Effects of conservation practices on agricultural sustainability

by Qinsi He

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under the supervision of Alfredo Huete

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Certificate of Original Authorship

I, Qinsi He, declare that this thesis is submitted in fulfillment of the requirements for the award of Doctor of Philosophy in the School of Life Sciences/Faculty of Sciences at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Publications arising from this thesis

<u>*Journal papers directly included in this thesis:*</u>

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Abstract

Establishing sustainable agriculture requires balancing food production with environmental security. Conservation agriculture, as a sustainable farming system comprising a set of farming practices such as diversified crop rotations, residue retention, and cover cropping, has garnered considerable attention worldwide. In this context, this thesis utilized the pre-validated APSIM model, driven by statistically downscaled daily climate data from 27 Global Climate Models (GCMs) under two Shared Socioeconomic Pathways (SSP245 and SSP585), to quantitatively assess the effects of various conservation practices on crop production and profitability, soil carbon sequestration, nitrous oxide emissions, and other environmental factors in the Riverina region of New South Wales (NSW) in southeast Australia under climate change. Moreover, the APSIM outputs were combined with footprint methods to investigate the food-energy-water-carbon composite sustainability of these practices, informing region-specific optimal strategies across three sub-regions of NSW. Furthermore, given the uncertain impacts of cover crops founded in the above results, a global meta-analysis was conducted to evaluate the effects of legume and non-legume cover crops on soil organic carbon, main crop yield and nitrous oxide emissions, and a machine learning approach was used to identify the best opportunities for promoting different cover crops.

Findings from these studies suggested that: (1) In the Riverina region, retaining all crop residues in cropland turned the soil from a carbon source to a carbon sink, although this was partially offset by increased N_2O emissions. The wheat-wheat-canola rotation with full residue retention was shown to yield both large potential of GHG abatement and a high gross margin compared to other rotations; (2) Cover crops decreased soil moisture but enabled greater sequestration of SOC and reduced nitrogen loss through leaching. The benefits of cover crops on yield and gross margin were more pronounced in areas with higher rainfall and lower temperatures in Riverina; (3) Across three sub-regions of NSW, residue retention and cover crops reduced GHG emissions, but cover crops consumed more energy and water per hectare. In northern NSW (with a sorghum-wheat-chickpea-wheat rotation), residue retention with cover crops proved optimal, while in southern NSW (with a wheat-field pea-wheat-canola rotation), residue retention with fallow yielded greater benefits; (4) Globally, both legume and non-legume cover crops significantly increased SOC content. Legume cover crops improved yield but also raised N_2O emissions, which can be mitigated by combining with no-tillage, deficit irrigation and diversified crop rotations. Legume cover crops showed greater SOC and yield advantages in farming systems with low nitrogen fertilizer, low crop diversity (especially cereal-dominated systems), and low initial SOC, under humid and warm climates.

This study confirmed the potential of crop rotation and residue retention practices for climate change mitigation and adaptation in NSW cropland and highlighted the context-based performance of incorporating different types of cover crops. This thesis enhances systematic understanding of how conservation practices impact agricultural sustainability and offers helpful information for decision-making.

Keywords: APSIM; Meta-analysis; Conservation agriculture; Crop rotation; Residue retention; Cover crops; Climate change; Agricultural sustainability

Chapter 1. Introduction

1.1 Research background

1.1.1 Agriculture under climate change in Australia

The climate of Australia is undergoing noticeable changes, marked by a temperature increase of approximately 0.8°C since 1960 with more frequent heat waves and more intense droughts (Wang et al., 2018). In the future, the mean annual temperature in Australia is projected to increase by approximately 1.4-2.7°C for RCP4.5 and 2.8-5.1°C for RCP8.5 by 2080-2099 (CSIRO and BoM, 2015). Changes in mean annual precipitation are likely to decline across much of the cropping belt during the winter half of the year (Dreccer et al., 2018). A temperature variation of 2°C during the crop growing season can lead to up to a 50% reduction in grain production in Australia's croplands (Asseng et al., 2011). The climate variation in the state of New South Wales (NSW) contributed to 31%-47% of the inter-annual wheat yield from 1922 to 2000 (Shen et al., 2018). The NSW in southeastern Australia, characterized by the Mediterranean climate with wet cool winters and hot dry summers, is dominated by dryland winter crops such as wheat, barley, canola and oat. The wheat production in this area contributes to 26% of the total national wheat planted area and 27% of the total national wheat production (ABARES, 2023). Considering the significant role of dryland cropping in NSW in the grain market and the strong climate variability within the region, there is a pressing concern regarding the long-term crop productivity under future climate conditions (Anwar et al., 2015; Dreccer et al., 2018; Hochman et al., 2020; Simmons et al., 2022; Wang et al., 2015).

Agriculture in Australia undertakes not only the climate change adaptation but also the climate change mitigation. However, Australia's dryland soils typically exhibit nutrient depletion and higher C: N and C: P ratios compared to global dryland soils (Eldridge et al., 2018), which means that the soil organic matter may have slower turnover rates into the SOC pool due to limited nitrogen availability for soil microorganisms. Rossel et al. (2023) have highlighted climate as the primary factor influencing the variation in mineral-associated organic carbon across the continent. They also underscored the significant potential for management practices to enhance C sequestration in regions where climatic conditions permit. However, the warming climate poses a challenge, as it could turn Australia's soils into net emitters of CO_2 unless proactive measures are taken. Consequently, there is a growing emphasis on modeling soil organic carbon (SOC) dynamics and optimizing C sequestration strategies without compromising food security under future climate scenarios in Australia (Conyers et al., 2015; Luo et al., 2014; Luo et al., 2010; Wang et al., 2022) to achieve the target of net-zero emissions by 2050 (Wood et al., 2021a).

1.1.2 Conservation agriculture in Australia

Australia's agricultural sector, while relatively young compared to many major agricultural nations, has rapidly developed into a significant exporter of various commodities, including wheat, barley, sugar, dairy, wool, wine, and beef (Bellotti and Rochecouste, 2014). To sustain and enhance agricultural productivity, conservation agriculture practices, primarily involving no-tillage (growing crops without disturbing the soil) and residue retention (retaining leftover crop materials after harvesting), have been widely adopted by a majority of Australian farmers, particularly in the cultivation of winter cereals (Serafin et al., 2019). Additionally, there is a growing trend towards incorporating rotations of cereals with oilseeds and legumes, reflecting a broader shift towards diversified cropping systems over time (Hatfield-Dodds et al., 2020). In 2011, 60% of land in Australia's dryland grain production was managed using no-tillage methods (equating to 13.8 million hectares), 60.5% was managed with residue retention (equating to 13.9 million hectares), and only 6.8% of farmers utilized legume-based rotations (Rochecouste et al., 2015). Globally, Australia and New Zealand account for 12.6% of the total area under conservation agriculture (equating to 22.7 million hectares), following South America (38.7%) and North America (35.0%) (Kassam et al., 2018).

Australia's farmers embraced conservation agriculture primarily to maintain crop productivity and profitability in the face of a changing climate, while also sustainably intensifying production with enhanced environmental outcomes. In particular, the Australian government is developing policy initiatives aimed at encouraging farmers to adopt management practices that reduce emissions from the agricultural sector (Hatfield-Dodds et al., 2020; Rochecouste et al., 2015). Currently, a lot of studies have assessed the effects of no-tillage and residue retention for soil C sequestration and crop profitability in Australia (Liu et al., 2009; Wang and Dalal, 2015; Zhao et al., 2013). However, there are still unresolved issues, such as cover cropping options that may impact yield or new rotational legume crops that may increase nitrous oxide emissions, which require additional research to identify the opportunities for Australia’s cropping systems (Li et al., 2017; Ma et al., 2018; Rose et al., 2022).

1.1.3 Impacts of cover crops at a global scale

Cover cropping is a key component of conservation agriculture and is becoming increasingly popular in many agricultural regions in the world (Deines et al., 2023). There is a consensus that planting the off-season crops can effectively draw carbon from the atmosphere and store it underground in plant biomass (Hu et al., 2023; Jian et al., 2020; Qin et al., 2023; Vendig et al., 2023; Wooliver and Jagadamma, 2023). Some studies have also reported that cover crops can mitigate the net greenhouse gas balance (Abdalla et al., 2019; Tribouillois et al., 2018), while they may increase soil nitrous oxide emissions, especially for legume cover crops (Li et al., 2023; Muhammad et al., 2019; Quemada et al., 2020). Most importantly, despite the climate and environmental benefits of cover crops, many farmers still hesitate to adopt this practice due to fears of yield loss as a small drop in cash crop yield can mean a big cost.

To date, research on cover crops has gained traction worldwide, with particular prominence in the United States due to the financial supports from government and private organizations (Eerd et al., 2023). Between 2012 and 2017, the acreage dedicated to planting cover crops surged from 10.3 million acres to 15.4 million acres, and in 2018 alone, the USDA's Environmental Quality Incentives Program allocated $155 million in planned payments for cover crops on about 2 million acres (Wallander et al., 2021). In the European Union, farmers incorporating cover crops into their agricultural practices under the new Common Agricultural Policy are eligible for subsidies (Fendrich et al., 2023). Cover crops have also been recently promoted in China (Fan et al., 2021), but their costs and potential trade-offs in southern Australian cropping systems remain major concerns (Rose et al., 2022).

Process-based models parameterize the daily dynamics of management, weather, soil, and plant processes, and can be used to make projections (Basche et al., 2016; Chen et al., 2019; Huang et al., 2020; Quemada et al., 2020). Statistical models, which summarize observed relationships between dependent and independent variables, are increasingly used for the same purpose (Su et al., 2021; Xiao et al., 2024; You et al., 2023; Zhao et al., 2022). Meta-analyses that combine and compare results from numerous studies can be a useful way to summarize the range of projected outcomes in the literature and assess consensus (Challinor et al., 2014). Previous works based on experimental plots or crop modeling indicate cover crops may have positive (Nouri et al., 2019), negative (Eash et al., 2021; Martinez-Feria et al., 2016), or neutral (Basche et al., 2016) effects on cash crop yields. Understanding how to effectively utilize cover crops for climate change mitigation, while ensuring minimal or even beneficial impacts on crop yields, is crucial for their widespread adoption. Therefore, in addition to applying the APSIM model in southeast Australia, a global meta-analysis is conducted to evaluate the effects of cover crops across diverse climatic conditions, soil environments, and agronomic contexts, providing a more comprehensive assessment of this practice.

1.2 Research questions and objectives

Agriculture is facing multiple challenges, such as water scarcity, energy crises, escalating greenhouse gas emissions, and dwindling farm profitability. This is particularly pronounced in Australia, where approximately 80% of the continent is characterized by arid or semi-arid climates, rendering cropping systems highly susceptible to the impacts of climate change (Shi et al., 2020). In regions like New South Wales and Queensland, the volatility of climate conditions over the past two decades has led to a significant 36% decline in profits on average, compared to the period from 1950 to 2000, with projections indicating a continuation of this downward trend (Wood et al., 2021b). Responding to this challenging production landscape, various agricultural research and development funding initiatives have been implemented to incentivize farmers in Australia to embrace conservation agriculture principles in crop cultivation (Bellotti and Rochecouste, 2014). These principles encompass practices aimed at minimizing soil disturbance, diversifying crop rotations, retaining crop residues, and incorporating cover crops, collectively known as "conservation agriculture". Despite widespread recommendations for their adoption, the full potential of conservation agriculture in terms of its impact on crop production, soil organic carbon, greenhouse gas emissions, and other environmental factors in New South Wales, Australia, remains inadequately assessed. Further, given the varied performance of cover crops across diverse environmental contexts, expanding the analysis from New South Wales to a global scale to assess the effects of different cover crop types could be helpful to understand this practice.

Therefore, this study will provide answers to the following important questions:

(1) What are the effects of different conservation agriculture practices on crop production/profitability, SOC changes, N_2O emissions, water and energy consumption in New South Wales?

(2) Which practices could reduce GHG emissions while benefiting crop production/profitability in New South Wales under future climate change?

(3) How do different drivers influence the effects of cover crops on crop production, SOC changes, and N_2O emissions at a global scale?

The specific goals of this research are to:

(1) Identify effective management practices that could achieve co-benefits of crop yield and GHG abatement under climate change.

(2) Assess the sustainability of different practices quantitatively using modelling and meta-analysis approaches.

(3) Uncover the underlying factors that contribute to the different effects of conservation practices and point the optimal opportunities for their adoption.

1.3 Significance and outline of this thesis

The adoption of conservation agriculture practices to sustainably enhance crop production has implications for several Sustainable Development Goals (SDGs, https://sdgs.un.org/goals), such as zero hunger (SDG 2), clean water (SDG 6), clean energy (SDG7) and climate action (SDG13). This PhD study, dedicated to investigating the potential co-benefits of conservation agriculture, aims to provide insights into how these practices can effectively contribute to the sustainable agriculture. The outcomes of this study will provide helpful information for farmers and policymakers to optimize the advantages of conservation agriculture to adapt and mitigate climate change.

The thesis is structured as follows: First, a general introduction (Chapter 1) is provided to outline the study's background and significance, followed by a literature review (Chapter 2). The subsequent four main chapters aim to investigate the following questions: Chapter 3 examines the effects of residue retention and crop rotation on net GHG emissions, crop production and gross margin under climate change in Riverina; Chapter 4 explores the interactions between cover crops and residue retention on soil water balance, SOC and nitrogen dynamics, crop production and gross margin under climate change in the same region. In Chapter 5, the focus shifts to examining the effects of conservation agriculture on the food-energy-water-carbon nexus in three regions in New South Wales. Finally, Chapter 6 investigates the effects of different cover crop types across global croplands. Concluding the thesis, Chapter 7 summarizes the general conclusions, discusses limitations, and provides directions for future research.

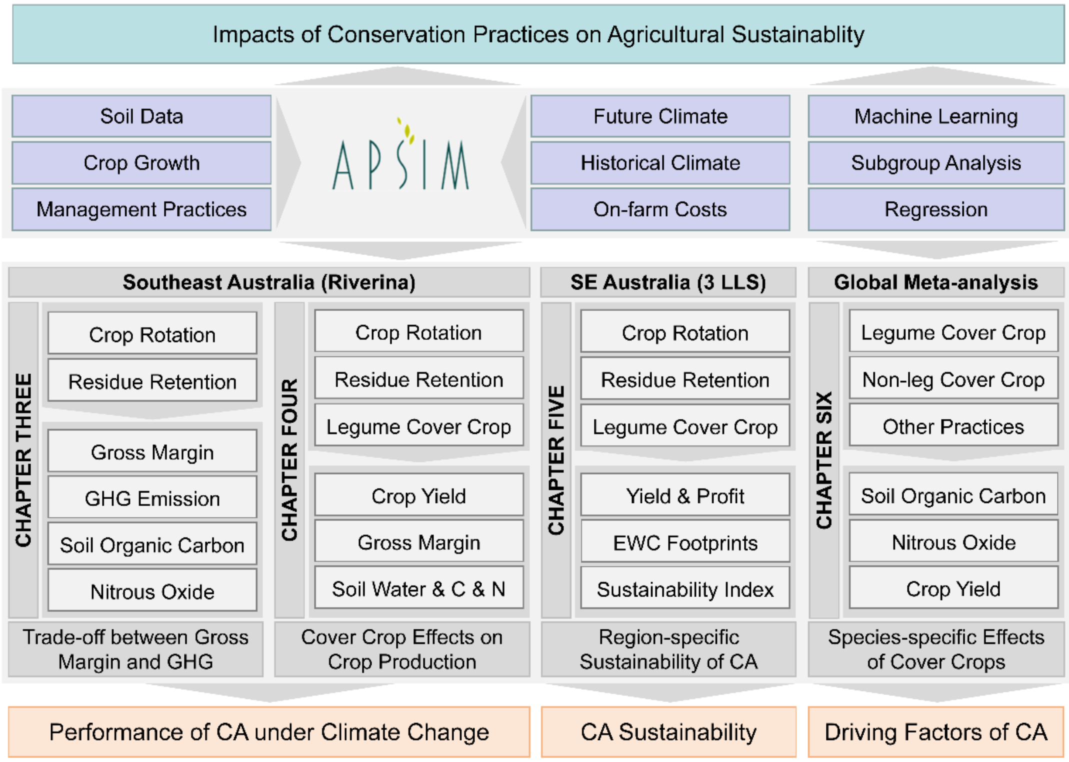

Fig. 1-1. Framework illustrating the four main chapters assessing the effects of conservation agriculture (CA) in this study. APSIM is the Agricultural Production Systems sIMulator (https://www.apsim.info), and LLS is the Local Land Services region (https://www.lls.nsw.gov.au/regions).

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Chapter 2. Literature review

This chapter provides a brief overview of the literature on the effects of conservation agriculture practices on food crop production, greenhouse gas mitigation, and environmental security under climate change, offering essential background for understanding the need to promote conservation agriculture.

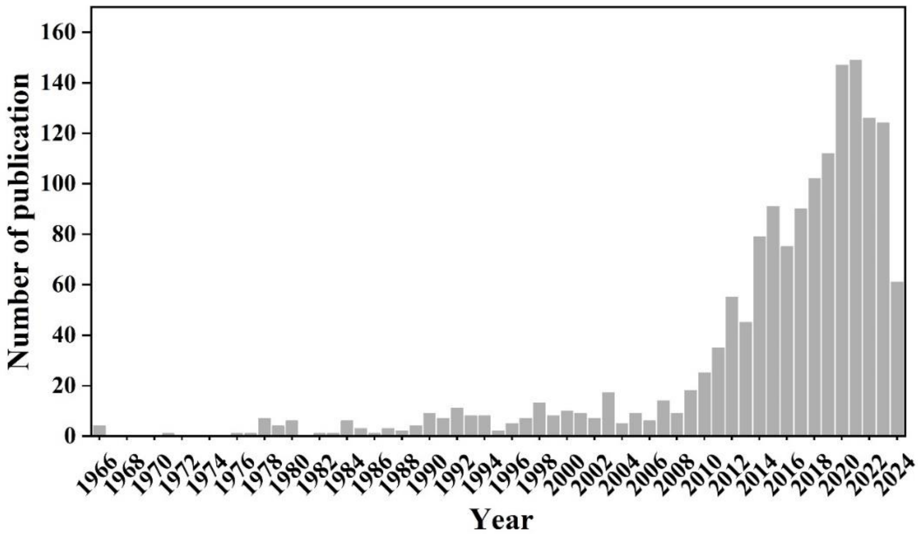

Fig. 2-1. Number of publications per year from a web of science search for articles with a topic of conservation agriculture, taken August 28, 2024.

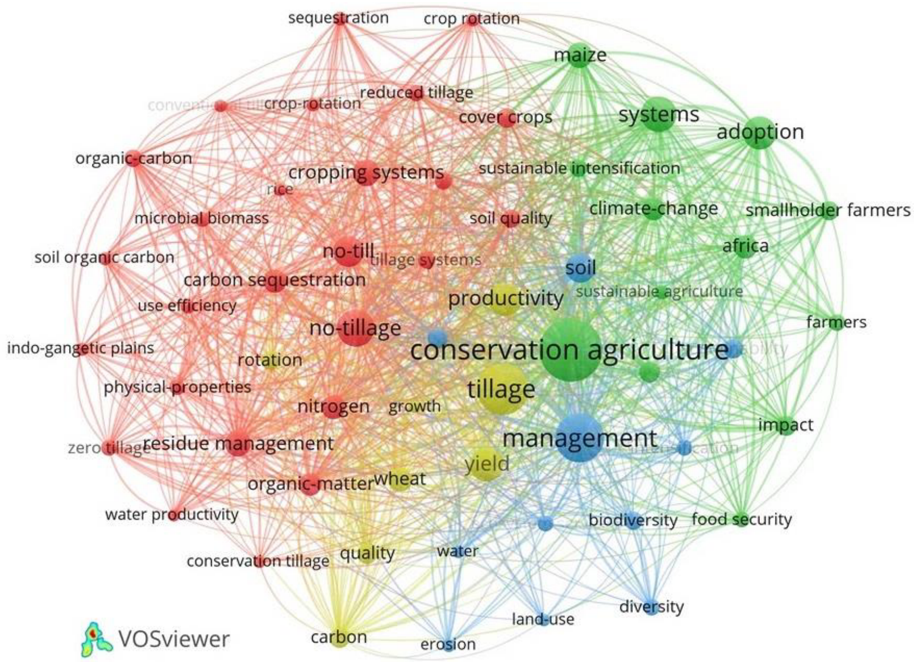

Fig. 2-2. Network visualization map for the keyword co-occurrence networks related to conservation agriculture research.

2.1 Definition of conservation agriculture

In the past century, the global population has quadrupled, leading to a surge in food demand. To meet this rising demand, the Green Revolution, such as mechanization of plowing and other farm operations, the widespread use of chemical fertilizers, herbicides, and pesticides, emerged in the 1960s (Lal, 2015; Xie et al., 2023). While this agricultural revolution brought about unprecedented increases in global food supply, it also resulted in several notable negative impacts over time (Godfray et al., 2010). For example, excessive and inappropriate use of fertilizers and pesticides has caused serious water pollution (John and Babu, 2021); intensive simple cropping systems have led to depletion of soil nutrients (Bommarco et al., 2013); and burning of agricultural wastes has released a large amount of greenhouse gases (Olesen et al., 2023). These conventional agricultural practices, initially devised to enhance farming efficiency, come at a significant environmental cost.

The damages caused by conventional farming will persist unless we alter our approach for food production. Thereby conservation agriculture was developed by the Food and Agriculture Organization of the United Nations (FAO) to preserve soil health and sustain production level (Wittwer et al., 2021). Conservation agriculture emphasizes cooperation with natural systems rather than working against them, based on three principles of minimum mechanical soil disturbance, permanent soil organic cover and species diversification (https://www.fao.org/conservation-agriculture/en/). Backed by strong recommendations from scientists, the global adoption of conservation agriculture on cropland increased from 7.5% in 2008/09 to 12.5% in 2015/16 (Kassam et al., 2018). In Australia, approximately 80% to 90% of the 23.5 million hectares allocated for winter crops are now cultivated using conservation agriculture principles (Bellotti and Rochecouste, 2014). Today, conservation agriculture practices are receiving considerable attention worldwide.

2.1.1 Minimal soil disturbance

As the basic principle of conservation agriculture, minimal soil disturbance often refers to minimum tillage or zero tillage practices (Hobbs, 2007). Conventionally, soil preparation for planting involves digging, stirring, and overturning to loosen and aerate the soil. However, since tillage fractures the soil, it disrupts soil structure, thereby accelerating soil erosion (Mariappan et al., 2021), increasing the likelihood of nutrient runoff (Page et al., 2019), and stimulating the release of greenhouse gas emissions (Huang et al., 2022b). Conversely, minimum or zero tillage advocates planting crops without turning the soil and leaving the soil with at least 30% mulch cover. Despite the fact that no-tillage can be easier, cheaper, and faster than conventional tillage, it significantly improves soil quality (Blanco-Canqui and Ruis, 2018).

2.1.2 Permanent soil organic cover

By covering the soil either in the form of residue mulching, which is naturally decomposed by microorganisms, or in the form of cover cropping, which is planted during the fallow period, the soil can be protected from direct sunlight, extreme rainfall, and wind (Chen et al., 2022). Unlike residues, which only contribute soil organic matter (Ntonta et al., 2022), cover crops as living plants, can serve as a food source for organisms that utilize root by-products (Griffiths et al., 2022), and also provide habitat for pollinators and other beneficial insects (Bowers et al., 2020). Moreover, cover crops can scavenge residual nitrogen after harvesting cash crops, thereby reducing nitrogen leaching (Nouri et al., 2022). As a radiative land management option, cover crops generally increase the albedo compared to bare soil, thus contributing to climate change mitigation (Lugato et al., 2020).

2.1.3 Species diversification

Contrary to conventional farming systems that prioritize a few high-value products, rotating various crop species sequentially in the same field has been recognized as a promising approach to mitigate the adverse impacts of climate change (Renard et al., 2023). Generally, including legumes into cereal rotations can reduce the reliance on synthetic fertilizers, and improve soil fertility for increased crop production (Zhao et al., 2022). Diversified crop rotations also prove to be effective in disrupting weed and pest cycle. Following the rotation, the increased heterogeneity of the crop production system can contribute to a more geographically even distribution of carbohydrates, proteins, and nutrient (Smith et al., 2023). Beyond these benefits, crops have a selective influence on microbial communities, and diversified rotations facilitate the support of a broader range of microbial communities to improve soil health (Iheshiulo et al., 2023).

2.2 Effects of conservation agriculture

2.2.1 Crop production

Boosting crop production stands as one of the paramount goals in agricultural development. The decision to adopt or abstain from certain conservation agriculture practices largely hinges on their impact on crop yield for most farmers (Tilman et al., 2011). However, the debate continues regarding whether conservation practices can effectively increase crop yield. For example, a meta-analysis of global yield data from 48 crops across 63 countries reported limited yield gains with no-tillage and its combinations with the other two principles (Pittelkow et al., 2015), but the probability of yield gains tends to increase under future climate scenarios by using a data-driven machine learning model for global projection (Su et al., 2021). Prestele and Verburg (2020) emphasized the spatial variability behind the averaged effects. Climates can be one of the main drivers for yield changes under conservation agriculture. Garba et al. (2022) found that, when followed by cover crops, cash crop yields changed by +15%, +4%, -12% and -11% in tropical, continental, dry, and temperate dryland climates, respectively. While a modelling study found that the effects of residue incorporation on yield were more effective in dry sites (Liu et al., 2017).

The yield advantages from conservation agriculture are also moderated by local management practices. For example, the benefits from diversified legume-based rotations decreased with nitrogen fertilizer application (-7% for each 50 kg N ha^{-1} application), as well as with crop diversification (-2.1% for each unit of diversity) (Zhao et al., 2022). The potential competition between cover crops and cash crops for soil water and nitrogen underscores the need for careful management, which includes selecting suitable species, timely termination, and proper growing season (Deines et al., 2023; Fan et al., 2021; Qin et al., 2021). Moreover, some recent studies have suggested the importance of soil quality for crop production (Ma et al., 2023; Qiao et al., 2022), indicating that conservation agriculture may be more effective for infertile soils, such as those with low-carbon content, where greater yield benefits from cover crops have been reported (Vendig et al., 2023).

2.2.2 Greenhouse gas mitigation

To keep the rise of global temperature well below 2°C above pre-industrial levels and an ambition to limit to 1.5°C as suggested by the Paris Agreement in 2015 (https://unfccc.int/process-and-meetings/the-paris-agreement), it is necessary to both reduce greenhouse gas (GHG) emissions and remove atmospheric carbon dioxide (CO_2) (Field and Mach, 2017). Soil is a vast reservoir of soil organic carbon (SOC) with approximately 2400 Gt C to a depth of 2 meters at a global scale, which is three times the amount of carbon in the atmosphere (800 Gt C) (Launay et al., 2021). Thus, even minor fluctuations in soil carbon pools can lead to significant changes in atmospheric CO_2 concentrations. After the natural ecosystem was reclaimed, soil carbon was lost massively due to traditional agricultural management methods, becoming one of the primary sources of GHG emissions (Marin et al., 2022). The international initiative “4 per 1000”, which suggests an increase in SOC stock of 4‰ per year to offset annual anthropogenic emissions from fossil-fuel combustion (9.6 Gt C), has emerged (https://4p1000.org/), emphasizing the increase in SOC through sustainable practices (Lessmann et al., 2022; Rodrigues et al., 2021).

Conservation agriculture practices play a crucial role in soil carbon sequestration. Crop residues, as precursors of the soil organic matter pool, are generally associated with an increase in SOC concentration through increased residue retention (Liu et al., 2023a). Some studies have demonstrated that returning crop residues significantly increased SOC stock (Liu et al., 2014; Zhao et al., 2013). However, it is noteworthy that increased residue retention can also lead to elevated soil N_2O emissions, potentially offsetting the benefits derived from SOC enhancement (Haas et al., 2022; Lugato et al., 2018). Moreover, the rate of decomposition is influenced by both the quantity of retained crop residues and the characteristics of residues. For example, crop residues with a high C:N ratio decompose slowly and can lead to nutrient limitations in the soil, thereby fostering competition for nutrients between crops and microbes (Liu et al., 2023b). In contrast, crop residues with a low C:N ratio decompose rapidly, but can generate more N_2O emissions (Chen et al., 2013).

Similarly, cover crops, particularly nitrogen-fixing varieties often referred to as green manure, can also pose trade-offs between SOC sequestration and soil N_2O emissions. Incorporating residues into the topsoil can accelerate decomposition processes, but the stimulated microbial respiration may deplete soil oxygen, leading to anaerobic conditions conducive to denitrification and N_2O production. Hence, some studies suggested that the combination of no-tillage and cover crops can be a viable GHG mitigation strategy (Huang et al., 2020; Taghizadeh-Toosi et al., 2022). In addition, cover crops can counteract the effects of crop residue removal on soil carbon, thereby preserving residues for use in biofuel production or as livestock feed (Ruis and Blanco-Canqui, 2017; Ruis et al., 2017). Nevertheless, a recent study has highlighted that the average carbon sequestration rate (0.32 t C ha^{-1} $year^{-1}$) reported by several meta-analyses might be overestimated, and there are high uncertainties in current field procedures to evaluate short-term changes in SOC stocks (Chaplot and Smith, 2023).

Diversified crop rotations encompass a wide range of practices involving various crop combinations, with the impact on GHG emissions being contingent upon the specific crops chosen for diversification, as well as the fertilization and tillage methods associated with each crop (Li et al., 2023b; Liu et al., 2022). A recent six-year field experimental study revealed that incorporating legumes into crop rotations resulted in an 8% increase in SOC, and diversified rotations led to a reduction of 39% in N_2O emissions and 88% in overall GHG emissions (Yang et al., 2024). Another modelling study also indicated that integrating legumes into rotations helps mitigate N_2O emissions in rain-fed cropping systems amidst climate change (Ma et al., 2018). The quality of residues inputs to the soil is changed due to the diversified cropping systems, thereby affecting soil GHG fluxes.

No-tillage can effectively mitigate GHG emissions through minimized soil disturbance and enhanced soil aggregate stability (Huang et al., 2022b). Particularly concerning the particulate organic matter (POM), which is less protected, tillage can swiftly disrupt the soil matrix, exposing POM to microbial decomposition (Lavallee et al., 2020). Although no-tillage enhances carbon stabilization, this practice alone does not add additional carbon to the soil, so it is often combined with other conservation practices to achieve synergistic effects (Huang et al., 2020; Yadav et al., 2020). It is important to note that the final performance of conservation agriculture in mitigating GHG emissions can be influenced by various factors such as soil properties, climatic conditions, duration of practices and other agronomic factors.

2.2.3 Environmental security

Approximately 50% to 70% of nitrogen (N) fertilizer applied in agricultural systems is lost to the environment, primarily through nitrate leaching (Li et al., 2023a). Nitrate, being highly mobile, can easily migrate to groundwater through the soil profile during drainage events, posing risks of watercourse eutrophication and potential hazards to human health (Coskun et al., 2017). Cover crops have been shown to reduce N leaching by 49% to 84% (Elhakeem et al., 2023; Nouri et al., 2022; Taghizadeh-Toosi et al., 2022). This is attributed to the ability of cover crops to absorb N from the soil, consequently reducing the vulnerability of soil nitrate N content to leaching during fallow periods (Valkama et al., 2015). Further, non-legume cover crops or mixed cover crops were found to have a more pronounced effect in reducing nitrogen leaching compared to legume cover crops (Thapa et al., 2018; Valkama et al., 2015). Given that N leaching is closely linked to water drainage, the adoption of no-tillage has been proposed as a method to mitigate N leaching, though its effectiveness may vary depending on soil texture (Li et al., 2023a).

