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Assessing residue and tillage management options for carbon sequestration in future climate change scenarios

Kumari Aditi [a], Kumar Abbhishek [a,*], Girish Chander [a,*], Ajay Singh [a], Thomas Falk [b,c], Melesse B. Mequanint [a], Perumal Cuba [a], G. Anupama [a], Roja Mandapati [a], Satish Nagaraji [a]

[a] International Crops Research Institute for Semi-Arid Tropics (ICRISAT), Patancheru 502324, India
[b] International Food Policy Research Institute (IFPRI), Washington, DC 20005, USA
[c] Philipps-University Marburg, 35032 Marburg, Germany

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ABSTRACT

Soil carbon depletion is a major concern for food security in drylands. The objective of this study is to test tillage with residue management under sequential and intercropping systems for carbon sequestration in semi-arid tropical drylands of India. We report the findings from a long-term field experiment (9 years) used to simulate the effect of residue and tillage management in Maize-chickpea sequential and Maize-Pigeonpea intercropping systems for the four possible future climate projections using APSIM model. These findings demonstrate a sustainable route with inclusive growth, as pledged at the UN climate change summit. A comparison of results under SSP 2.6 and 4.5 Wm^{-2} with SSP 8.5 shows that demand pressure from competitive marketplaces inhibits the establishment of soil carbon sinks and significantly reduces crop yields, likely due to indiscriminate chemical fertilizer use. We observed that a better decision in selecting cropping system might improve soil organic carbon content (SOC). SOC content ranging from 0.9 to 1.2% in Maize-pigeonpea intercropping and 0.85–1.1% in maize-chickpea sequential cropping systems, demonstrate good potential in the climate change mitigation exertions. Early SOC saturation (20 years) led to a decreased carbon stock in topsoil without residue addition practises. The addition of crop residues significantly increased SOC levels under both conventional and minimum tillage and created additional income for farmers. Simulation analysis showed impact of SOC changes on crop yield which remained nearly stable for 85 years. Therefore, hardy straw biomass of crops covering a large tract in dryland tropics, can be a scalable and sustainable solution to yield losses, while mitigating climate change through carbon sequestration.

1. Introduction

In the ensuing decades, climate change will pose a major threat to global food security and to the world's capacity to nourish its people (Raj et al., 2022). The underlaying causes of climate change like imbalanced use of chemical fertilizers and removal or burning of crop residues have also exacerbated the loss of soil carbon, impairing the quality of the soil (Sharma et al., 2020). Sustainable climate change adaptations and increased agricultural ecosystem resilience in vulnerable ecosystems like drylands through recycling crop residues and limited tillage operations hold the key to overcoming such issues as drylands occupy 40% 0f world's total area (Aditi et al., 2019). However, agricultural ecosystem in drylands needs serious replanning of current agricultural practises to achieve the targets of global food security (Asmamaw et al., 2015; Ahmed et al., 2022; Aich et al., 2022). Besides, special adaptations like genetically drought tolerant crop varieties to deal with climate change in drylands, conserving the soil plays a crucial role in sustaining productivity (Lal, 2010a, 2010b). The drylands' soil quality is worst affected, and widespread C loss presents an ongoing barrier to achieving productivity potential (UNEP-WCMC, 2006;

Abbreviations: APSIM, Agricultural Production systems Simulator; CEY, Equivalent yield; EC, Electrical conductivity; EQM, Empirical quantile mapping; ESGF, Earth System Grid Federation; GCMs, Global circulation models; ICAR, Indian Council for Agricultural Research; MSP, Minimum support price; nRMSE, Normalized root mean square error; NSE, Nash–Sutcliffe efficiency; RMSEn, Normalized Root Mean Square Error; SAT, Semi-arid tropics; SI, sustainability index; SOC, Soil Organic carbon; SPAW, Soil-plant-air-water; SSP, Shared Socio-economic Pathway; SYI, Sustainable yield index.

* Corresponding authors.
E-mail addresses: mishra.aditi20@gmail.com (K. Aditi), abbhishek.k@drreddysfoundation.org (K. Abbhishek), g.chander@cgiar.org (G. Chander).

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Shepherd et al., 2009; Gomiero, 2016; Chander, 2017).

Crop residue retention has been suggested a feasible approach to improve SOC, but its efficacy under varied tillage practices needs to be evaluated. (Blanco-Canqui and Lal, 2009; Pu et al., 2019). Chaki et al. (2022) assessed the effect of conservation agricultural practices like residue addition, cropping system, tillage, and nitrogen fertilization rates using the Agricultural Production systems Simulator (APSIM) model. They reported that the model could capture the residue-tillage effects in rainfed agriculture. Furthermore, the simulated results were found to be within the bounds of experimental uncertainties. Once properly parametrized, cropping system models (e.g., APSIM) can capture the interactions between soil-water and nutrient dynamics, crop growth, climate, and farmers' management practices (Gaydon et al., 2017). Begum et al. (2022) modeled soil carbon for diverse cropping systems under varied management practices and reported that adding cover crops increases soil carbon pools and has an impact on the dynamics of carbon. The addition of crop residues to soil alters labile and passive soil carbon pools and causing carbon to be released as gaseous emissions, while the resistant fraction contributes towards C sequestration (Lorenz and Lal, 2014). A contrasting effect on SOC has been reported under varied tillage schemes followed by soil residue retention, which can be attributed to variations in soil enzymatic activities (Jin et al., 2009). Conventional tillage practices of agriculture in drylands would lead to potential loss in soil quality and fertility (Kautz et al., 2013). Minimum-tillage activities have been proposed to sequester carbon in dryland soils to reverse such effects of tillage practices (Lal, 2004; West and Post, 2002). At the same time, adding crop residues reduces evaporation, soil compaction and leaching losses of critical nutrients and increases the ion exchange capacity of soils (Chander, 2017). However, there are divergent and ambiguous opinions on the implementation of practices together, like minimum soil disturbance (tillage), soil cover (residues) and crop diversification/rotation/intercropping for climate change adaptation (Aditi et al., 2022). Nevertheless, even modest increases in soil C content through such practices, can have a significant impact on soil properties and crop yield in dryland cropping systems, especially when soils are far from carbon saturation (Wani and Raju, 2017). Cropping system in drylands involve cereals (e.g., Maize, Sorghum) and legumes (e.g., Chickpea, Pigeon pea) usually grown in rotation with drought-tolerant legumes, like chickpea, or intercropped with deep-rooted legumes as improved practice (e.g., Pigeonpea) in drylands (Bontpart, 2020).

The impact of long-term management practices in maize-based cropping systems (e.g., maize-chickpea, maize-pigeon pea) has been explained using the modelling approaches in the recent past (Beah et al., 2021; Kisaka et al., 2016; Puntel et al., 2016). The primary advantage of modelling approaches is the possibility of integrating different scenarios representing various climatic stress thresholds into cropping system performance (Bahri et al., 2019). Long-term simulations can predict the quantum of resilience developed by adopting mitigation/adaptation measures through management practices in a cropping system. Therefore, the outcomes of such simulations may be valuable input for policymakers and farmers dwelling in the most vulnerable regions of semiarid tropical drylands in future climate change scenarios. However, there is a dearth of information highlighting the effect of a package of practices like landform, soil-test-based nutrients, crop cultivars, residue recycling and tillage (Prasad et al., 2016; Wani et al., 2017).

Accurate quantification of the effect of package of practices on crop yields in the rainfed rotation system under global climate change is urgently required (Yang et al., 2018). This study aims to provide predictive answers to the most pertinent questions based on system performance as crop yields and soil carbon sequestration in Maize-based cropping systems after deploying a package of practice involving residue and tillage management under different crop rotations. Sequential or intercropping of legumes with maize reduce nitrogen and phosphorus fertilizer needs in subsequent years (Sogbedji and McIsaac, 2006) while ensuring efficient utilization of natural resources (Willey and Reddy, 1981). However, we must evaluate long-term projections of such diversifications to gain policy insights from such interventions. Such predictions should focus but not be limited to underlining the benefits of crop diversification, instead should also emphasize the co-benefits of balanced fertilizer use, reduced tillage, improved varieties, and residue mulching or incorporation for the efforts to reduce environmental footprints (Lencucha et al., 2020).

