function of the trend and the variability of indicators are described in Fig. 2. Both SOC and yield indices are calculated from annual rates, therefore SCSI will tend to zero when annual SOC and yield responses to the CSA treatment begin to plateau.

2.2. Evaluation of Soil-based Climate-Smartness Index (SCSI)

Data from 11 experiments published in peer-reviewed journals and data from 2 long-term experiments at Rothamsted Research unit were used to assess the application of the SCSI. All the experiments assessed CA practices that are compared with conventional management or control treatments without N fertilization, often used as a "blank" treatment. The experiments assess the CA practices in different crops (wheat, maize, rice, sorghum, soybean, yam, spring barley and tomato) and different evaluation periods that ranged from 2 to 147 years. Details about the location of the study, crop, agronomic management, treatments and period of evaluation are shown in Table 1.

For each treatment in the studies a set of SCSI scores were obtained. The SCSI were calculated for the minimum data points required (3 data points). Data points were then added one-by-one, with SCSI recalculated each time. The resulting SCSI values were analysed by comparing the CSCI across the time and between treatments. Results from the analysis were used to draw conclusions on the climate-smartness of CA, and on the broad applicability of SCSI to quantify trade-offs and synergies between CSA pillars across timescales.

3. Results

A total of 240 SCSI scores resulted from the 11 peer-reviewed publications and 2 long-term experiments from Rothamsted Research unit. From the total data, 55.4% of scores correspond to Conservation Agriculture (CA) practices like Minimum Soil Disturbance (MSD), Crop Diversification (CD), Permanent Organic Soil Cover (PSOC) and Organic Fertilization (OG). For its part, 19.6% of scores correspond to conventional practices (treatments with conventional management like mechanical tillage or synthetic fertilizer) and 25% from control treatments (treatments used as a "blank" treatment without N fertilization). From the total of SCSI scores, 33% correspond to treatments with duration <5 years. The SCSI scores calculated for treatments with a duration between 5 and 10 years were 13% of total data, whereas 12% correspond to treatments with a duration between 11 and 20 years. Most of the SCSI scores (41%) correspond to treatments with duration >20 years.

3.1. $Yield_{Norm}$: Sustainable Yield Index (SYI) and normalized yield trends ($yield\Delta(\%)_{Norm}$)

The YieldNorm resulted from multiplying the SYI by the yield normalized trends ($\mathrm{yield}\Delta(\%)_{\mathrm{Norm}}$). The results are summarized in Fig. 3 (lower panels), and the heatmap scale represents the possible values that $\mathrm{Yield_{Norm}}$ could take. The observed temporal changes in YieldNorm as well as the differences among the practices (CA, Conventional and Control), varied in function of temporal dynamic in SYI and the $\Delta(\%)_{\mathrm{Norm}}$.

Based on SYI results, annual changes in yield have high variability in

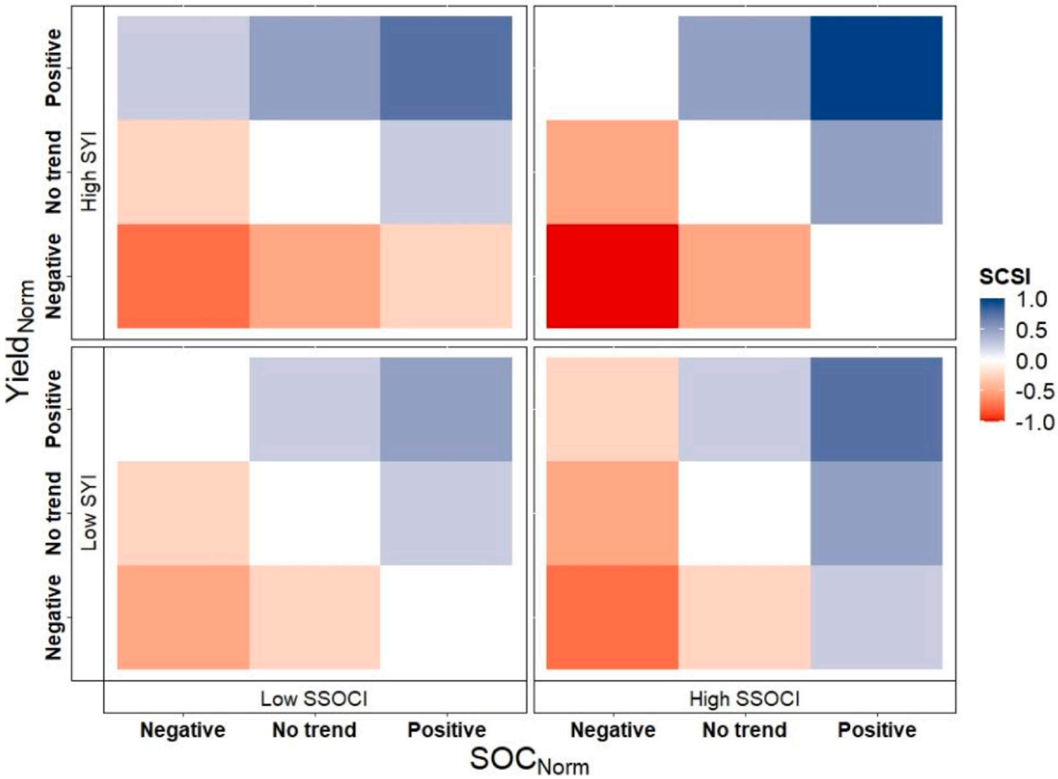

Fig. 2. Values of Soil-based Climate-Smartness Index (SCSI) in relation with the trends (Negative, No trend, Positive) and the Sustainable indices (SYI and SSOCI) of SOC and yield Normalized indices. (High $\geq$ 0.5; Low $\leq$ 0.5).