Due to water, wind, or gravity, soil particles can undergo breakdown, detachment, transport, and redistribution, thereby leading to soil erosion (Chen et al., 2022). One of the primary methods for controlling soil erosion is to ensure sufficient vegetative cover on the soil. Consequently, cover crops that replace bare fallow soil are often regarded as the “last man standing” (Chaplot and Smith, 2023), and all conservation practices that cover the soil surface (e.g. residue mulching) can help protect the soil from erosion. Additionally, the benefits of conservation agriculture on crop production can potentially mitigate the need for expanding croplands, which often comes at the expense of biodiversity and environmental degradation (Zabel et al., 2019).

2.3 Conservation agriculture under climate change

2.3.1 Climate change adaptation

There has been widespread discussion and promotion of climate change adaptation as a critical objective for all human systems, with particular emphasis on agriculture (Challinor et al., 2014; Lesk et al., 2016; Zhu et al., 2022). Recent projections indicate that over the next several decades, climate change could substantially reduce crop yields and amplify yield variability in many regions across the globe (Rezaei et al., 2023; Schmidhuber and Tubiello, 2007). However, by implementing advanced preparation and careful management of agricultural systems, these risks could be diminished. For example, in a 29-year experiment conducted in the United States, the results demonstrated that no-tillage practices improved agroecosystem resilience and yield stability under climate extremes (Nouri et al., 2021). Su et al. (2021) found that the probability of achieving yield gains with conservation agriculture practices tended to increase under future climate scenarios across most areas by using a global modelling approach, and within these practices combining soil cover with no-tillage practices had a particularly strong positive effect. Soil cover provided by residues or cover crops in no-tillage systems can effectively mitigate extreme summer heat by insulating the soil surface and enhancing albedo, resulting in local surface cooling (Kaye and Quemada, 2017; Lugato et al., 2020). Greater crop diversity also serves as an adaptive strategy to increase the resilience of agricultural production systems, especially for poorer developing countries that are more likely to suffer a disproportionate burden from climate change impacts (Degani et al., 2019; Renard et al., 2023).

Soil as one of the most critical biophysical factors, interacts with climate change to affect the productive capacity of croplands. On the one hand, the use of conservation agriculture practices improves the climate resilience of soil systems. That is, such management practices increase permeability during heavy rainfall, enhance water retention during drought, and improve gas exchange to support biological respiration and thermal regulation, thereby maintaining soil functions and services even amidst climate perturbations (Nouri et al., 2021; Quinton et al., 2022). In addition, high-quality soils contribute to reduce the sensitivity of crop yield to climate variability and are reported to enhance yield outcomes under climate change (Chen et al., 2024; Feng et al., 2022; Qiao et al., 2022). Therefore, soil amelioration by conservation agriculture can be the pivotal mechanism for adapting crop production to climate change.

2.3.2 Climate change mitigation

As discussed above regarding the effectiveness of conservation agriculture in reducing GHG, there is also concern about its long-term persistence for mitigation under climate change. Many modelling studies have been conducted to project changes in SOC by conservation practices under future climate change. For example, APSIM is a comprehensive model developed to simulate biophysical processes in agricultural systems and has been widely applied around the world. Basche et al. (2016) used the APSIM model for maize-soybean rotation in the United States and found that cover crops were able to offset a 3% loss in SOC compared to scenarios without cover crops during 2015-2060. Teixeira et al. (2021) applied the APSIM model for grazing systems in New Zealand and found that by the end of the century, cover crops were still effective in reducing N leaching, particularly in warmer locations compared to colder ones. While as future temperature rises, the sequestration of SOC may decrease. For example, incorporating all wheat residues into the soil increased SOC by 100 kg ha^{-1} yr^{-1} under current climate conditions, but this increase decreased to 80 kg ha^{-1} yr^{-1} under future climate projections from 18 general circulation models (GCMs) in Australia (Liu et al., 2014). On the other hand, the future elevated CO_2 concentration and warming climate may enhance the biomass production of cover crops, thereby resulting in greater accumulation of SOC stocks (Huang et al., 2020).

Although the performance of conservation agriculture practices on climate change mitigation has mostly been assessed through modelling in the long run, there remains large uncertainties of the results especially in the far future (Huang et al., 2022a; Shi et al., 2018). In addition, some studies also suggest that existing management practices may not be adequate to consistently generate benefits (Ma et al., 2023), indicating the need for the development of novel technologies to enable greater SOC sequestration and yield improvement beyond current limitations under future climate change (Gerber et al., 2024; Six et al., 2002).

2.3.3 Co-benefits and trade-offs

Although conservation agriculture initially emerged to offer opportunities for mitigation and adaptation co-benefits, it may also entail certain socio-economic and environmental trade-offs. For instance, the average cost of planting cover crops in the US Midwest is estimated to be around $35-45 per acre per year, but the recently introduced Pandemic Cover Crop Program provides only a $5 per acre per year discount on growers' crop insurance premiums (Qin et al., 2023). Additionally, the potential yield penalties associated with cover crops currently render them economically unviable for most growers in the Midwest, necessitating additional subsidies to sufficiently offset these costs (Deines et al., 2023). Technical assistance from both government agencies and industries plays an important role in realizing the promise of cover crops. It should be noted that despite the SOC sequestration from most conservation practices, the potential concurrent releases of CO_2, N_2O, and CH_4 should be carefully considered. A meta-analysis revealed that all cover crop species led to increased CO_2 emissions but reduced N_2O emissions compared to no cover crop, except for legumes, which increased N_2O emissions (Muhammad et al., 2019). Similarly, straw return in paddy rice cultivation resulted in significantly increased CH_4 emissions, but it also led to a significant increase in grain yield (Shang et al., 2021). Therefore, there are a large number of studies aimed at identifying management practices that can reduce GHG emissions without compromising yield or economic income (Li et al., 2019; Li et al., 2021; Luo et al., 2017; Shang et al., 2021; Wang et al., 2018; Zou et al., 2022).

In summary, how to optimize the use of conservation agriculture to synergize food production, resource conservation, and climate change mitigation remains unclear. To realize its full potential, conservation agriculture should not only be seen as a set of agronomic practices at the plot scale but as a holistic approach that operates across multiple scales, in which both experimental and modelling approaches are essential to address this challenge (Hobbs, 2007; Prestele and Verburg, 2020). In this way, conservation agriculture does not necessarily oppose Green Revolution agricultural development strategies. Instead, it can be viewed as a means of refining such approaches to reduce input dependency, enhance sustainability, and improve adaptation to climate change and other environmental pressures (Wittwer et al., 2021).

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Chapter 3. Identifying effective agricultural management practices for climate change adaptation and mitigation: A win-win strategy in South-Eastern Australia

This chapter is based on the following manuscript:

Qinsi He, De Li Liu, Bin Wang, Linchao Li, Annette Cowie, Aaron Simmons, Hongxu Zhou, Qi Tian, Sien Li, Yi Li, Ke Liu, Haoliang Yan, Matthew Tom Harrison, Puyu Feng, Cathy Waters, Guangdi D. Li, Peter de Voil, Qiang Yu. Identifying effective agricultural management practices for climate change adaptation and mitigation: A win-win strategy in South-Eastern Australia. Agricultural Systems, 203, 103527, 2022.

Highlights

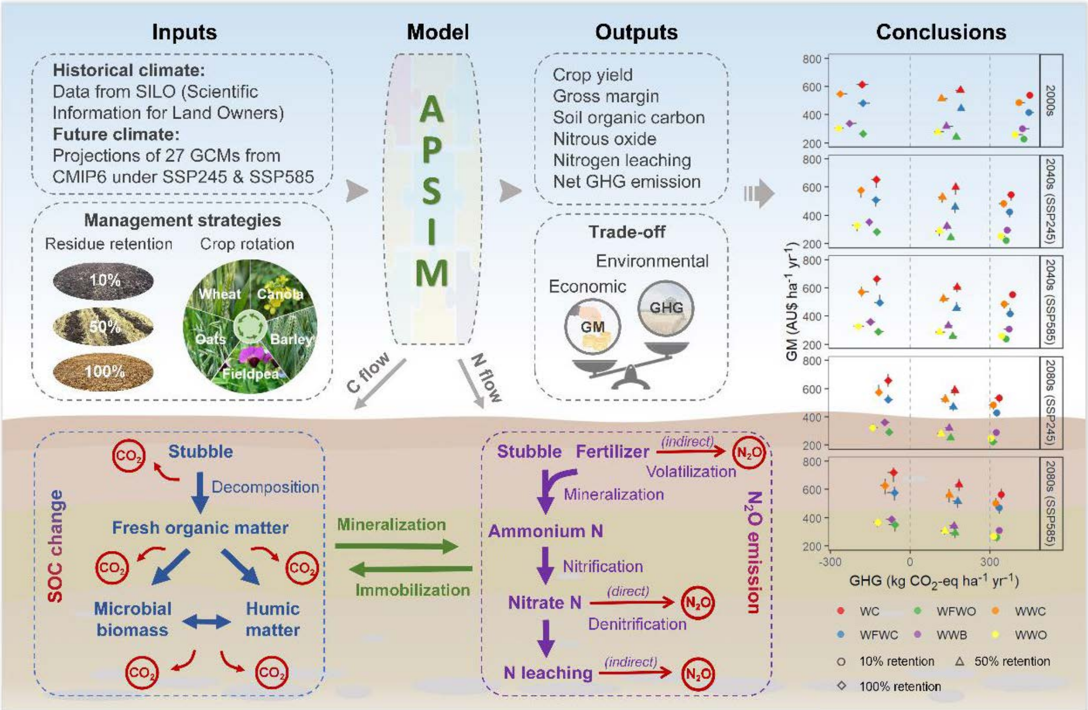
- APSIM was used to simulate the effects of residue retention and crop rotation on GHG emissions and gross margins.
- Retaining all crop residues could turn the soil from a carbon source to a carbon sink and benefit gross margins.
- Enhancement of residue retention on GHG abatement outweighed adverse effects of climate change under SSP245 and SSP585.
- The wheat-wheat-canola rotation was the most beneficial in terms of GHG mitigation and profitability compared with others.

Abstract

Farming systems face dual pressures of reducing greenhouse gas (GHG) emissions to mitigate climate change and safeguarding food security to adapt to climate change. Building soil organic carbon (SOC) is proposed as a key strategy for climate change mitigation and adaptation. However, practices that increase SOC may also increase nitrous oxide (N_2O) emissions, and impact crop yields and on-farm income. A comprehensive assessment of the effects of different management practices on trade-offs between GHG emissions and agricultural systems profitability under climate change is needed. In this study, we aimed to: (1) analyze the long-term trends of SOC and N_2O emissions, and ascertain whether the croplands of the study region are net GHG sources or sinks under climate change; (2) quantify the GHG abatement on a gross margin basis; (3) identify effective management practices that could achieve a win-win strategy; and (4) investigate sources of uncertainty in estimates of GHG emissions and gross margins under climate change. APSIM was used to simulate the effects of three crop residue retention rates (10%, 50% and 100%), and six representative crop rotations (wheat-canola, wheat-field pea-wheat-canola, wheat-field pea-wheat-oats, wheat-wheat-barley, wheat-wheat-canola, and wheat-wheat-oats) under two Shared Socio-economic Pathways scenarios (SSP245 and SSP585) using climate projections from 27 GCMs. GHG emissions and gross margins from 1961 to 2092 were assessed across 204 study sites in southeastern Australia. Our results showed that residue retention can turn the soil from a carbon source (10% retention, 304~450 kg CO_2-eq ha^{-1} yr^{-1}) to a carbon sink (100% retention, -269~-57 kg CO_2-eq ha^{-1} yr^{-1}), and the potential of carbon sequestration was partly offset by concomitantly increased N_2O emissions. The wheat-wheat-canola rotation with full residue retention was shown to be a win-win solution with both large potential of GHG abatement and high gross margin compared with other rotations. Spatial analysis showed that the southeastern part of the study region, with higher rainfall, had higher gross margins, while the drier northwestern part had greater GHG emission reduction potentials. Although climate change led to increased GHG emissions and decreased yields for some crops, these adverse effects were outweighed by the higher SOC and yield advantages from full residue retention. This study emphasizes the significant potential for agronomic management to maximize gross margin and reduce GHG emissions under climate change in southeast Australia. Results from this study could be used by farmers and policymakers to mitigate climate change without compromising agroecosystem profitability.

Keywords: Soil carbon sequestration, Nitrous oxide emission, Gross margin, Crop rotation, Residue retention, Climate change

Graphical abstract



Note: GCMs, General Circulation Models; CMIP6, Coupled Model Intercomparison Project Phase 6; SSPs, Shared Socio-economic Pathways; GM, gross margin; GHG, greenhouse gas emissions; WC, wheat-canola; WFWC, wheat-field pea-wheat-canola; WFWO, wheat-field pea-wheat-oats; WWB, wheat-wheat-barley; WWC, wheat-wheat-canola; and WWO, wheat-wheat-oats rotations.

3.1 Introduction

To meet the goal of the Paris Agreement to limit global warming to 1.5 °C above pre-industrial levels, both reductions of greenhouse gas (GHG) emissions and removal of atmospheric carbon dioxide (CO_2) are necessary (Field and Mach, 2017). Soil is a large carbon (C) reservoir in terrestrial ecosystems with a pool size of around 2400 Gt C (2 m depth), which is three times the amount of atmospheric carbon (Launay et al., 2021). Of the soil C pool, cropland soil plays a significant role in the global C budget, with a high and attainable mitigation potential of 1.4-2.3 Gt CO_2-eq yr^{-1} through improved management (Smith et al., 2019). According to the IPCC Special Report on Climate Change and Land, approximately 23% of global GHG emissions came from the agriculture, forestry and other land use (AFOLU) sector (Jia et al., 2019), and, without intervention, the anthropogenic GHG emissions from agriculture are projected to increase by 30-40% by 2050 (Mbow et al., 2019). To mitigate AFOLU GHG emissions, the international initiative “4 per 1000” that aims to increase global agricultural soil organic carbon (SOC) stocks through sustainable practices has been launched. The emphasis on increasing SOC has resulted in many studies conducted to assess the effects of different agricultural practices on SOC and promote various measures to enhance carbon sequestration (Farina et al., 2021; He et al., 2021; Lessmann et al., 2022; Rodrigues et al., 2021; Sándor et al., 2020).

Soil carbon sequestration is considered as one of the most important GHG mitigation opportunities for the agriculture sector, but its capacity can be overestimated if not assessed in a holistic manner as part of an integrated system (Harrison et al., 2021; Harrison et al., 2016; Meier et al., 2020b). For example, the retention of residue could not only increase the SOC but also increase the N_2O emissions via stimulating nitrification/denitrification and soil urease activity (Xia et al., 2018); longer crop rotations could impact multiple soil physicochemical and biological properties associated with releasing N_2O (Lehman et al., 2017) and building SOC (Renwick et al., 2021). Thus, the amount of N_2O emissions can determine whether the soils are net sinks or sources of GHG, depending on how other aspects of a system change under a given intervention (Christie et al., 2020; Ehrhardt et al., 2018). Moreover, the potential for SOC sequestration to continue is limited by the saturation ceiling, reflecting the capacity of soil to protect organic matter from decomposition (Lehmann and Kleber, 2015), but N_2O emissions continue each year (Lugato et al., 2018). Furthermore, SOC sequestration and N_2O emissions will be influenced differently by climate change-induced warming and rainfall variation (Meier et al., 2020b), since the microbial production of CO_2 and N_2O in soils have different sensitivities to temperature and moisture (Butterbach-Bahl et al., 2013). Therefore, the real mitigation effectiveness of C-sequestration management practices remains uncertain in space and time under climate change.

Greenhouse gas emissions mitigation and climate change adaptation must occur without compromising food security or causing loss of biodiversity, farm prosperity and social license to operate (Harrison et al., 2021). Altered management practices may impact food production and farmers' income (Dumbrell et al., 2017; Meier et al., 2020a), resulting in trade-offs between food security, GHG emissions, and farmer prosperity (Li et al., 2021b; Luo et al., 2017; Wang et al., 2018b; Xing et al., 2017). Recently, several practices intending to balance the trade-off between crop yields and GHG emissions, such as manure application, cover crop and no-tillage, have been assessed in China (Wang et al., 2018b), Europe (Quemada et al., 2020) and USA (Huang et al., 2022). In dry and hot environments such as experienced in Australian mainland cropping regions, the capacity for SOC sequestration is limited because of the high decomposition rates (soil CO_2 efflux increases due to increased microbial respiration under high temperature) and low amount of crop residues (low rainfall reduces the organic matter inputs) (Liu et al., 2016). Combined with the highly variable and changing distribution of seasonal rainfall, Australia is facing great risks to crop productivity and profitability (Wang et al., 2022; Wang et al., 2018a). In New South Wales (NSW) and Queensland cropping systems, the climate variability over the past 20 years contributed to a 36% decline in profits on average (relative to 1950-2000) and this trend is expected to continue (Wood et al., 2021). Understanding the relationships among crop profitability, GHG emissions, and climate change is essential for designing improved management practices that offer win-win-win in terms of productivity, profitability and GHG emissions (Harrison et al., 2021). The GHG emissions per unit farm gross margin (in other words, the gross margin-scaled emissions) is a useful indicator to contrast the GHG impacts of the cropping system without neglecting the economic performance, especially for multi-crop rotation systems where different crops have different economic values (Li et al., 2017).

Alternative management practices can affect SOC sequestration, N_2O emissions, and crop profitability simultaneously. Although numerous studies have assessed the effects of management practices, most of them focus on one aspect only, leaving the integrated effects of practices poorly understood. For example, Mohanty et al. (2020) found that nutrient management helped to turn soils into C sinks by increasing SOC stocks, but the possible concomitant increase in N_2O emission was not considered. In addition, although many field experiments have been conducted to assess the effects of agricultural practices on soil gas fluxes and crop growth, few practices can be evaluated in an individual field experiment, and these results cannot readily be extrapolated to regional scales due to variation in climate, soil type, management and other factors. Moreover, the trade-offs between GHG emissions and gross margins are not often reported and the interactions between climate change and management interventions are rarely considered over long time-scales (Huang et al., 2022).

In this study, we used APSIM to simulate the economic performance and net GHG emissions for a range of on-farm practices under climate change across a cropping region in southeastern Australia. We aimed to: (1) analyze the trends of SOC and N_2O emissions, and ascertain whether the agricultural soils of the study region are net GHG sources or sinks under climate change; (2) quantify the GHG abatement on the gross margin basis; (3) identify effective management practices that could achieve a win-win strategy; and (4) investigate sources of uncertainty in estimates of GHG emissions and gross margins under climate change.

3.2 Materials and methods

3.2.1 Study area

The 204 sites selected for this study were distributed across the cropping area in the Riverina region of NSW, in south-eastern Australia (Fig. 3-1a), which is responsible for a large proportion of Australia's grain production. The region is characterized by a semi-arid climate with a long-term annual rainfall of 477 mm and an average temperature of 16.5 °C (Fig. 3-1b-c). The main soil types are Chromosols, Dermosols, and Vertosols (Isbell and National Committee on Soil and Terrain, 2021). Agriculture is the major economic activity and the region generates 12.7% of all agricultural production in NSW (Department of Planning and Environment, 2017). Wheat, barley, and canola are the three major crops grown in this region. However, increasingly frequent extreme weather events, such as drought and heat waves are likely to continue to pose economic and environmental challenges on many agricultural sectors in this region (Chang-Fung-Martel et al., 2017).

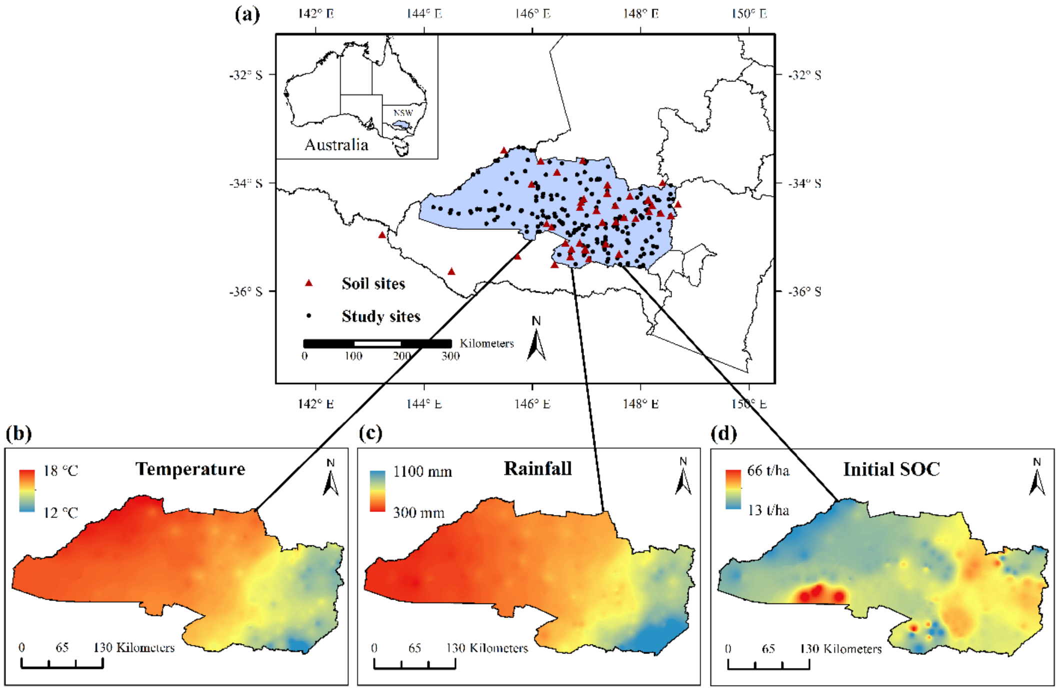


Fig. 3-1. Locations of the Riverina region, 204 study sites and 41 soil sites in southern New South Wales (NSW) in southeastern Australia (a), the average historical climate during 1985 to 2020 (b-c), and the average SOC content before implementing management practices during 1958 to 1960 (d). The spatial distributions (b-d) were interpolated using inverse distance weighting method (IDW).

3.2.2 Climate and soil data

Daily climate data comprising global solar radiation, rainfall, maximum and minimum temperature were required to drive the crop model. The historical climate data during 1900-2020 at the 204 study sites were downloaded from SILO dataset (Scientific Information for Land Owners) (https://www.longpaddock.qld.gov.au/silo/) (Jeffrey et al., 2001). For future climate scenarios, we selected two SSPs to represent an intermediate "middle of the road" scenario (SSP245) and a high emissions "fossil-fueled development" scenario (SSP585) (O'Neill et al., 2016). Basic information for 27 available GCMs from the Coupled Model Intercomparison Project Phase 6 (CMIP6, https://pcmdi.llnl.gov/CMIP6/) is presented in Table S3-3. As APSIM input requires daily climate data but raw GCMs are at coarse temporal (monthly) and spatial (100-300 km grid solution) resolutions, these gridded data were downscaled to each study site using the method developed by Liu and Zuo (2012). The statistical downscaling model involved three steps. In the first step, the gridded monthly GCM data in 1900-2100 were spatially downscaled to each of 204 weather stations using the inverse distance weighting method (IDW). The second step was the bias-correction of the GCM data towards the observed climate data for each site by using the quantile mapping technique. In the third step, the monthly bias-corrected data were disaggregated to daily data using a modified version of the WGEN stochastic weather generator (Richardson and Wright, 1984).

We used soil data from APSoil database, which contains information including soil description, soil classification, site, region, country, latitude, longitude, and data source recording the experiments from where the soil was sampled (http://www.asris.csiro.au/mapping/hyperdocs/APSRU/) (Dalgliesh et al., 2012). Each soil dataset has the layer-wise parameters including bulk density, organic carbon, saturated water content, crop specified lower limit, and drained upper limit. Some other parameters such as soil pH, electrical conductivity, chloride and exchangeable cations are also recorded for some profiles. This database was constructed for the explicit purpose of providing input soil parameters required for running APSIM. Soils that were identified to be geographically closest to our study sites were ultimately selected (Fig. 3-1a). Using the closest soil data for each site could reduce the bias from using an unrepresentative soil in spatial analysis, and this method had been used in many other crops modelling studies in Australia (Feng et al., 2020; Wang et al., 2019b).

3.2.3 APSIM model

The Agricultural Production Systems Simulator (APSIM, version 7.10) (Keating et al., 2003) is a process-based biophysical model, and has been widely used to simulate crop growth and soil processes in response to management practices and/or environmental change (Li et al., 2021b; Liu et al., 2017; Liu et al., 2020; O'Leary et al., 2016; Wang et al., 2019a). In APSIM Classic, the SoilN module simulates SOC dynamics on a daily time step, coupling with modules of SoilWat/SWIM (soil moisture), SurfaceOM (surface organic matter), and crop modules. Soil organic matter (SOM) is divided into three conceptual pools, namely fresh organic matter (FOM), microbial biomass (BIOM), and humic pool (HUM). The FOM pool has three types of organic matter including carbohydrate, cellulose, and lignin. The BIOM pool contains the soil microbial biomass and microbial products. The HUM pool contains the rest of the SOM, and a fraction of HUM is considered indecomposable (inert carbon). Decomposition of each pool is treated as a first-order decay process modified by temperature, moisture, and nutrient availability (Probert et al., 1998). Simulation of the decomposition of crop residues takes into account the degree of contact between residues and soil to modify the maximum potential decomposition rate (Thorburn et al., 2001). Crop residues can be burnt, removed from the system, incorporated into soil or left at the surface for decomposition, as specified in Manager and SurfaceOM modules. Retention of residues via tillage moves the surface residues directly into the FOM pool, thereafter resulting in C transfer to other pools and the release of CO_2 to the atmosphere.

Daily N_2O emissions from soil are simulated as the sum of N_2O emissions from daily denitrification and nitrification. Denitrification rates (R_{denit}, kg N ha^{-1} day^{-1}) are estimated as a function of the denitrification coefficient (K_{denit}, = 0.001379), the amount of NO_3^- in soil (NO_3-N, kg N ha^{-1}), active carbon (C_A, ppm), and the limiting factors (scaled from 0 to 1) for soil temperature (T) and moisture (M), which can be expressed as (Thorburn et al., 2010):

$$R_{denit} = K_{denit} \times NO_3^- \times C_A \times f(T) \times f(M) \quad (3\text{-}1)$$

N_2O emissions during denitrification are then calculated by combining the denitrification rate with the ratio of N_2 to N_2O emitted during denitrification predicted by the model of Del Grosso et al. (2000). Simulation of the nitrification rate (R_{nit}, kg N ha^{-1} day^{-1}) follows the Michaelis-Menten response to available soil ammonium (NH_4, mg kg^{-1}), and is modified by soil temperature (T), moisture (M), and pH, represented as:

$$R_{nit} = K_{max} \times \frac{NH_4}{NH_4 + K_{NH_4}} \times f(T) \times f(M) \times f(pH) \quad (3\text{-}2)$$

where, K_{max} is the maximum nitrification rate and K_{NH_4} is the NH_4 concentration for half the maximum reaction velocity. N_2O emissions during nitrification are calculated as a proportion of nitrified N (0.2%) (Li et al., 2007). A detailed description of the method used in APSIM to simulate N_2O emissions from soil is given by Thorburn et al. (2010).

3.2.4 Model validation and scenario analysis

The performance of APSIM in simulating crop yields (Meier et al., 2020a; Wang et al., 2018b; Yan et al., 2020), SOC dynamics (Godde et al., 2016; Luo et al., 2011; O'Leary et al., 2016), and N_2O emissions (Bilotto et al., 2021; Mielenz et al., 2016a; Thorburn et al., 2010) has been widely and explicitly tested and verified under different cropping systems, and could be applied for various rotation systems (Hochman et al., 2020). In this study, we used the previously calibrated and validated varieties in each crop module released by APSIM. Similar to some regional modelling studies (Choi et al., 2021; Jin et al., 2022; Kheir et al., 2021), we further evaluated the ability of APSIM in simulating SOC, N_2O and crop yields, using the experimental data collected at Wagga Wagga site before the simulation for all sites. We also compared our simulated yields with the regional average from Yield Gap (https://yieldgapaustralia.com.au/maps/). Specifically, the SOC and wheat yields were validated using data from a long-term experiment (SATWAGL) conducted from 1979 to 2004 at Wagga Wagga (Liu et al., 2009). N_2O emissions were validated using experimental data from Li et al. (2016); Li et al. (2021a); and Li et al. (2018). Details of the two experiments and APSIM performance are provided in supplementary material. To evaluate the model performance, we used root mean squared error (RMSE) and mean absolute percentage error (MAPE) to measure the difference between predicted and observed values as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (3\text{-}3)$$

$$MAPE = 100\% \times \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_i - O_i}{O_i}\right| \tag{3-4}$$

where, P_i and O_i are the predicted and observed values, and n is the number of samples.

As the SOC recorded in the APSoil database for each site represents different cropping histories and farming management at the time of the data collected, it was necessary to establish a comparable initial SOC level for each site to enable an unbiased comparison of the spatial-temporal changes across different managements. To achieve this, APSIM was run at the 204 sites from 1920 to 1960 for a continuous wheat cropping system with 50 kg N ha^{-1} at sowing and 25% retention of wheat residues. The rate of retention represents a farming practice with most of the residues removed from the field and the N application amount is the rate typically applied across the study area. The accumulation of SOC could reach a steady state after the 41-year spin-up period (O'Leary et al., 2016), and the outputs were used as the initial values for the following 132-year simulation. From 1961 to 2092, APSIM was used to simulate six crop rotations: wheat-canola (WC), wheat-field pea-wheat-canola (WFWC), wheat-field pea-wheat-oats (WFWO), wheat-wheat-barley (WWB), wheat-wheat-canola (WWC) and wheat-wheat-oats (WWO), which were chosen based on crop rotations practiced in this region. For each rotation, we set three residue retention rates: 10% (removing stubble from simulation, i.e., typical burning practices in the study region), 50% (removing half of the stubble), and 100% (retaining all stubble from the previous year). Fertilizer application for field pea was 10 kg N ha^{-1} at sowing, while for cereals and canola, fertilizer N amount varied with the average precipitation of each site using a fitted relationship (Simmons et al., 2022):

$$N = \frac{(WU - A)\times C}{WU - B} \tag{3-5}$$

where, WU is the sum of the precipitation during growing season and one quarter of the precipitation during the fallow period at each study site. A, B, and C are empirical parameters. The amount of N applied at sowing was calculated by $A = 150$, $B = 10$ and $C = 25$ for all crops. The total N applied (sum of N application at sowing and top dressing) was calculated by $A = 150$ and $B = 90$ for all crops, while $C =$ 108, 130, 80 and 64.8 for wheat, canola, barley and oats, respectively. The total N application in the range from 43 to 121 kg N ha^{-1}, representing the local farming practices under rainfed conditions.

The sowing times and the length of sowing windows were set according to the NSW Department of Primary Industries sowing guidelines (Matthews et al., 2015). Different sowing windows were set for wheat (15 March to 30 June), barley (15 April to 15 July), canola (8 April to 15 June), field pea (1 May to 30 June), and oats (1 May to 22 June). We used two generic cultivars for each site: a longer season “winter-type” was used when crop was sown before the mid-point of the sowing window, and a shorter season “spring-type” was used when crop was sown after the mid-point of the sowing window (Liu et al., 2016). The soil water requirement for sowing was nonlinearly declined from 1.2 plant available water capacity (PAWC) for the start of the sowing-window to 0.8 PAWC at the end of the sowing-window. If soil water that met the criteria was less than PAWC, crop was sown on the same day, otherwise, sowing date was delayed by 1 day (1.0-1.1 PAWC), 2 days (1.1-1.2 PWAC) or 3 days (>1.2 PAWC). If these sowing criteria were not met, crop was sown at the end of the sowing-window. In addition, the APSIM also requires atmospheric CO_2 concentrations to simulate crop growth. We calculated [CO_2] for SSP245 and SSP585 following the approach used by Bai et al. (2022):

$$[CO_2]_{SSP245} = 62.044 + \frac{34.002 - 3.8702y}{0.24423 - 1.1542y^{2.4901}} + 0.028057 \times (y - 1900)^2 + 0.00026827 \times (y - 1960)^3 - 9.2751 \times 10^{-7} \times (y - 1910)^4 - 2.2448 \times (y - 2030) \quad (3\text{-}6)$$

$$[CO_2]_{SSP585} = 757.44 + \frac{84.938 - 1.537y}{2.2011 - 3.8289y^{-0.45242}} + 2.4712 \times 10^{-4} \times (y + 15)^2 + 1.9299 \times 10^{-5} \times (y - 1937)^3 + 5.1137 \times 10^{-7} \times (y - 1910)^4 \quad (3\text{-}7)$$

where, y is the calendar year from 1920-2092 (i.e., y = 1920, 1921, …, 2092).