Our objective is to analyse the long-term effect of residue and tillage management in Maize-chickpea sequential and Maize-Pigeonpea intercropping strategies for four possible future climate projections in India (Riahi et al., 2017). We are also evaluating the sustainability and, thus, scalability of residue addition and minimum tillage practices in two cropping systems (Maize-chickpea and Maize-Pigeonpea) in these future climate projections. As the economy of India is primarily dependent on agriculture and most pulses are produced in semi-arid tropics, the findings of our study are domineeringly pertinent for current climate change mitigation efforts in the country. However, in the wake of food security, this study focusing on semiarid tropical drylands would guide the policy makers for sustainable intensification of dryland cropping systems globally (Vijayan, 2016).

2. Data and methods

2.1. The experiment

Long-term field experiment was conducted during 2009–2017 at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT)'s on-station farm (17°50′ N, 78°26′ E and altitude 545 m). The experimental site is a dryland located in semi-arid tropics (SAT) of India, which is the most vulnerable to future climate change and represents 34% of total area in India and approximately one-tenth of the global SAT drylands. The experimental design and management practices are briefly explained in table S1(a-d), and further details of the field experiments are described in Aditi et al. (2022). The experiments examined two tillage practices (minimum and conventional tillage) with addition and complete removal of previous crop residues for the long-term changes in soil organic carbon, and crop yields were evaluated under two cropping systems viz. Maize-chickpea sequential cropping and maize-pigeonpea intercrop for 9 years. The conventional tillage without addition of previous crop residues acted as a management control for the combination of different practices as interventions or treatments (Table S1(b)). Soil disturbance in minimum tillage plots was restricted to refreshing of furrows (0.45 m wide) before the start of kharif (Rainy) season and sowing on raised beds (1.05 m wide) with the help of seed cum fertilizer drill (strip-till drill), while, in conventional tillage plots, thorough ploughing of field as normal farmers' practice was undertaken. The residues were completely removed from the no-residue addition treatment plots, while entire crop residues were chopped into finer sizes and spread evenly to cover the beds (0.05 m thick) after end of the crop season in the residue addition plots.

2.2. Equivalent yield and sustainability index

The equivalent yield (CEY) and sustainability index (SI) of each

$$\text{CEY}\ \left(\text{t ha}^{-1}\right) = \frac{\left[\text{Grain yield of cereal}\ \left(\text{t ha}^{-1}\right) + \left\{\text{Seed yield of legumes}\ \left(\text{t ha}^{-1}\right) \times \text{price of legume seeds}\ \left(\text{INR kg}^{-1}\ \text{seed}\right\}\right]\right.}{\text{price of cereal grain}\ \left(\text{INR t}^{-1}\ \text{grain}\right)}$$

treatment over 9 years is calculated in terms of maize equivalent yield to compare the system performance using sustainability index (Mandal et al., 2014). The formulae used are:

$$SI = \frac{\left[\text{Average yield over years (n)} \left(\text{t ha}^{-1}\right) - \text{s.d.}\right]}{\text{Maximum Yield in any of the year} \left(\text{t ha}^{-1}\right)}$$

The prices were taken as the minimum support price (MSP) of each crop produce provided at the website of Department of Agriculture & Farmers Welfare, Government of India.[1]

2.3. Model description

Prediction of crop yields using different crop simulation models like DSSAT, APSIM, Oryza etc., aids to farmers as decisions support systems, and support policy makers in famine prevention efforts (Zhao et al., 2020; Gumma et al., 2021). To check the performance of the cropping systems and interventions in future climate, we used the APSIM model. APSIM is a comprehensive model developed to simulate biophysical processes in agricultural systems, particularly as they relate to economic and ecological outcomes of management practices in the face of climate risk (Keating et al., 2003). Ample studies with interventions focussing on plant, soil, and management modules of APSIM and their effect on crop yield have been reported. These modules include a diverse range of crops and soil processes, including water balance, N and P transformations, soil pH, and a full range of management controls. The APSIM model was initially developed to estimate crop production as influenced by water and nitrogen availability (McCown et al., 1996), but it was later modified to include additional agricultural systems and environmental processes (Cichota et al., 2021). The APSIM software framework's set of modules enables the modelling of farming systems for a wide range of applications like plant (Archontoulis et al., 2014), crop types (Brown et al., 2018), cropping systems rotations (Yang et al., 2020), management (Balboa et al., 2019), soil water (Yang et al., 2018), soil organic carbon (Sinha et al., 2021), soil nutrients (Vogeler et al., 2022) climate (Xiao et al., 2020) and genotype, environment and management interactions (Seyoum et al., 2015). The simulator is globally renowned as a highly advanced modelling and simulation platform for agricultural systems and well validated in Indian context (Gaydon et al., 2017; Chaki et al., 2022). APSIM can accurately estimate crop growth and soil C dynamics in various agroecosystems (Luo et al., 2014). To obtain a best fit, APSIM (version 7.9) modules for climate, soil and cultivars for maize, chickpea and pigeon pea were set in this experiment using experimental datasets from the long-term on station experiments. The soil module in APSIM is calibrated based on site-specific measurements.

2.4. Model calibration

Profile soil parameters, such as bulk density, volumetric water content at saturation, drained upper limit, and lower limit, used by APSIM-soil-water module for vertisols were taken from analysis results published and unpublished for experimental location (Patancheru, India) as reported by Robertson et al. (2001). The soil chemical analysis results used to parametrize the soil inputs for ICRISAT farms (Table S2) include pH, organic carbon, EC (electrical conductivity) and macro/secondary nutrients for soil profile (0–120 cm) (Aditi, 2020; Wani et al., 2017). Soil texture was obtained from Aditi et al. (2019) and additional data for the other soil layers (e.g., 70–100, 100–130 cm) were set by referring to the data of other similar soils in the APSIM standard soil database. The soil water characteristics was estimated using SPAW (soil-plant-air-water) model and confirmed with the model input data (Saxton and Rawls, 2006). Daily weather data (maximum and minimum temperatures, solar radiation, and precipitation) were obtained from the weather station at the experimental location. The meteorological module for the APSIM (APSIM met generator) was provided with the temperature (Tav), maximum amplitude of monthly average temperature (Amp), and time (year and day) using software included with APSIM 7.9.

2.5. Cultivar parameterization

Cultivar values for thermal time accumulation (thermal degree days) was set as described in Msongaleli et al. (2014). High air temperatures, as with low temperatures, may drastically reduce plant development and growth rates, or even stop development (Bootsma, 1994; Roltsch et al., 1999; Snyder et al., 1999). In addition, in sub-tropical environments, it has been observed that the daily maximum temperature often exceeds the maximum developmental temperature thresholds for crops (Ruiz et al., 1998). This is why Russelle et al. (1984) have used a maximum temperature threshold of 30 °C to improve the accuracy in forecasting phenological phases in maize. Narwal and Dahiya (1989) also concluded that phenological models with a 7 °C base temperature were better for prediction of development phases in Maize grown in Indian conditions. The base and optimal temperature for maize, chickpea and pigeonpea was selected as 7°, 5°, 10 °C and around 27°, 24°, 28 °C, respectively in this study (Gaur et al., 2010; Carberry et al., 2002). Maize (HTM-5401), chickpea (ICCV-2) and pigeonpea (ICPH-2671) were set in model framework using default medium duration cultivars available in APSIM directory. The experimental observations on number of days to emergence (Days_to_emergence_after_sowing), 50% flowering (Days_to_flowering) and physiological maturity (Days_to_physiological maturity), dry weight and grain yield obtained after drying the plant sample at 80 °C for 72 h, were used to adjust the respective coefficient values in default cultivar files. A "trial and error" method was used to tune the genetic parameters (e.g., tt_emerg_to_endjuv; tt_flower_to_maturity) of respective cultivar files as suggested in Zhao et al. (2020). The method targeted the normalized root mean square error (nRMSE) values obtained through comparing the observed and simulated LAI, and days to flowering. The lower values of nRMSE (approx-10-13%) were targeted through adjusting the thermal time to end-juvenile, maturity phenological data collected during the experiment.