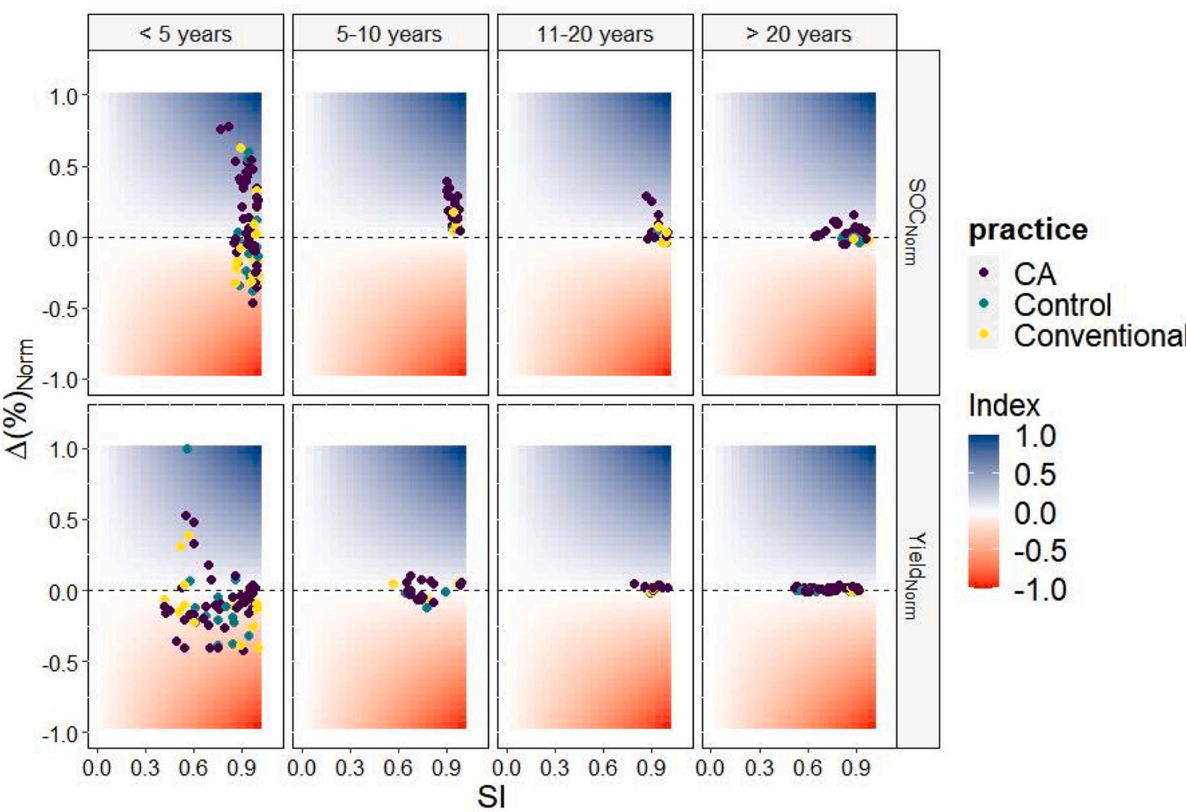

Fig. 3. SOC$_{Norm}$ and Yield$_{Norm}$ heatmaps calculated from the multiplication between Sustainable Indices (SSOCI and SYI) and Normalized change rate (SOC Δ(%)$_{Norm}$ and YieldΔ(%)$_{Norm}$). Vertical panels correspond to evaluation periods and horizontal panels correspond to SOC$_{Norm}$ and Yield$_{Norm}$ values. CA: Conservation Agriculture.

the first 5 years of soil strategies implementation where the SYI fluctuated between 0.41 and 0.99 during this period without marked differences among practices (CA, Control and Conventional). The variability in yield changes tends to decrease, as can be seen in the SYI values that range between 0.6 and 0.9 after 5 years and closer to 1 in treatments assessed between 11 and 20 years. Although the SYI tends to decline with time, some treatments with >20 years of assessment, presented lower SYI values towards the end of this timespan, than observed in previous years, indicating that even if the annual changes tend to decrease, long-term yield fluctuations may continue to be observed.

The greatest annual changes in yield occurred in treatments with a duration between 2 and 5 years (−25 to 60%). During this period, 78% of the annual changes were negative and 21% were positive. This proportion between negative and positive annual changes was similar in all the practices (77%:22%). However, the proportion changed to 60%:40% in periods between 5 and 10 years and then 32%:68% in treatments with periods between 11 and 20 years. When the data were disaggregated by practices, we found that CA, Control and Conventional still have a very similar proportion of negative and positive changes even after 5 years. However, the positive and negative annual changes observed in CA practices were higher than Control and Conventional, with an exception of a data point from a Control practice.

The relation between negative and positive changes across the time indicated that regardless of the practice, the yield losses are higher than yield gains at the beginning of the implementation of soil-oriented strategies. Although the trends tend to be positive with time, the magnitude of such changes is lower than initial years. The yield$\Delta(\%)_{Norm}$ range was −0.41 to 1 in the first 5 years and − 0.1 to 0.09 in periods between 5 and 10 years. After 20 years, annual changes were unnoticeable that was reflected in the yield$\Delta(\%)_{Norm}$ range − 0.01 to 0.04. These results are reflected in the values of Yield_{Norm} that conserved the same proportion between negative: positive annual changes and were higher during the first 5 years (−0.33 to 0.56) and then tended towards zero after 10 years (−0.06 to 0.06).