3.2.5 Greenhouse gas emissions and gross margins

To assess the long-term impacts of management practices on soil GHG emissions and gross margins, APSIM was continuously run from 1961 to 2092. The 132-year simulation was used because a 36-year period can provide full rotation cycles for all six rotations, i.e., 18, 12, and 9 full rotation cycles for the two-year (WC), three-year (WWB, WWC, and WWO) and four-year rotations (WFWC and WFWO), respectively. Downscaled climate projections of 27 GCMs under SSP245 and SSP585 were used. In total, we ran 198,288 simulations (204 sites × 27 GCMs × 2 climate scenarios × 6 rotations × 3 residue retentions). Each simulation quantified the GHG flux in CO_2 equivalents (CO_2-eq), which was calculated as the sum of soil CO_2 and N_2O fluxes using 100-year global warming potential (GWP) of 273 for N_2O according to AR6 (Forster et al., 2021):

$$GHG = 273 \times N_2O - \Delta SOC \times 44/12 \tag{3-8}$$

where, ΔSOC is the difference between the SOC (0-30cm) after t years (from 1 to 132 years) of the simulation and the initial SOC content. Positive and negative values of GHG indicate that the soil is a net sink and source of atmospheric CO_2, respectively. N_2O emissions are estimated as the sum of direct emissions from soil via nitrification and denitrification processes (predicted by APSIM as specified above, N_2O_d) and indirect emissions from atmospheric deposition of N volatilized from soil as well as from N leaching/runoff. For the indirect emissions resulting from N volatilization, we adopted the IPCC approach as Hergoualc'h et al. (2019):

$$N_2O_V = N \times F_V \times EF_V \times 44/28 \tag{3-9}$$

where, N is the annual amount of fertilizer being applied (kg N ha^{-1} yr^{-1}), F_V (= 0.11) is the fraction of total N input that is volatilized as NH_3 and NO_X (kg N volatilized per kg N applied), EF_V (= 0.01) is the emission factor for N_2O emission resulting from N volatilization (kg N-N_2O per kg N volatilized). Emissions from N leaching/runoff were similarly estimated using the IPCC approach (Hergoualc'h et al., 2019):

$$N_2O_L = N_L \times EF_L \times 44/28 \tag{3-10}$$

where, N_L is the amount of N leaching/runoff which is estimated by the APSIM model (kg N ha^{-1} yr^{-1}), and EF_L (= 0.011) is the emission factor for N_2O emission resulting from the N leaching/runoff (kg N-N_2O per kg N leached/runoff). Thus, the total N_2O emissions were calculated as:

$$N_2O = N_2O_d + N_2O_V + N_2O_L \tag{3-11}$$

To compare the six rotations, the income of each crop was estimated using gross margins (GM, AU\$ ha^{-1} yr^{-1}), that were calculated using the method given in Li et al. (2017) and Xing et al. (2017):

$$GM = (GI - C_S - C_T - C_F - C_H - C_I) \times (1 - L) \tag{3-12}$$

where, GI is the on-farm grain income estimated as the on-farm price (\$ t^{-1}) multiplied by crop yield (t ha^{-1}). L is the government levy (%). C_S, C_T, C_F, C_H and C_I are the costs for sowing, tillage, fertilizer, harvest and pest control, respectively (\$ ha^{-1}). The on-farm price for each crop is given in Table 3-1. Costs and calculations were coded in the Manager module of APSIM. Thus, GMs for the rotations were calculated as the sum of the single crop gross margins in each treatment. When studying the trade-offs between GHG mitigation and GM, emissions from tractor use associated with each operation were also considered. Fuel use for sowing, spraying, spreading, harvesting and grain collection were estimated as 4.4, 0.7, 1.15, 5.8 and 2.1 L ha^{-1} according to the AusAgLCI (Grant et al., 2014), with emissions of 2.7174 kg CO_2-eq per liter of fuel burned (NGA, 2021).

Table 3-1. Details of economic costs of agricultural management for wheat, barley, canola, field pea, oats and the on-farm prices used to calculate gross margins of these five crops.

Variable costs	Unit	Wheat	Barley	Canola	Field pea	Oats
Income						
On-farm grain price	$ t^{-1}	317	243	757	400	204
Cost						
Cultivation	$ ha^{-1}	0	0	17	6	38
Sowing	$ ha^{-1}	30.2	28.7	47.2	100.9	33.6
Fertilizer	$ ha^{-1}	72.5	58.5	108.7	37.6	40.0
Pest control	$ ha^{-1}	80.7	67.6	61.7	90.6	56.2
Harvest [a]	$ ha^{-1}	50.5	37.0	52.0	49.4	37.1
Total cost	$ ha^{-1}	233.9	191.8	286.6	284.5	204.9
Levies	%	1.02	1.02	1.02	1.02	1.02

Data are from DPI gross margin budgets (https://archive.dpi.nsw.gov.au/).

[a] The prices of harvest are for the first 2.5 t of grain yield, beyond which a factor of 0.01 is multiplied.

3.2.6 Secondary bias correction of simulation outputs

The statistical downscaling model procedure we used in this study was applied to correct stationary bias and systemic errors in the GCM data (Liu and Zuo, 2012). Theoretically, a perfect procedure could generate downscaled climate data that are the same as the observations. Consequently, the APSIM model outputs driven by the downscaled data should be the same as the outputs driven by observations. However, due to imperfections in the bias correction and non-stationary biases in the GCM data, there are some differences between the simulation outputs driven by downscaled GCM data and by climate observations for the historical period. These differences can be corrected, denoted as a secondary bias correction (SBC) procedure after the bias correction in the downscaling procedure (Liu et al., 2017). Therefore, prior to the analysis of soil GHG emissions and crop gross margins, all the APSIM outputs driven by the downscaled climate data were subjected to SBC as (Yang et al., 2016):

$$X = X_G - (\bar{X}_{G_{bl}} - \bar{X}_{O_{bl}}) \quad (3\text{-}13)$$

where, X is the value after correction, $\mathrm{X_G}$ is the value from APSIM simulation driven by downscaled GCM data, $\overline{\mathrm{X}}_{\mathrm{G_{bl}}}$ and $\overline{\mathrm{X}}_{\mathrm{O_{bl}}}$ are the mean values over a historical baseline period driven by GCM data and observed climate data, respectively. In this study, we used the period from 1961 to 2020 as the historical baseline period and all following analyses are based on the corrected values.

3.2.7 Analyses and partitioning uncertainty

We assessed the uncertainties in soil GHG emissions and gross margins due to 27 GCMs, two SSPs with two future periods (SSP245 for the 2040s, SSP245 for the 2080s, SSP585 for the 2040s, and SSP585 for the 2080s), and their interaction for each residue retention rate using the ANOVA method following Wang et al. (2020). The total uncertainty can be expressed as:

$$SST = SS_{SSP} + SS_{GCM} + SSI \tag{3-14}$$

where, SST is the total sum of the squares, $\mathrm{SS_{SSP}}$ and $\mathrm{SS_{GCM}}$ are the sum of squares due to the two main factors, and SSI is their interaction (SSP×GCM). In this study, we used the percentages of these three sources to compare their contributions to total uncertainty.

3.3 Results

3.3.1 Model performance

The APSIM model simulated SOC change reasonably well in the 0-30 cm soil layer for the SATWAGL experiment at Wagga Wagga from 1979 to 2004. The RMSE (root mean square error) ranged between 1.3 and 2.5 t C ha^{-1}, and MAPE (mean absolute percentage error) ranged between 2.6 and 5.3% (Fig. S3-1a-d). Despite large inter-annual variation in SOC observations, APSIM captured the declining trend in SOC well. APSIM was also well constrained for simulating the observed N_2O emissions in the top 30 cm soil layer, with a RMSE of 0.02 kg N ha^{-1} and MAPE of 11.3%, although the N_2O data were very limited (Fig. S3-1e). In addition, the observed wheat yield of the SATWAGL experiment during 1979-2002 was 3.26 t ha^{-1} on average, and the average simulated wheat yields in the same period were 2.99, 3.13 and 3.32 t ha^{-1} under 10%, 50% and 100% residue retentions, respectively (Fig. S3-1f). The average yields of different crops over the study region were also compared with the data from an open database, in which the simulated yields were similar to the actual yields for wheat and barley but close to the water-limited yields for canola (Fig. S3-2).

3.3.2 Temporal trend of cumulative soil fluxes

For the SSP245 scenario, when 10% residue was retained, SOC stock decreased gradually and soil released CO_2 into the atmosphere (Fig. 3-2A a-f), with cumulative emissions of 15.8, 24.5 and 30.6 t CO_2-eq ha^{-1} across six rotations during the 2000s, 2040s and 2080s, respectively (Table S3-4). The cumulative N_2O emissions were relatively small compared to the SOC loss, with average values of 0.6, 0.8 and 0.9 t CO_2-eq ha^{-1} during the three periods, respectively. Under this residue management, average net GHG flux increased up to 31.6 t CO_2-eq ha^{-1} by 2080s, in which WWO had the lowest emission of 30.3 t CO_2-eq ha^{-1}, and WC had the highest emission of 33.7 t CO_2-eq ha^{-1} (Table S3-5).

When 50% of residue was retained, inputs of C provided by crop residues were still inadequate to compensate for decomposition loss, resulting in a net loss of SOC and positive net GHG emissions (Fig. 3-2A g-l). Compared with the 10% retention, the cumulative CO_2 emission from soil decreased to 10.3 t CO_2-eq ha^{-1}, while N_2O emission increased to 2.0 t CO_2-eq ha^{-1} by the 2080s. Consequently, net GHG emissions fell by more than half in the 10% retention treatment, with an average value of 12.2 t CO_2-eq ha^{-1} (Table S3-4). Similar to 10% residue retention, the WC rotation had the highest GHG emission of 14.6 t CO_2-eq ha^{-1}, while WWO contributed the least GHG of 8.7 t CO_2-eq ha^{-1} by 2080s (Table S3-5).

When 100% residue was retained, all of the six rotations switched from carbon sources to carbon sinks. Although the N_2O emissions quadrupled during the whole period compared with 10% retention treatment, SOC sequestration was great enough to completely offset the additional N_2O emissions, thus the cumulative soil GHG fluxes were always negative (Fig. 3-2A m-r). The SOC stocks for all rotations increased asymptotically until the 2040s, reaching a new steady-state equilibrium, and thereafter the sequestration rates slowed down. For example, the amounts of SOC sequestration in WWB increased from 12.3 t CO_2-eq ha^{-1} during 2000s to 17.9 t CO_2-eq ha^{-1} during 2040s, but for the following 36 years the sequestration only reached 19.5 t CO_2-eq ha^{-1} by 2080s. The gradually saturated SOC and cumulative N_2O emissions finally caused inflection points of net GHG fluxes, that is, GHG removal of WWB was -15.3 t CO_2-eq ha^{-1} by the 2040s, but decreased to -15.0 t CO_2-eq ha^{-1} by the 2080s (Table S3-5). However, the SOC content in WWO increased steadily until the end of the simulation with low N_2O emissions, showing the largest potential of GHG removal of -20.5 t CO_2-eq ha^{-1} by the 2080s (Fig. 3-2A r).

For the SSP585 scenario, simulated outcomes from all rotations were consistent with those under SSP245 scenario (Fig. 3-2B). Specifically, WC with 10% and 50% residue retention had the largest cumulative net GHG emissions, releasing up to 34.7 and 16.5 t CO_2-eq ha^{-1} by 2080s, respectively. WWO emitted the least GHG of 31.5 and 10.4 t CO_2-eq ha^{-1} under 10% and 50% retention respectively, and removed the most GHG (-18.2 t CO_2-eq ha^{-1}) under 100% retention by 2080s (Table S3-5). However, the mitigation potential of all treatments was reduced under SSP585 compared to SSP245. It is noteworthy that, although GHG emissions were always negative when 100% residue was retained, the benefits of SOC sequestration would be partly negated by N_2O emissions. The net mitigation increased until around the 2040s, after which the mitigation potential decreased.

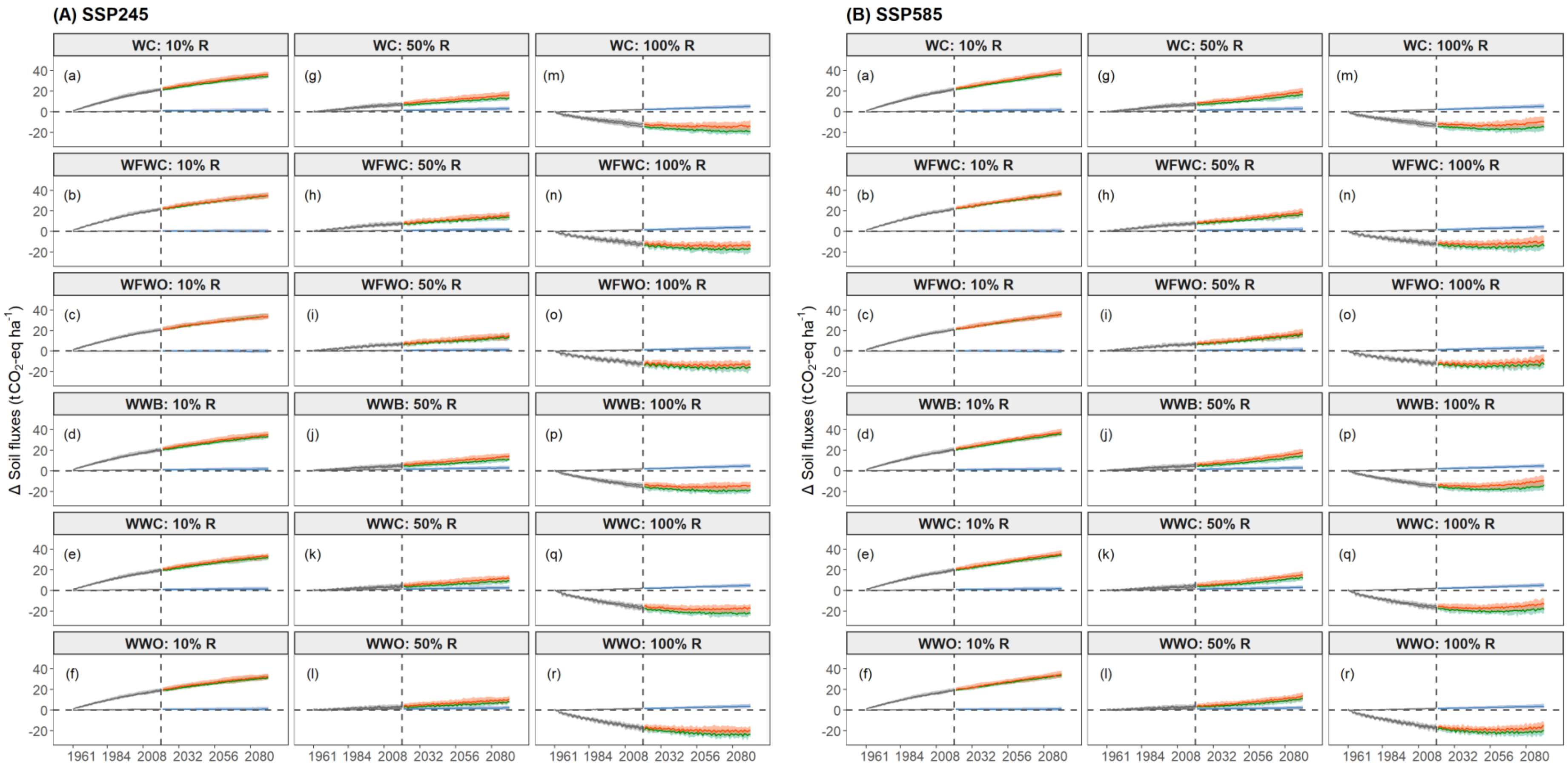


Fig. 3-2. Temporal trend of cumulative CO_2 emissions from soil (green lines), N_2O emissions (blue lines) and net GHG soil fluxes (orange lines) over six rotations (WC, wheat-canola; WFWC, wheat-field pea-wheat-canola; WFWO, wheat-field pea-wheat-oats; WWB, wheat-wheat-barley; WWC, wheat-wheat-canola; and WWO, wheat-wheat-oats) and three residue retention rates (10%, 50%, and 100%) during historical (gray lines, 1961-2020) and future (2021-2092) periods under SSP245 (A) and SSP585 (B). The lines are the median values, and the shaded areas are the 10^{th} and 90^{th} percentiles of APSIM simulations based on 27 GCMs. Negative and positive values indicate an atmospheric sink and source, respectively.

3.3.3 Trade-offs between greenhouse gas emissions and gross margin

When 10% and 50% residues were retained, the average annual GHG emissions of WWO were always lower than other rotations, and WC had relatively higher annual values (Fig. 3-3A a-d). The differences among rotations became more pronounced under 100% retention, in which average annual GHG emissions were negative for all rotations, WC, WFWC and WFWO had the lowest annual GHG removals, while WWC and WWO had the highest values (Fig. 3-3A e-f). With respect to the average annual GHG emissions of historical simulations for 1985-2020, GHG emissions decreased with time under 10% retention, while removals decreased over time under 100% retention. GHG emissions differed little between climate change scenarios.

The WC rotation, which always showed the largest annual GHG emissions, also had the highest gross margin, while the WWO had both the lowest GHG emission and gross margin (Fig. 3-3B). For example, with 100% retention under SSP585 scenario, gross margins of WC and WWO were 719 and 365 AU\$ ha^{-1} yr^{-1} in 2080s, respectively, with net GHG removals of -62 and -122 kg CO_2-eq ha^{-1} yr^{-1}, respectively (Table S3-6). In addition, residue retention increased gross margins under both SSP245 and SSP585 scenarios. For example, the gross margins of WWO were 265, 305 and 365 AU\$ ha^{-1} yr^{-1} in 2080s under 10%, 50%, and 100% retention, respectively (Table S3-6).

The GM-scaled GHG emissions of WFWO, WWB, and WWO were significantly higher than other rotations, and those of WC and WWC were the lowest under 10% and 50% residue retention (Fig. 3-3C a-d). For example, the GM-scaled GHG emission of WC was 0.63 kg CO_2-eq AU\$$^{-1}$ with 10% retention in 2080s under SSP585, which was half of the WWO with 1.22 kg CO_2-eq AU\$$^{-1}$ (Table S3-6). Under 100% residue retention, WC and WFWC had larger values of GHG/GM, while WWO had the most negative GHG/GM. Overall, WC had the highest gross margins and WWO had the greatest GHG abatement, WWC could achieve both high gross margin and large potential for GHG removal (Fig. 3-4).

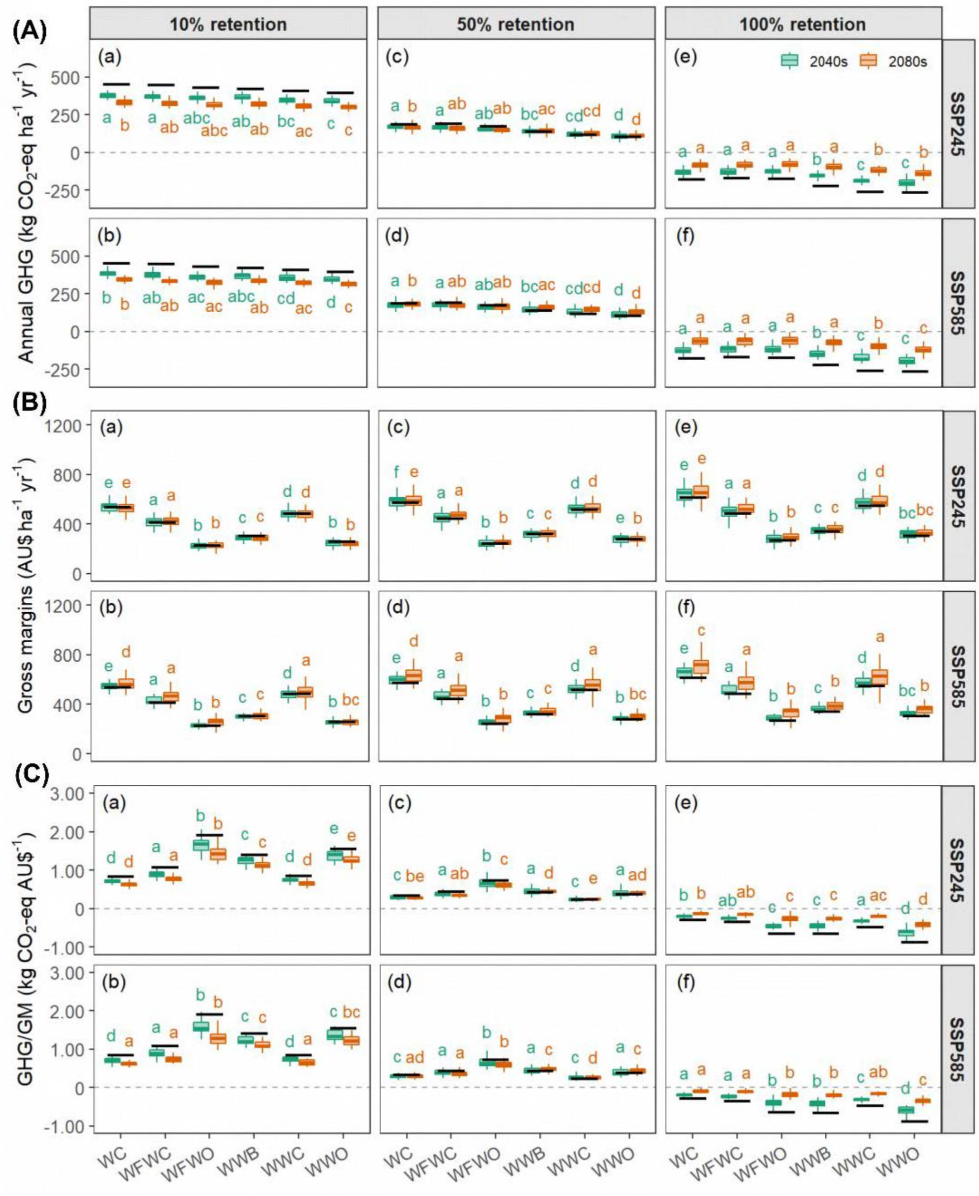


Fig. 3-3. Effects of management practices on annual GHG (A), GM (B) and GHG/GM (C) during 2021-2056 (2040s) and 2057-2092 (2080s) under SSP245 and SSP585 scenarios. Horizontal black lines represent the average historical values (1985-2020). Each box summarizes 27 values of the APSIM simulations based on 27 GCMs. Boxplots show the median, and the 25th and 75th percentiles. Different letters indicate significant differences between groups with Tukey post-hoc test ($p < 0.05$). Green and orange letters denote significant differences during the 2040s and 2080s, respectively, and no comparison was done between the two periods. Crop rotation abbreviations are defined in Fig. 3-2.

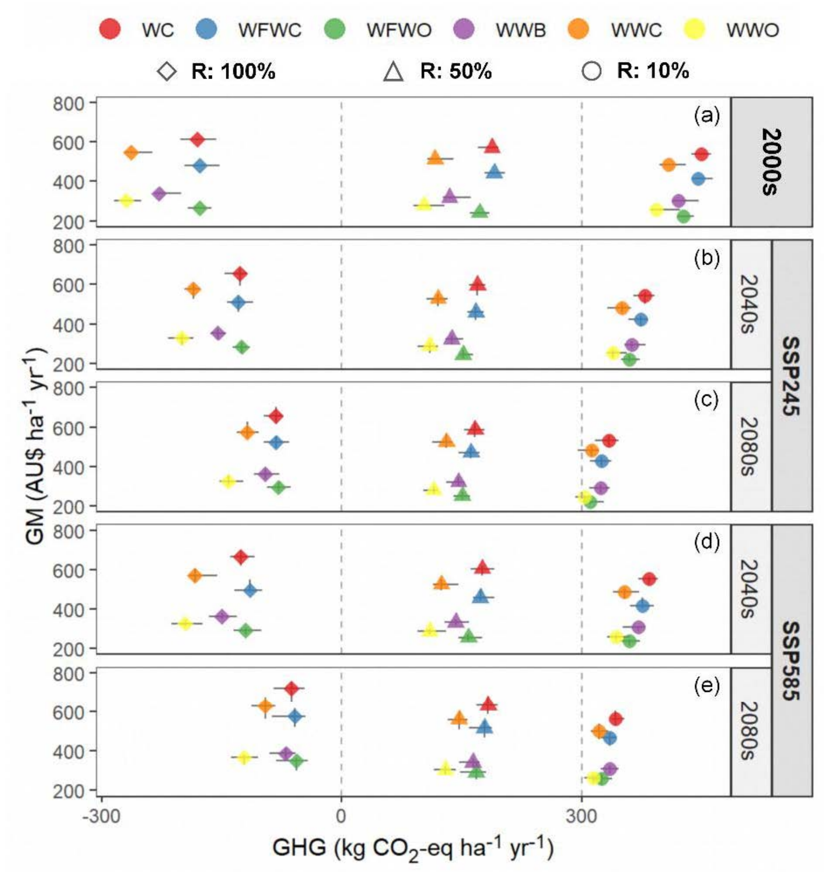


Fig. 3-4. Overall effect of management practices on relationships between GHG and GM during 2000s (a), 2040s (b and d) and 2080s (c and e) under SSP245 and SSP585 scenarios. Data are presented as the median values from APSIM simulations based on 27 GCMs. Horizontal and vertical error bars represent the 25th to 75th percentile range around the median for GHG and GM, respectively. The vertical dashed lines represent GHG emissions that are equal to 0 and 300 kg CO_2-eq ha^{-1} yr^{-1}, respectively. Crop rotation abbreviations are defined in Fig. 3-2.

3.3.4 Spatial pattern of gross margin-scaled greenhouse gas emissions

Spatially, the southeastern part of the study region always had greater GHG emissions from all rotations than those of the northwestern region (Fig. S3-3). The whole region was a carbon source under 10% retention and a carbon sink under 100% retention. Furthermore, we found that under 50% residue retention with the same rotation, the southeastern region was a carbon source, but the northwestern region was a carbon sink (Fig. S3-3g-l). However, the GM showed the opposite spatial patterns, decreasing from east to west, and this trend became more obvious with increasing residue retention (Fig. S3-5). Therefore, the GM-scaled GHG were less positive (with 10% retention) and more negative (with 50% and 100% retention) in the north-west compared to the south-east, though a small southwestern part showed large GHG emissions per unit of GM (Fig. 3-5). Overall, the northwestern region performed better in GHG abatement, while the southeastern region showed higher gross margins, and the whole region showed benefits from residue retention.

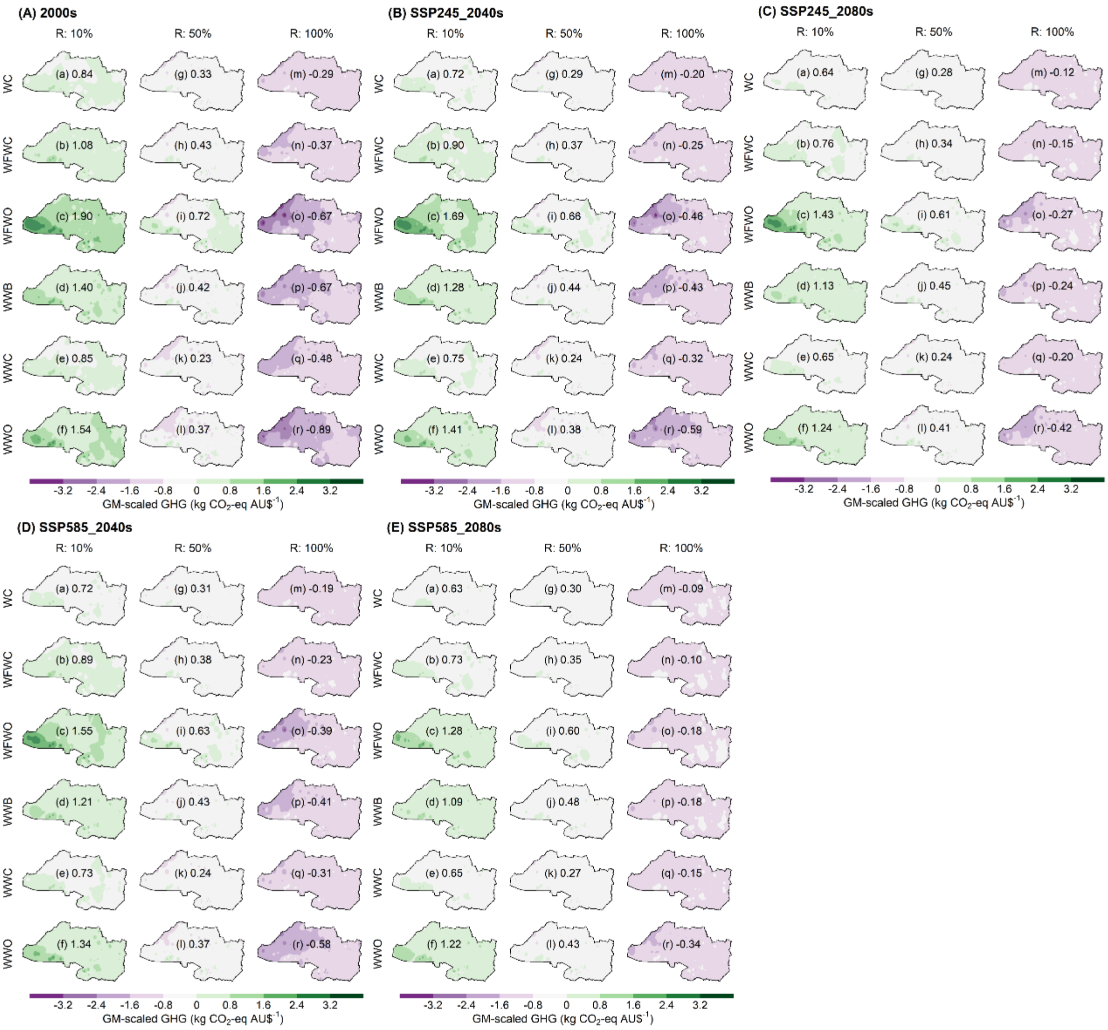


Fig. 3-5. Effects of management practices on the GM-scaled GHG (GHG/GM, kg CO_2-eq AU\$$^{-1}$) during 2000s (1985-2020), 2040s (2021-2056) and 2080s (2057-2092) under SSP245 and SSP585 scenarios across the study area. The spatial distributions of GHG/GM were interpolated using inverse distance weighting method (IDW) with median values from 27 GCMs. Numbers on the figure are spatial averages across the study region. Crop rotation abbreviations are defined in Fig. 3-2.

3.3.5 Sources of uncertainty

Since the WWC rotation was optimal in terms of the trade-off between GHG and GM, we analyzed the contributions of SSP, GCM and their interaction to the total uncertainty in simulating annual GHG emissions and GM under each residue retention rate (Fig. 3-6). For annual GHG, SSP was the major source of uncertainty under 100% residue retention (64%), while the contribution decreased to 43% and only 9% under 10% and 50% retention, respectively. Conversely, GCM contributed the least of 29% and the most of 74% to total uncertainty in simulating GHG under 100% and 50% residue retention, respectively (Fig. 3-6a). For GM, GCM contributed the most to total uncertainty independent of residue retention rates, with contribution rates ranging from 64% to 66% (Fig. 3-6b). The interaction of GCM and SSP was also an important source of uncertainty in simulating GM, accounting for 31-32%. In contrast to GHG, SSP was the smallest source of uncertainty for GM, with negligible contributions of only 2-6%.