2.6. Crop management data

The crop management details followed during the long-term field experiments (Aditi et al., 2022) were provided to the model as initial conditions and were used to simulate for the effects of future climate on SOC and crop yields in the maize-chickpea and maize + pigeonpea system. In brief, the intercropping system comprised two rows of maize (interspaced at 0.75 m) inter-cropped with one row of pigeonpea. However, in maize-chickpea system, two rows of maize were grown during rainy season, followed by four rows of chickpea (interspaced at 0.30 m) during the post-rainy season. Plant to plant spacing was kept 30 cm in pigeonpea, 15 cm in maize and 10 cm in chickpea in a total experimental area of 1acre. Seeds were sown at a depth of 5 cm and fertilizer schedule adopted for maize crop was 150, 60 and 40 kg ha^{-1} of N, P and K, respectively, and for chickpea was 25 and 50 kg ha^{-1} of N and P, respectively. Entire doses of phosphorus and potassium were applied as basal in the form of Single-super phosphate and Muriate of potash, respectively. The model was given input for fertilizers as nitrogen in the form of urea in three splits as per schedule: 1/3rd N as basal, 1/3rd N at 30 DAS (Days after Sowing) and remaining 1/3rd N at 60 DAS. The fertilizer recommendations were as prescribed by ICAR (Indian Council for Agricultural Research) accredited state agricultural

[1] https://agricoop.nic.in/en

university under local conditions for respective crops.[2]

2.7. Future climate projections data

Quantification of the impact of climate on crop yields and food security requires reasonably accurate long-term daily weather data to inform a robust conclusion. The daily weather data of 13 CMIP6-GCMs is taken from open-source data portal provided by Earth System Grid Federation (ESGF).[3] The data were processed to produce bias-corrected daily time series for the long-term experiment site using empirical quantile mapping (EQM) method (Mishra et al., 2020). The 13 global circulation models (GCMs) were selected based on the availability of all the variables at daily time scale for the historical runs under four scenarios (SSP2.6, SSP4.5, SSP7.0, SSP8.5) as **r1i1p1f1** initial condition (Tebaldi et al., 2021), indicating the **r**ealization, **i**nitialization, **p**hysical, and **f**orcing indices for creating a multimodal ensemble (Fan et al., 2022). The scenarios used in the CMIP6 combine SSP and target radiative forcing levels at the end of the 21st century. For instance, SSP2.6 indicates target radiative forcing at the end of the 21st century 2.6 W/m^2. On the other hand, SSP 8.5 is based on the emission scenario with radiative forcing of 8.5 W/m^2 at the end of the 21st century. The other scenarios (SSP 4.5 and SSP 7.0) are considered in the mid of these two scenarios (Gidden et al., 2019). These data are used as input met files for future APSIM simulations.

2.8. Model performance and statistical analysis

Model performance in this study was evaluated using nRMSE and Nash–Sutcliffe efficiency (NSE). Residual variance is the difference between the measured and simulated values, often estimated by the residual mean square error. Additionally, NSE is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance (Nash and Sutcliffe, 1970). nRMSE and NSE indices were calculated using the following equations:

$$nRMSE\ (\%) = \left| \sqrt{1/N} \sum \left(\widehat{Y}i - Yi\right)^2 \right| \times 100 \Big/ \bar{Y}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} \left(Yi - \widehat{Y}i\right)^2}{\sum_{i=1}^{n} \left(Yi - \bar{Y}i\right)^2}$$

where $\hat{Y}$, Y and $\bar{Y}$ are, respectively, the simulated, observed and mean of the observed values, and n is the number of observations. Observed crop yield free from any insect-pest damage was selected for normal meteorological years in the evaluation process of model simulations using above indices (Moriasi et al., 2007). The performance of the model and thereafter efficiency of simulation was evaluated using the post-harvest surface (0–0.15 m) soil samples collected and analysed before the start of experiment and after completion of 2016–17 cropping system. For SOC, standard methods described in the literature (Jackson, 1973) were used to evaluate the system performance on the development of long-term carbon sink after the crop harvest in each cropping cycle. However, the annual average SOC for each treatment averaged for 4 replications in the experimental design ($n = 32$) during the experimental period of 2009–2017 was used to compare with model outputs. We used Non-parametric Mann-Kendall test was used to obtain S statistics and Z-value for analysing trends in the future simulated results ($n = 85$) using following equations (Wang et al., 2020):

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_i - x_k)$$

$$sgn(x_i - x_k) = \begin{cases} +1, if\ (x_i - x_k)\rangle 0 \\ 0, if\ (x_i - x_k) = 0 \\ -1, if\ (x_i - x_k)\langle 0 \end{cases}$$

$$var(S) = \left\{ \frac{n(n-1)(2n+5)}{18} \right\}$$

Where n is sample size, X_k and X_j are from k = 1,2, …n-1 and j = k + 1, …,n.

The test statistics Z calculated as

$$Z = \begin{cases} \left\{ S - 1 \middle| \sqrt{var(S)} \right\}, if\ S > 0 \\ 0, if\ S = 0 \\ \left\{ S + 1 \middle| \sqrt{var(S)} \right\}, if\ S < 0 \end{cases}$$

The trend in simulated results was calculated using Sen's slope estimate using the equation:

$$\beta(Sen's\ slope) = Median\left\{ \frac{(x_i - x_k)}{j - i} \right\}, j > i$$

where ß is Sen's slope estimate, indicating an upward or downward trend in the time series.

3. Results and discussion

3.1. Model performance

The validation plots for Maize-chickpea and maize + Pigeonpea systems are presented in Fig. 1. Maize-chickpea system was observed to better capture the changes in SOC over the years with lower residual error (RMSEn: 8.7%) and a better model efficiency (NSE: 0.71). However, the intercropping of maize with pigeonpea performed just satisfactorily with a modelling efficiency of 0.66 and 13% residual error in simulated results. This might be because the decomposition rate of hardy biomass, like that of pigeon pea, do not match with the provided potential organic matter decomposition rate in model framework. Struijk et al. (2020) reported that the hardy biomass should be mixed with a low quality (lower C:N) biomass in order to improve carbon use efficiency, which further supports the hypothesis. Furthermore, observed crop yield obtained through destructive sampling from an area of 3 × 3 square meter (expressed in kg ha^{-1}) from the conventional tillage without residue addition in both the cropping system experiments is compared with simulated crop yield results for the same intervention. In a rainfed system, kharif crops are largely affected with the uncertainty in rainfall, which can also introduce large biases in simulated yields like that of maize (Ramarohetra et al., 2015). Furthermore, Baron et al. (2005) showed that aggregating daily weather information like rainfall using multi-model ensemble approach as done in projections produces some bias in simulated yields using APSIM in semi-arid regions. However, we analysed and observed that the model efficiency expressed as NSE lies in a range of 0.60–0.89, which is considered acceptable for simulation outputs (Lin et al., 2017). Additionally, while evaluating model performance and determining the acceptability of performance we also have calculated RMSE apart from NSE between simulated and observed values. Our analyses presented in Table S3 and Fig. S6 show that values of normalized RMSE (RMSEn) for maize, chickpea and pigeon pea crops are 12%, 3%, and 9%, respectively. We ascertained from the observed and simulated data comparisons that it is around the same quantum (and ideally smaller) than the standard deviation within the observed values (for example, across experimental replicates). When this is true, it essentially demonstrates that the model can simulate the observed behaviour within the bounds

[2] https://www.pjtsau.edu.in/crop.html.
[3] https://esgf-node.llnl.gov/search/cmip6/