3.2. SOC_{Norm}: Sustainable SOC Index (SSOCI) and normalized SOC trends ($SOC\Delta(\%)_{Norm}$)

SOC_{Norm} results from the multiplication between SSOCI and $SOC\Delta(\%)_{Norm}$, which are summarized in the upper panels of Fig. 3. The SSOCI range was higher than the SYI range, suggesting that SOC annual changes are more constant than yield changes. In contrast to SYI, SSOCI presented differences between practices. Conventional and Control practices presented higher SSOCI (0.8 to 0.99) than CA practices (0.64 to 0.9), evidencing that some CA treatments are prone to present higher fluctuations in annual SOC changes. It is important to point out that such variations occurred in the treatments with >20 years, which brings evidence of the long-term effect of CA practices on the soil.

The $SOC\Delta(\%)_{Norm}$ also showed differences among practices across time. In treatments with assessed periods between 2 and 5 years, $SOC\Delta(\%)_{Norm}$ ranged between −0.46 and 0.77 (53% of these cases displayed negatives annual change and 46% were positive). However, this proportion of negative and positive annual changes differed among practices. While 44% of annual changes in CA were negative, in Control and Conventional practices 66% of annual changes were negative. Likewise, SOC gain in Control and Conventional treatments were observed in 22% of the cases; less than half as frequent as the SOC gains cases found in CA treatments (54%).

As with yield, SOC annual changes (positive and negatives) became smaller over time. After 5 years, all $SOC(\%)_{Norm}$ values were positive but with a higher trend in CA. After 10 years, the $SOC(\%)_{Norm}$ was nearly zero in almost all cases with some exceptions in CA practices that showed a larger positive trend (0.04 to 0.38) compared with Control (−0.05 to 0.05) and Conventional (0.03 to 0.17) practices. Although to a lesser extent, SOC changes in periods >20 years, were still relatively larger in CA compared with Conventional and Control, supporting the evidence that under CA, the SOC gain is still likely to happen at long-term.

The SOC_{Norm} resulted from the multiplication of SSOCI and $SOC(\%)_{Norm}$. The SOC_{Norm} in Control and Conventional practices showed similarities that contrasted with CA practices over time. In the first 5 years, the SOC_{Norm} ranged between −0.45 to 0.63 in CA practices, which was higher than Control (−0.36 to 0.56) and Conventional (−0.31 to 0.55) ranges, in both, gains and losses of SOC. Although SOC_{Norm} tended to decrease over time in all practices, the annual rates in CA practices did not decrease as much as in Control/-Conventional practices, generating a bigger difference between CA and Control/Conventional practices over time.

Between 5 and 20 years, the SOC_{Norm} in Control and Conventional practices ranged between 0.04 and 0.1. After 20 years, the SOC_{Norm} in such practices were mostly negative (96% of the cases), with values near to zero (−0.04 to −0.02), evidencing that Control and Conventional conditions lead to SOC losses at long-term. These results contrasted with the SOC_{Norm} range found for the periods between 5 and 20 years in CA, that was relatively higher (0.04 to 0.38) than in Conventional-Control practices. This difference is higher after 20 years, where CA practices showed a range between (−0.05 to 0.16). In this case, the negative SOC_{Norm} values in CA represented 45% of the data; however, the range of these negative values was between −0.05 to −0.001, while positive SOC_{Norm} values represented 55% of the data and ranged between 0.003 and 0.16) which is even higher than the range of positive SOC_{Norm} in Control and Conventional practices in periods <20 years.

3.3. Soil-based Climate-Smartness Index (SCSI)

The visualization of the synergies and trade-offs between Yield_{Norm} and SOC_{Norm} are summarized in Fig. 4, where the heatmaps represent the possible scores that SCSI can take. The results show that independently of the practices implemented, it is more likely to have a negative synergy than a positive synergy between yield and SOC during the first years of implementation. In the first 5 years, 46% of the data presented negative synergies (Yield Loss-SOC Loss). During the same period, 13.6% of the experiments had positive synergies (Yield Win-SOC Win) and 32% had the 'Yield Loss- SOC Win' trade-off that was more frequent than the 'Yield Win - SOC Loss' trade-off (7.5%).

The relationship between Yield and SOC appears to become more synergistic over time. Between 5 and 20 years, the cases of positive synergies (Yield Win-SOC Win) passed from 13% to 38%, while no negative synergies (Yield Loss-SOC Loss) were present. During this period, 36% of the experiments were 'Yield Loss- SOC Win' trade-offs, which did not differ too much from past years. Although the practices were not equally represented in all periods, the disaggregated data indicated that most of the positive synergies during the period 5 to 20 years corresponded to CA practices (18 out of 24 cases).

After 20 years, 19% of data represented positive synergies, all of which correspond to CA practices; this means that after 20 years just CA maintained positives synergies between SOC and Yield. On the contrary, overall negative synergies represented 29% of the cases. From this percentage, just the equivalent to 7% of data came from CA treatments (2 out of 29 cases). The temporal dynamic of such synergies and trade-offs determined the values observed in the SCSI.