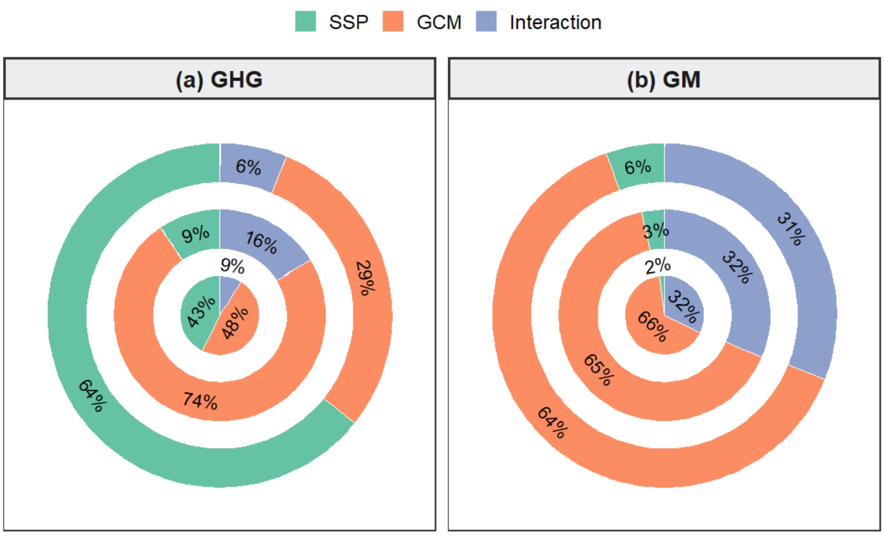


Fig. 3-6. Proportion of uncertainty in the simulated annual GHG (a) and GM (b) of WWC (wheat-wheat-canola) rotation. The sources of uncertainty were separated into SSP (e.g., SSP245_2040s, SSP245_2080s, SSP585_2040s, and SSP585_2080s), GCM, and their interaction. The inner-to-outer rings represent the uncertainty share for 10%, 50% and 100% residue retention, respectively.

3.4 Discussion

3.4.1 Responses of soil organic carbon to management practices

Residue retention is widely considered to be one of the most sustainable and economically viable management practices for sequestering atmospheric CO_2 and improving global C storage in agricultural soils (Jin et al., 2020; Paustian et al., 2016). Our simulation results demonstrated that residue retention in dryland crops significantly decreased net GHG emissions, mainly due to the enhanced SOC sequestration especially in the northwestern part of the Riverina region (Fig. 3-2 and Fig. S3-3). This result can be explained by the lower initial SOC content in northwest than in southeast (Fig. 3-1d). In general, the rate at which SOC increases is related to the initial content (Farina et al., 2021; Xia et al., 2018; Zhao et al., 2013). Soils with a lower initial C content have a greater saturation deficit, which may result in a higher C sequestration rate and a longer duration to reach a new equilibrium (West and Six, 2007), depending on the extent to which management is changed from its original state (Henry et al., 2022).

Over the simulation period full residue retention increased SOC stocks, with the averaged SOC sequestration rates ranging from 77 kg C ha^{-1} yr^{-1} (2000s) to around 43 kg C ha^{-1} yr^{-1} (2080s) (Table S3-4). The sequestration rates are small in comparison to a study for the Australian wheat belt that reported an increase of soil C sequestration for 80-100 kg C ha^{-1} yr^{-1} by incorporating all straw into soil (Liu et al., 2014b), and are similar to results from Lugato et al. (2014) who reported an average SOC change rate for a cereal straw incorporation and reduced tillage scenario for EU-27 of 20-100 kg C ha^{-1} yr^{-1} from 2000 to 2050. It should be noted that the rates of soil C sequestration following total residue retention decreased after the first 80 years (around 2040), as a new C equilibrium was reached (Fig. 3-2m-r). The possible mechanism that might underpin the soil C saturation with long-term residue C input is that, the soil capacity to maintain organic C is regulated by the clay content (i.e., chemical stabilization), aggregation (i.e., physical protection) and recalcitrant compounds (i.e., bio-chemical stabilization) (Liu et al., 2014a). Dryland soils in Australia have greater C:N ratios than other land uses (Eldridge et al., 2018), which means that the crop stubble may have slower turnover rates into the SOC pool because of the relatively higher nitrogen demands of soil microorganisms (Jin et al., 2020). A meta-analysis in China showed that SOC responses were the greatest in the initial starting phase of straw incorporation but declined after 28-62 years (Han et al., 2018), and a simulation study in south-east UK using RothC model found that the SOC accumulation rate declined after 50-100 years of cereal straw addition (Powlson et al., 2008).

3.4.2 Responses of N_2O emission to management practices

Although the soil GHG fluxes were dominated by SOC change, our results indicated a reduction in GHG removal potential due to the enhanced N_2O emissions when residues were retained (Fig. 3-2 m-r). The addition of crop residues increased SOC stocks by 38% on average, but the annual N_2O emissions also went up by 35% (Fig. S3-7), implying that crop residues supply N as a substrate for N_2O production (Abalos et al., 2022). The N_2O emissions for the whole simulated period ranged from 0.34 kg N ha^{-1} yr^{-1} for no residue retention to 0.46 kg N ha^{-1} yr^{-1} for 100% retention, which are considerably smaller than some previous studies (Table S3-7). Simulation results from Chen et al. (2019) showed that the average N_2O emissions on the Loess Plateau of China increased from 1.03 kg N ha^{-1} yr^{-1} (no straw) to 1.19 kg N ha^{-1} yr^{-1} (straw mulching) during 1981-2016 with a total 375 kg N ha^{-1} application. While fertilizer in this study ranged between 10-121 kg N ha^{-1} which may be one of the reasons for the small N_2O emissions. Myrgiotis et al. (2019) estimated the N_2O emissions of around 0.66, 0.49, and 4.80 kg N ha^{-1} yr^{-1} for barley, wheat, and oilseed rape cropping systems in eastern Scotland, suggesting the importance of N contained in crop residues on N_2O emissions. Li et al. (2017) reported lower N_2O emissions of 0.15-0.40 kg N ha^{-1} yr^{-1} from rotations including legume compared with 0.42-0.66 kg N ha^{-1} yr^{-1} from canola rotated with cereals under four RCP scenarios. Crop residues of cereals typically have higher C/N ratios (>40) than those of pulse crops, and thereby impact the substrate availability for nitrification and denitrification reactions (Wang et al., 2011). Moreover, the roots of cereal and pulse crops are generally distributed more evenly in the soil profile, while those of oilseed crops are accumulated more in the upper soil layers (Fan et al., 2016), which may also influence SOC inputs and N_2O emissions.

Crop residues, as the nutrient and energy resources for soil microbes, are subjected to microbial N mineralization and nitrification which result in N_2O production (Bilotto et al., 2021; Frimpong and Baggs, 2010), and meanwhile, they provide substrates for microbial growth and therefore increase SOC. There are some discrepancies between the results from different studies, which may be partly due to the different residue and fertilizer management. More importantly, these SOC and N_2O-related processes are parameterized in process-based models by using mathematical algorithms. Differences in model parameterization combined with different input datasets can be an important source of uncertainty across models and are still a great challenge (Tian et al., 2019). In this study, it should be pointed out that the soil C sequestration was compensated by accumulative N_2O emissions (in CO_2 equivalent) of 15-24% (for SSP245) and 16-28% (for SSP585) in 2080s when the soils reached an equilibrium with 100% residue retention (Fig. 3-2m-r and Table S3-4). This is in line with the results from Lugato et al. (2018), who reported that N_2O emissions from practices based on crop residue retention and lower soil disturbance would offset 13-47% of SOC gains (in CO_2 equivalent) by 2100 under the RCP4.5 scenario. A recent study using three biogeochemical models also found that the benefits of increased SOC sequestration by residue retention would eventually be compensated by N_2O emissions on the long run (50-100 years) (Haas et al., 2022). These results highlight that any strategy aiming at climate change mitigation in cropping systems should look at the coupled soil C sequestration and N_2O emissions together.

3.4.3 Responses of crop yield and gross margin to management practices

Apart from increasing soil SOC sequestration, residue retention also benefits crop yields (Table S3-8). Many studies have reported a positive correlation between SOC content and crop yield (Berhane et al., 2020; Han et al., 2018; Liu et al., 2014a). In this study, we found that residue retention increased or maintained yield of each crop in each rotation under both SSP245 and SSP585. Up to a point, crop growth benefits directly from increased soil organic matter (evidenced by higher SOC content) through the improvements in water and nutrient holding capacity, soil structure and biotic activity (Lal, 2004; Xia et al., 2018). Furthermore, the increased water use efficiency can enhance the resilience of agricultural production to climate change (Hao et al., 2020).

In Australia, most farmers are conscious of the weather-related risks to crop production (e.g., frost, flooding, and drought) and usually invest in practices based on economic optimum (Lam et al., 2013). Economic return is an important factor in farmers' decisions to adopt new management practices (Li et al., 2017; Meier et al., 2020a; Meier et al., 2017; Nash et al., 2013). Consistent with the above GHG and crop yield analysis, both increased GHG removal and increased gross margins were achieved under 100% residue retention (Fig. 3-3), which suggests that residue management provides an opportunity for economic and environmental co-benefits. In this study, we found that 100% residue retention increased gross margin by 22% on average compared with 10% retention (Table S3-6), which is consistent with the experimental findings of Li et al. (2021c) who reported that gross revenue increased by 22.1% with straw return, and the findings of Zhuang et al. (2019) who found that net profit increased by 53.4% with the combination of straw return and fertilizer optimization. The eastern region in Riverina had greater gross margins and higher GM-scaled GHG than the west (Fig. 3-5 and Fig. S3-5), suggesting that the eastern region would benefit less from residue retention.

Similar to results from Smith et al. (2013), we found that the wheat-canola rotation systems (WC and WWC) had high gross margins because canola price was high relative to other crops (Fig. 3-3B and Table 3-1). Leguminous rotations (WFWC and WFWO) were less profitable, which is contradictory to the findings of Xing et al. (2017) who reported that including legumes in cereal-based (wheat and canola) crop rotations were more profitable due to reduced N applications. The apparent discrepancy may be because our study applied 10 kg N ha^{-1} for field pea at sowing, and 43-121 kg N ha^{-1} for cereals and canola, without including the likely economic benefit of N contribution from legumes to subsequent crops. Southern Australia is characterized by a winter-dominated precipitation pattern, in which canola has become an important break crop for wheat-based rotations (Maaz et al., 2018). More importantly, the WWC combined with 100% residue retention can achieve both large gross margins and GHG abatement (Fig. 3-4), which may be closely linked to the quantity and quality of crop residues.

3.4.4 Climate change effect

A recent global meta-analysis reported that the climate drove SOC and crop yield changes under conservation agriculture (Sun et al., 2020). Our results show that climate change could hamper SOC accumulation as well as stimulate GHG emissions (Fig. 3-2). The negative effects were marginal compared with residue management practices, such as the 100% residue retention in which soils are always carbon sinks (Fig. 3-2m-r). However, taking the historical simulations as references, the annual GHG under 10% residue retention decreased with time for both SSP245 and SSP585 (Fig. 3-3A a-b). Generally, rates of chemical and microbial processes increase exponentially with temperature only when other factors (substrate or moisture availability) are not limiting (Meixner and Yang, 2006). The substrate (crop stubble in this study) under 10% retention would be exhausted with time and limiting GHG emissions, while for 100% retention, with large annual substrate addition, annual GHG emissions increased greatly in the future (Fig. 3-3A e-f). Moreover, the rainfall showed an increased trend in most parts of this study region (Fig. S3-8b and d), which may favour soil N_2O production (Chen et al., 2019; Schaufler et al., 2010; Wu et al., 2020).

Increased temperature, particularly during anthesis and grain filling, could result in decreased yields due to infertility and advanced maturity dates (Liu et al., 2020; Muleke et al., 2022). While elevated atmospheric CO_2 concentration can increase crop yields by enhancing photosynthetic rate and water use efficiency (Fitzgerald et al., 2016). Our results showed that the overall average crop yields for 2080s with 10% residue retention changed by -1.6% (wheat), -7.0% (oats), -5.7% (barley), +3.2% (canola) and +16.0% (field pea) relative to the historical periods, and all the crop yield changes became positive, with increases of 4.7-14.7% for 100% residue retention (Table S3-8). This is consistent with the results from Liu et al. (2017), who suggested that residue incorporation could improve water use efficiency and mitigate the negative climate change impacts on crop yields. Interestingly, compared to canola and field pea, cereals (wheat, oats and barley) benefited more from residue retention shifting from negative response under 10% retention to positive under 100% retention, which may be partly due to their higher amounts of biomass (Flower et al., 2021). These results indicated that positive effects of residue retention on gross margins could overcome the adverse effects from climate change. However, the potential income from utilization of the crop residues removed under 10% and 50% retention scenarios was not considered in this study. Biomass can be used as livestock feed or bioenergy for climate change mitigation, but evaluating these scenarios requires more sophisticated modelling practices or life cycle assessment. The western part of Riverina region always had lower gross margins than the eastern part due to the hotter and drier climate (Fig. S3-5), suggesting a need to investigate a wider range of practices (e.g., pasture rotation, Meier et al. (2017)) and use of dry or heat tolerant cultivars to build a climate-resilient crop system in the future (Pequeno et al., 2021; Zhao et al., 2022).

3.4.5 Limitations and future research

We constrained our analysis to concentrate on the environmental and economic effects of management practices under climate change. There are still some limitations requiring additional research as well as providing insights into future studies. First, we did not consider the future fluctuation of on-farm prices and agrotechnology innovations (Schmidhuber and Tubiello, 2007). There are many factors influencing the crop yield and the subsequent price variability, such as pest or disease outbreaks, domestic policies, macro-economic conditions, and changing agrometeorology (Chatzopoulos et al., 2020), which need to be further assessed. Second, we aimed to evaluate the effectiveness of conservation farming practices, specifically residue retention and crop rotation, but did not consider the potential changes of these practices in the future. Although our N application rates are based on local practices and climate, and the six rotations comprised common rotation cycles across the Riverina, they are still simplified simulations of the real world. For example, breeding efforts may result in the adaptation of crops to climate change, and changes in social and other environmental factors may affect the choice of planting systems in the future. Therefore, the implications of the modelling results should be cautiously interpreted. In addition, although APSIM has been widely applied for agricultural management assessment globally, a single crop model may be overconfident. The uncertainties of GHG and gross margins from 27 GCMs were assessed (Fig. S3-4 and Fig. S3-6), but extending the simulation to a multi-model comparison with different model structures would provide additional information and greater confidence. Thus, a useful future extension would be to evaluate some other management options (e.g., fertilizer management, cover crop and green manure) based on conclusions from this study with multi-model ensembles to explore the mitigation and adaption potentials of management practices under climate change.

3.5 Conclusions

In this study, we conducted a comprehensive simulation analysis to quantify the interaction effects of crop rotation, residue retention, and climate change on both soil GHG emissions and gross margins at the regional level. Our results indicated that retaining all crop residues in cropland can turn the soil from a carbon source to a carbon sink, while the benefit was partly offset by the concomitantly increased N_2O emissions. The wheat-wheat-canola rotation with full residue retention could achieve a win-win solution with both large GHG abatement and high gross margin compared to other rotations. Spatial analysis showed the eastern Riverina region had higher gross margins while the western region had higher GHG abatement potentials. Climate change led to increased GHG emissions and decreased yields for some crops, but the adverse effects were smaller than the advantages provided from adopting residue conservation and wheat-wheat-canola rotation regarding the GHG abatement. The results from this study are expected to provide helpful information for farmers and policymakers to guide mitigation and adaptation strategies to meet the net-zero emission target of NSW government.

3.6 Supporting information

3.6.1 Model validation

3.6.1.1 SOC experiment

The SATWAGL experiment (Sustainable Agriculture through Wheat and Grain Legumes) was conducted from 1979 to 2004 at Wagga Wagga Agricultural Institute, Wagga Wagga, NSW (Lat. 35°05' S; Long. 147°20' E; Elev. 147 m), which is one of the 204 sites in this study. The Wagga site was often used to represent the region for many studies. This experiment was designed to monitor changes in agronomic performance and soil quality under a range of tillage, residue management and rotation practices. Four treatments were selected for the APSIM validation (Table S3-1). All treatments were arranged randomly in four blocks with 16 plots within each block, such that each phase of the rotation was represented every year. Plot size was 50 m × 4.3 m. SOC was measured by randomly sampling at least five cores per plot before tillage and sowing of wheat in autumn each year. Sampling depth was normally to 20 cm, but to 40 cm in 1983 and 50 cm in 1991. Since there were no significant changes in SOC in the 20-30 cm layer between treatments from 1983 to 1991, we assumed SOC of this layer was the same for all treatments throughout the experiment.

Composite soil samples were bulked, living roots and coarse litter were removed. Soil samples were air-dried in a forced draught oven at 40 °C and ground to pass through a 2 mm sieve. SOC of all soil samples was determined by a chromic acid-hydrogen peroxide method (Walkley and Black, 1934), denoted as $\mathrm{C_{WB}}$. On two occasions, the same soil samples were analyzed by the LECO combustion method of Nelson and Sommers (1982), denoted as $\mathrm{C_{LECO}}$. A linear calibration ($\mathrm{C_{LECO}} = 0.112 + 1.074 \times \mathrm{C_{WB}}$, $R^2 = 0.95$) was determined, and all the SOC data were expressed in a LECO equivalent basis for 0-30 cm layer. More details of the experiment and SOC measurement are available in Chan et al. (2002); Heenan et al. (2004); and Liu et al. (2009).

Table S3-1. Summary of treatment parameters for SATWAGL experiment.

Treatment	Tillage	Residue management	Rotation
T1	No tillage	Retained	Wheat-Lupins
T2	Conventional cultivation	Retained	Wheat-Lupins
T3	No tillage	Burnt	Wheat-Lupins
T4	Conventional cultivation	Burnt	Wheat-Lupins

3.6.1.2 N_2O experiment

The experiment was conducted from 2012 to 2015 at the Wagga Wagga Agricultural Institute, Wagga Wagga, NSW (Lat. 35°01’45’’ S; Long. 147°20’36’’ E; Elev. 210 m). A 4-year rotation was established with wheat-canola-field pea-wheat in sequence (Table S3-2). The site was cropped for at least 5 years using no-tillage before this experiment. The experiment was a randomized split-plot design with tillage (tilled vs no-till) as the whole plots and N application rates (0 and 100 kg N ha^{-1}) as the subplots, replicated three times. Each plot size was 5 m × 9 m. The auto-chamber gas chromatograph (GC) system was installed in each plot, and was fully functioning before crops being sowed (Li et al., 2018). The GC system consisted of 12 pneumatically operated static chambers linked to an automated sampling system (SRI GC8610, Torrance, CA, USA), and an LI-820 infrared gas analyzer (LI-COR, Lincoln, NE, USA).

The clear acrylic glass chamber (0.5 m × 0.5 m) with a height of 0.15 m was secured to stainless steel bases and inserted permanently into the soil to a depth of 0.1 m. Each chamber covered two crop rows. When crop height exceeded 0.15 m, the chamber height was extended to 0.65 m. When crop height exceeded 0.65 m, the plants in the chambers were periodically trimmed above 0.65 m until harvesting. To minimize the glasshouse effect on plant growth and soil moisture, two bases were installed in each plot to enable the chamber to be swapped between two bases every 1-2 weeks during the growing season and every 3-4 weeks during other times (Li et al., 2016; Li et al., 2021a). The automated chambers continuously monitored N_2O emissions with 8 measurements per day. Daily N_2O emission for each chamber was calculated by averaging the eight emission measurements for that day. Cumulative N_2O emission was then calculated by integrating daily N_2O fluxes throughout the measurement.

Table S3-2. Cumulative N_2O emissions used for the APSIM validation.

Year	Crop	Cumulative N_2O	Number of days	Treatment
2012	Wheat	2012.08.07 – 2013.03.14	219	0/100 kg N ha^{-1}
2013	Canola	2013.04.15 – 2014.04.14	364	0/100 kg N ha^{-1}
2014	Field pea	2014.04.22 – 2015.05.15	388	Tilled/No-till
2015	Wheat	2015.05.18 – 2016.05.11	358	No-till
2015	Wheat	2015.05.16 – 2016.05.23	372	Tilled/No-till

3.6.1.3 APSIM performance

(I) Comparison of experimental and simulated data

Data from above SOC and N_2O experiments were used to validate the APSIM model. The SOC data for four treatments (T1-T4) were from Liu et al. (2009). The data of N_2O emissions were reproduced from Li et al. (2016); Li et al. (2021a); and Li et al. (2018). In addition, the observed wheat yields of the SATWAGL experiment were collected to compare with the simulated values under 10%, 50% and 100% residue retention rates, respectively.

(II) Comparison of regional yields

In order to compare the regional yields, we used the actual and water-limited yields obtained from Yield Gap (https://yieldgapaustralia.com.au/maps/). The selected ten subregions cover most of our study region, including Cootamundra, Junee, Wagga Wagga, Albury Region, Temora, Narrandera, Corowa Region, Tocumwal - Finley - Jerilderie, Griffith Region, and Deniliquin Region.

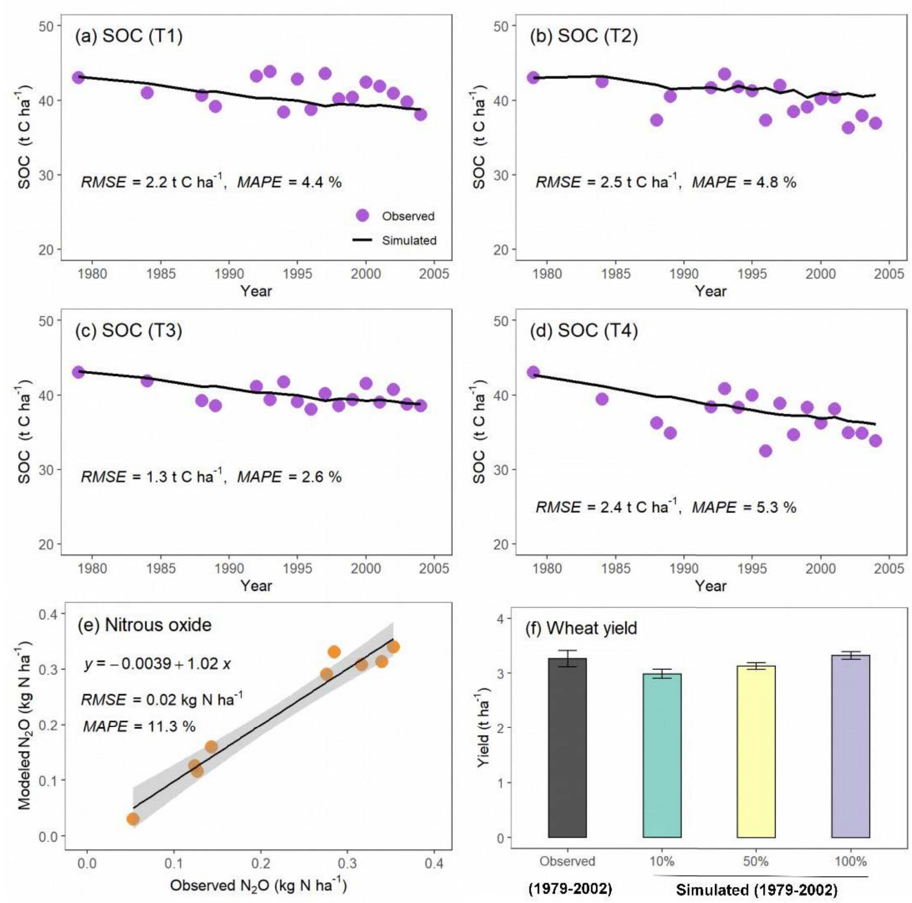


Fig. S3-1. Simulated and observed SOC (a-d), N_2O emissions (e), and wheat yields (f). RMSE is the root mean square error and MAPE is the mean absolute percentage error. Error bars represent the standard error of the mean.

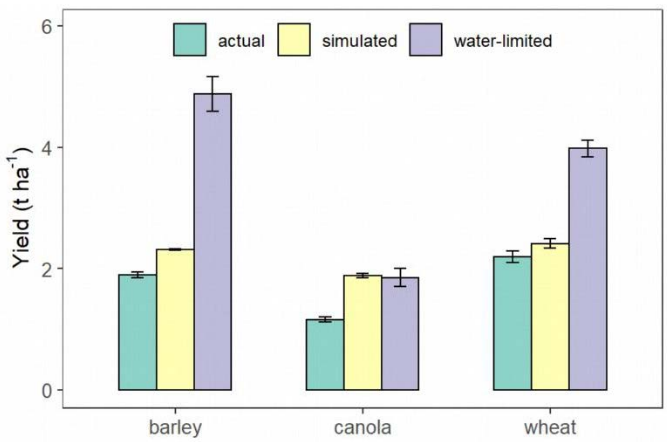


Fig. S3-2. Comparison of the average actual yield and water-limited potential (the maximum possible yield) of barley, canola and wheat in ten subregions of NSW during 2000-2014, with the simulated yield of our study region during the same period. Error bars represent the standard error.

3.6.2 Supplementary tables

Table S3-3. List of 27 available GCMs used in this study for statistical downscaling outputs of 204 sites to drive the APSIM model.

Model ID	Name of GCM	Abbreviation	Institute ID	Country
01	ACCESS-CM2	ACC1	BoM	Australia
02	ACCESS-ESM1-5	ACC2	BoM	Australia
03	BCC-CSM2-MR	BCCC	BCC	China
04	CanESM5	Can1	CCCMA	Canada
05	CanESM5-CanOE	Can2	CCCMA	Canada
06	CIESM	CIES	THU	China
07	CMCC-CM2-SR5	CMCS	INGV CMCC	Italy
08	CNRM-ESM2-1	CNR1	CNRM	France
09	CNRM-CM6-1	CNR2	CNRM	France
10	CNRM-CM6-1-HR	CNR3	CNRM	France
11	EC-Earth3	ECE1	EC-EARTH	Europe
12	EC-Earth3-Veg	ECE2	EC-EARTH	Europe
13	FGOALS-g3	FGOA	FGOALS	China
14	GFDL-CM4	GFD1	NOAA GFDL	USA
15	GFDL-ESM4	GFD2	NOAA GFDL	USA
16	GISS-E2-1-G	GISS	NASA GISS	USA
17	HadGEM3-GC31-LL	HadG	NIMR/KMA	Korea
18	INM-CM4-8	INM1	INM	Russia
19	INM-CM5-0	INM2	INM	Russia
20	IPSL-CM6A-LR	IPSL	IPSL	France
21	MIROC6	MIR1	MIROC	Japan
22	MIROC-ES2L	MIR2	MIROC	Japan
23	MPI-ESM1-2-HR	MPI1	MPI-M	Germany
24	MPI-ESM1-2-LR	MPI2	MPI-M	Germany
25	MRI-ESM2-0	MTIE	MRI	Japan
26	NESM3	NESM	NUIST	China
27	UKESM1-0-LL	UKES	Met Office	UK

Table S3-4. Median average cumulative SOC change, N_2O emissions and GHG emissions of six rotations during 2000s (1985-2020), 2040s (2021-2056) and 2080s (2057-2092) under SSP245 and SSP585 scenarios estimated by 27 GCM models. The 25th and 75th percentiles are presented in brackets. Change is the percentage variation of median values in 2040s and 2080s relative to that of 2000s.

Residue retention	**Period**	**SOC (t CO_2-eq ha^{-1})**		**N_2O (t CO_2-eq ha^{-1})**		**GHG (t CO_2-eq ha^{-1})**	
		SSP245	**SSP585**	**SSP245**	**SSP585**	**SSP245**	**SSP585**
10%	2000s	**15.8** (14.9, 16.5)		**0.6** (0.3, 1.0)		**16.4** (15.5, 17.3)	
	2040s	**24.5** (23.2, 25.5)	**24.7** (23.6, 25.7)	**0.8** (0.2, 1.7)	**0.8** (0.2, 1.6)	**25.1** (24.0, 26.6)	**25.4** (24.1, 26.8)
	2080s	**30.6** (29.4, 32.3)	**32.2** (30.9, 33.4)	**0.9** (0, 2.1)	**0.9** (0, 2.0)	**31.6** (30.3, 33.3)	**33.1** (31.5, 34.5)
	Change in 2040s	*55%*	*56%*	*33%*	*33%*	*53%*	*55%*
	Change in 2080s	*94%*	*104%*	*50%*	*50%*	*93%*	*41%*
50%	2000s	**4.1** (2.5, 5.2)		**0.9** (0.5, 1.2)		**5.0** (3.6, 6.2)	
	2040s	**7.2** (5.0, 8.5)	**7.4** (5.4, 8.9)	**1.5** (0.8, 2.2)	**1.5** (0.8, 2.2)	**8.8** (6.5, 10.1)	**8.9** (7.0, 10.6)
	2080s	**10.3** (8.0, 12.2)	**11.8** (10.0, 14.0)	**2.0** (1.1, 3.1)	**2.0** (1.1, 3.2)	**12.2** (9.9, 14.5)	**14.1** (11.9, 16.2)
	Change in 2040s	*76%*	*81%*	*67%*	*67%*	*76%*	*78%*
	Change in 2080s	*151%*	*188%*	*122%*	*122%*	*144%*	*182%*
100%	2000s	**-11.9** (-13.4, -10.2)		**1.2** (0.9, 1.6)		**-10.5** (-12.1, -9.1)	
	2040s	**-17.1** (-19.4, -15.1)	**-16.4** (-18.9, -14.6)	**2.4** (1.8, 3.1)	**2.4** (1.8, 3.2)	**-14.4** (-17.1, -12.7)	**-13.9** (-16.4, -12.0)
	2080s	**-19.3** (-21.7, -16.9)	**-17.0** (-19.4, -14.4)	**3.7** (2.7, 4.7)	**3.8** (2.9, 4.9)	**-15.4** (-18.0, -12.9)	**-13.3** (-15.7, -10.3)
	Change in 2040s	*44%*	*38%*	*100%*	*100%*	*37%*	*32%*
	Change in 2080s	*62%*	*43%*	*208%*	*217%*	*47%*	*27%*

Table S3-5. Median average cumulative SOC change, N_2O emissions and GHG emissions during 2000s (1985-2020), 2040s (2021-2056) and 2080s (2057-2092) under SSP245 and SSP585 scenarios estimated by 27 GCM models for different crop rotations. The 25th and 75th percentiles are presented in brackets.