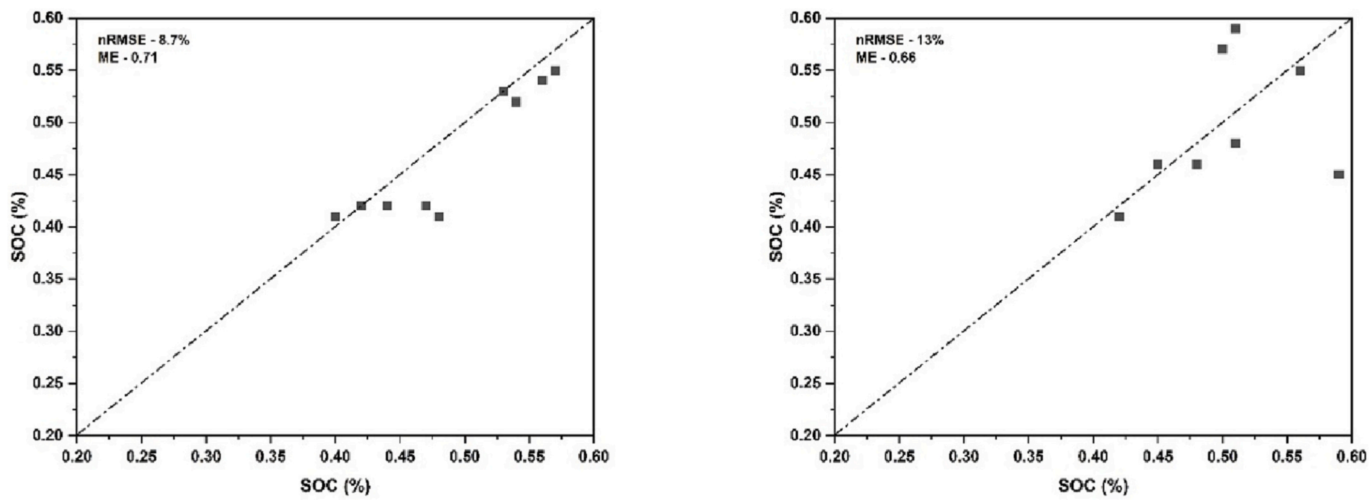

Fig. 1. Validation curve for soil organic carbon (SOC) measured during long-term experiments over a period of 9 years (2009–2017), ME represents model efficiency as Nash-Sutcliffe efficiency (NSE) and nRMSE is normalized root-mean square error. X-axis shows observed SOC (%), while Y-axis shows simulated SOC (%).

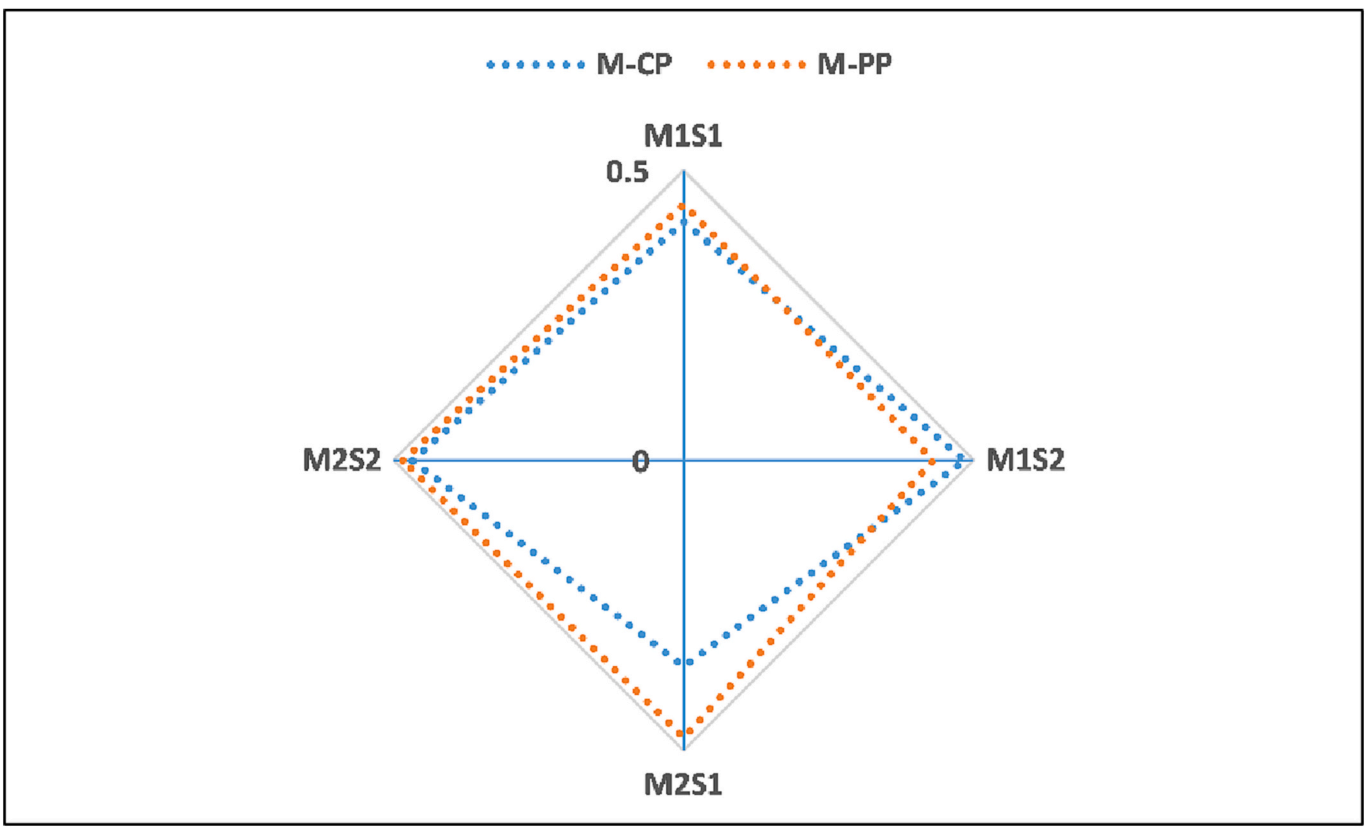

Fig. 2. Sustainability index calculated with system equivalent yield over a period of 9 years (2009–2017), M1S1 represents conventional tillage without residue addition (management control), M1S2 represents conventional tillage with addition of crop residues, M2S1 represents minimum tillage without addition of crop residues and M2S2 represents minimum tillage with addition of crop residues. M-Cp is maize-chickpea sequential system and M-PP is maize pigeonpea intercropping system.

of experimental uncertainty. This is all we can ever expect a model to do, knowing that it is highly idealistic to expect modeled results to be perfectly the same as the average of the observed values. Furthermore, as we know (via experimental replicates) there is uncertainty in the observed data and 'being the same as the average' provides no additional meaning above 'being within the range of experimental uncertainty.' Therefore, we feel that it would be better to state that model performance is acceptable if the RMSE's are within the range of the experimental uncertainty (Moriasi et al., 2007).

3.2. Sustainability index

While the current cropping systems are facing the heat of climate change (Wanjari et al., 2004), we evaluated the sustainability of long-term maize-chickpea sequential and maize-pigeonpea intercropping systems through the system equivalent yield approach (Fig. 2).

Sustainable yield index (SYI) showed the benefits of adopting residue and tillage management practices in relation to the changes in status of SOC and soil fertility over the 9 years. As the current agro-practices are depleting the soils with organic carbon (Abbhishek et al., 2021); intercropping of maize with a long-duration legume (e.g., pigeonpea in this case) showed better response for all interventions expect when the residue addition is done under conventional tillage scheme. This might be because chickpea stovers having comparatively less lignin content than pigeonpea decompose faster in the soil when added to the conventional tillage scheme. The difference between the sustainability index was very distinct for minimum tillage among both cropping systems indicating that the benefits of soil aggregate formation are augmented by addition of deep-rooted legumes like pigeonpea (Mula and Saxena, 2010).The addition of residue in minimum tillage showed a better sustainability index for both maize-chickpea sequential and maize-pigeonpea intercropping systems indicating that the current yield of crops are supposed to be sustained in future with such interventions despite the adversities of climate. Intercropping results in higher organic C and other nutrients, microbial biomass, and enzyme activities, in soil than the monoculture soil showing better SYI (Yang et al., 2020). However, adding chickpea residues under conventional or minimum tillage in monoculture under field conditions improved soil nutrient dynamics which matched them with intercropping (Danga et al., 2013).

3.2.1. Future climate scenarios

We selected the future climatic scenarios as explained in Riahi et al. (2017). We present the trends in maximum temperature (Max T), minimum temperature (Min T), rainfall (Rain), and solar radiation (S. Rad.) in all SSP scenarios in Fig. S1(a-d). Both the maximum and minimum temperature showed increasing trends for different scenarios whereas rainfall and solar radiation were consistent over years in all the scenarios. The changes observed in meteorological variables reflect combined effect of demographic, socio-economic, energy, land-use, and other resource availability or uses.