In relation to the Yield_{Norm} and SOC_{Norm} results, the most negative and positive SCSI scores occurred in the 5 first years (−0.28 to 0.34). Although the positive synergies increased and the negatives were absent after 5 years, the SCSI range was lower (−0.09 to 0.15) than the calculated in the first years. After 20 years, all the SCSI scores ranged between −0.02 to 0.06 indistinctively of the practices. This suggests that after this point, the SCSI provided little information about the impact of soil management on the Yield and SOC trend and variability.

The mean SCSI during this period was not only higher in CA (mean SCSI = 0.28) than Control (mean SCSI = −0.03) and Conventional (mean SCSI = −0.0185) practices, but also showed a higher number of

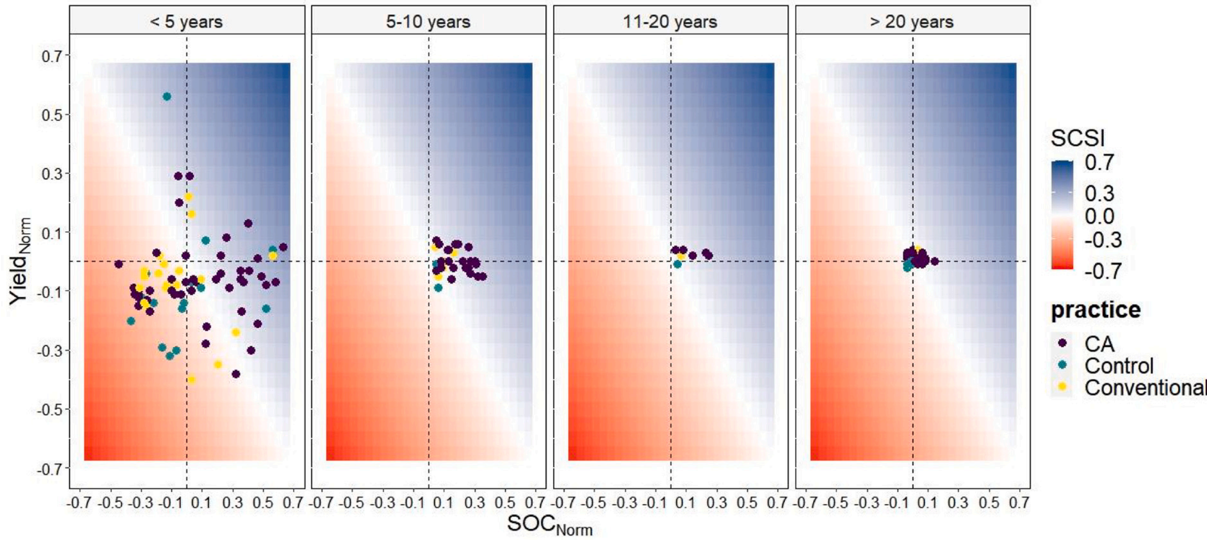

Fig. 4. Soil-based Climate-Smartness Index (SCSI) heatmaps calculated for Conservation Agriculture (CA), Control and Conventional practices. Vertical panels correspond to evaluation periods.

positive SCSI scores (Fig. 5). The positive SCSI scores in CA represent both, positive synergies and trade-offs that favoured an increase in yield or SOC over a potential decrease of such indicators. According to the SCSI scores, the climate-smartness are also mediated by the response time of the system to soil management; however, CA always presented a higher climate-smartness than Conventional and Control independently of the period.

The SCSI scores were fitted to a local polynomial curve regression, that showed a similar pattern in the data distribution across 50-year time span. The fitted curves pointed out a "SCSI peak" in CA and Conventional practices in approximately the tenth year, which started to fall until flattening around 20 years. In the Control practices, there was no peak since there are not any soil management activities involved. The differences between CA and Conventional curves are that the peak in CA