Rotation & Residue retention		Period	**SOC (t CO_2-eq ha^{-1})**		**N_2O (t CO_2-eq ha^{-1})**		**GHG (t CO_2-eq ha^{-1})**	
			SSP245	SSP585	SSP245	SSP585	SSP245	SSP585
WC	10%	2000s	**16.4** (16.0, 16.8)		**0.7** (0.5, 1.3)		**17.3** (16.8, 17.8)	
		2040s	**25.2** (24.7, 26.1)	**25.8** (24.9, 26.4)	**1.1** (0.7, 2.0)	**1.1** (0.7, 1.9)	**26.6** (25.4, 27.5)	**27.0** (25.9, 27.9)
		2080s	**32.2** (30.5, 32.9)	**33.5** (32.4, 34.4)	**1.4** (0.6, 2.6)	**1.5** (0.6, 2.4)	**33.7** (31.7, 35.1)	**34.7** (34.0, 35.9)
	50%	2000s	**4.9** (4.5, 5.6)		**1.1** (0.9, 1.6)		**6.3** (5.5, 6.6)	
		2040s	**8.4** (7.5, 8.9)	**8.9** (8.1, 9.7)	**1.8** (1.4, 2.7)	**1.8** (1.4, 2.6)	**10.3** (9.5, 11.0)	**10.7** (9.6, 11.9)
		2080s	**11.9** (10.6, 13.1)	**14.0** (12.8, 14.9)	**2.6** (1.7, 3.7)	**2.7** (1.8, 3.5)	**14.6** (13.1, 16.0)	**16.5** (14.8, 17.9)
	100%	2000s	**-10.8** (-11.9, -9.8)		**1.5** (1.3, 2.0)		**-9.2** (-10.1, -8.2)	
		2040s	**-16.9** (-17.3, -15.1)	**-15.8** (-16.5, -14.6)	**2.9** (2.4, 3.7)	**2.9** (2.5, 3.6)	**-12.9** (-14.4, -12.2)	**-12.8** (-13.9, -11.5)
		2080s	**-18.8** (-19.7, -16.6)	**-16.4** (-17.5, -14.3)	**4.5** (3.6, 5.5)	**4.6** (3.6, 5.3)	**-13.8** (-15.4, -12.7)	**-11.5** (-14.1, -9.6)
WFWC	10%	2000s	**16.8** (16.2, 17.0)		**0.4** (0.2, 0.9)		**17.1** (16.8, 17.9)	
		2040s	**25.4** (24.8, 26.3)	**25.7** (25.3, 26.8)	**0.5** (0, 1.2)	**0.5** (0, 1.2)	**26.2** (25.0, 26.9)	**26.3** (25.1, 27.4)
		2080s	**32.0** (30.5, 33.0)	**33.3** (32.4, 34.3)	**0.4** (-0.4, 1.5)	**0.6** (-0.4, 1.3)	**32.6** (31.1, 34.1)	**33.8** (32.5, 34.7)
	50%	2000s	**5.6** (5.1, 6.2)		**0.7** (0.5, 1.1)		**6.4** (5.9, 6.9)	
		2040s	**8.9** (8.1, 9.8)	**9.4** (8.9, 10.6)	**1.2** (0.7, 1.9)	**1.3** (0.7, 1.8)	**10.1** (9.3, 10.9)	**10.5** (9.8, 11.9)
		2080s	**12.2** (10.8, 13.6)	**14.2** (12.7, 15.4)	**1.6** (0.7, 2.5)	**1.9** (0.7, 2.4)	**14.0** (12.2, 15.3)	**16.0** (13.8, 17.0)
	100%	2000s	**-10.2** (-11.3, -8.9)		**1.2** (0.9, 1.5)		**-9.1** (-9.8, -8.0)	
		2040s	**-15.2** (-16.5, -13.9)	**-14.3** (-15.7, -13.0)	**2.3** (1.8, 2.9)	**2.4** (1.7, 2.8)	**-13.1** (-14.2, -11.6)	**-11.9** (-13.5, -10.8)
		2080s	**-17.2** (-18.9, -15.3)	**-14.4** (-16.5, -13.2)	**3.7** (2.7, 4.4)	**3.9** (2.5, 4.2)	**-13.8** (-15.4, -11.8)	**-11.0** (-14.3, -9.5)
WFWO	10%	2000s	**16.2** (15.7, 16.3)		**0.2** (0, 0.8)		**16.3** (16.0, 16.9)	
		2040s	**24.6** (24.2, 25.7)	**25.0** (24.4, 25.9)	**0.1** (-0.3, 1.0)	**0.1** (-0.4, 0.9)	**25.0** (24.3, 26.1)	**25.1** (24.2, 26.1)
		2080s	**31.4** (30.2, 32.3)	**32.5** (31.6, 33.5)	**0** (-0.9, 1.0)	**0** (-0.9, 0.7)	**31.0** (30.0, 33.0)	**32.6** (31.2, 34.1)
	50%	2000s	**4.9** (4.5, 5.5)		**0.5** (0.3, 1.0)		**5.6** (5.1, 6.1)	
		2040s	**8.1** (7.5, 9.0)	**8.4** (7.8, 9.9)	**0.8** (0.4, 1.6)	**0.8** (0.3, 1.5)	**8.8** (8.6, 9.9)	**9.4** (8.4, 10.7)
		2080s	**11.4** (10.2, 12.8)	**13.4** (11.9, 14.7)	**1.2** (0.3, 2.1)	**1.3** (0.3, 1.9)	**12.8** (11.6, 13.9)	**14.8** (12.5, 16.2)

	100%	2000s	**-10.2** (-10.7, -9.2)		**0.9** (0.7, 1.4)		**-9.1** (-9.7, -8.4)	
		2040s	**-14.5** (-15.6, -13.7)	**-14.5** (-15.1, -12.9)	**1.8** (1.4, 2.5)	**1.9** (1.3, 2.4)	**-12.7** (-13.6, -11.9)	**-12.3** (-13.6, -10.8)
		2080s	**-16.3** (-17.8, -14.4)	**-13.5** (-15.8, -12.5)	**3.0** (2.2, 3.7)	**3.0** (1.9, 3.6)	**-13.4** (-15.0, -11.7)	**-10.8** (-13.7, -9.2)
WWB	10%	2000s	**15.3** (15.1, 15.8)		**0.8** (0.5, 1.3)		**16.1** (15.7, 17.1)	
		2040s	**24.1** (23.4, 25.1)	**24.5** (23.6, 25.3)	**1.2** (0.5, 2.0)	**1.2** (0.5, 2.0)	**25.3** (24.6, 26.6)	**25.9** (24.4, 26.7)
		2080s	**30.9** (29.5, 32.2)	**32.4** (31.2, 33.5)	**1.5** (0.4, 2.6)	**1.5** (0.4, 2.5)	**32.5** (30.9, 33.8)	**33.8** (32.5, 35.1)
	50%	2000s	**3.2** (2.8, 3.7)		**1.0** (0.7, 1.5)		**4.0** (3.7, 5.1)	
		2040s	**5.8** (5.1, 7.0)	**6.3** (5.4, 7.4)	**1.8** (1.1, 2.6)	**1.8** (1.1, 2.5)	**7.7** (7.1, 8.9)	**8.1** (7.0, 9.5)
		2080s	**9.4** (8.2, 10.9)	**11.5** (10.2, 12.9)	**2.5** (1.4, 3.6)	**2.6** (1.4, 3.5)	**12.3** (10.5, 13.2)	**14.3** (12.4, 15.3)
	100%	2000s	**-12.3** (-12.8, -11.8)		**1.3** (0.9, 1.7)		**-11.2** (-11.4, -10.0)	
		2040s	**-17.9** (-18.6, -16.5)	**-17.1** (-18.4, -16.0)	**2.6** (1.9, 3.3)	**2.6** (1.9, 3.3)	**-15.3** (-15.7, -14.2)	**-14.6** (-15.9, -13.2)
		2080s	**-19.5** (-20.6, -17.4)	**-17.0** (-18.3, -14.6)	**4.2** (2.9, 4.9)	**4.2** (3.0, 5.1)	**-15.0** (-16.9, -13.2)	**-12.3** (-14.6, -10.9)
WWC	10%	2000s	**14.8** (14.5, 15.2)		**0.8** (0.4, 1.2)		**15.6** (15.1, 16.4)	
		2040s	**23.2** (22.1, 24.2)	**23.6** (22.6, 24.5)	**1.2** (0.5, 1.9)	**1.2** (0.4, 1.9)	**24.3** (22.9, 25.2)	**24.6** (23.5, 26.0)
		2080s	**29.7** (28.0, 30.6)	**31.4** (29.7, 31.9)	**1.3** (0.3, 2.5)	**1.5** (0.4, 2.5)	**31.3** (29.2, 32.3)	**32.3** (31.1, 33.6)
	50%	2000s	**2.4** (1.9, 3.1)		**1.0** (0.6, 1.4)		**3.3** (2.9, 4.3)	
		2040s	**4.5** (3.7, 6.0)	**5.4** (4.4, 6.6)	**1.8** (1.0, 2.4)	**1.7** (1.0, 2.5)	**6.4** (5.3, 7.4)	**6.7** (5.9, 8.4)
		2080s	**8.3** (6.4, 9.0)	**10.6** (8.4, 11.2)	**2.3** (1.3, 3.4)	**2.6** (1.4, 3.4)	**10.6** (8.6, 11.5)	**12.3** (10.8, 13.6)
	100%	2000s	**-13.7** (-14.3, -13.1)		**1.4** (1.0, 1.8)		**-12.7** (-13.0, -11.5)	
		2040s	**-20.2** (-21.1, -18.7)	**-19.4** (-20.6, -17.7)	**2.8** (2.0, 3.4)	**2.7** (2.0, 3.4)	**-17.4** (-18.3, -16.8)	**-17.3** (-17.8, -15.1)
		2080s	**-21.8** (-23.7, -20.3)	**-19.4** (-21.2, -18.0)	**4.1** (3.1, 5.2)	**4.3** (3.2, 5.2)	**-17.8** (-19.3, -16.1)	**-15.2** (-17.2, -13.8)
WWO	10%	2000s	**14.5** (14.1, 15.0)		**0.6** (0.3, 1.0)		**14.9** (14.6, 16.2)	
		2040s	**22.7** (21.8, 23.8)	**23.2** (22.3, 24.0)	**0.8** (0.2, 1.6)	**0.8** (0.1, 1.6)	**23.5** (22.9, 24.8)	**23.8** (22.9, 25.1)
		2080s	**29.1** (27.8, 30.3)	**30.6** (29.4, 31.6)	**0.9** (-0.1, 2.0)	**0.9** (-0.1, 2.0)	**30.3** (28.9, 31.2)	**31.5** (30.3, 32.9)
	50%	2000s	**2.0** (1.5, 2.4)		**0.8** (0.5, 1.3)		**2.7** (2.2, 3.8)	
		2040s	**3.5** (2.9, 5.2)	**4.3** (3.3, 5.3)	**1.4** (0.8, 2.1)	**1.3** (0.7, 2.1)	**5.6** (4.4, 6.4)	**5.6** (4.4, 7.2)
		2080s	**6.4** (5.2, 7.9)	**8.4** (7.0, 10.1)	**1.9** (0.9, 2.9)	**2.0** (0.8, 2.8)	**8.7** (7.3, 9.4)	**10.4** (8.8, 11.9)
	100%	2000s	**-14.0** (-14.4, -13.4)		**1.1** (0.7, 1.5)		**-12.9** (-13.6, -12.1)	
		2040s	**-21.0** (-21.8, -18.9)	**-20.3** (-21.6, -18.9)	**2.1** (1.4, 2.8)	**2.0** (1.4, 2.7)	**-18.5** (-19.9, -17.5)	**-18.2** (-19.6, -16.6)
		2080s	**-23.5** (-25.2, -21.9)	**-21.7** (-23.3, -19.2)	**3.4** (2.3, 4.1)	**3.4** (2.2, 4.1)	**-20.5** (-21.7, -18.3)	**-18.2** (-20.1, -16.3)

Table S3-6. Median annual GHG, gross margins (GM) and GM-scaled GHG (GHG/GM) during 2000s (1985-2020), 2040s (2021-2056) and 2080s (2057-2092) under SSP245 and SSP585 scenarios estimated by 27 GCM models. The 25th and 75th percentiles are presented in brackets.

Residue retention	Rotation	Period	GHG (kg CO_2-eq ha^{-1} yr^{-1})		GM (AU$ ha^{-1} yr^{-1})		GHG/GM (kg CO_2-eq $AU\$^{-1}$)	
			SSP245	SSP585	SSP245	SSP585	SSP245	SSP585
10%	WC	2000s	**450** (438, 462)		**537** (537, 537)		**0.84** (0.81, 0.86)	
		2040s	**379** (364, 392)	**384** (371, 396)	**545** (504, 561)	**552** (526, 568)	**0.72** (0.68, 0.75)	**0.72** (0.65, 0.75)
		2080s	**334** (317, 346)	**343** (337, 354)	**532** (501, 559)	**563** (528, 604)	**0.64** (0.60, 0.66)	**0.63** (0.59, 0.65)
	WFWC	2000s	**446** (437, 464)		**414** (414, 414)		**1.08** (1.06, 1.12)	
		2040s	**374** (359, 383)	**376** (360, 390)	**424** (386, 442)	**417** (405, 457)	**0.90** (0.83, 0.96)	**0.89** (0.83, 0.99)
		2080s	**325** (311, 338)	**335** (323, 343)	**428** (399, 450)	**467** (426, 494)	**0.76** (0.72, 0.81)	**0.73** (0.67, 0.79)
	WFWO	2000s	**427** (420, 441)		**225** (225, 225)		**1.90** (1.86, 1.96)	
		2040s	**360** (350, 373)	**360** (349, 373)	**222** (206, 244)	**238** (215, 244)	**1.69** (1.50, 1.77)	**1.55** (1.47, 1.70)
		2080s	**310** (302, 328)	**325** (312, 338)	**221** (212, 248)	**260** (231, 278)	**1.43** (1.27, 1.54)	**1.28** (1.15, 1.39)
	WWB	2000s	**421** (413, 447)		**301** (301, 301)		**1.40** (1.37, 1.48)	
		2040s	**363** (354, 380)	**371** (351, 380)	**294** (273, 310)	**307** (289, 314)	**1.28** (1.17, 1.33)	**1.21** (1.14, 1.33)
		2080s	**324** (310, 335)	**335** (324, 346)	**289** (267, 310)	**307** (283, 324)	**1.13** (1.07, 1.19)	**1.09** (1.05, 1.18)
	WWC	2000s	**409** (397, 430)		**484** (484, 484)		**0.85** (0.82, 0.89)	
		2040s	**350** (332, 362)	**354** (339, 372)	**482** (456, 503)	**485** (455, 507)	**0.75** (0.71, 0.78)	**0.73** (0.69, 0.79)
		2080s	**313** (295, 321)	**322** (311, 333)	**483** (453, 503)	**499** (460, 538)	**0.65** (0.61, 0.69)	**0.65** (0.59, 0.72)
	WWO	2000s	**394** (386, 424)		**256** (256, 256)		**1.54** (1.51, 1.65)	
		2040s	**340** (332, 356)	**343** (332, 360)	**253** (227, 267)	**258** (240, 266)	**1.41** (1.25, 1.48)	**1.34** (1.26, 1.48)
		2080s	**304** (292, 312)	**315** (304, 327)	**246** (226, 255)	**265** (239, 275)	**1.24** (1.21, 1.35)	**1.22** (1.12, 1.31)
50%	WC	2000s	**188** (170, 196)		**572** (572, 572)		**0.33** (0.30, 0.34)	
		2040s	**170** (160, 180)	**176** (161, 191)	**598** (545, 611)	**604** (568, 621)	**0.29** (0.27, 0.33)	**0.31** (0.26, 0.34)
		2080s	**167** (153, 179)	**183** (168, 195)	**588** (550, 625)	**632** (586, 673)	**0.28** (0.25, 0.30)	**0.30** (0.27, 0.33)
	WFWC	2000s	**191** (179, 204)		**443** (443, 443)		**0.43** (0.40, 0.46)	
		2040s	**168** (157, 178)	**173** (164, 191)	**460** (418, 486)	**456** (440, 499)	**0.37** (0.34, 0.42)	**0.38** (0.34, 0.45)
		2080s	**162** (146, 172)	**178** (159, 188)	**471** (442, 495)	**516** (468, 550)	**0.34** (0.31, 0.37)	**0.35** (0.31, 0.40)
	WFWO	2000s	**172** (160, 184)		**240** (240, 240)		**0.72** (0.67, 0.77)	
		2040s	**152** (148, 165)	**159** (146, 176)	**244** (223, 270)	**256** (238, 270)	**0.66** (0.57, 0.75)	**0.63** (0.57, 0.73)

		2080s	**151** (140, 161)	**168** (148, 180)	**250** (234, 270)	**292** (254, 307)	**0.61** (0.55, 0.66)	**0.60** (0.53, 0.65)
	WWB	2000s	**135** (127, 161)		**319** (319, 319)		**0.42** (0.40, 0.50)	
		2040s	**137** (130, 152)	**143** (129, 160)	**323** (294, 341)	**332** (316, 344)	**0.44** (0.39, 0.51)	**0.43** (0.39, 0.51)
		2080s	**146** (131, 154)	**164** (147, 173)	**322** (298, 345)	**342** (315, 365)	**0.45** (0.42, 0.48)	**0.48** (0.45, 0.52)
	WWC	2000s	**117** (107, 140)		**514** (514, 514)		**0.23** (0.21, 0.27)	
		2040s	**121** (106, 133)	**125** (114, 146)	**528** (490, 550)	**525** (494, 553)	**0.24** (0.21, 0.27)	**0.24** (0.21, 0.30)
		2080s	**131** (114, 139)	**147** (133, 158)	**525** (496, 561)	**559** (508, 599)	**0.24** (0.22, 0.27)	**0.27** (0.23, 0.30)
	WWO	2000s	**103** (90, 128)		**278** (278, 278)		**0.37** (0.32, 0.46)	
		2040s	**110** (95, 120)	**110** (95, 131)	**288** (253, 305)	**287** (272, 300)	**0.38** (0.33, 0.46)	**0.37** (0.32, 0.47)
		2080s	**115** (102, 121)	**130** (116, 143)	**280** (263, 298)	**305** (279, 321)	**0.41** (0.37, 0.43)	**0.43** (0.38, 0.48)
100%	WC	2000s	**-180** (-202, -157)		**615** (615, 615)		**-0.29** (-0.33, -0.25)	
		2040s	**-127** (-146, -118)	**-126** (-139, -109)	**656** (594, 681)	**664** (619, 689)	**-0.20** (-0.23, -0.18)	**-0.19** (-0.21, -0.17)
		2080s	**-82** (-97, -73)	**-62** (-85, -46)	**656** (613, 704)	**719** (650, 754)	**-0.12** (-0.14, -0.11)	**-0.09** (-0.11, -0.06)
	WFWC	2000s	**-177** (-196, -152)		**482** (482, 482)		**-0.37** (-0.41, -0.32)	
		2040s	**-129** (-143, -110)	**-114** (-134, -99)	**510** (461, 534)	**497** (486, 550)	**-0.25** (-0.29, -0.24)	**-0.23** (-0.25, -0.20)
		2080s	**-82** (-97, -65)	**-58** (-87, -45)	**522** (495, 558)	**577** (521, 618)	**-0.15** (-0.18, -0.12)	**-0.10** (-0.14, -0.08)
	WFWO	2000s	**-177** (-192, -163)		**266** (266, 266)		**-0.67** (-0.72, -0.61)	
		2040s	**-125** (-136, -115)	**-119** (-135, -100)	**284** (252, 308)	**291** (273, 306)	**-0.46** (-0.48, -0.42)	**-0.39** (-0.46, -0.34)
		2080s	**-79** (-93, -64)	**-57** (-82, -42)	**294** (274, 321)	**349** (300, 362)	**-0.27** (-0.32, -0.21)	**-0.18** (-0.24, -0.13)
	WWB	2000s	**-228** (-234, -201)		**338** (338, 338)		**-0.67** (-0.69, -0.59)	
		2040s	**-154** (-163, -144)	**-149** (-166, -131)	**355** (322, 372)	**361** (350, 380)	**-0.43** (-0.50, -0.40)	**-0.41** (-0.47, -0.36)
		2080s	**-95** (-109, -78)	**-69** (-90, -57)	**361** (332, 385)	**386** (359, 414)	**-0.24** (-0.30, -0.22)	**-0.18** (-0.23, -0.16)
	WWC	2000s	**-263** (-272, -236)		**547** (547, 547)		**-0.48** (-0.50, -0.43)	
		2040s	**-185** (-197, -177)	**-183** (-190, -155)	**579** (527, 601)	**571** (537, 606)	**-0.32** (-0.35, -0.30)	**-0.31** (-0.34, -0.28)
		2080s	**-118** (-130, -103)	**-95** (-112, -82)	**574** (546, 626)	**628** (563, 674)	**-0.20** (-0.23, -0.18)	**-0.15** (-0.18, -0.13)
	WWO	2000s	**-269** (-284, -250)		**304** (304, 304)		**-0.89** (-0.93, -0.82)	
		2040s	**-199** (-217, -185)	**-195** (-213, -174)	**330** (289, 346)	**327** (311, 342)	**-0.59** (-0.71, -0.57)	**-0.58** (-0.66, -0.50)
		2080s	**-141** (-152, -122)	**-122** (-138, -104)	**323** (309, 352)	**365** (331, 379)	**-0.42** (-0.47, -0.37)	**-0.34** (-0.40, -0.30)

Table S3-7. Recent publications simulating the N_2O emissions under different N fertilizer, irrigation and residue management based on different models.

Reference	Model	Region	N_2O emission (kg N ha^{-1} yr^{-1})	Simulation period	Future climate	N amount (kg ha^{-1})	Residue	Crops
Carozzi et al. (2022)	CERES-EGC	Europe	1.44-1.93	1978-2099	RCP4.5 RCP8.5	~100 (with irrigation)	Around half return	wheat, barley, sunflower, rye, oats, pulses, rapeseed, maize, potato, sugar beet
Haas et al. (2022)	CERES-EGC, LandscapeDNDC, LandscapeDNDC-MeTrx	Europe	1.14-1.36	2000-2100	RCP4.5 RCP8.5	~92 (with irrigation)	All return (buried/ surface)	wheat, barley, rye, oats, maize, soya, rapeseed, potato, pulses, sunflower, sugar beet
Myrgiotis et al. (2019)	LandscapeDNDC	Eastern Scotland	~0.66 (barley) ~0.49 (wheat) ~4.80 (oilseed)	2011-2013	/	80-220	Return	wheat, barley, oilseed rape
Chen et al. (2019)	DNDC	Yangling, China	1.03-1.72/ 1.19-2.41	1981-2100	RCP4.5 RCP8.5	375 (with irrigation)	No straw/ straw mulching	winter-wheat and summer-maize rotation
Tesfaye et al. (2021)	CCAFS-MOT, IPCC Tier-I, IPCC Tier-II, Tropical-N_2O	Australian wheat fields	~0.45	2013	/	~27	/	wheat
Tian et al. (2019)	DLEM, LPJ-GUESS, LPX-Bern, O-CN, ORCHIDEE, ORCHIDEE-CNP, VISIT	Global cropland	~2.1 (~0.46 for Oceania land surface)	2007-2016	/	/	/	/
Li et al. (2017)	WNMM	NSW, Australia	0.15-0.66	2015-2098	RCP2.6 RCP4.5 RCP6.0 RCP8.5	40-80	/	Rotation: canola -wheat-barley, chickpea-wheat-barley, chickpea -sorghum, chickpea-wheat-chickpea
Mielenz et al. (2016b)	APSIM	SE QLD, Australia	0.2-6.1	1981-2010	/	0-200 (rainfed/ irrigated)	/	wheat, cotton, maize, sorghum

Table S3-8. Median annual crop grain yields (t ha^{-1} $year^{-1}$) of six cropping systems during 2000s (1985-2020), 2040s (2021-2056) and 2080s (2057-2092) under SSP245 and SSP585 scenarios estimated by 27 GCM models. The 25th and 75th percentiles are presented in brackets.

Treatment		2000s	SSP245		SSP585	
			2040s	2080s	2040s	2080s
WC						
Wheat	10%	**1.99**	**1.87** (1.78, 1.95)	**1.81** (1.73, 1.91)	**1.90** (1.77, 1.96)	**1.88** (1.76, 1.96)
	50%	**2.14**	**2.11** (2.00, 2.27)	**2.18** (2.07, 2.34)	**2.17** (1.95, 2.28)	**2.36** (2.12, 2.44)
	100%	**2.35**	**2.41** (2.24, 2.66)	**2.70** (2.45, 2.86)	**2.47** (2.26, 2.73)	**2.84** (2.64, 3.07)
Canola	10%	**2.09**	**2.12** (2.02, 2.20)	**2.15** (2.01, 2.21)	**2.16** (2.08, 2.23)	**2.23** (2.09, 2.32)
	50%	**2.17**	**2.21** (2.10, 2.30)	**2.21** (2.10, 2.30)	**2.27** (2.18, 2.34)	**2.36** (2.17, 2.44)
	100%	**2.26**	**2.29** (2.17, 2.43)	**2.28** (2.17, 2.40)	**2.35** (2.26, 2.46)	**2.43** (2.25, 2.50)
WFWC						
Wheat	10%	**2.20**	**2.13** (2.01, 2.22)	**2.09** (1.99, 2.20)	**2.12** (1.99, 2.25)	**2.20** (2.04, 2.29)
	50%	**2.49**	**2.45** (2.34, 2.67)	**2.54** (2.46, 2.73)	**2.48** (2.35, 2.62)	**2.67** (2.46, 2.84)
	100%	**2.84**	**2.91** (2.64, 3.17)	**3.13** (2.89, 3.25)	**2.91** (2.71, 3.07)	**3.31** (3.01, 3.55)
Canola	10%	**2.10**	**2.09** (1.95, 2.22)	**2.13** (2.01, 2.19)	**2.14** (1.96, 2.28)	**2.21** (2.05, 2.36)
	50%	**2.13**	**2.12** (1.98, 2.27)	**2.18** (2.04, 2.22)	**2.17** (1.97, 2.35)	**2.27** (2.07, 2.42)
	100%	**2.18**	**2.14** (2.03, 2.36)	**2.22** (2.10, 2.35)	**2.26** (1.99, 2.44)	**2.34** (2.13, 2.48)
Field pea	10%	**2.38**	**2.52** (2.33, 2.73)	**2.58** (2.42, 2.74)	**2.69** (2.42, 2.85)	**2.91** (2.71, 3.25)
	50%	**2.33**	**2.48** (2.29, 2.67)	**2.47** (2.34, 2.67)	**2.60** (2.36, 2.78)	**2.87** (2.60, 3.14)
	100%	**2.27**	**2.41** (2.21, 2.59)	**2.38** (2.25, 2.60)	**2.51** (2.28, 2.71)	**2.82** (2.51, 3.04)
WFWO						
Wheat	10%	**2.37**	**2.25** (2.14, 2.36)	**2.27** (2.15, 2.40)	**2.26** (2.14, 2.42)	**2.38** (2.20, 2.50)
	50%	**2.43**	**2.38** (2.24, 2.50)	**2.42** (2.32, 2.57)	**2.37** (2.21, 2.54)	**2.54** (2.32, 2.70)
	100%	**2.61**	**2.64** (2.40, 2.82)	**2.79** (2.53, 2.98)	**2.63** (2.43, 2.81)	**2.93** (2.68, 3.20)
Field pea	10%	**1.68**	**1.57** (1.49, 1.69)	**1.54** (1.45, 1.63)	**1.58** (1.53, 1.73)	**1.60** (1.48, 1.66)
	50%	**1.81**	**1.75** (1.67, 1.88)	**1.70** (1.63, 1.83)	**1.72** (1.70, 1.96)	**1.83** (1.63, 1.91)
	100%	**1.96**	**1.92** (1.84, 2.13)	**1.89** (1.79, 2.12)	**1.97** (1.87, 2.25)	**2.07** (1.83, 2.26)
Oats	10%	**2.23**	**2.40** (2.18, 2.59)	**2.41** (2.26, 2.57)	**2.53** (2.27, 2.67)	**2.78** (2.55, 3.08)
	50%	**2.28**	**2.43** (2.25, 2.63)	**2.46** (2.30, 2.63)	**2.54** (2.30, 2.74)	**2.81** (2.57, 3.14)
	100%	**2.30**	**2.46** (2.25, 2.62)	**2.47** (2.29, 2.65)	**2.53** (2.31, 2.75)	**2.81** (2.57, 3.12)
WWB						
Wheat	10%	**2.71**	**2.68** (2.48, 2.81)	**2.66** (2.50, 2.78)	**2.77** (2.66, 2.82)	**2.79** (2.62, 2.91)
	50%	**2.82**	**2.84** (2.60, 2.99)	**2.84** (2.62, 2.98)	**2.90** (2.81, 2.98)	**2.99** (2.77, 3.15)
	100%	**2.94**	**3.03** (2.75, 3.18)	**3.07** (2.84, 3.21)	**3.11** (2.98, 3.20)	**3.25** (3.02, 3.45)
Barley	10%	**2.46**	**2.41** (2.36, 2.51)	**2.30** (2.22, 2.42)	**2.46** (2.28, 2.64)	**2.34** (2.18, 2.49)
	50%	**2.49**	**2.53** (2.43, 2.62)	**2.46** (2.39, 2.56)	**2.60** (2.35, 2.79)	**2.58** (2.35, 2.66)
	100%	**2.50**	**2.60** (2.46, 2.74)	**2.59** (2.47, 2.68)	**2.67** (2.39, 2.87)	**2.70** (2.49, 2.85)
WWC						
Wheat	10%	**2.54**	**2.53** (2.34, 2.64)	**2.46** (2.39, 2.57)	**2.58** (2.47, 2.65)	**2.61** (2.47, 2.76)
	50%	**2.73**	**2.76** (2.56, 2.90)	**2.81** (2.63, 2.90)	**2.82** (2.73, 2.92)	**2.93** (2.72, 3.10)
	100%	**2.89**	**2.98** (2.74, 3.14)	**3.07** (2.83, 3.18)	**3.08** (2.92, 3.19)	**3.29** (2.99, 3.44)
Canola	10%	**2.00**	**2.03** (1.93, 2.10)	**1.99** (1.91, 2.09)	**1.99** (1.88, 2.13)	**2.08** (1.91, 2.24)
	50%	**2.02**	**2.07** (1.97, 2.16)	**2.04** (1.94, 2.15)	**2.04** (1.88, 2.19)	**2.14** (1.94, 2.32)
	100%	**2.07**	**2.14** (2.05, 2.24)	**2.13** (2.02, 2.27)	**2.11** (1.93, 2.31)	**2.27** (2.00, 2.49)
WWO						
Wheat	10%	**2.64**	**2.62** (2.43, 2.75)	**2.60** (2.44, 2.72)	**2.66** (2.57, 2.77)	**2.75** (2.56, 2.85)
	50%	**2.74**	**2.72** (2.58, 2.94)	**2.78** (2.62, 2.91)	**2.83** (2.73, 2.94)	**2.96** (2.75, 3.07)
	100%	**2.89**	**2.90** (2.76, 3.16)	**3.01** (2.84, 3.17)	**3.04** (2.92, 3.19)	**3.25** (3.01, 3.44)
Oats	10%	**1.77**	**1.73** (1.69, 1.84)	**1.62** (1.60, 1.68)	**1.69** (1.59, 1.81)	**1.64** (1.55, 1.71)
	50%	**1.86**	**1.90** (1.81, 2.02)	**1.82** (1.79, 1.89)	**1.91** (1.73, 1.99)	**1.87** (1.76, 1.96)
	100%	**1.97**	**2.10** (1.95, 2.24)	**2.09** (2.00, 2.18)	**2.14** (1.88, 2.29)	**2.18** (2.04, 2.27)

3.6.3 Supplementary figures

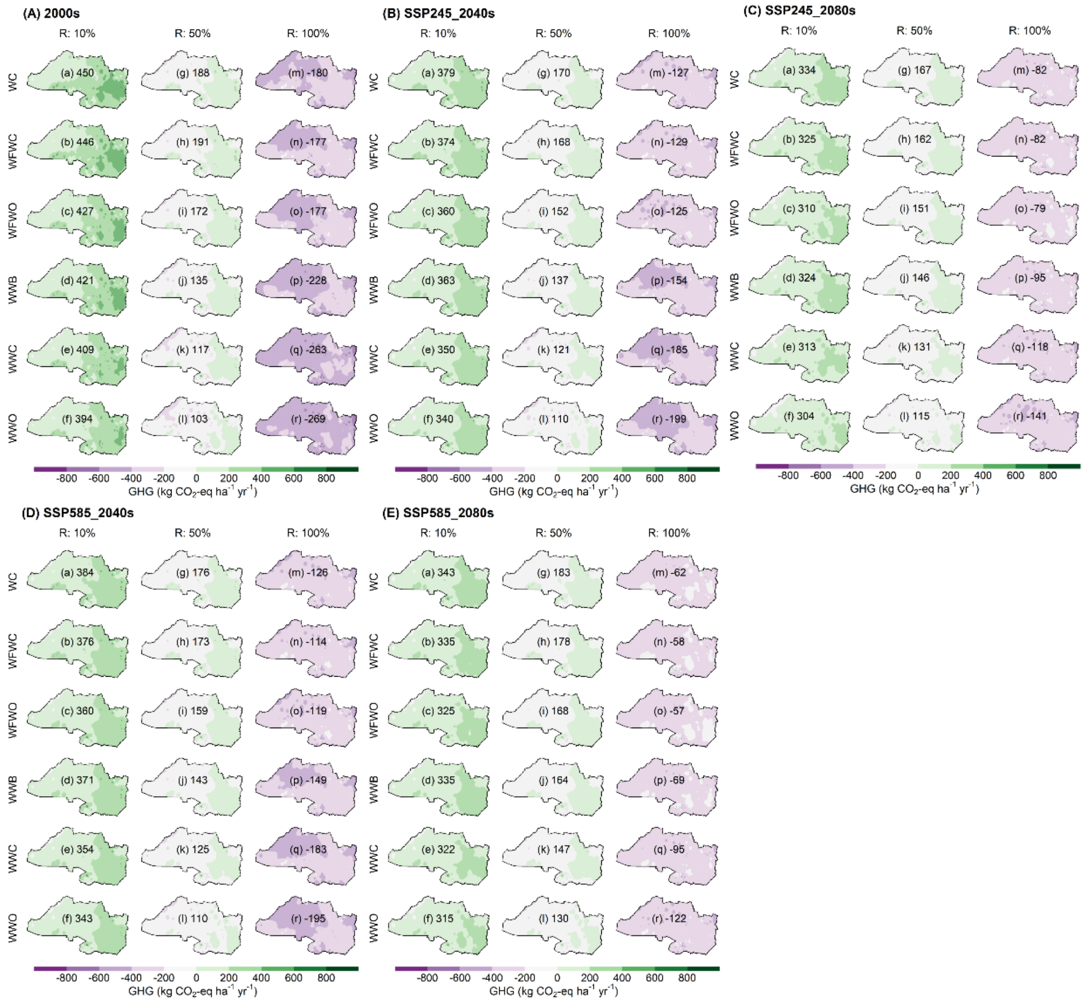


Fig. S3-3. Spatial pattern of the effects of management practices on GHG during 2000s (1985-2020), 2040s (2021-2056) and 2080s (2057-2092) under SSP245 and SSP585 scenarios. The spatial distributions of GHG are interpolated using inverse distance weighting method (IDW) with median values from 27 GCMs. Labels are IDW mean values for the study region.