3.3. Effect of SSP scenarios on cropping system performance

3.3.1. Maize-chickpea system

We analysed the effect of SSP scenarios on long-term trends in SOC variations due to addition of crop residues in Maize-chickpea sequence under conventional tillage (Fig. 3) and minimum tillage (Fig. 4) schemes. The conventional tillage practice without residue addition (Fig. 3 left panel) showed early saturation (around 2040) in all future climatic scenarios, except in SSP 4.5, where slight (~0.04%) increase in SOC is observed in later years. However, conventional tillage with addition of crop residue (Fig. 3 right panel) sustained a constant increment in SOC irrespective of SSP scenarios. The saturation under residue addition is observed around year 2080 as depicted by simulation results. Simulation of minimum tillage practices without residue addition (Fig. 4 left panel) and with residue (Fig. 4 right panel) showed similar trends (z = 11–12) in SOC as of conventional tillage (Table 1). However, addition of crop residues significantly improved the rate of increment in SOC levels under conventional tillage (7– 31E-4) and minimum tillage practices (9 –33E-4).

The variations in yield of maize and chickpea crops are presented under different future climate scenarios (Fig. S2). The yield of maize is clearly improved with addition of crop residues irrespective of the type of tillage operation in all SSP scenarios. However, in high emission scenario (SSP 7.0), the yield seems comparable for residue addition and no-residue addition, which might be due to large variations in the simulated yield values. The yield in chickpea crop did not show any response to the residue and tillage operations in any future climatic scenarios. However, this might be because of phosphorus insensitivity in the APSIM model that could cause it to fail to capture long-term changes occurring in soil with the recycling of crop residues and tillage management practices. The poor understanding of P dynamics in Vertisols and the inability to partition soil P into measurable P pools is hindering the development of a mechanistic P module in APSIM (Raymond et al., 2021). There are limited studies which describe the calibration of APSIM soil-P module. The only dataset where soil-P and a calibrated maize module (which includes routines to enable the crop to respond to P limitations) has been tested against observed data is for an experiment in Kenya described by Probert and Okalebo (1992).

3.3.2. Maize-pigeonpea system

Similarly, we analysed the SOC variations due to addition of crop residues in maize-pigeonpea intercropping systems (Figs. 5 and 6). The increasing trends in SOC (Table 2) indicate improvement in SOC in either cases of addition or no-addition of crop residues. However, the increment in case of intercropping seemed more uniform, which might result from little disturbance of soil during crop growth period. The less disturbed soil seemingly had enhanced macroaggregate stability and microaggregate formation leading to better protection of C from microbial decomposition (Ogle et al., 2019). Our simulation results for maize-pigeonpea intercropping system show higher magnitude of SOC for all future climatic scenarios compared to maize-chickpea sequential system. Our results agree with findings of Cong et al. (2015), emphasizing on greater belowground productivity owing to greater inputs from root litter in intercrops. Additionally, prodigious accretion of root nodules in case of pigeonpea under future climate change scenarios leads to significantly enhanced photosynthetic rates and carbon fixation reflecting in significant addition to SOC (Sreeharsha and Reddy, 2015). Addition of crop residues in case of intercrops showed higher (~0.10–0.20%) SOC than no-residue addition in conventional tillage practice. Nevertheless, minimum tillage practice had a skimpy difference for residue addition and no-residue addition practices. This can be attributed to little soil incorporation of finely chopped stubbles laying above-ground in case of minimum tillage practice.

In the maize-pigeonpea system, the trends in yields of maize crop were consistent for all treatments (Fig. S3a-d). However, our model was able to capture the trends in maize and pigeonpea yields with the changes in the meteorological parameters with different climatic scenarios. The low emission scenario (SSP2.6) showed a feebly increasing trend (4.26–5.22 kg ha^{-1} yr^{-1}) in the yield of maize crop for all treatments, whereas the yield of pigeonpea crop was observed to be nearly stable over the years (0.28–0.31 kg ha^{-1} yr^{-1}). The medium emission scenario (SSP4.5) showed slightly decreasing yield trends (2.46–3.27 kg ha^{-1} yr^{-1}) for maize and (0.86–0.90 kg ha^{-1} yr^{-1}) for pigeonpea across the treatments. However, the high emission scenarios (SSP7.0 and 8.5) showed a clear decline in yield over years in both crops. The negative yield trends ranging from 8.32 to 10.10 kg ha^{-1} yr^{-1} for maize and 2.48–2.76 kg ha^{-1} yr^{-1} for pigeonpea crops can be attributed to the increase in the daily maximum and minimum temperature in the climate projections. Pigeonpea is a short-day legume species and the genotypes, which have comparatively longer growing period (e.g., medium, long duration cultivars), are more photosensitive than early types (Saxena et al., 2021). Therefore, the variation in the accumulation in thermal units in pigeonpea owing to the variation in average daily temperature in different climatic scenarios may be a reason for the decline in yield. However, the main reason for decline in maize yields during future climate is the increase in temperatures that will shorten the length of growing seasons (Luhunga, 2017).

3.3.3. Comparison of cropping systems

We compared both cropping systems for the net benefits over conventional practice and observed that the residue addition in both cropping systems resulted in better C- storage than the conventional practice under either of tillage scheme. Our results agree with Stella et al. (2019) reporting that crop residues contribute to the maintenance of SOC stores, a key component of soil fertility and soil-based climate change mitigation strategies, such as the '4per1000' initiative. The highest SOC storage in maize-chickpea (approx. 0.79–0.83) and maize-