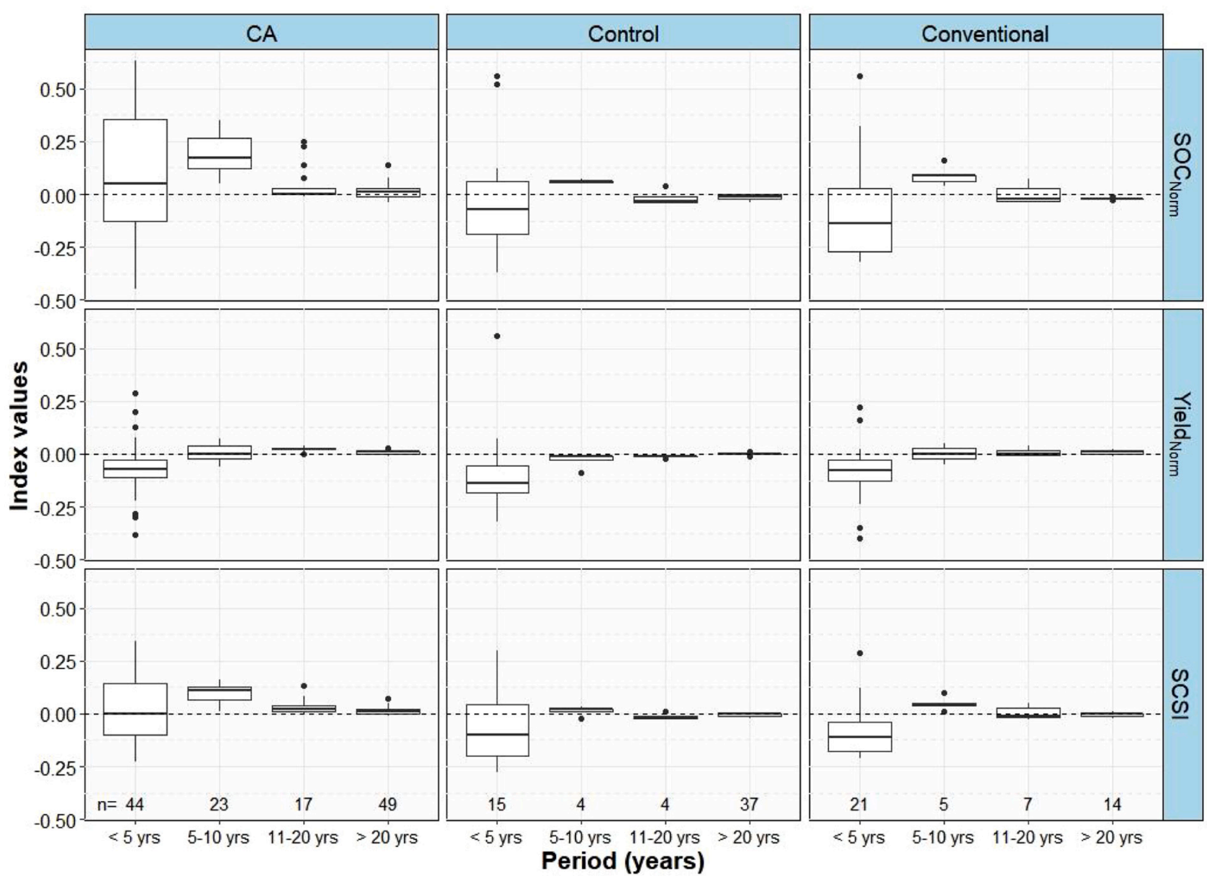

Fig. 5. Boxplots of SOC_{Norm}, $Yield_{Norm}$ and SCSI for Conservation Agriculture (CA), Control and Conventional practices at different periods. Numbers in the bottom of SCSI panel correspond to the number of data per practices and period.

is higher than Conventional indicating that CA data tend to reach higher SCSI scores. There is a further difference in the timescale over which the line flattens. In the case of CA, the curve flattens approximately after 30 years, while in Conventional it is approximately at 20 years. This confirms that CA has an impact on the system's properties for a longer span of time as compared to Conventional practices.

The high variability in the CA treatments reflects the broad responses of the different CA practices grouped in this category. In Fig. 6b, The CA category was disaggregated into 3 CA practices mentioned in the first section of results. The CA practices with the greater data representation were OG (Organic Fertilization) and PSOC (Permanent Soil Organic Cover). Of these practices, PSOC practices reached the highest peak. It is important to point out that some of the PSOC treatments also included chemical fertilization, while most of the OG case use just organic sources. The curves also showed that CA practices differ in their temporal response and in the implementation span in which the major impacts are achieved. For instance, even when OG achieved a similar peak to PSOC, its curve started to flat almost 10 years later than all the other practices, suggesting that positive changes under such practices might take a longer period to achieved potential thresholds.

4. Discussion

The Soil-based Climate-Smartness Index (SCSI) can provide a measure of the climate-smartness and capture its temporal behaviour in cropping systems under different soil practices. The analysis of SCSI showed that scores range between highly positive to highly negative during the initial years of implementation and then, tend to stabilise towards zero in the long term. Consequently, all possible trade-offs and synergies (illustrated in Fig. 7) between yield and SOC occurred during the first years of implantation. Overall, the synergy (with negative trends) and the trade-off 'yield loss and SOC gain' are the most common among the practices, also evidencing a transitory lack of climate-smartness in some treatments under climate-smart practices. These results underscore the importance of considering the temporal response of the crop systems to the soil-oriented strategies within climate-smartness assessments.

The negative SCSI values in CA resulted from the synergy between SOC and Yield (most of negative SCSI) or from the trade-offs between negative trends on yield with the SOC. In both cases, the lack of climate-smartness resulted from the yield penalties in early stages of CA implementation. This yield penalty is reported by several studies as a constraint on CA adoption and scaling-up (Brouder and Gomez-Macpherson, 2014; Cooper et al., 2016; Giller et al., 2009; Van den Putte et al., 2010). Pittelkow et al. (2015), found some negative yield response in several crops during the first 1–2 years of No-till adoption. Nyamangara et al. (2013) reported similar results from 48 CA experiments conducted in semi-arid regions of Zimbabwe, where 26 to 50% of the experiments presented negative changes on yield. Likewise, Corbeels et al. (2020) indicate that the limited yield benefits (<4% compared to conventional tillage systems) from CA constrains its adoption for small-scale farmers.

Along with yield penalties, some treatments also showed negative SOC. The SOC depletion in Conventional and Control practices are expected due to the limited OM recycling in such practices (Ogle et al., 2005). However, the negative SOC changes (19% of SOC_{Norm} in <5 years) also occurred in CA practices. Negative SOC_{Norm} in CA were evidenced in negative synergies with yield and in positive trade-offs of yield, where negative SOC outcomes were compensated by large positive yield benefits. Although SOC depletion under CA is unexpected and most of the studies highlight the potential of CA to increase the soil carbon, some studies reported this effect for some CA practices (Liang et al., 2016; Mrabet, 2002). A meta-analysis carried by Luo et al. (2010) found that the benefits of no-tillage on SOC are inconclusive since significant SOC depletion was also observed along with SOC increment. For their part, Poeplau and Don (2015) reported that 9% of the experiments reviewed in their meta-analysis indicated SOC stock depletion after implementation of cover crops.