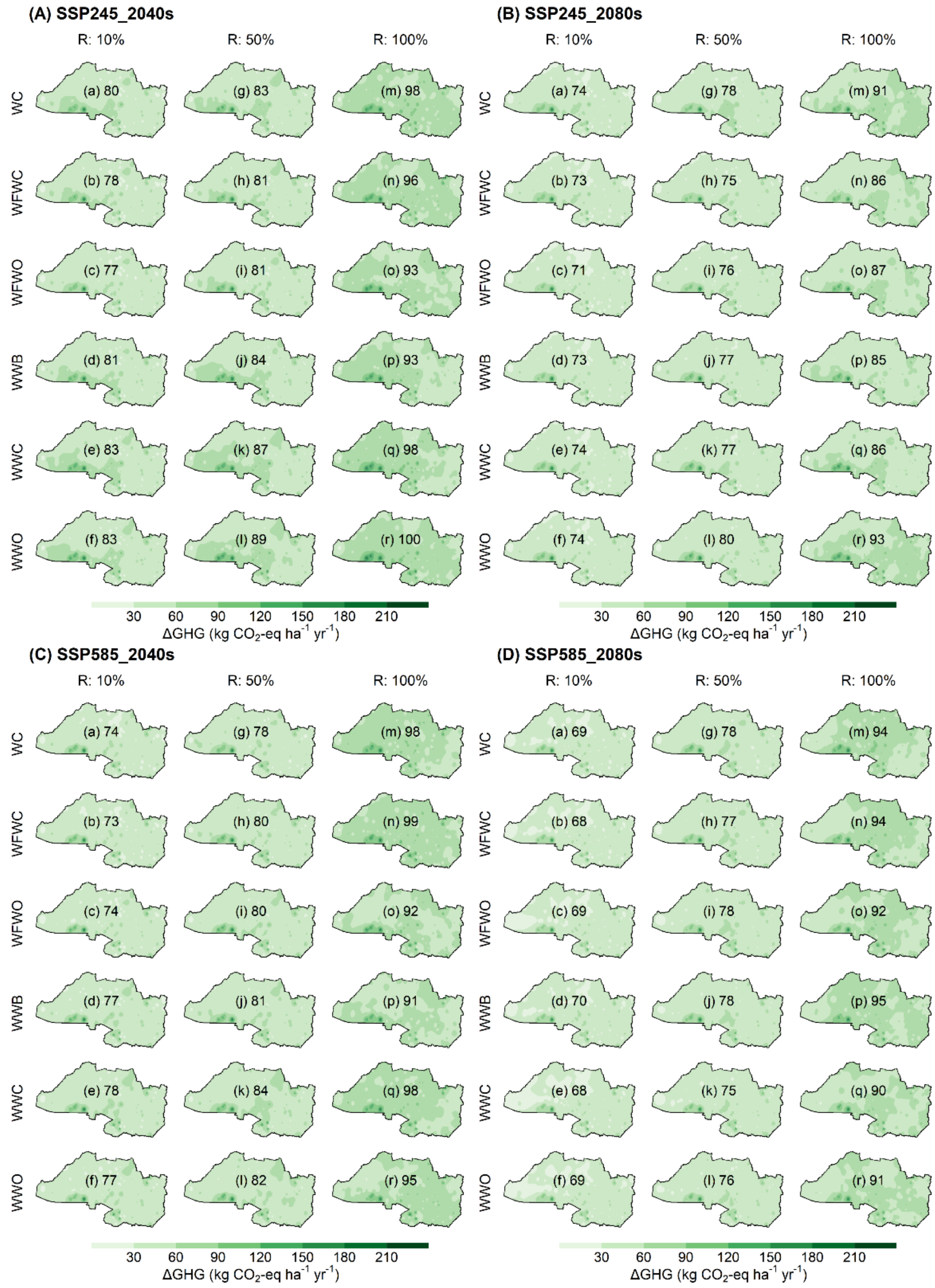


Fig. S3-4. The uncertainty of GHG change during 2040s (2021-2056) and 2080s (2057-2092) under SSP245 (A-B) and SSP585 (C-D) scenarios. The spatial distributions were the differences between the 90th and 10th percentiles of APSIM simulations based on 27 GCMs. Labels are the mean values of inverse distance weighting interpolation.

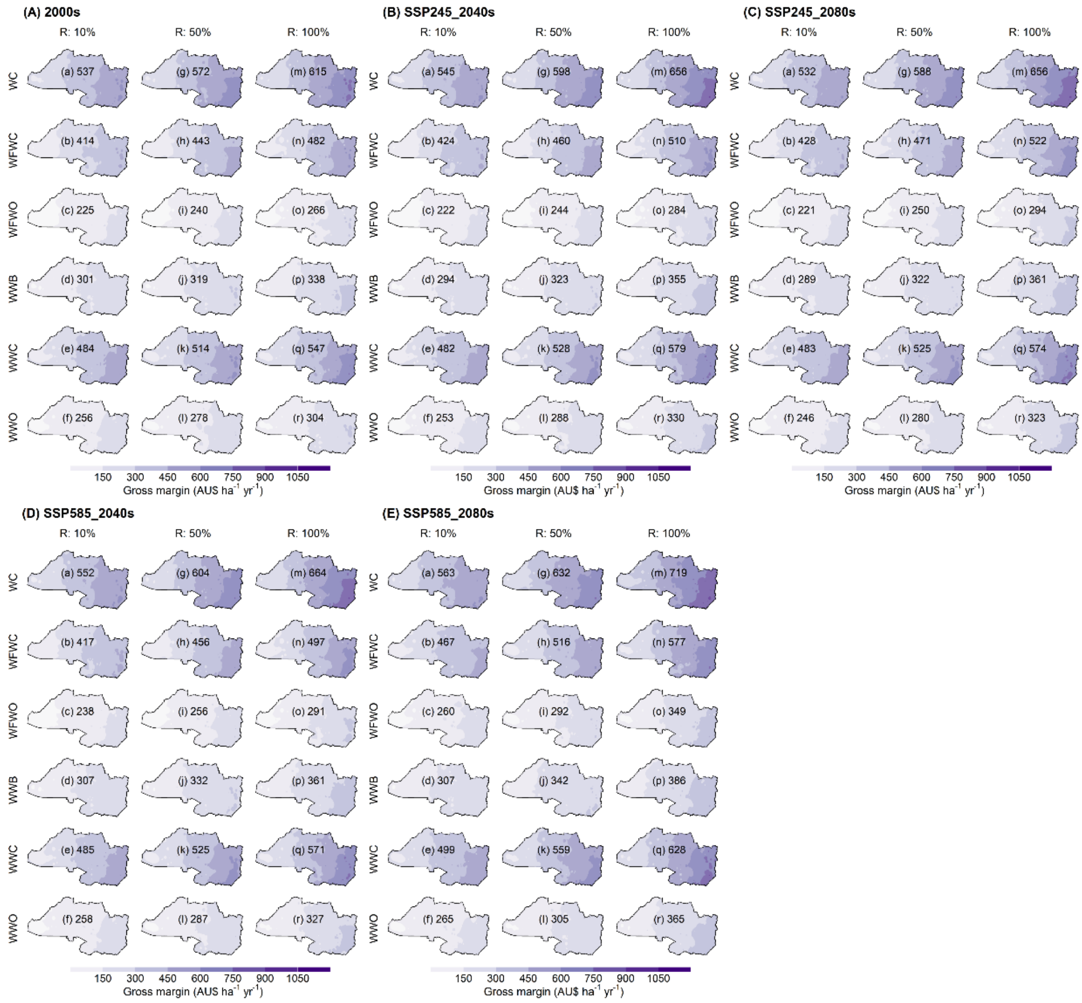


Fig. S3-5. Spatial pattern of the effects of management practices on GM during 2000s (1985-2020), 2040s (2021-2056) and 2080s (2057-2092) under SSP245 and SSP585 scenarios. The spatial distributions of GM are interpolated using inverse distance weighting method (IDW) with median values from 27 GCMs. Labels are IDW mean values for the study region.

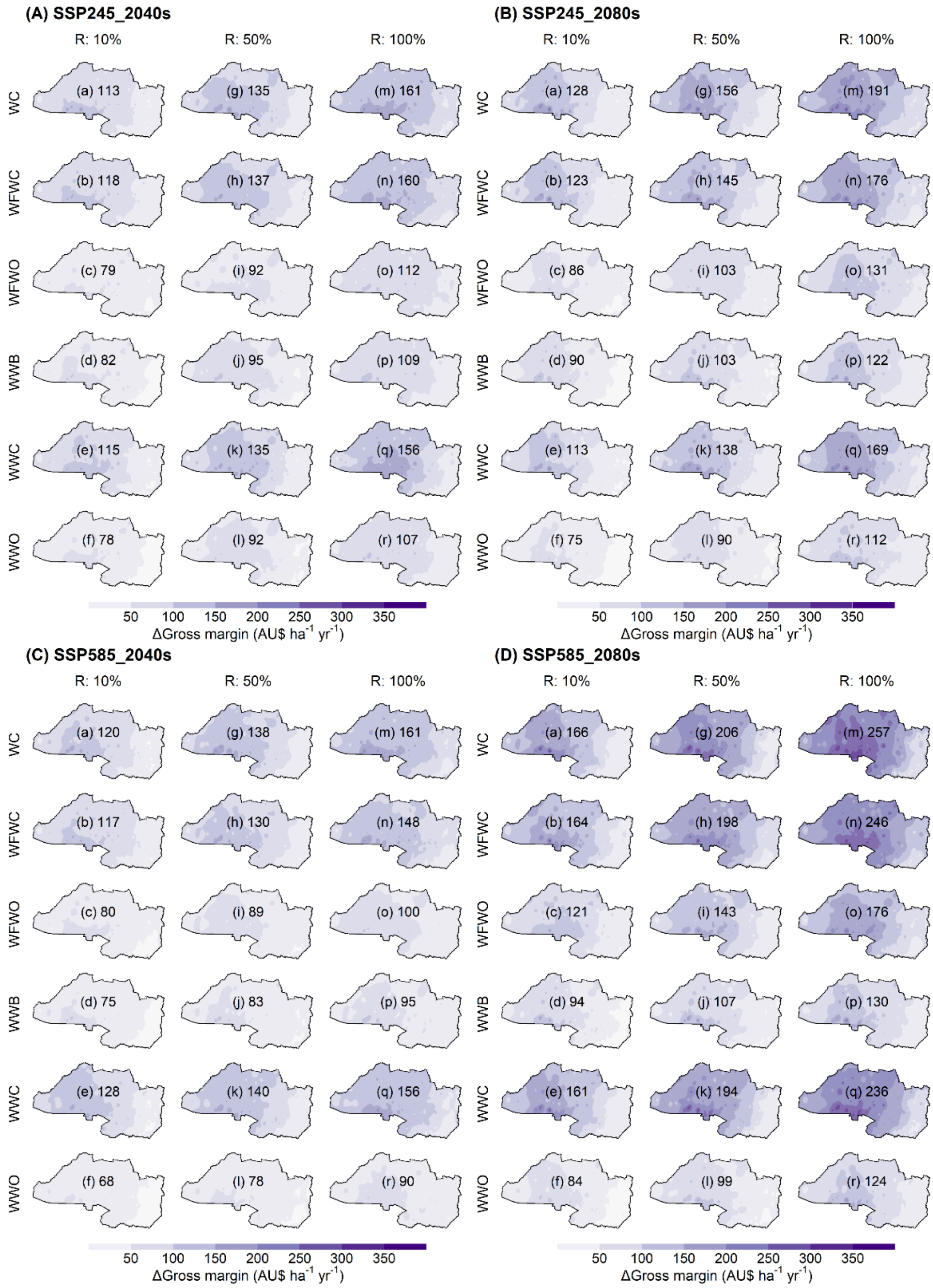


Fig. S3-6. The uncertainty of GM change during 2040s (2021-2056) and 2080s (2057-2092) under SSP245 (A-B) and SSP585 (C-D) scenarios. The spatial distributions were the differences between the 90th and 10th percentiles of APSIM simulations based on 27 GCMs. Labels are the mean values of inverse distance weighting interpolation.

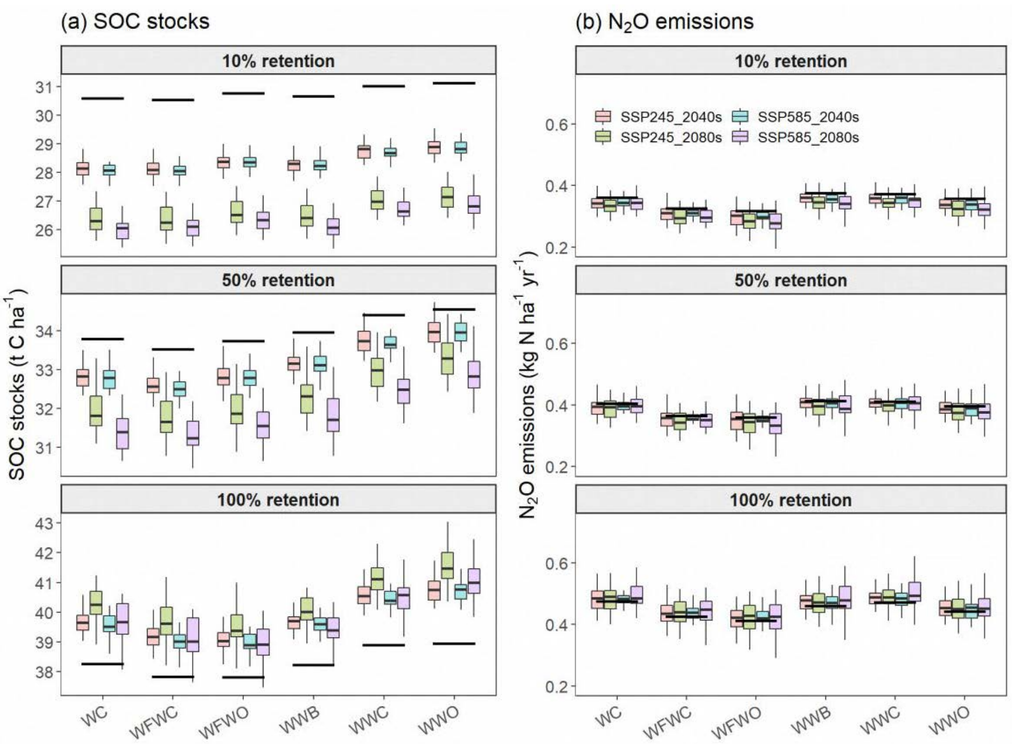


Fig. S3-7. Effects of management practices on SOC stocks (a) and annual N_2O emissions (b) during 2021-2056 (2040s) and 2057-2092 (2080s) under SSP245 and SSP585 scenarios. Horizontal black lines represent the average historical values (1985-2020). Each box summarizes 27 values of the APSIM simulations based on 27 GCMs. Boxplots show the median, and the 25th and 75th percentiles.

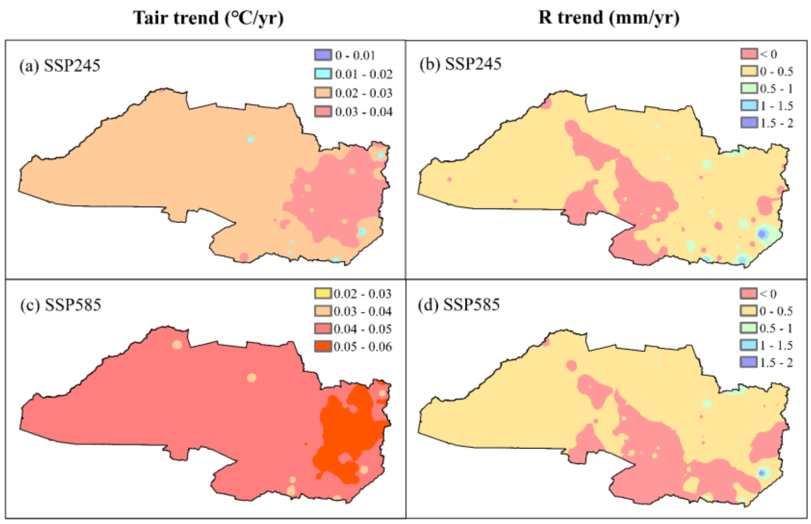


Fig. S3-8. Change trends in annual air temperature (a, c), and rainfall (b, d) in the study area between historical period (1985-2020) and far future (2056-2092) under SSP245 and SSP585 scenarios.

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Chapter 4. Modelling interactions between cowpea cover crops and residue retention in Australian dryland cropping systems under climate change

This chapter is based on the following manuscript:

Qinsi He, De Li Liu, Bin Wang, Annette Cowie, Aaron Simmons, Cathy Waters, Linchao Li, Puyu Feng, Yi Li, Peter de Voil, Alfredo Huete, Qiang Yu. Modelling interactions between cowpea cover crops and residue retention in Australian dryland cropping systems under climate change. Agriculture, Ecosystems & Environment, 353, 108536, 2023.

Highlights

- Cover crops increase SOC, N availability, and cash crop yields except for field pea.
- Benefits to yield increase under climate change but decrease with residue retention.
- Cover crops are profitable in the wetter area but not in the drier part of the study region.
- Long-term use of cover crops may achieve co-benefits for production and environment.

Abstract

Conservation agriculture management practices (e.g., cover crops and residue retention) have been widely promoted to improve soil quality and environmental sustainability. However, little is known about the long-term interactive effects of cover crops and residue retention on yield of the cash crops and environmental outcomes in dryland cropping systems under climate change. We used the pre-validated APSIM model, driven by statistically downscaled daily climate data from 27 Global Climate Models (GCMs) under two Shared Socioeconomic Pathways (SSP245 and SSP585), to assess the combined influences of cowpea cover crops and three residue retention levels on soil water balance, soil organic carbon (SOC), nitrogen (N) dynamics, crop yield and gross margin across six crop rotation systems during the historical period (1985-2020), near future (2021-2056), and far future (2057-2092) in southeast Australia. Our results showed that, on average, cover crops decreased soil moisture on the day of sowing the succeeding cash crop (by 22%), but led to greater SOC stock (21%), reduced N loss through leaching (71%), and enhanced N uptake and yield of cereals, but decreased N uptake and yield of field pea. The effects of cover crops on yield and gross margin became more positive in the far future under both SSPs, which may be attributed to the SOC increase and greater N availability in the long term. These benefits were more evident under residue removal due to the partly compensatory effects from cover crop residues. Furthermore, cover crops were profitable in the wetter parts of the study region (east), but reduced gross margin in the drier west due to depletion of soil water reserves for the next cash crop. We conclude that particularly where residues are removed, the long-term adoption of cowpea cover crops could be a potential practice to sustain crop productivity with environmental co-benefits under climate change in the wetter parts of the dryland cropping region of southeast Australia.

Keywords: Conservation agriculture, Rotation systems, APSIM, Climate change

4.1 Introduction

Meeting projected food demand by a growing population presents an enormous challenge for global agriculture (Godfray et al., 2010). Intensive conventional agriculture (e.g., using high inputs of synthetic fertilizer and pesticide) has been successful in boosting crop yields (Knapp and Heijden, 2018), but has also raised many environmental issues such as water pollution, soil degradation, and nutrient loss (Beyer et al., 2022; Bommarco et al., 2013). A shift to conservation agriculture has been proposed as a feasible solution to enhance food security, provide environmental services and improve the resilience of cropping systems to climate change (Lal, 2015; Nouri et al., 2021).

Conservation agriculture encompasses three principles: minimum soil disturbance (i.e. no tillage), permanent soil cover with crop residues or cover crops, and diversified crop rotations (FAO, 2022). In recent years, conservation agriculture has been rapidly adopted, growing from 106 million ha (7.5% of global cropland) in 2008/09 to 205 million ha (14.7% of global cropland) in 2018/19 (CA GLOBAL, https://www.ca-global.net/ca-stat). However, due to the complex interactions between different management practices, local climate conditions and soil characteristics, the effects of conservation agriculture on crop yields are unclear and strongly debated (Brouder and Gomez-Macpherson, 2014; Pittelkow et al., 2015; Su et al., 2021; Sun et al., 2020).

Growing cover crops is a typical conservation agriculture practice that involves planting a non-cash crop during the fallow period (Griffiths et al., 2022). The adoption rate of cover crops in the U.S. has increased from 3.4% of cropland in 2012 to 5.1% in 2017 (Wallander et al., 2021) and in Canada, from 8.2% of farms in 2010 to 13.7% in 2015 (Statistics Canada, 2015). The growing interest in cover crops around the world is due to its potential to provide multiple agroecosystem services, such as soil quality improvement (Qi et al., 2022; Simon et al., 2022), nutrient recycling (Teixeira et al., 2021; White et al., 2017), and pest control (Bowers et al., 2020; Schipanski et al., 2014), which are key factors for more resilient agroecosystems under climate change. However, planting a cover crop is likely to consume soil water, which could reduce subsequent cash crop yields especially in water-limited environments. A meta-analysis has demonstrated that cover crops reduced cash crop yields by 11% and 12% in temperate dryland and dry climates, but increased cash crop yields by 4% and 15% in continental and tropical climates, respectively (Garba et al., 2022). Olin et al. (2015) found that grass cover crops reduced nitrogen leaching by 15% but also decreased cash crop yields by 5%. Thus, several studies have shown a trade-off between environmental benefits of cover crops and cash crop yields. To encourage the adoption of cover crops, it is necessary to identify conditions in which yield penalties could be avoided.

The impacts of planting cover crops may be synergistic with residue retention, for example, residues from both cash crops and cover crops build soil organic matter and release nitrogen for the succeeding crops (Fontaine et al., 2020; Qi et al., 2022). Legume cover crops, that fix N from the atmosphere, can also be ploughed in as 'green manure' to release additional mineral N (Jensen et al., 2021b). In addition, residues and cover crops can benefit water conservation by increasing infiltration and reducing surface runoff, soil evaporation and drainage (Liu et al., 2017; Wang et al., 2021a). The water retention from crop residue mulching could also offset part of the water consumption of cover crops. Taghizadeh-Toosi et al. (2022) found that straw retention was more important than cover crops for soil C storage, and cover crops played a more important role in suppressing N leaching in a wet temperate climate. Furthermore, Qi et al. (2022) reported that cover crops and residues both increased the soil structural stability, but through aggregation (due to binding agents from roots) and increased soil organic carbon, respectively. These studies focused on the effects of cover crops on soil properties and functions, however, the interactive effects of cover crops and residue management on cash crop yields and farm income are still unclear. In addition, increasing the diversity of crop rotations has been promoted as a conservation agriculture strategy to benefit crop production (Degani et al., 2019; Renwick et al., 2021; Zhao et al., 2022), but few studies have investigated the holistic performance of cover crops and residue retention levels across different rotation systems.

The Australian dryland cropping area expanded by 7.7% from 2010/11 to 2015/16, with the greatest expansion occurring in New South Wales (ABS, 2021). Dryland crop production in Australia is threatened by the highly variable distribution of seasonal rainfall (Anwar et al., 2015; Feng et al., 2018; Wang et al., 2018). Further, increases in rainfall variability and temperature in the future could exacerbate the climate-driven decline in dryland crop yields (Hochman et al., 2017). This challenging production environment has spawned some agricultural research and development funding measures that encouraged farmers to grow crops using conservation agriculture principles (Bellotti and Rochecouste, 2014). Therefore, there is a need to assess the potential of conservation agriculture as an adaptation to future climate change in

Australian dryland cropping systems.

Process-based models such as APSIM (Agricultural Production Systems sIMulator) can explicitly simulate the water-carbon-nutrient balance and crop growth in climate-soil-plant systems, thus complementing field trials and controlled environment studies to assess the effects of different conservation agriculture practices on crop productivity under climate change (Bahri et al., 2019; Basche et al., 2016; Liu et al., 2014; Liu et al., 2017; Teixeira et al., 2021). In this study, based on simulated outputs from APSIM, we aimed to: (1) investigate the interactions between cover crops and residue retention on soil water balance, soil organic carbon and nitrogen dynamics under six common rotation systems; (2) assess the influence of cover crops on cash crop yields and gross margins under climate change; and (3) explore the impacts of climate conditions and residue retention levels on cover crop performance. These results are expected to provide insights into the suitability of cover crops to increase resilience to climate change of dryland cropping in southeast Australia.

4.2 Materials and methods

4.2.1 Study area and soil data

The 204 sites selected for this study were distributed across the Riverina cropping region in southern NSW, in southeast Australia (Fig. 4-1). The annual total rainfall is low in the west (~300 mm) and high in the east (~1000 mm), and the annual mean temperatures range from around 12 to 18 °C. The main soil types are Chromosols, Dermosols, and Vertosols (Isbell and National Committee on Soil and Terrain, 2021). Dryland cereals (e.g., wheat, barley, and oats), oilseeds (e.g., canola) and pulses (e.g., field pea) are the major crops grown (Department of Primary Industries, 2020).

Soil data from APSoil database (Dalgliesh et al., 2012), a component of APSIM that provides input values for soil parameters of each soil layer, were used within the APSIM framework. Soil sites that were identified to be geographically closest to the study sites were selected, and in total 41 soil sites were used. Using the geographically closest APSoil soil profiles as APSIM input is a common practice that has been used in many crop modelling studies in Australia (Houshmandfar et al., 2019; Innes et al., 2015; Western et al., 2018).

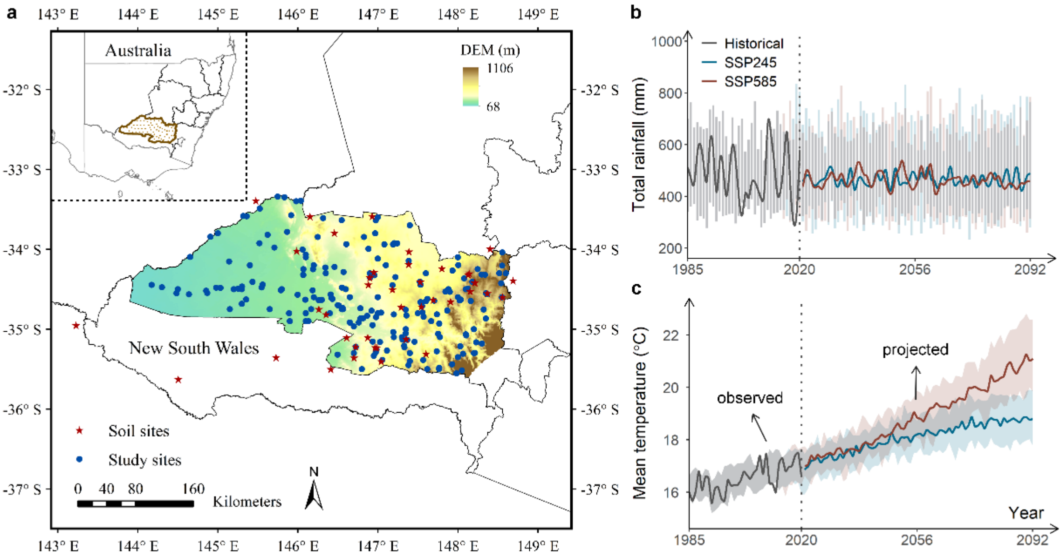

Fig. 4-1. Locations of the 204 study sites and 41 soil sites in the Riverina cropping region in southeast Australia (a), annual rainfall (b) and mean annual temperature (c) under the SSP245 and SSP585 scenarios. The grey line represents the observed historical climate. The red and blue lines represent the median values, and shaded ranges represent the 10th and 90th percentiles based on 27 GCM projections for SSP245 and SSP585, respectively.

4.2.2 Climate change scenarios

Daily minimum and maximum temperature, solar radiation and precipitation at the 204 study sites during the historical period of 1920-2020 were downloaded from the Scientific Information for Land Owners patched point (SILO-PPD) dataset, which is available at https://www.longpaddock.qld.gov.au/silo. The SILO-PPD dataset (Jeffrey et al., 2001) has been extensively used for running point-scale models in Australia (Liu et al., 2020). The representative Shared Socio-economic Pathways (SSPs) with intermediate (SSP2-4.5, hereafter SSP245) and very high (SSP5-8.5, hereafter SSP585) emission trajectories were employed to represent future climate scenarios during 2021-2092. These two scenarios have nominal radiative forcing of 4.5 and 8.5 W m^{-2}, and atmospheric CO_2 concentrations of 603 and 1135 ppm for SSP245 and SSP585 by 2100, respectively (Meinshausen et al., 2020).

In order to cover variations in future climate projections, an ensemble of 27 global climate models (GCMs) was used for downscaled climate projections. Gridded monthly radiation, temperature and precipitation data were extracted from the GCM simulations in the Coupled Model Intercomparison Project Phase 6 (CMIP6, https://pcmdi.llnl.gov/CMIP6). As APSIM requires daily climate data, these GCM-generated monthly gridded data were downscaled to each study site using the method developed by Liu and Zuo (2012). First, inverse distance-weighted interpolation (IDW) was used to spatially downscale the monthly data for each of the 204 sites. Second, a bias correction was applied based on the interpolation relationship between historical observed climate and GCM projected climate data. Finally, a modified WGEN stochastic weather generator (Richardson and Wright, 1984) was used to disaggregate the corrected monthly data into daily values.