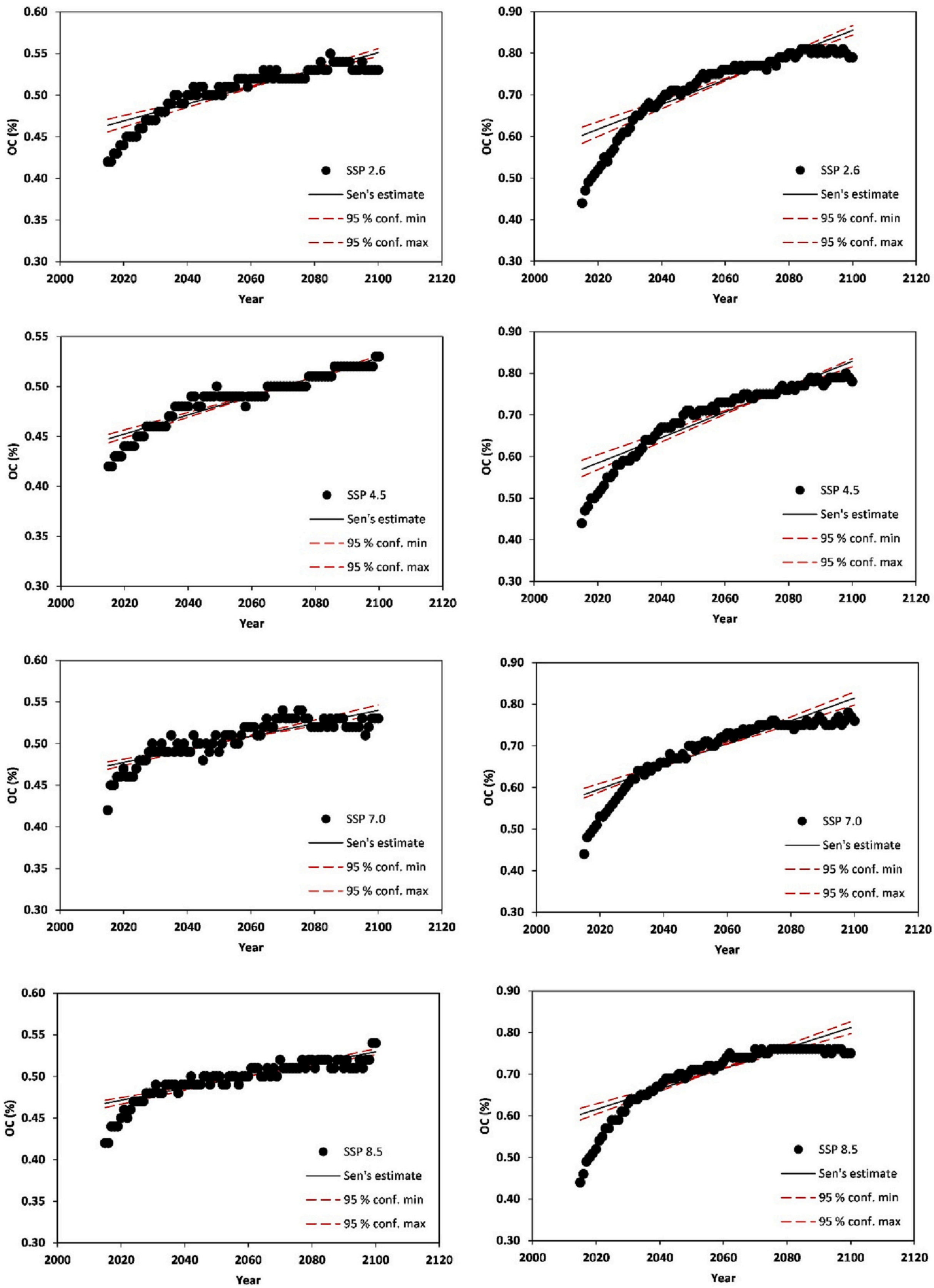

Fig. 3. Trend analysis in SOC under combination of conventional tillage without residue (left column) and with residue (right column) addition from 2105 to 2100 in maize-chickpea system.

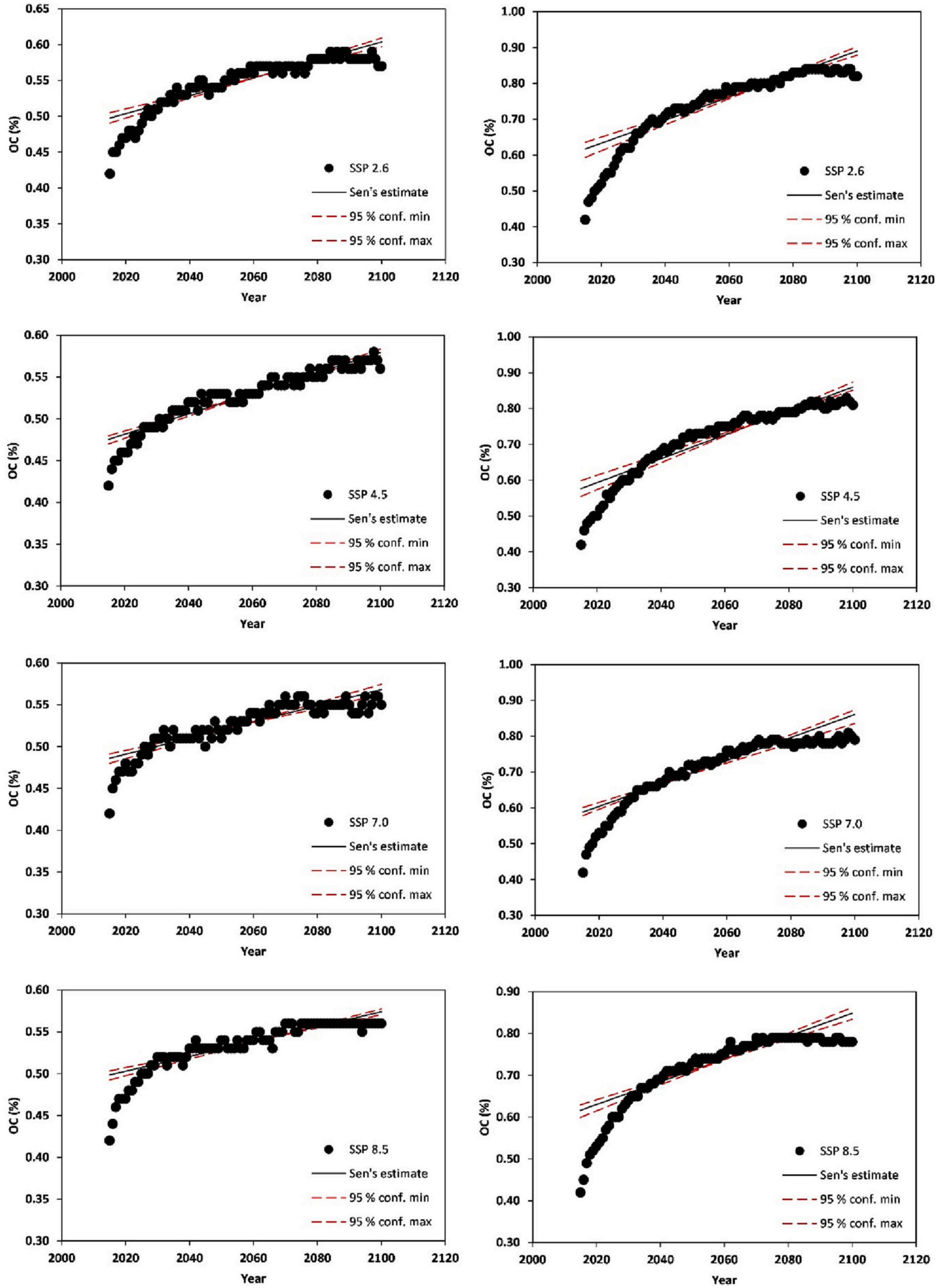

Fig. 4. Trend analysis in SOC under combination of minimum tillage without residue (left column) and with residue (right column) addition over a period of 85 years (2105–2100) in Maize-chickpea system.

Table 1
The Z-value and Sen's estimator for the true slope of linear trend (i.e., change per unit time period/year) in SOC for Maize-Chickpea system under minimum tillage (MT) and conventional tillage (CT) with residue (R+) and without residue (R-) additions.

Minimum Tillage	Scenarios	Z-value	Significance	Q	Qmin95	Qmax95	B	Bmin95	Bmax95
MTR-	SSP2.6	11.30	***	0.0012	0.0011	0.0014	0.4975	0.5050	0.4906
	SSP4.5	11.91	***	0.0012	0.0011	0.0013	0.4755	0.4798	0.4700
	SSP 7.0	10.25	***	0.0010	0.0008	0.0011	0.4860	0.4913	0.4800
	SSP 8.5	11.05	***	0.0009	0.0008	0.0010	0.4984	0.5033	0.4925
MTR+	SSP2.6	12.37	***	0.0032	0.0029	0.0036	0.6170	0.6357	0.5936
	SSP4.5	12.80	***	0.0033	0.0030	0.0038	0.5767	0.5991	0.5550
	SSP 7.0	11.96	***	0.0032	0.0028	0.0035	0.5884	0.6015	0.5789
	SSP 8.5	11.29	***	0.0027	0.0024	0.0031	0.6164	0.6293	0.5993

Conventional Tillage	Scenarios	Z-value	Significance	Q	Qmin95	Qmax95	B	Bmin95	Bmax95
CTR-	SSP2.6	11.19	***	0.0010	0.0009	0.0012	0.4638	0.4710	0.4559
	SSP4.5	11.85	***	0.0010	0.0009	0.0010	0.4476	0.4522	0.4435
	SSP 7.0	9.29	***	0.0008	0.0007	0.0009	0.4734	0.4780	0.4691
	SSP 8.5	10.81	***	0.0007	0.0006	0.0008	0.4677	0.4713	0.4625
CTR+	SSP2.6	12.28	***	0.0030	0.0026	0.0033	0.6026	0.6225	0.5833
	SSP4.5	12.82	***	0.0031	0.0026	0.0033	0.5690	0.5911	0.5517
	SSP 7.0	12.16	***	0.0027	0.0024	0.0030	0.5827	0.5979	0.5745
	SSP 8.5	11.48	***	0.0025	0.0021	0.0028	0.6030	0.6182	0.5900

*CT: conventional Tillage; MT: Minimum Tillage; R+: addition of Residue; R-: Removal of Residue.
Qmin95: the lower limit of the 95% confidence interval of Q ($\alpha = 0.05$); Qmax95: the upper limit of the 95% confidence interval of Q ($\alpha = 0.05$); B: estimate of the constant B in equation f(year) = Q*(year-first-Year) + B for a linear trend; Bmin95: estimate of the constant Bmin95 in equation f(year) = Qmin95*(year-first-Year) + Bmin95 for 95% confidence level of a linear trend; Bmax95: estimate of the constant Bmax95 in equation f(year) = Qmax95*(year-first-Year) + Bmax95 for 95% confidence level of a linear trend.