Although less common during the first years of implementation the SCSI also resulted from positive synergies between indicators, showing a positive outcome in yield as has also been reported by previous studies. For instance, some CA experiments in Southern Africa reported an increase in maize yield during the first and second cropping seasons after starting the implementation (Thierfelder et al., 2014). Similarly, in their meta-analysis, Zhao et al. (2017) reported an increase on rice yield to 2.6% during <5 years of implementation of No-tillage, and Huang et al. (2013) found that crop residue retention has an impact of 4.7% on rice yield in experiments with <3 years of evaluation in China.

The SCSI results come from different experimental and agro-climatic conditions, that led to a different response of SOC and yield in the CA experiments. It is important to remember that potential yields will depend on a combination of non-limiting agronomic and climate conditions, reducing the gap between actual to potential yield, which also might vary according to crop genotype.

The period needed to reach the soil carbon saturation under certain agronomic practices may depend on the interaction between geographic location, climate, and land transition scenarios. Qin et al. (2016) reported in their meta-analysis that the magnitude of SOC depletion after cropland conversion and the former land use influence the C sequestration rates, which generally results in a negative correlation between initial SOC stock and SOC accumulation rates (Georgiadis et al., 2017). Moreover, soils in the tropics might reach a SOC equilibrium faster than soil in temperate regions where it could take around 100 years after the land-use change (Smith et al., 2008).

At a smaller scale, the soil texture partially determines SOC accumulation; clay and silt content generate an advantage to SOC storage by the stabilization of SOC in Sil + Clay particles and reducing its microbial decomposition (Chenu et al., 2019; Stewart et al., 2008). At a regional scale, the OM turnover rates may differ among climate zones; the wet-tropical and warmer areas prone to have faster decomposition rates (Chenu et al., 2019; Stewart et al., 2008; Sommer et al., 2018). For its part, yield also depends highly on climate and soil conditions (Nyagumbo et al., 2020). Pittelkow et al. (2015) reported yield response to CA practices varies among dry and humid climates. Likewise, the soil proprieties that control the water infiltration have a strong influence in the yield on CA practices, several authors reported reduction on yields when CA practices are implemented in poorly drained soils (Corbeels et al., 2014; Thierfelder and Wall, 2012).

In contrast with the high variability inthe SCSI scores observed in the early periods of implementation, the positive synergies and trade-offs of SOC were the most common relationships between both indicators, resulting in positive SCSI scores during the period between 5 and 10 years. These results evidence that changes in SOC may have a greater contribution to climate smartness in the mid and long term. Although the trade-offs and synergies become more climate-smart over the time, the magnitude of such climate-smartness tends to decrease according to the attainable yield and SOC in a given the context and the CA practices performance. Thus, the SCSI can help to identify the point where the soil management (or any agricultural management that could be attributed) can generate the greater changes (negative or positive) and from what point such changes, are redirected or became inconstant.

After 10 years, the SCSI tends towards zero because of a deceleration of the SOC and yield rates. The peaks observed in the SCSI data coincided with the behaviour of SOC sequestration rates observed in several CA experiments. Tadesse et al. (2018) and Yang et al. (2015) observed the highest soil carbon stock after 10 years of CSA implementation. Similarly, Zanatta et al. (2007) identified for a subtropical location that, the higher SOC changes in the first years but the peak of SOC accumulation occurred in the 9th year.

Although the SCSI in the first years of CA implementation seems to contain most of the information, the response period (For how long SCSI are changing) also inform about the climate-smartness and the "lifetime"

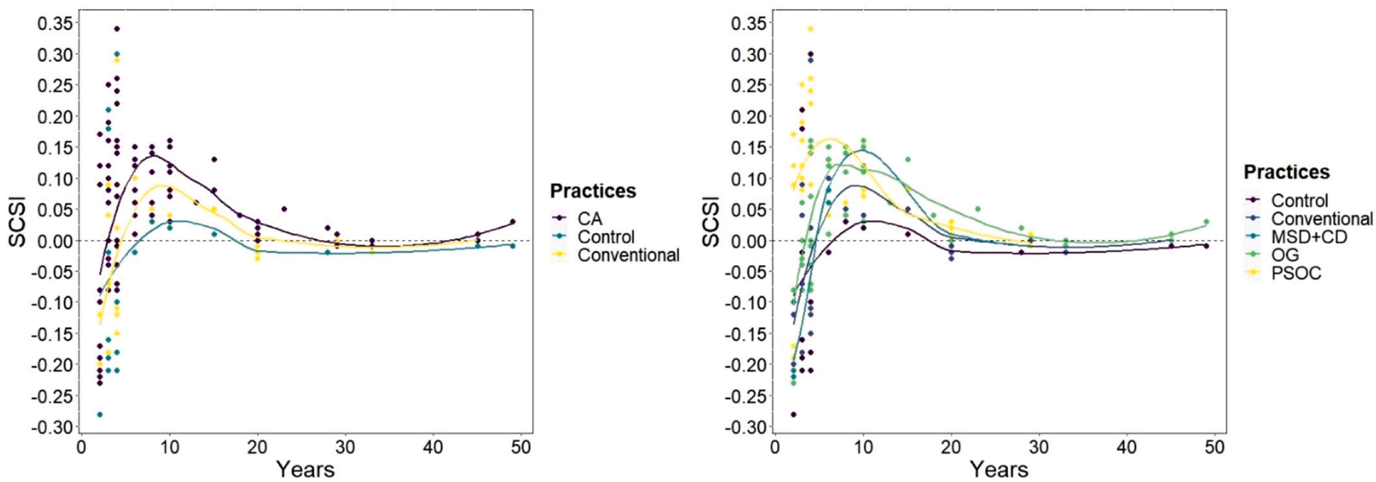

Fig. 6. Scatterplots of Soil-based Climate-Smartness Index (SCSI) across 50 years period for A) Conservation Agriculture (CA), Control and Conventional practices, and B) Control, Conventional, Minimun Soil Disturbance + Crop diversiofication (MSD + CD), Organic Fertilization (OG) and Permanent Soil Organic Cover (PSOC) practices.