In addition, APSIM requires atmospheric CO_2 concentrations to simulate crop growth. The yearly atmospheric [CO_2] was calculated using empirical functions that were obtained by non-linear least-squares regression, based on the concentration pathway given by the Scenario Model Inter-comparison Project for CMIP6 (O'Neill et al., 2016), which can be expressed as (He et al., 2022):

$$
\begin{aligned}
[CO_2]_{SSP245} = 62.044 + \frac{34.002 - 3.8702\mathrm{y}}{0.24423 - 1.1542y^{2.4901}} + 0.028057 \times (\mathrm{y} - 1900)^2 \\
+ 0.00026827 \times (\mathrm{y} - 1960)^3 - 9.2751 \times 10^{-7} \\
\times (\mathrm{y} - 1910)^4 - 2.2448 \times (\mathrm{y} - 2030)
\end{aligned}
\tag{4-1}
$$

$$
\begin{aligned}
[CO_2]_{SSP585} = 757.44 + \frac{84.938 - 1.537\mathrm{y}}{2.2011 - 3.8289y^{-0.45242}} + 2.4712 \times 10^{-4} \times (\mathrm{y} + 15)^2 \\
+ 1.9299 \times 10^{-5} \times (\mathrm{y} - 1937)^3 \\
+5.1137 \times 10^{-7} \times (\mathrm{y} - 1910)^4
\end{aligned}
\tag{4-2}
$$

where y is the calendar year from 1985-2092 (i.e., y = 1985, 1986, …, 2092).

4.2.3 APSIM modeling

APSIM (https://www.apsim.info) is a daily time-step model that contains a suite of modules with comprehensive physical and biological process representations to simulate the response of farming systems to different management practices and climate change (Holzworth et al., 2014; Keating et al., 2003). In this study, APSIM version 7.10 was used to simulate crop growth, soil water balance, soil carbon and nitrogen dynamics.

(I) Soil water balance

The APSIM *SoilWat* module was used to simulate the soil water balance at a daily scale. The water balance during the growing season (from sowing date to harvesting date) can be expressed as:

$$P - E - T - RO - DD = \Delta SWS \tag{4-3}$$

where, E, T, RO, DD and P are soil evaporation, actual crop transpiration, runoff, deep drainage, and cumulative precipitation from the day of sowing to harvest, respectively. ΔSWS is soil water change, calculated as the difference in soil water storage between the end and beginning of the crop growing season.

(II) Soil organic carbon

Two APSIM modules, *SoilN* and *SurfaceOM*, control the carbon transformation in the soil and on the soil surface. The *SoilN* module divides total SOC into four conceptual pools, namely fresh organic matter pool (FOM), microbial biomass pool (BIOM), humic organic matter pool (HUM), and inert organic matter pool (IOM). Except for IOM which is indecomposable, the decomposition of the other three pools is calculated as first-order processes with the rates modified by soil water content and temperature. Decomposition of any pool leads to the release of CO_2 and carbon transfer into BIOM and HUM pools. The *SurfaceOM* module deals with decomposition of crop residue based on the C and N ratio of the residue and its degree of contact with soil. Decomposition of surface residue releases CO_2 into the atmosphere and transfers remaining C to the BIOM and HUM pools.

(III) Nitrogen dynamics

The *SoilWat* and *SoilN*, coupled with *SurfaceOM* module, control the N dynamics on a daily time-step, including N mineralization, N immobilization and nitrification, and the N losses from denitrification and leaching. Mineralization or immobilization of mineral N is determined as the balance between the N release from decomposition and N immobilization through microbial synthesis and protection of organic matter. Nitrification in *SoilN* is assumed to follow Michaelis-Menten kinetics with limiting factors of soil moisture, temperature and pH. Denitrification is calculated as a function of NO_3-N multiplied by active carbon, soil moisture and temperature. More details can be found in Thorburn et al. (2010). In this study, we focused on N dynamics (balance between N inputs through fertilizer and biological nitrogen fixation and N losses through leaching and harvest, respectively). The cumulative amount of NO_3-N leaching in APSIM is calculated from daily drainage multiplied by daily NO_3-N concentrations. Grain N, controlled by both soil and crop modules, is translocated from other plant parts until the tissues reach their defined minimum N concentrations. The N demand of grain is also affected by water stress and temperature (Keating et al., 2001).

(IV) Crop yield and gross margin

APSIM is comprised of a set of modules for simulating growth, development and yields for different crops. Crop phenology from emergence towards maturity is driven by thermal time of each specific growth stage, which is determined by accumulating growing degree-day (GDD, °C). Daily biomass production is determined by available water for transpiration and radiant energy for potential photosynthesis, with the minimum of these two variables determining the actual biomass production for the day. Crop response to increasing atmospheric CO_2 concentration is simulated by modifying the radiation use efficiency and crop transpiration efficiency. Grain formation is simulated through assimilate partitioning to different organs. Grain yield is calculated as the product of grain weight and grain number.

For the direct comparison of different rotations, the calculation of gross margin for each crop was coded in the *Manager* module to be incorporated with other APSIM outputs. The gross margin was calculated as the difference between the grain yield income and the variable costs of production, which can be expressed as:

$$GM = (GI - C_S - C_T - C_F - C_H - C_I - C_C) \times (1 - L) \quad (4\text{-}4)$$

where GI is the crop yield (t ha^{-1}) multiplied by price for that crop (\$ t^{-1}). C_S, C_T, C_F, C_H and C_I are the costs for sowing, tillage, fertilizer, harvest and pest control, respectively (\$ ha^{-1}). C_C is the cost of sowing and terminating the cover crop, and L is the government levy (%). The on-farm costs and prices are given in Table 3-1.

4.2.4 Simulation scenarios

Similar to Liu et al. (2017) and O'Leary et al. (2016), APSIM was initialized for each location using a 41-year spin-up period to establish stable SOC fractions before simulating cropping scenarios. This was necessary because SOC recorded in the APSoil database reflected different cropping histories and farming management for each site at the time of sampling. During initialization, the model was run from 1920 to 1960 for a continuous wheat cropping system with 50 kg N ha^{-1} added as fertilizer at sowing and 25% residue retention. After the initialization, six different rotations were simulated from 1961 to 2092, with three levels of residue retention and with or without cowpea sown as a cover crop. The details of model configuration are shown in Fig. 4-2.

(I) Crop rotation cycle

We simulated five typical crops, including wheat (W), canola (C), field pea (F), barley (B) and oats (O), in six rotations (WC, WFWC, WFWO, WWB, WWC, and WWO), which are common rotation cycles grown across the study region. For comparison of the two-year, three-year and four-year rotations, a 36-year period was used as it gives 18, 12, and 9 complete cropping cycles, respectively. Thus, three 36-year periods (1985-2020, 2021-2056, and 2057-2092) were used to represent the historical period, near future and far future, respectively. The annual mean values using inverse distance weighted interpolation method across the study region were averaged over each of the three periods, to compare results between rotations. The sowing windows were set for each crop following the sowing guidelines of NSW Department of Primary Industries (Matthews et al., 2015). The sowing dates were determined as a function of soil water content, rainfall in the preceding day, the day of year, and plant available water capacity as described in Liu et al. (2019), to avoid failure of crop establishment under the widely varied soil and climate conditions across the region (GRDC, 2013), as described in Supplementary materials and shown in Fig. S4-1. Nitrogen fertilizer for cereals and canola varied between 43 and 121 kg N ha^{-1} based on the rainfall at each site, and was 10 kg N ha^{-1} for field pea. More details of fertilization can be found in He et al. (2022).

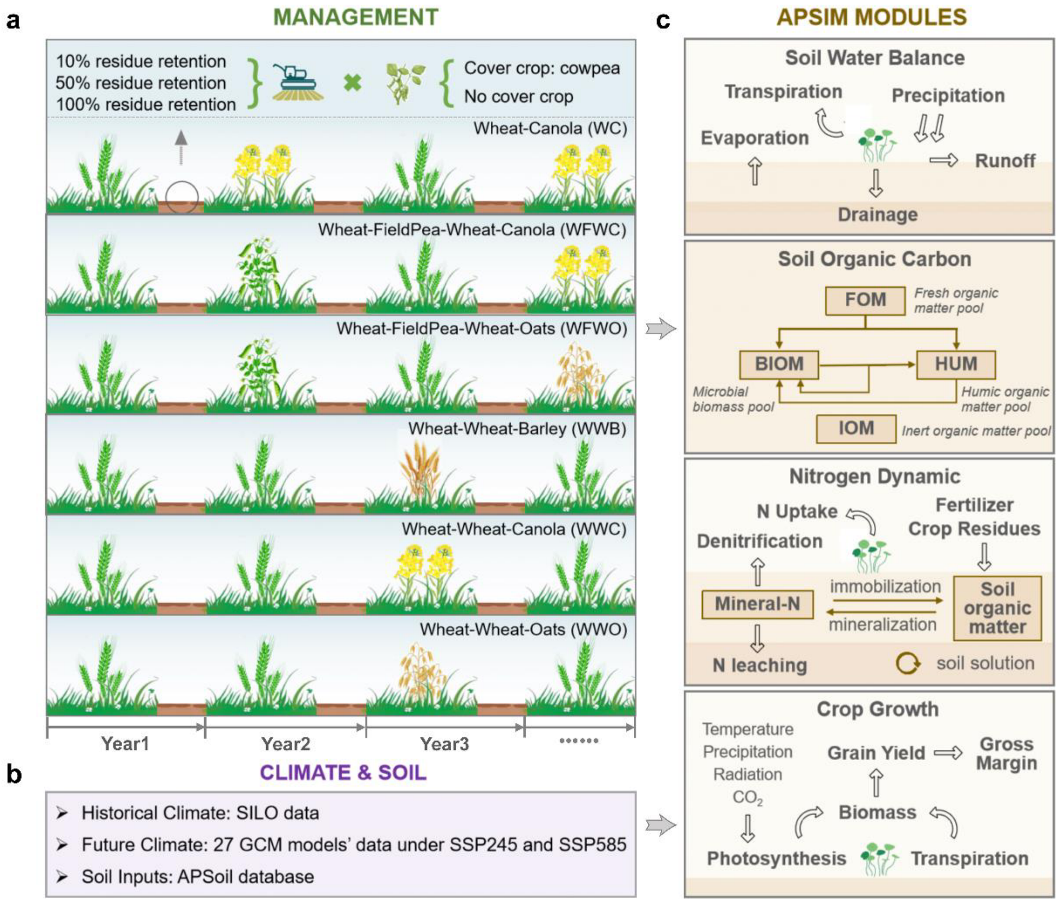

Fig. 4-2. The framework of the model simulation showing multiple management options (a), climate and soil data inputs (b), and different APSIM modules used to simulate the soil water balance, soil carbon, nitrogen (N) dynamics and crop growth (c). SILO, Scientific Information for Land Owners; GCM, General Circulation Model; SSP, Shared Socioeconomic Pathway. See more detailed description of the climate and crop models in Section 2.2 and 2.3.

(II) Residue retention and cover crop

For each rotation, three residue retention rates (10%: R10, 50%: R50, 100%: R100) were simulated. The three levels represent a typical burning, a moderate rate of residue removal, and retaining all crop residues, respectively. In each rotation system, a cowpea cover crop was sown (CC) or not sown (NC) during the fallow period. The sowing window of cowpea started four days after the harvesting of the cash crop and ended 50 days before sowing the next cash crop. The criteria to determine sowing date were soil moisture ≥ 0.85 PAWC and soil temperature ≥ 18 ℃ at 9:00 am for three consecutive days. The soil temperature at 9:00 am was estimated as (Simmons et al., 2022):

$$T = T_{min} + (T_{max} - T_{min}) \times 0.375 \tag{4-5}$$

where, T_{min} and T_{max} are the minimum and maximum air temperature.

If the requirements of soil moisture and temperature were not met during the sowing window, cowpea was sown on the last day of the sowing window. Cowpea was assumed to be terminated mechanically at the flower initiation stage, but if this stage was not achieved, cowpea was forced to be terminated 20 days before the start of the sowing window of the next cash crop. No fertilizer was applied to cowpea, and cowpea residues were not removed from the field.

4.2.5 Secondary bias correction

Due to the non-stationary bias in the GCM data and imperfections in the bias correction during the downscaling procedure (Haerter et al., 2011), there are some differences between the GCM climate data and observations. These differences can be corrected, denoted as a secondary bias correction procedure. By reducing residual biases that may remain after the primary bias correction in the downscaling procedure of climate data, a secondary bias correction can strengthen the comparability of outputs from different GCMs, allowing for a more reliable assessment of potential impacts under future climate conditions. We applied this method between the model outputs driven by the downscaled GCM climate and outputs driven by the observed climate data, following the method used by Yang et al. (2016):

$$Y = S_{GCM} - (S_{BL} - S_{OB}) \tag{4-6}$$

where Y is the output after the secondary bias correction. S_{OB}, S_{GCM} and S_{BL} are the APSIM simulated values derived from observed climate data (1985-2020), GCM projected climate data for future period (2021-2092), and GCM projected climate data for baseline period (1985-2020), respectively.

4.3 Results

4.3.1 Soil water change

The inclusion of a cowpea cover crop in rotations significantly decreased runoff and deep drainage during the cash crop growing season compared to no cover crop, with average reductions of -16.1% and -47.8% under SSP245 (Fig. S4-2A-B), and -17.7% and -48.5% under SSP585 (Fig. S4-3A-B), respectively, across the period 1985-2092. Growing a cash crop after a cover crop rather than fallow also generally reduced soil evaporation and increased cash crop transpiration on average by -3.0% and +4.4% under SSP245 (Fig. S4-2C-D), and -3.4% and +5.3% under SSP585 (Fig. S4-3C-D), respectively. These effects were more obvious under R10 compared to R100, and also more obvious in the far future compared to the historical period (Fig. S4-2 and Fig. S4-3). After growing cover crops during the traditional fallow period, the simulated soil water contents on the day of sowing the succeeding cash crop were lower than without cover crop for all rotation systems (Fig. 4-3). The average reductions in soil moisture of the whole soil profile were 33 mm (-21.8%) and 35 mm (-22.8%) under SSP245 and SSP585, respectively. The soil water storage in topsoil 0-50 cm (the main depth of crop water uptake in early growth) on the day of sowing the next cash crop was lower after cover crops by 9 mm (-15.3%) and 2 mm (-2.3%) compared to fallow under SSP245 and SSP585, respectively (Fig. S4-4).

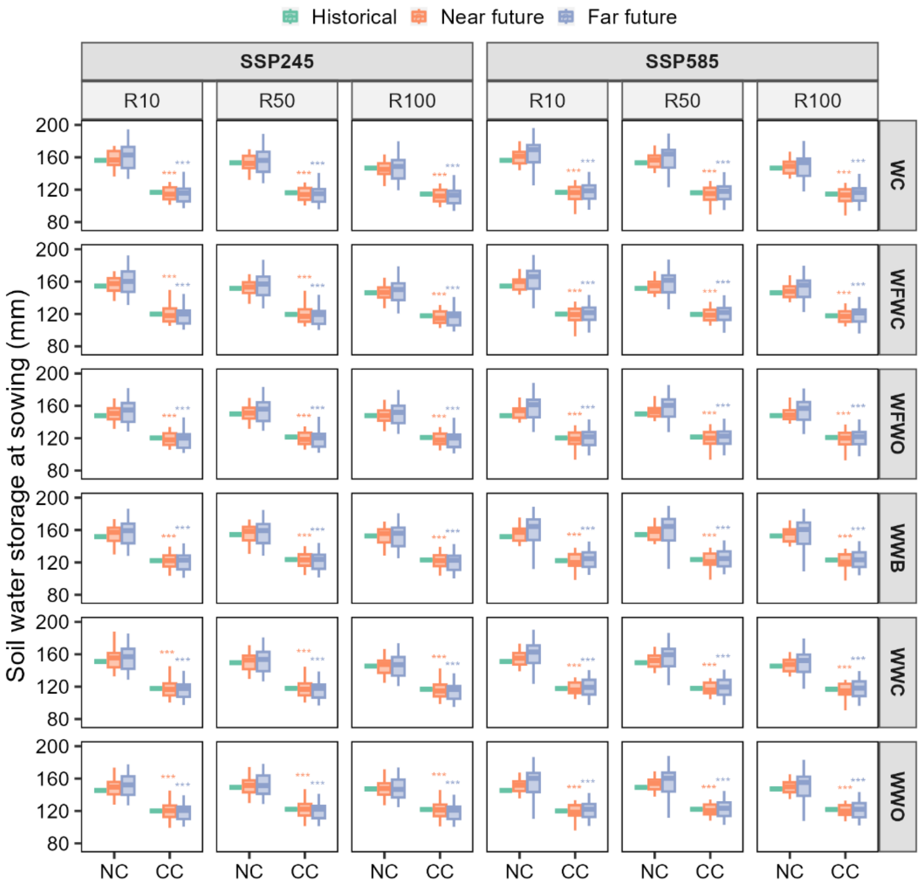

Fig. 4-3. Simulated soil water storage in the whole profile on the day of sowing the next cash crop with cover crop (CC) and without cover crop (NC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats) during three time periods (historical period: 1985-2020, near future: 2021-2056, and far future: 2057-2092) under SSP245 and SSP585. The boxplots for the historical period and future periods are based on the simulations with observed climate data and 27 GCMs, respectively. Asterisks represent significant differences between CC and NC for each treatment with 27 GCMs using paired t-test (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

4.3.2 Soil organic carbon

Without cover crops, the SOC stocks (0-30 cm) decreased steadily over time for both R10 and R50, and increased slightly but then plateaued for R100. With cover crops, however, SOC stocks increased throughout the simulation period for R50 and R100, and remained constant for R10 under all rotations and both SSPs (Fig. 4-4). For R100, the long-term implementation of cover crops showed a positive effect on SOC stock, with an average sequestration rate of 0.08 t ha^{-1} $year^{-1}$ from 1985 to 2092 compared to no cover crop (0.02 t ha^{-1} $year^{-1}$). Residue retention also contributed to SOC sequestration, and the sequestration rate was maximized when cover crops were combined with full residue retention.

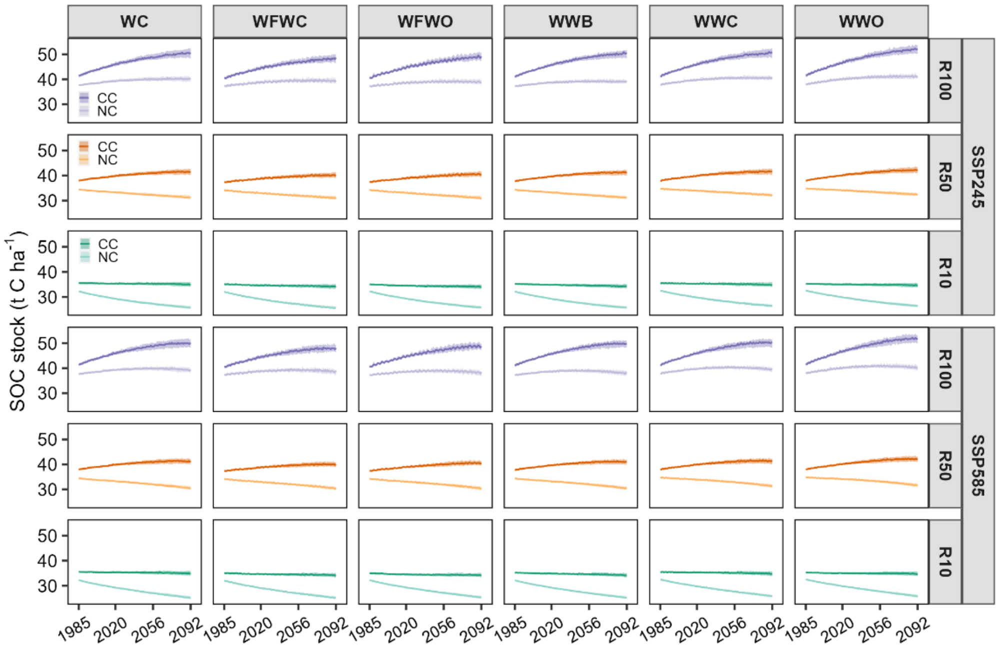

Fig. 4-4. Simulated annual soil organic carbon (SOC, 0-30 cm) stock from 1985 to 2092 without cover crop (NC) and with cover crop (CC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats) under SSP245 and SSP585. The lines represent the median values, and the shaded areas represent the 10^{th} and 90^{th} percentiles based on APSIM simulations using 27 GCMs.

4.3.3 Nitrogen dynamics

Cover crops reduced annual N leaching by 71.2% on average (median values) under both SSPs (Fig. 4-5). The reduced N loss through leaching was accompanied by increased soil N availability. Thus, the soil mineral N content on the day of sowing the next cash crop was increased by cover crops, and the effect was more positive in the far future (9.3% for SSP245 and 11.1% for SSP585 on average) than that in the historical period (6.9% on average) (Fig. S4-5).

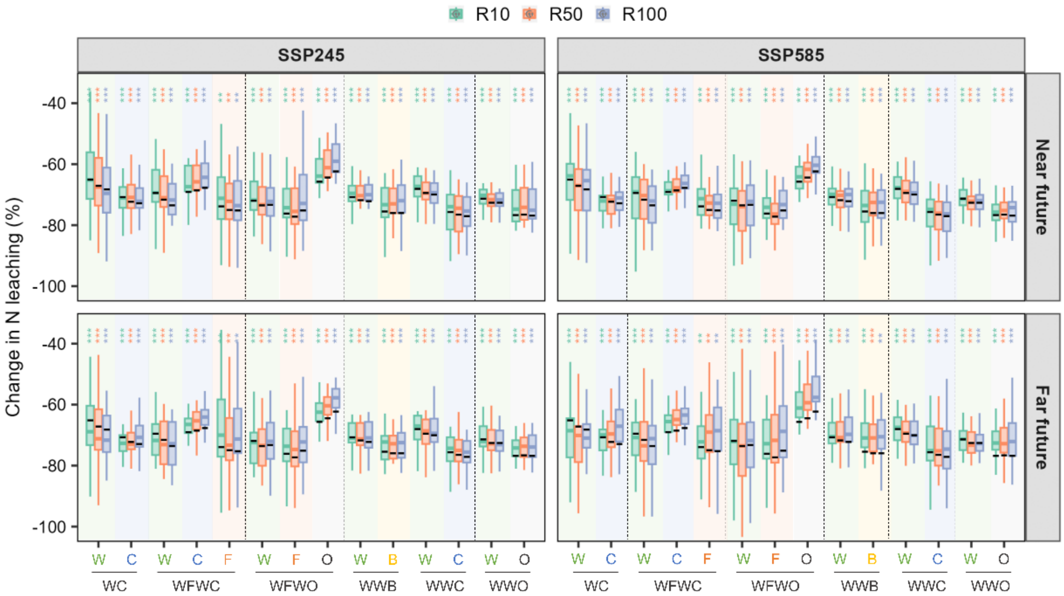

Fig. 4-5. The change (%) in simulated annual N leaching with cover crop (CC) compared to without cover crop (NC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats). The black dashes represent historical simulations based on observed climate data. The boxplots for two future periods are based on the simulations from 27 GCMs. Asterisks represent significant differences between CC and NC for each treatment with 27 GCMs using paired t-test (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

The inclusion of cover crops increased N uptake in grain for wheat, barley, and oats by 13.6% (from 6.2 to 7.1 g m^{-2}), 14.9% (from 5.4 to 6.2 g m^{-2}), and 40.7% (from 4.7 to 6.5 g m^{-2}) on average (Fig. S4-6). Consistently, the total N uptake of cash crops (including the N in grain and biomass) was also increased by cover crops (9.3-48.3% for wheat, 28.8-61.4% for oats, 15.1-28.5% for barley, and 4.1-34.8% for canola), except for field pea which decreased by 14.7-25.8% across each treatment and scenario

(Fig. 4-6). The positive effects of cover crops on N uptake were greater in the far future compared to historical period, and also were more evident with R10 compared to R100 for most crops.

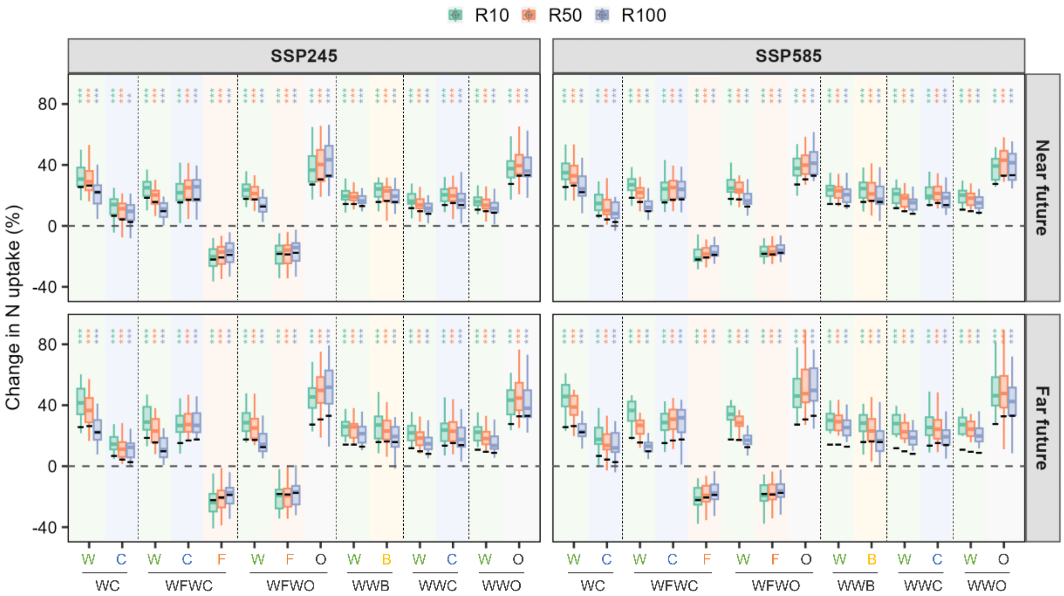

Fig. 4-6. The change (%) in simulated N uptake by cash crops with cover crop (CC) compared to no cover crop (NC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats). The black dashes represent historical simulations based on observed climate data. The boxplots for two future periods are based on the simulations from 27 GCMs. Asterisks represent significant differences between CC and NC for each treatment with 27 GCMs using paired t-test (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

4.3.4 Crop yield and gross margin

The inclusion of cover crops increased cereal yields on average by 7.6%, 13.5%, 33.8% (SSP245) and 10.3%, 13.4%, 34.3% (SSP585) for wheat, barley, and oats, respectively across the study region, but had a negative effect on the yields of canola in some rotations and field pea in all rotations (Fig. 4-7). The positive effects decreased with residue retention for wheat (14.1% to no effect), barley (15.0% to 12.0%), and oats (34.9% to 31.4%) from R10 to R100 on average under SSP245 (Table S4-1).

Positive effects of cover crops on cereal yields were more evident in the future compared to the historical period. For example, the average effects of cover crop on wheat, barley and oats increased from 6.8%, 12.0% and 28.4% (historical) to 10.7%, 15.5% and 39.6% (far future) under SSP245, respectively (Table S4-1). Similar trends were found for SSP585. The effects of cover crops on yields varied widely across the region, and were generally negative in the drier western part and positive in the wetter eastern part, as reflected in the gross margins (Fig. S4-10 and Fig. S4-11). Residue retention also contributed to yield enhancement. Relative to R10, crop yields for R100 increased by 13.3% (SSP245) and 14.1% (SSP585) for without cover crop, and 6.6% (SSP245) and 6.9% (SSP585) with cover crops, respectively (Fig. S4-7).

The inclusion of cover crops decreased the gross margin of most rotations during the historical period, and the negative effect was greater with residue retention but weakened (or became positive) in the future, under climate change (Fig. 4-8). For example, cover crops reduced the gross margin by -4.6% (R10) and -9.1% (R100) on average during the historical period (Table S4-2). In contrast, the effect on gross margin changed from -4.6% (historical) to +1.4% (SSP245) and +7.3% (SSP585) in the far future under R10, and from -9.1% (historical) to -8.2% (SSP245) and -4.5% (SSP585) in the far future under R100 (Table S4-2).

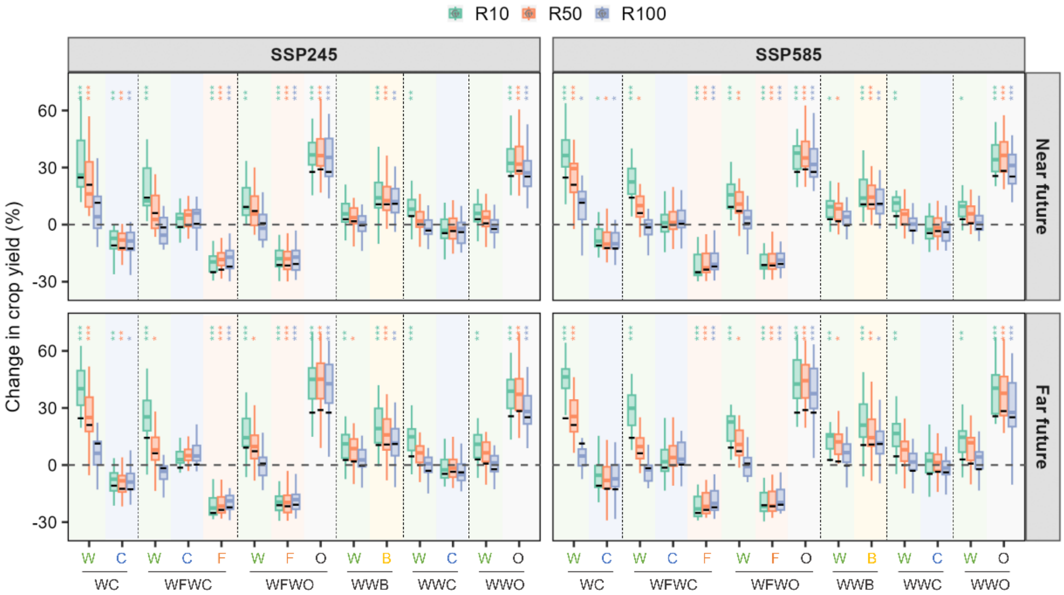

Fig. 4-7. The change (%) in simulated crop yields with cover crop (CC) compared to without cover crop (NC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats). The black dashes represent historical simulations based on observed climate data. The boxplots for two future periods are based on the simulations from 27 GCMs. Asterisks represent significant differences between CC and NC for each treatment with 27 GCMs using paired t-test (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

Overall, rotations that included canola (e.g., WC, WFWC and WWC) had higher gross margins because of the higher price received for canola relative to cereals, but yields of canola were reduced by sowing cover crops in some rotations (Fig. 4-7), thus gross margins of these rotations were negatively affected (Fig. 4-8). In contrast, due to the yield benefits provided by cover crops on cereals, gross margins of WWB and WWO were greater when cover crops were sown (Fig. 4-8). Importantly, the effects of cover crops on gross margins varied widely across the region, generally increasing with cover crops in the east, especially where residue was removed and rotations were dominated by cereals, but decreasing in the west in all rotations and residue treatments (Fig. S4-10 and Fig. S4-11).