pigeonpea system (approx. 1.15–1.25) was observed in low emission scenario (SSP 2.6) under minimum tillage operations. However, our analyses with equilibrium conditions of SOC in maize-chickpea (Fig. S4) and maize-pigeonpea (Fig. S5) cropping systems show that the time for reaching the maximum threshold value of equilibrium SOC concentration varies with SSP scenarios and addition of crop residues. We observed 60% rise in equilibrium SOC with residue addition in 62 years as compared to conventional practice in maize-chickpea sequential system under SSP 4.5. The higher emission scenarios of SSP 7.0 and 8.5 showed lower benefits in SOC was (around 40%) under conventional tillage scheme. This might result from increased temperatures caused by climatic change increasing the turnover of soil organic matter and hence reduce SOC (Webb et al., 2003). In line with our finding, temperature is reported as the main driver explaining differences in SOC dynamics, followed by crop age and root depth (Ledo et al., 2020). However, minimum tillage showed a similar rise of equilibrium SOC concentration (60%) in 65 years with residue addition under SSP 7.0. This might be because the effectiveness of minimum tillage is mostly contributed through aggregate stability and microbial biomass which in turn appears to be highly dependent on-site conditions such as pH, soil texture, and climatic conditions (Engell et al., 2022). In maize-pigeonpea intercropping (Fig. S4) the soil carbon sink strength showed a similar trend in SSP 4.5, 7.0, and 8.5 scenarios where the benefit in equilibrium SOC under conventional tillage was limited to 25% with residue addition. However, in low emission scenario 2.6 the highest rise in equilibrium SOC (71%) with residue addition was observed in conventional tillage scheme. This might be because intercrops have greater belowground productivity than sole crops and sequester more soil carbon over time (Cong et al., 2015). Our results match the trend of change in SOC over future period showing that the SOC in maize-pigeonpea intercropping system attained higher threshold saturation values (0.5–0.8 Vs 0.8–1.2) in later decades of the century than maize-chickpea sequential cropping system.

3.3.4. *Policy implications of study*

Our results indicated that adding crop residues is beneficial in both conventional and minimum tillage practices as it adds to SOC and may reduce the menace of weeds in minimum tillage practice. The Government of India has undertaken "National policy for management of crop residue" to control wasteful burning of hardy residues in open field and encourage their diversified use like mulching and incorporation to soil (NPMCR: National Policy for Management of Crop Residues (NPMCR), 2014). Our results of model simulation showing carbon build-up without significant loss in crop yield in anticipated harsher climate support the government initiative to improve soil health without any apprehension to food security. The promotion of such interventions would promote the strategic policies targeting optimum in-situ utilization and management of crop residues to prevent the irreparable nutrient mining and minerals from soil and improve soil health, as such. However, we suggest looking forward in preparing the value-added products from crop residue through additional technological interventions (e.g., preparation of enriched bio-vermicompost, biochar etc.) and testing them for semiarid environment using field experiments (Singh et al., 2022). The effects of such recycled crop residue on crop yield and soil carbon can further be simulated in climate change perspective to test their scalability and support the National mission for sustainable Agriculture to sustainably enhance agricultural productivity and soil health. Also, the policy makers must think about implementing a carbon credit policy more sternly. Rewarding farmers through carbon credit which is globally tradable would compensate for any loss in yield and further improve their benefits and returns (Abbhishek et al., 2022). Furthermore, providing subsidies on purchase of farm machinery like happy seeder, shredder, zero-seed-cum-fertilizer drill is also a necessary step to popularize the suggested management practices.

4. Conclusions

Soil carbon is one of the most important parameters that determines the suitability of management interventions in any cropping system in the perspective of future climate change. However, SOC changes are not ever increasing as usual and reaches saturation depending on the interaction of climate forcings and interventions. This study suggests the best management practice to be followed in semi-arid tropical drylands as a climate smart measure obtained with varied combination of residue, tillage and cropping system in future climate forcings. We propose that cereal legume sequences need to be designed as per the climate

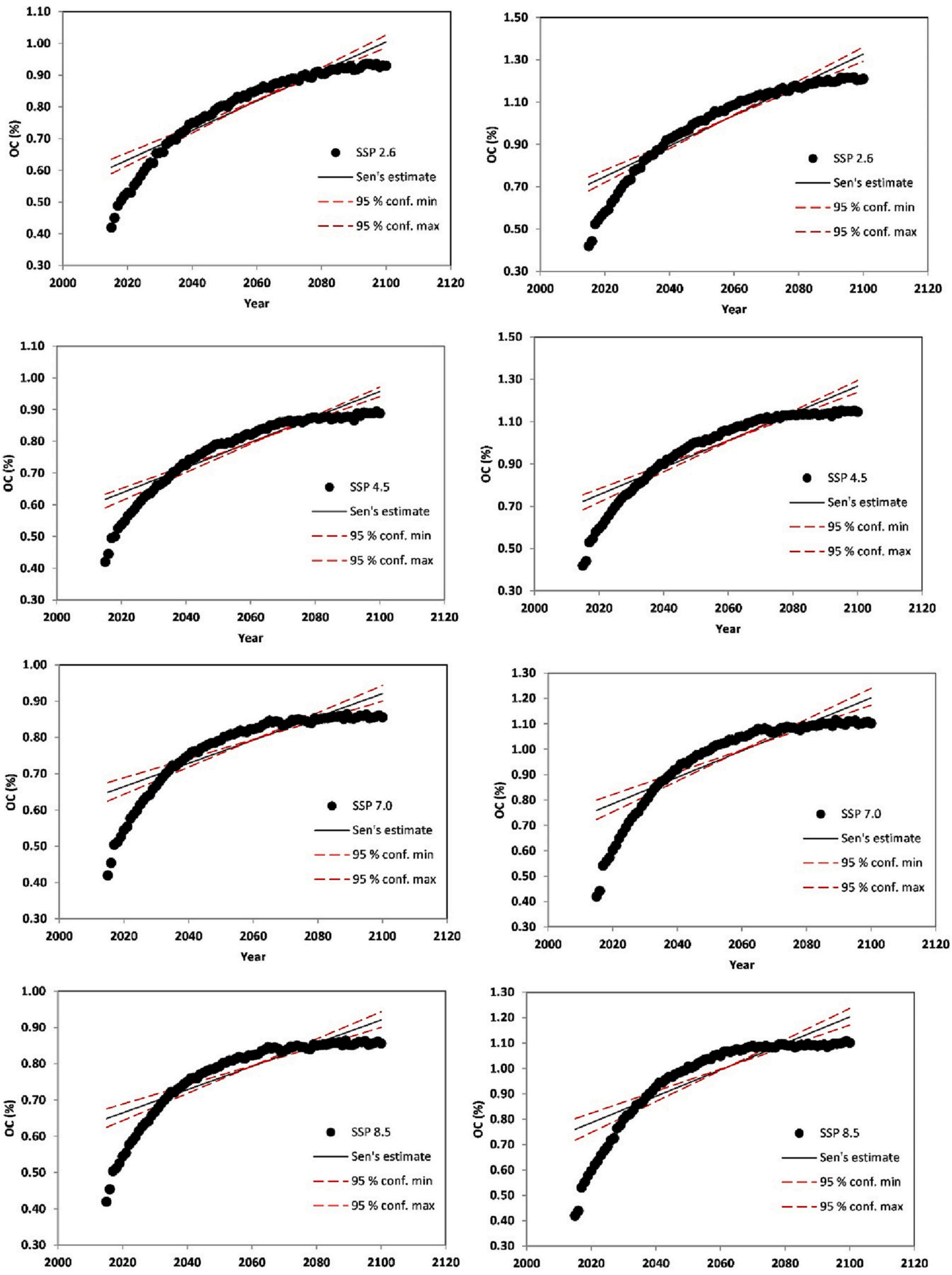

Fig. 5. Trend analysis in SOC under combination of conventional tillage without residue (left column) and with residue (right column) addition over a period of 85 years (2105–2100) in Maize+pigeonpea intercropping system.