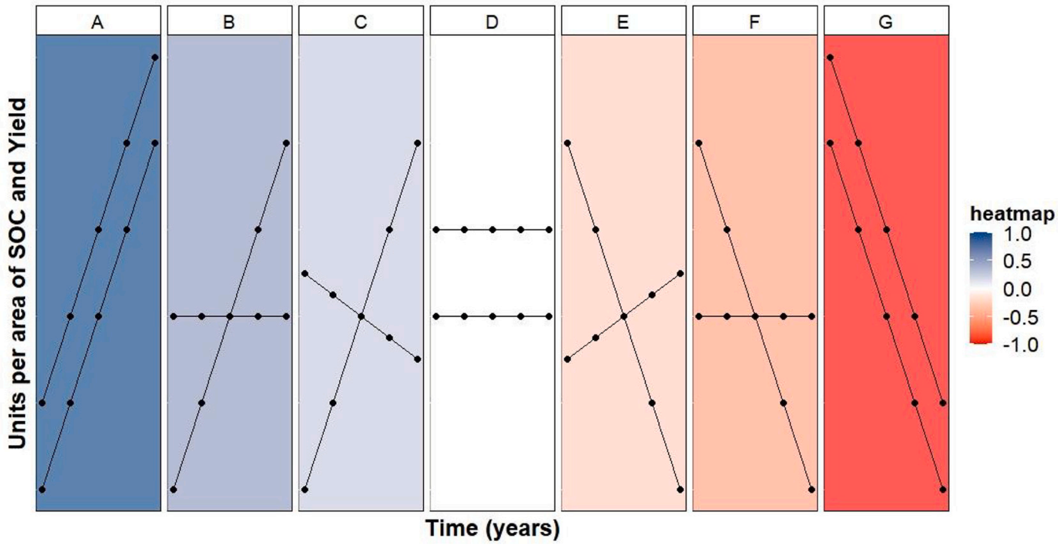

Fig. 7. Synergies exist where both trends are of the same size, and these can be positive (panel A) or negative (panel G). Trade-offs exist when the slops are of opposite sign (Panels B,C,E and F).

of CA practices. These results ~~remark~~ reflect the importance of long-term monitoring of CA treatments, especially for the temporal dynamic of SOC sequestration. In this study, most of the data come from periods <10 years which is the period when most of the changes happened, however, the representation of all periods was unequal, and data gaps were observed, particularly in the periods comprised between 20 and 50 years.

Overall, CA practices showed higher climate-smartness than Control and Conventional, however, the SCSI scores presented high variability in CA practice, suggesting that some practices under certain context might present higher climate-smartness than others. The regression curves calculated for each practice within CA were based on some experiments located in temperate regions and correspond to specific conditions. Thus, the curves can bring new insight about the temporal dynamic of the climate-smartness but cannot be seen as definitive conclusions.

These differences in CA practices can be explained by the suitability of the practices and the context. For instance, no-till and crop diversification do not involve direct incorporation of organic matter and may have a little effect on SOC, (especially in tropical moist or dry conditions) but could improve if is complemented with crop residue retention, (Das et al., 2013; Ogle et al., 2005; Thierfelder et al., 2014; Thierfelder et al., 2017). On the contrary, practices like PSOC and OG that involve the incorporation of organic matter can contribute more with the soil carbon storage.

However, OM incorporation also has important implications on crop yield and in the decision to replace partially or completely the chemical fertilization by organic amendments. In this study, the PSOC practices achieved the highest SCSI scores but were also characterized by the use of chemical fertilization, which probably helped to support the yield during the early stages of the OM turnover in the soil (Yan and Gong, 2010).

Along with the decision to replace the chemical fertilization, the quality of the crop residues contributes to the climate-smartness of the practices. The source of the residues determines its composition and its decomposition rates that might vary according to soil moisture and temperature conditions. For instance, crop residues with high lignin content have slower decomposition rates, and could result in low SOM (Stewart et al., 2015); likewise, crop residues with high C:N ratio decompose slowly and contribute poorly to N inputs (Kong et al., 2005; Palm et al., 2010; Wang et al., 2017). Thus, the replacement of chemical fertilization in CA practices is a key technical decision that needs understanding about the relationship between soil conditions, organic inputs quality and crop requirements, not only to estimate SOC sequestration potential but also to protect yield stability.

The crop nutrient management and its influence on the SCSI score also will depend on other initial experiment conditions. For instance, the timing and N fertilizer rates, or the use of *Rhizobium* inoculants used in the experiments reported by Datta et al. (2010) and Campbell et al. (2007), might influence the N use efficiency (Davies et al., 2020). Moreover, the use of high-yielding varieties like the high yielding wheat used by Campbell et al. (2007) and the high-yielding with low lodging potential of sorghum variety used by Dou et al. (2014) might also represent an advantage independently of CA implementation and will influence the SCSI overall score.