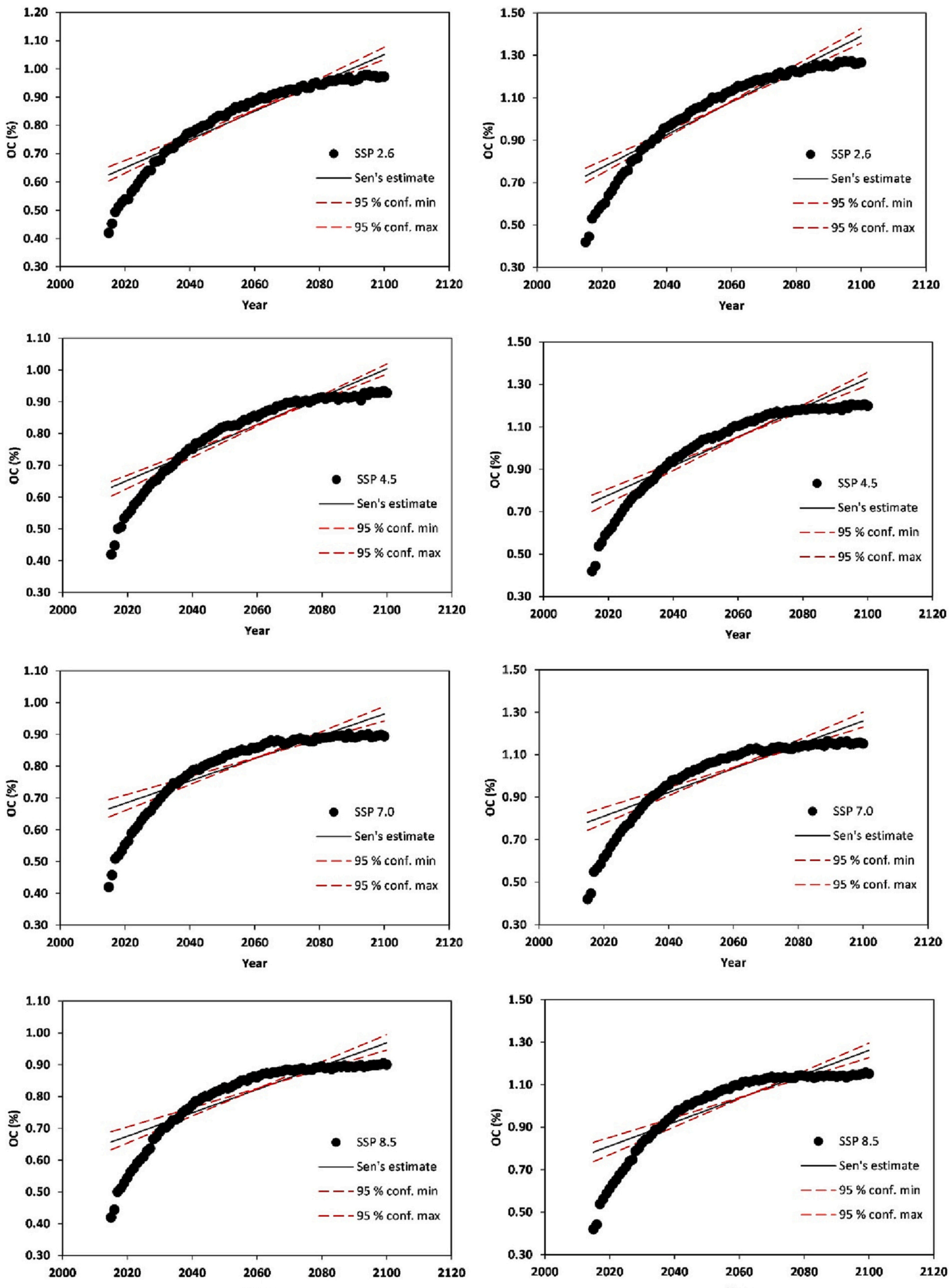

Fig. 6. Trend analysis in SOC under combination of minimum tillage without residue (left column) and with residue (right column) addition over a period of 85 years (2105–2100) in Maize+pigeonpea intercropping system.

Table 2
The Z-value and Sen's estimator for the true slope of linear trend (i.e., change per unit time period/year) in SOC for Maize-Pigeonpea intercropping system under minimum tillage (MT) and conventional tillage (CT) with residue (R+) and without residue (R-) additions.

Minimum tillage	Scenarios	Z-value	Significance	Q	Qmin95	Qmax95	B	Bmin95	Bmax95
MTR-	SSP2.6	13.18	***	0.0050	0.0045	0.0056	0.6255	0.6540	0.6035
	SSP4.5	13.13	***	0.0044	0.0040	0.0049	0.6310	0.6494	0.6034
	SSP 7.0	12.78	***	0.0035	0.0029	0.0041	0.6659	0.6946	0.6398
	SSP 8.5	13.11	***	0.0037	0.0030	0.0043	0.6568	0.6893	0.6322
MTR+	SSP2.6	13.26	***	0.0077	0.0069	0.0085	0.7320	0.7684	0.7010
	SSP4.5	13.19	***	0.0069	0.0061	0.0077	0.7438	0.7783	0.7014
	SSP 7.0	12.94	***	0.0056	0.0047	0.0065	0.7821	0.8272	0.7435
	SSP 8.5	12.73	***	0.0056	0.0047	0.0066	0.7828	0.8281	0.7374

Conventional tillage	Scenarios	Z-value	Significance	Q	Qmin95	Qmax95	B	Bmin95	Bmax95
CTR-	SSP2.6	13.15	***	0.0046	0.0041	0.0051	0.6097	0.6351	0.5894
	SSP4.5	13.07	***	0.0040	0.0036	0.0045	0.6170	0.6333	0.5900
	SSP 7.0	12.69	***	0.0032	0.0026	0.0038	0.6487	0.6758	0.6246
	SSP 8.5	13.03	***	0.0033	0.0028	0.0039	0.6405	0.6699	0.6175
CTR+	SSP2.6	13.23	***	0.0072	0.0064	0.0080	0.7123	0.7464	0.6805
	SSP4.5	13.17	***	0.0064	0.0057	0.0072	0.7225	0.7542	0.6828
	SSP 7.0	12.88	***	0.0052	0.0044	0.0061	0.7590	0.7996	0.7229
	SSP 8.5	12.67	***	0.0052	0.0043	0.0061	0.7598	0.8020	0.7169

*CT: conventional Tillage; MT: Minimum Tillage; R+: addition of Residue; R-: Removal of Residue.
Qmin95: the lower limit of the 95% confidence interval of Q ($\alpha = 0.05$); Qmax95: the upper limit of the 95% confidence interval of Q ($\alpha = 0.05$); B: estimate of the constant B in equation f(year) = Q*(year-first-Year) + B for a linear trend; Bmin95: estimate of the constant Bmin95 in equation f(year) = Qmin95*(year-first-Year) + Bmin95 for 95% confidence level of a linear trend; Bmax95: estimate of the constant Bmax95 in equation f(year) = Qmax95*(year-first-Year) + Bmax95 for 95% confidence level of a linear trend.

mitigative goals to secure food in future. Our simulation results show that sequential cropping in cereal-legume systems works well only when previous crop residues are well incorporated in soils. However, intercropping helps to build upon the benefits of minimum tillage when deep rooted legumes are included in the system. The high emission scenarios in future would need to have minimum disturbance to soils as in minimum tillage to reduce mineralization of carbon and addition of residues as mulch would help to reduce the exposure of soil-C to atmospheric temperature. Our study also highlights that in the maize-chickpea sequential and maize-pigeonpea intercropping, portion of straw/residue having less competitive use as fodder can be recycled back to soil for creating a sink for photosynthetically fixed carbon from atmosphere. This will reduce the wasteful residue burning on farms having a heavy toll on environment and soil health. This study, however, reports the stimulation results for a particular agro-ecology, this can be extended to other agro-ecologies and varied cropping systems. Nevertheless, the results from this study would guide policymakers to plan for climate action in line of food security targets. Therefore, our study, suggests that crop residue addition, which has little competitive alternative uses, can be a climate-smart scalable proposition in future climate scenarios, with prospects of further improvement in business models for arrangements of chopping the crop biomass back to soil.

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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.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crsust.2023.100210.

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