4.1. Soil-based Climate-Smartness Index (SCSI): Strengths, limitations and future work

The design of the SCSI was motivated by an evidence gap around CSA practices and the lack of available metrics that allow standardized comparisons and facilitate a simultaneous interpretation of three CSA pillars at different temporal and spatial scale (Lankoski et al., 2018; Rosenstock et al., 2018). For the metric presented in this study, we defined climate-smartness under the context to cropping systems under soil-based management practices. Under such systems we identified climate-smartness as representing a synergy between climate resilience and productivity with added benefits of mitigation via soil as a carbon sink.

The SCSI presented here can provide a measure of the temporal response of cropping systems and its impact on soil and productivity. However, the SCSI is insufficient to provide a climate-smartness measure from a social or economic view that might be partially represented by the yield indicator. In any case, the SCSI could be analysed along with social-economic indicators to find associations between the climate-smartness and the improvement of farmers livelihoods, or the yield indicator could be combined with a food availability index or an income indicator. Within the concept boundaries, metrics like SCSI can provide simple and quantitative assessments for policymakers which are needed for tracking the effectiveness of plans and projects framed within the Climate-smart Agriculture approach (Bell et al., 2018).

The interpretation of the SCSI, just as any index, should be subject to the data context. Although the positive scores are associated with climate-smartness and negative scores with unsustainable conditions, is the researcher criterion that discerns the contribution (negative or positive) of agronomic and experimental conditions to the SCSI score. This statement takes greater relevance if we intend to compare the SCSI scores from different sites that differ in their experimental layout, climate conditions and land-use history.

Along with the different perspectives (social, economic, environmental), the meaning of climate-smartness varies in function temporal and spatial scales. However, Prestele and Verburg (2019) pointed out that climate-smartness assessments still ignore the spatially variable impacts of CSA practices, especially at large scales. The temporality of the climate-smartness needs further consideration and discussion by the those supporting, leading and funding CSA implementation. The SCSI could contribute with a measure of climate-smartness at different spatial and temporal scales. Where applied in a spatially-explicit manner, the SCSI provides a means to objectively compare the climate-smartness of specific practices between sites or landscapes. However, as the idea of climate-smartness is closely attached to the context, their interpretation in each case should be relative to technically feasible thresholds.

The importance of context implies that a specific SCSI score can be only considered “too high” or “too low” relative to other practices implemented under similar conditions. For example, a positive but low SOC-index can result from highly contrasting situations, such as a site where soils are near to SOC saturation, and a site with a high SOC deficit and low return of biomass to the soil. In both cases, the CA practices can barely help to increase the soil carbon (reflected in the SCSI score). However, only in the second case is the low SCSI the result of poor application of CA practices.

The SCSI can be calculated using yield and SOC data from experiments across spatial scales (farm to regional scale) for a minimum duration of 2 years. As the SCSI uses the annual rates and their variability, the periods for which the SCSI are calculated depends on the data availability (annual, bi-annual, every 5 years), or according to project timelines and plans. As field measuring could be expensive and time demanding, simulated SOC and yield data represent a means of projecting SCSI across space and time. The SCSI also can be calculated for studies that simulated both yield and SOC. The modelling approach allow the assessment of a wide combination of agricultural practices, adaptation scenarios and time frames like the study published by Soler et al. (2011) where simulated SOC and crop yield from different crop rotations treatments in a semi-arid region, or the study published by Zhang et al. (2017) who simulated the long-term effect of the continuous and discontinuous fertilization and straw incorporation on yield and SOC.

The additive aggregation method used in the SCSI is the most used aggregation method for the design of composite indices because of its low computation complexity and because allow a compensatory relationship between indicators (Gan et al., 2017). In the SCSI, this type of aggregation allowed the association of negative SCSI scores with the negative synergies/trade-off and the positive SCSI scores with positive relationships. However, as any composite index, the aggregation of the indicators involves loss of information that could lead to a simplistic conclusion about a complex concept (Saisana and Tarantola, 2002). This limitation becomes more evident for the SCSI values resulting from trade-offs, where it is unclear which indicator is reducing and which is increasing. Regarding to this limitation, the normalized method selected for SCSI become crucial to the reliability of the SCSI.

Given that indicators were not assigned any weights, the changes in SOC and yield have the same importance. However, the weighting of the indicators can be set by the normalization method (Mazziotta and Pareto, 2013). This internal weighting depends on the reference values, which generate equivalences between the annual changes on both indicators (e.g. 5% of annual change in SOC, would obtain a higher normalized score than the same percentage in yield). This normalization method could represent an advantage for the type of metrics needed in CSA. Since the min-max normalization method can be calculated using reference values according to the context, these can be adjusted and set based on a specific annual crop, management, climatic regions or even based on policy targets and regional stats. However, a challenge of this normalization method is that it limits the comparison between studies that use contrasting reference values.

5. Conclusions

A Soil-based Climate-smartness Index (SCSI) was designed using the variability and the annual changes of soil organic carbon and yield. The SCSI provides a measure of climate-smartness based on the trade-offs and synergies observed between both indicators. The SCSI results confirmed that Conservation Agriculture (CA) practices are climate-smart compared with conventional management, mainly due to its effect on increasing SOC in the long term. The SOC and yield changes that result from the implementation of climate-smart practices are temporally dynamic, thus, the climate-smartness varied across the time in all CA practices. The temporal dynamic of the climate-smartness reflects the practices performance under a given context, hence, the overall impact of CA practices can be better understood when the temporal dimension is considered.

Declaration of Competing Interest

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

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