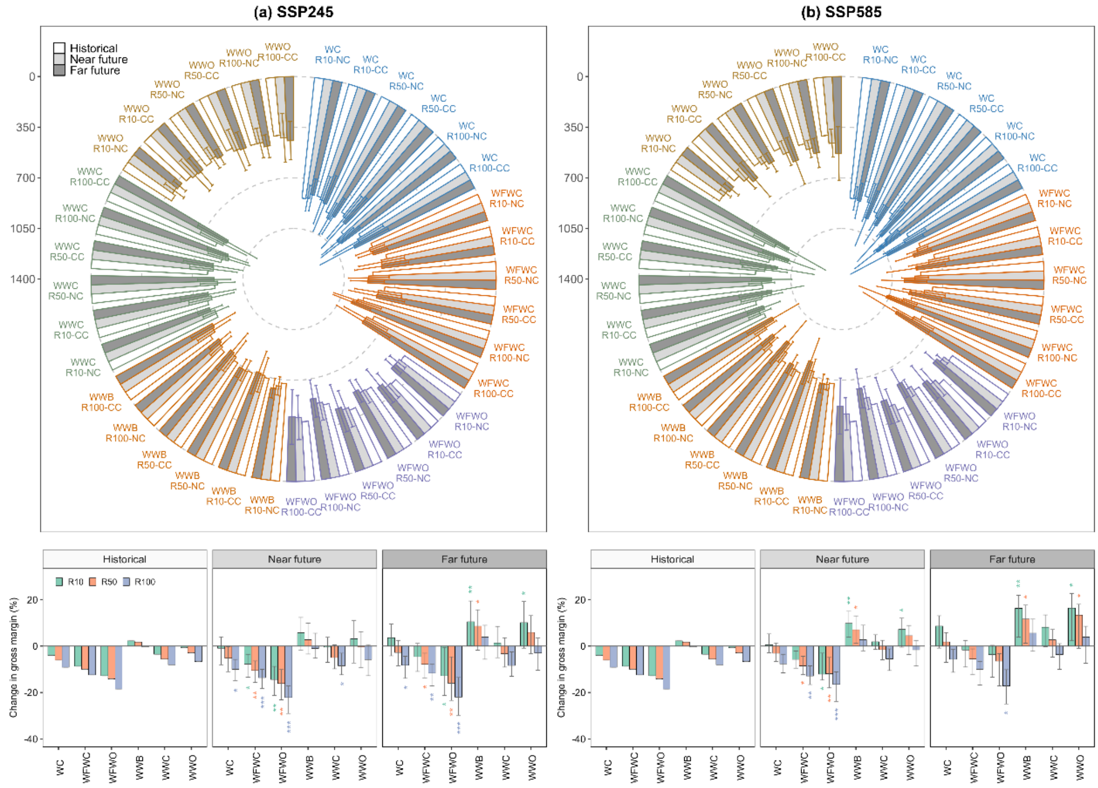

Fig. 4-8. Median values of gross margin (AUD ha^{-1}) with the 25th and 75th percentiles of simulations based on 27 GCMs under SSP245 (a) and SSP585 (b), and the corresponding change (%) in gross margin with cover crop (CC) compared to without cover crop (NC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats). Asterisks represent significant differences between CC and NC for each treatment with 27 GCMs using paired t-test (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

4.3.5 Climate effect on cover crop performance

Considering the large variations of rainfall and temperature across the study region, we further investigated the effects of climate variables on cover crop performance. Regression analysis showed that the responses of SOC, N uptake, yield and gross margin to cover crop implementation significantly increased with rainfall, while the reductions of soil water storage at sowing and N leaching from cover crops diminished with increasing rainfall (Fig. 4-9 and Fig. S4-8). In contrast, the responses of N uptake, yield and gross margin to cover crops were inversely related to temperature, but the reductions in soil water storage at sowing, and N leaching, induced by cover crops were greater with increasing temperature (Fig. 4-10 and Fig. S4-9).

The changes in gross margin induced by cover crops had closer relationships with both rainfall and temperature, giving the highest R^2 values compared to other variables. The relationships of yield and gross margin to rainfall and temperature were stronger under R10 than R100, showing more positive effects of cover crops where there was no residue retained. These responses varied spatially, reflecting the site-specific cover crop effects across the study region. Cover crop effects on gross margin under R10 were negative in the west and positive in the east, for example, 47-97% of the interpolating area "dry and warm west" showed negative changes, and 3-53% of "wet and cool east" had positive changes in the far future under SSP245 (Fig. S4-10c).

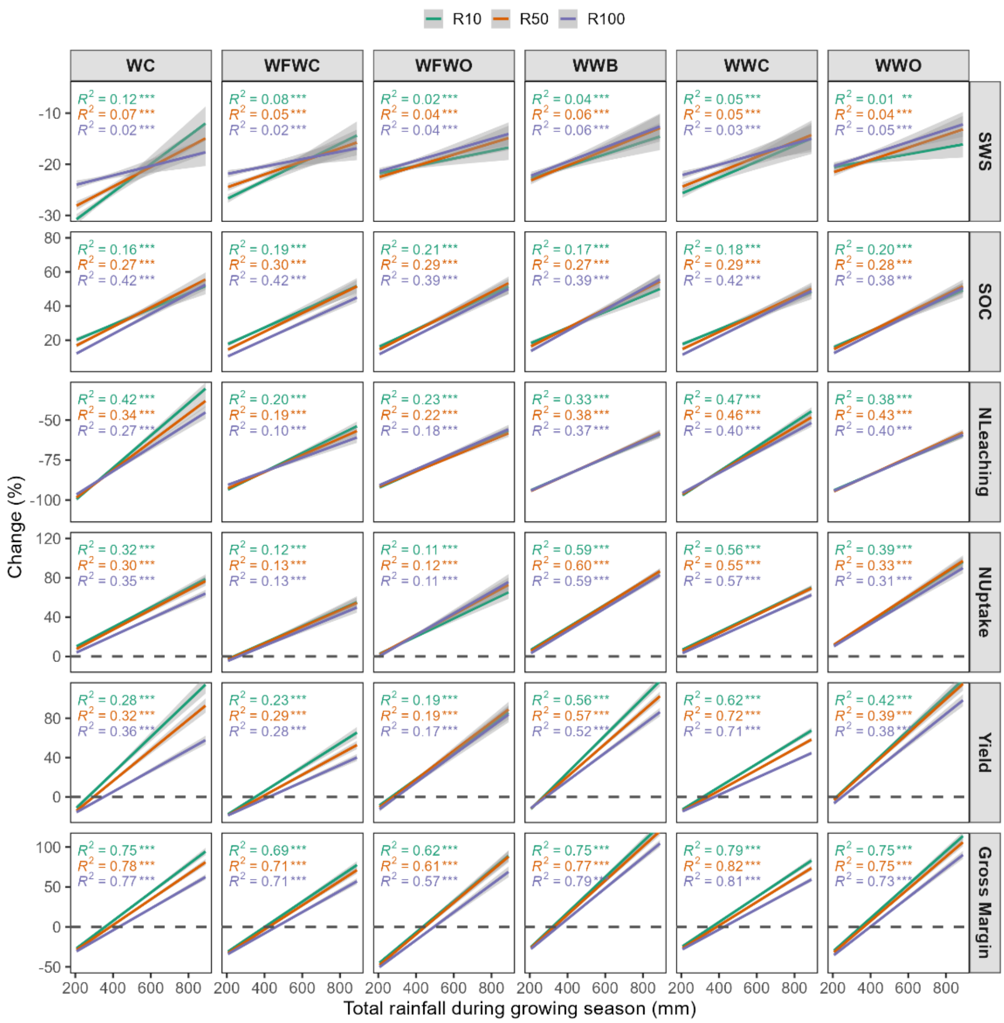

Fig. 4-9. The relationship between total rainfall during growing season (April to November) and change (%) induced by cover crop (CC) compared to no cover crop (NC) across three residue retention levels (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats) for simulated soil water storage on the day of sowing the next cash crop (SWS), soil organic carbon (SOC), N leaching (NLeaching), crop N uptake (NUptake), crop yield, and gross margin. Median values of changes (as shown in Fig. 4-3 to Fig. 4-8) and rainfall projected from 27 GCMs under SSP245 were averaged over three periods (1985-2020, 2021-2056, and 2057-2092). The linear regression with 95% confidence interval used simulations across 204 sites (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

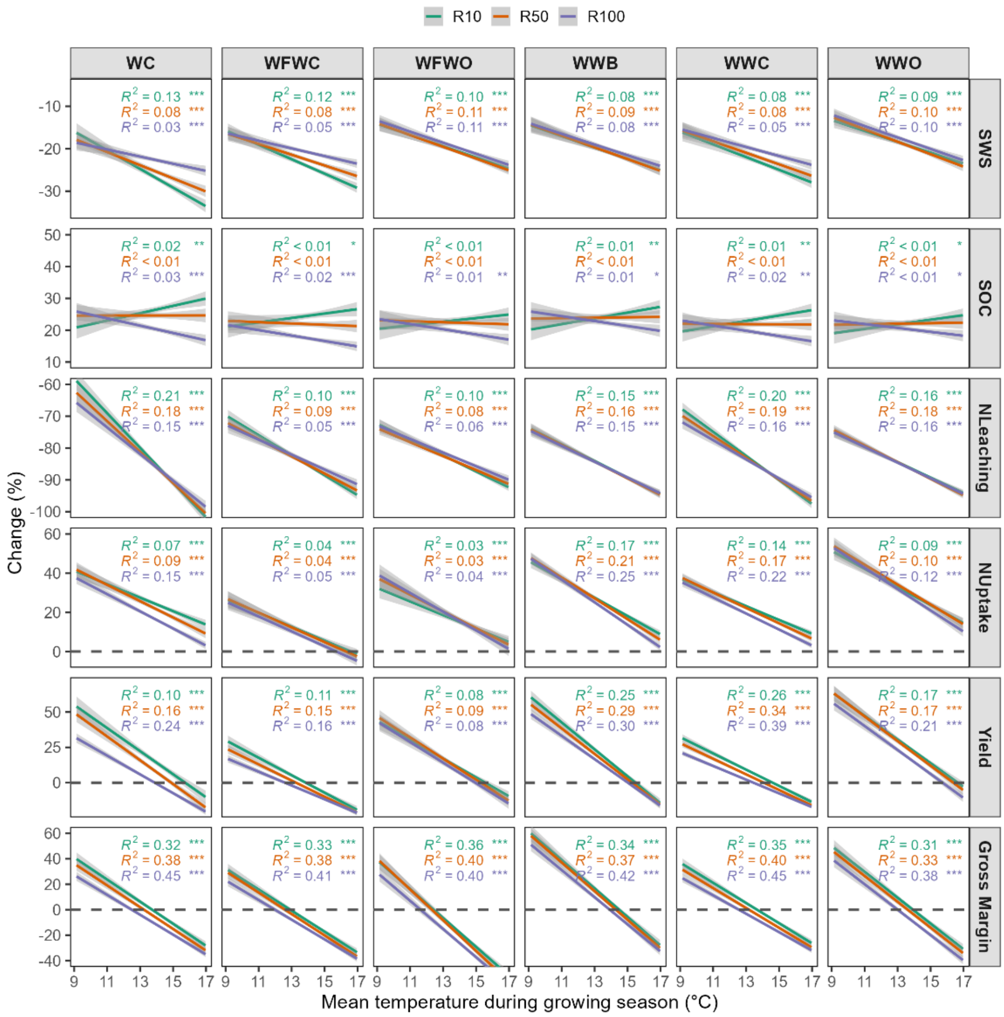

Fig. 4-10. The relationship between mean temperature during growing season (April to November) and change (%) induced by cover crop (CC) compared to no cover crop (NC) across three residue retention levels (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats) for simulated soil water storage on the day of sowing the next cash crop (SWS), soil organic carbon (SOC), N leaching (NLeaching), crop N uptake (NUptake), crop yield, and gross margin. Median values of changes (as shown in Fig. 4-3 to Fig. 4-8) and temperature projected from 27 GCMs under SSP245 were averaged over three periods (1985-2020, 2021-2056, and 2057-2092). The linear regression with 95% confidence interval used simulations across 204 sites (*** P < 0.001, ** P < 0.01, * P < 0.05).

4.4 Discussion

4.4.1 Overview of simulated cover crop effects compared to previous studies

APSIM has been widely applied to simulate cover crop performance in different cropping systems (Basche et al., 2016; Chatterjee et al., 2020; Martinez-Feria et al., 2016; Teixeira et al., 2021; Wunsch et al., 2017), and is recognized as a useful tool to investigate the long-term effects of management strategies under climate change. In this study, simulated effects of legume cover crops included increased soil organic carbon, increased crop N uptake except for field pea, and reduction in N leaching for the majority of the study region, but also reduced soil water storage at sowing of the subsequent cash crop in all rotation and residue treatments (see Table S4-3 for comparison with literature values). A major concern over the adoption of cover crops is whether the water used by the cover crop reduces subsequent cash crop growth and causes a yield penalty (Garba et al., 2022). Previous studies reported that legume cover crops enhanced yields by 9% across four farming systems in Switzerland (Wittwer et al., 2017), and legume and mixed cover crops were found to increase yields for wheat, barley and oats by 6% in the Nordic countries (Valkama et al., 2015). However, Olin et al. (2015) reported a decline of 5% in simulated yields for wheat and maize after cover crops, while retaining all residues increased yields, at the global scale. Our results showed that the impacts of cover crops on cash crop yields ranged from negative to positive, with large variations across the region, and between residue retention levels as well as crop types (Fig. 4-7 and Fig. S4-10).

4.4.2 Effects of long-term implementation of cover crops

Soil organic carbon is closely linked with soil quality, functionality and health (Lal, 2016). There is a strong consensus that cover crops have significant potential to increase SOC stocks in temperate environments (Blanco-Canqui et al., 2015; Kaye and Quemada, 2017; Poeplau and Don, 2015). For the Australian dryland cropping zone with generally nutrient-depleted soils, SOC sequestration from cover crops is limited by low productivity (McNee et al., 2022). Nevertheless, our simulations revealed small increments but substantial increases in SOC over the long term (Fig. 4-4), which could be because legume cover crops contributed to both organic matter addition and higher N availability. This is consistent with other reports of improved soil nutrient levels and physical properties over long-term implementation of cover crops (Nouri et al., 2019; Simon et al., 2022). Additionally, due to decreased deep drainage (Fig. S4-2B and Fig. S4-3B), cover crops reduced N leaching losses, and consequently increased the N uptake of most cash crops. These positive effects became more obvious over time, especially in the far future (Fig. 4-6 and Fig. S4-6). The reduction in N leaching and increase in crop N uptake induced by cover crops suggest the potential of cover crops to sustain cash crop growth with lower reliance on synthetic N fertilization (Martinez-Feria et al., 2016; Nouri et al., 2020; Porwollik et al., 2022).

Although soil carbon and nitrogen were increased by cover crops, our study found that they also reduced the soil water storage in the whole soil profile at cash crop sowing by 25-51 mm (Fig. 4-3). However, due to our sowing criterion based on soil moisture (Fig. S4-1), which delayed the sowing date for the cash crops by 14 days on average (Table S4-4), the soil water storage in top 0-50 cm at sowing was reduced by only 0-14 mm with cover crops (Fig. S4-4). Cash crops mainly use the soil water in topsoil at the early growth stage, so adverse effects of cover crop water use in the whole soil profile can be avoided if autumn rains replenish soil moisture later (Martinez-Feria et al., 2016). Previous studies have found that early termination of cover crops could mitigate yield loss (Krueger et al., 2011; Qin et al., 2021), and 1-2 months duration was suggested for cover cropping in southern Australia (Rose et al., 2022). In our study, the cover crop was terminated 20 days before sowing the succeeding cash crop (as described in section 2.4) with the aim to minimize adverse effects on cash crop yields, so cover crops were grown for about one month only.

With the short implementation of cover crops, yields of cereals (wheat, barley and oats) were increased in the long run (Fig. 4-7). Particularly, the larger increase for oats reflects that oats were N-limited in the no-cover crop treatment, due to the low rate of N fertilizer applied in our simulations (based on the local farmer practice). Thus, the legume cover crops boosted the growth of oats (Fig. 4-7), and led to a large increase in N uptake in grains (Fig. S4-6). However, the yields of broadleaf crops (canola and field pea) in most rotations were negatively impacted. A possible reason is that canola is generally more sensitive to water stress than cereals (Dreccer et al., 2018). Canola requires extra energy for oil production compared to the starch production in cereal grains, which is specified by a coefficient for conversion of assimilate to seed mass in APSIM (Robertson et al., 2002). Field pea is able to use biologically fixed N for growth when the N demand cannot be satisfied by mass flow or active uptake from soil, so may be insensitive to the N added by legume cover crops. The nitrogen fixation process requires additional water, and the APSIM model reduces N fixation capacity on the basis of the daily soil water status (Robertson et al., 2002), causing a more likely reduction in growth when water is limited (Alexieva et al., 2001; Couchoud et al., 2020). In addition, broadleaf crops were found to flower earlier than cereals (Liu et al., 2017). APSIM used a constant rate per degree-day to simulate leaf senescence after flowering, so greater soil evaporation caused by earlier leaf senescence occurred for canola and field pea than cereals (Fig. S4-2 and Fig. S4-3).

Consistently, cover crops increased water use efficiency (WUE) for cereals, with more positive effects in the far future (Fig. S4-12). Increased cereal yield but reduced soil water losses by deep drainage, runoff and evaporation, resulted in the increased WUE for wheat, barley and oats with cover crops compared to no cover crop, as also reported by Wang et al. (2021a). From the perspective of the whole rotation, cover crops decreased gross margins during the historical period but increased gross margins for most rotations in the far future, particularly where residues were removed (Fig. 4-8). The increased benefit from cover crops probably resulted from the greater N availability for crop growth, and the slow accumulation of soil organic matter which leads to a gradual improvement in soil nutrient and water availability (DeVincentis et al., 2020; Wang et al., 2021b). Note also the large uncertainty in the estimates of gross margin impacts. In many cases, while the average indicates positive effects of cover crop, the large range, from positive to negative values, suggests that there is a substantial risk associated with a choice to adopt cover cropping (Fig. S4-10).

4.4.3 Interaction of cover crop effects with residue retention and climate

Some studies reported that inclusion of cover crops in cropping systems offered an opportunity to counterbalance the negative effects of cash crop residue removal. For example, cover crops can maintain SOC and soil fertility where residues were removed for livestock feed or bioenergy (Klopp and Blanco-Canqui, 2022; Pratt et al., 2014; Ruis et al., 2017). Similarly, we found that positive effects of cover crops on cash crop yields were more evident under residue removal compared to residue retention (Fig. 4-7), which may be ascribed to the partly compensatory effects of cover crops on residue removal. However, under full residue retention, cover crops had small benefits on yields, which is probably because that legume cover crops produced less biomass than cash crops (during the short growth period of cover crops applied in our modelling), and thus cover crops provided little additional benefit to cash crop yields where residues were retained, as reported in some previous studies (Han et al., 2018; Wang et al., 2019; Xia et al., 2018).

The strong regional variation in cash crop yields in response to growing cover crops indicates that caution is needed in implementing cover crops in low rainfall drylands (Fig. S4-10 and Fig. S4-11). The impacts of cover crop are climate-driven, and therefore highly variable depending on where the crops are grown (Garba et al., 2022). In this study, cover crops grown during summer were reliant upon stored soil moisture, elevating the risk of depleting soil water reserves for the next cash crops especially in the drier area. Under wetter conditions, water used by cover crops has a greater likelihood of being replenished through rainfall during the growing season, so cash crops were less affected.

The interactions of cover crops with residue retention and climate are complex and dynamic. Our results showed that cover crops were more beneficial to yields and gross margins under future climate change (Fig. 4-7 and Fig. 4-8). This may be attributed to the elevated CO_2 concentration in the future which led to greater plant biomass production (Fig. S4-13) and increased organic matter input to soil, as also reported in some previous modeling studies (Banger et al., 2015; Huang et al., 2020; Tian et al., 2015). Moreover, residues of legume crops, with a lower carbon and nitrogen ratio, are decomposed faster than residues of other crops in APSIM, so provide a greater boost to soil nutrient levels. The stimulation of cover crops due to elevated CO_2 synergistically benefited cereal yields, with more positive changes under SSP585 compared to SSP245 (Table S4-1). Therefore, our results imply that inclusion of cover crops during the fallow period could contribute to building a climate-resilient agricultural system under certain climate conditions, but further work is necessary to examine the causes of yield declines in canola and field pea, and to clearly define the rainfall thresholds above which cover crops are likely to be profitable.

4.4.4 Limitations and implications

Our simulations captured the water, carbon and nitrogen dynamics under cowpea cover crops (or fallow) in rotations and the subsequent wheat, barley, oats, canola and field pea crops. One weakness of the biophysical simulations is that impacts of cover crops on weeds, pests, and diseases are not accounted for in the APSIM model. We also did not consider the option of reducing synthetic N fertilizer inputs after adopting cover crops. Farmers utilizing cover crops could potentially reduce insecticide and fertilizer inputs without yield penalty (Bowers et al., 2020; DeVincentis et al., 2020; Nouri et al., 2020). Thus, gross margins under cover cropping in this study may be underestimated. Furthermore, agricultural prices and management costs are likely to change with market demands in the future, which may shift the relative profitability between systems with or without cover crops. We also found that simulations had greater variation in the far future, because the variability of climate data from 27 different GCMs increased progressively into the future, as shown in Fig. 4-1b-c. Uncertainties in climate change impact projections, which increase with rising atmospheric CO_2 concentration and associated warming, could be reduced by further improving CO_2 and temperature relationships in models (Asseng et al., 2013).

The expected impacts at the cropping system level due to including cover crops vary depending on cash crop types, residue retention levels, and local climate conditions. In general, our simulations indicated that a reduction in soil water storage at sowing can lead to reduced plant growth and crop yields where water is limiting. For example, most crop yields with R100 were reduced by cover crops where total rainfall during the growing season is lower than around 400 mm (Fig. 4-9 and Fig. S4-8). The increase in soil organic carbon and N availability induced by cover crops can result in increased crop yields in the longer term, associated with improved soil fertility. However, it is important to note that cover crop management practices can also have a significant impact on the overall outcomes. For example, some studies have shown that effects on cash crop yields varied with cover crop types (Alvarez et al., 2017), planting and terminating time of cover crops (Qin et al., 2021), and soil texture (Wang et al., 2021a). The present study used a summer legume, cowpea, as a cover crop, because it could be adequately established during the dry and hot summers in southern Australia (McNee et al., 2022), and is adapted to a wide range of soils. Other species of cover crops may be more suitable to specific soil types, providing potentially greater benefits than demonstrated here. Thus, further investigation of alternative species and site-specific management may lead to greater advantages from cover crops.

Based on simulated outputs under the different scenarios considered in this study, we found that incorporating cover crops into conventional rotations could enhance sustainability and profitability of cereal-dominated rotations in higher rainfall regions, particularly under climate change. However, cereal dominated rotations are less likely to be grown in higher rainfall areas because rotations that include canola are more profitable in the study region, and growing canola in rotations can reduce disease incidence for cereal crops. Nevertheless, results of this study suggest that there may be potential for the adoption of cover crops to sustain yields in cereal crops, and to allow partial removal of crop residues for bioenergy or livestock feed. Further studies that consider other combinations of practices (e.g., fertilizer optimization, biochar, and intercropping) are needed to identify management that sustain crop yields in dryland cropping systems under climate extremes or climate change (Nouri et al., 2021; Su et al., 2021).

4.5 Conclusion

This modelling study, that presents temporal and spatial quantification of the impacts of a cowpea cover crop combined with residue management for six rotation systems, has identified important insights for the adoption of cover crops in southeast Australia. First, cover crops decreased soil moisture, but enabled greater SOC sequestration and reduced N loss through leaching. Second, declines in crop N uptake and yield induced by cover crops were found for field pea, but for wheat, barley and oats, the crop N uptake and yield generally increased. Third, benefits from cover crops on yield and gross margin increased with higher rainfall and lower temperature, thus cover crops were profitable in the east but not in the west of the study region. Finally, cover crop effects on yield were more positive under residue removal and future climate change. The long-term implementation of cover crops has the potential to improve current crop rotations and sustain crop productivity with reduced environmental impacts only under wetter conditions in Australian dryland cropping. Further work is required to clearly define the rainfall thresholds above which cover crops are profitable, and to optimize site-specific management for cover crop adoption.

4.6 Supporting information

4.6.1 Supplementary methods

Different sowing windows were set for wheat (74-181, day of the year), canola (98-166), barley (105-196), oats (121-173), and field pea (121-181). Within these windows, sowing date was based on soil water content, plant available water capacity, recent rainfall, and the day of year. This flexible sowing rule was developed to accommodate the large spatial variation in soils and climate across the Riverina region. Specifically, the soil water requirement for sowing was decreased nonlinearly from 1.2 times plant available water capacity (PAWC) to 0.8 PAWC with increased day of year (DOY). That means early sowing requires a higher soil moisture to avoid failed establishment of crops caused by high evaporation during early autumn. If soil water was 0.8-1.0 PAWC, the crop was sown on the same day, otherwise, sowing date was delayed by 1 day (1.0-1.1 PAWC), 2 days (1.1-1.2 PAWC), or 3 days (>1.2 PAWC). When the sowing date occurred before the mid-point of the sowing window, a longer season "winter-type" cultivar was used, whereas a shorter season "spring-type" cultivar was used if the sowing date was after the mid-point of the sowing window. In addition, if the sowing criteria were not met during the sowing window, the crop was sown at the end of the sowing window.

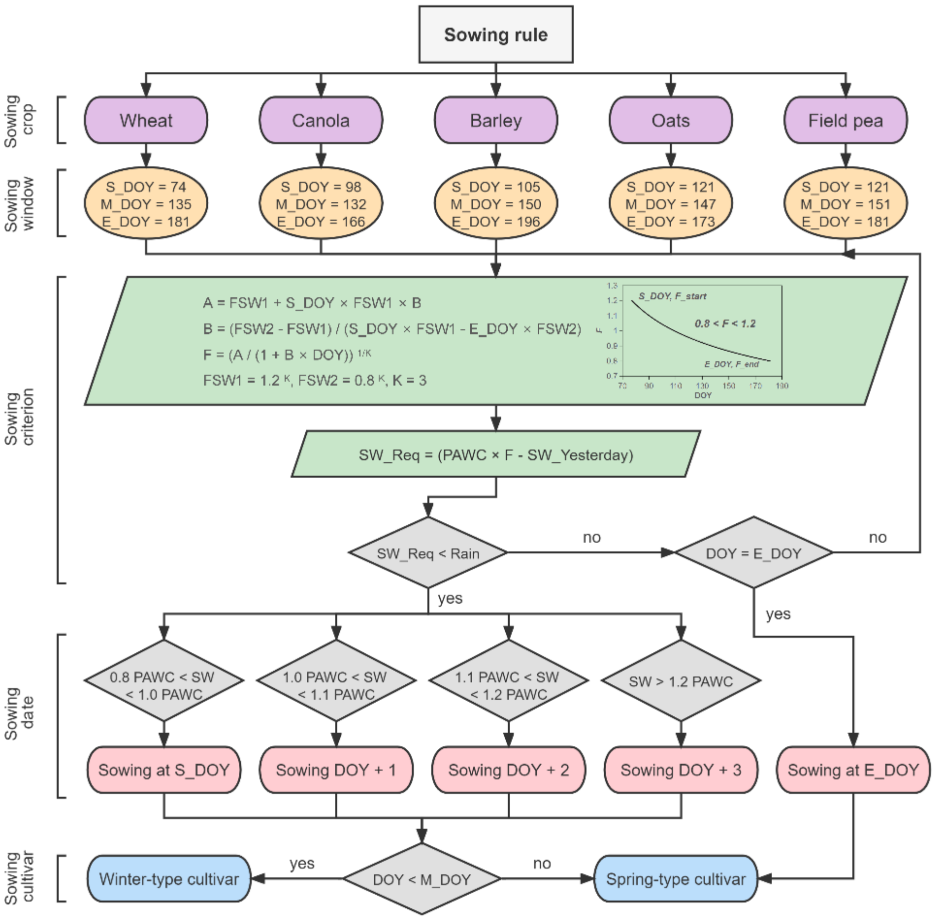

Fig. S4-1 The sowing rule used in APSIM modelling. DOY is the day of year, S_DOY, M_DOY, and E_DOY are the start, mid-point and end days of each sowing window. PAWC is plant available water capacity (mm); F is the fraction of PAWC required at sowing; A, B, FSW1, FSW2, and K are parameters used to calculate F. SW_Yesterday is the soil water (mm) on the previous day, SW_Req is the amount of additional soil water required for crop sowing, SW is the soil water on DOY.

4.6.2 Supplementary tables

Table S4-1. The change (%) in simulated crop yields with cover crop (CC) compared to no cover crop (NC). The ranges indicate the 10th (left) and 90th (right) percentiles of simulations based on 27 GCMs.

Rotation	Crop	Residue	Historical period	Near future				Far future			
				SSP245	*Range*	SSP585	*Range*	SSP245	*Range*	SSP585	*Range*
WC	Wheat	R10	**25.9**	**26.1**	*(16.1, 57.1)*	**36.3**	*(17.2, 53.6)*	**43.8**	*(27.0, 73.4)*	**47.4**	*(21.6, 64.9)*
		R50	**22.1**	**16.1**	*(7.1, 43.8)*	**29.5**	*(9.7, 40.7)*	**25.0**	*(10.7, 44.3)*	**25.5**	*(9.1, 37.4)*
		R100	**12.6**	**4.1**	*(-4.0, 27.4)*	**13.1**	*(-3.3, 19.6)*	**6.2**	*(-6.4, 18.4)*	**4.7**	*(-4.6, 11.9)*
	Canola	R10	**-9.8**	**-7.2**	*(-18.6, -1.0)*	**-8.7**	*(-13.2, 1.6)*	**-7.4**	*(-16.2, -1.1)*	**-5.4**	*(-15.8, 4.5)*
		R50	**-11.2**	**-8.1**	*(-20.1, -3.0)*	**-10.2**	*(-15.7, -0.7)*	**-8.3**	*(-17.8, -1.6)*	**-8.1**	*(-17.2, 3.9)*
		R100	**-11.5**	**-8.6**	*(-19.6, -1.5)*	**-10.1**	*(-16.7, -0.5)*	**-8.9**	*(-16.5, -0.8)*	**-7.3**	*(-16.2, 7.5)*
WFWC	Wheat	R10	**15.5**	**12.5**	*(7.2, 35.2)*	**22.4**	*(9.8, 32.7)*	**25.3**	*(14.6, 40.2)*	**30.2**	*(9.8, 41.7)*
		R50	**7.3**	**2.7**	*(-4.3, 18.9)*	**10.0**	*(-0.5, 18.3)*	**8.0**	*(0.2, 18.7)*	**9.7**	*(-2.4, 20.5)*
		R100	**-0.4**	**-5.5**	*(-11.3, 6.8)*	**0.0**	*(-8.3, 7.0)*	**-3.3**	*(-12.0, 3.8)*	**-2.5**	*(-10.4, 4.9)*
	Canola	R10	**-0.1**	**3.3**	*(-5.9, 9.5)*	**0.9**	*(-7.1, 9.9)*	**2.8**	*(-2.8, 12.7)*	**1.7**	*(-7.7, 15.8)*
		R50	**1.2**	**5.1**	*(-5.0, 10.7)*	**1.1**	*(-5.6, 11.2)*	**4.9**	*(-1.4, 15.8)*	**4.0**	*(-5.5, 19.6)*
		R100	**1.5**	**6.1**	*(-4.3, 10.8)*	**1.5**	*(-5.5, 10.8)*	**4.8**	*(-0.9, 16.5)*	**3.1**	*(-3.9, 22.1)*
	Field pea	R10	**-23.8**	**-24.6**	*(-38.2, -14.0)*	**-25.3**	*(-28.9, -14.2)*	**-28.0**	*(-36.7, -15.9)*	**-25.4**	*(-41.4, -12.2)*
		R50	**-22.5**	**-20.4**	*(-37.3, -13.0)*	**-23.3**	*(-28.2, -13.0)*	**-25.5**	*(-35.3, -13.8)*	**-23.0**	*(-37.8, -9.5)*
		R100	**-20.9**	**-19.9**	*(-36.5, -11.9)*	**-21.0**	*(-26.5, -11.4)*	**-22.6**	*(-33.4, -12.2)*	**-20.7**	*(-35.1, -7.9)*
WFWO	Wheat	R10	**10.4**	**8.9**	*(2.3, 24.4)*	**15.7**	*(5.4, 22.9)*	**14.4**	*(7.9, 27.6)*	**22.6**	*(4.9, 31.0)*
		R50	**8.4**	**5.6**	*(-3.3, 19.4)*	**10.8**	*(1.7, 20.0)*	**9.7**	*(0.6, 19.8)*	**10.8**	*(-0.8, 20.3)*
		R100	**2.0**	**-1.9**	*(-10.5, 9.6)*	**3.6**	*(-4.6, 9.7)*	**0.3**	*(-10.6, 6.6)*	**-0.8**	*(-8.1, 6.5)*
	Field pea	R10	**-19.9**	**-21.2**	*(-36.5, -10.7)*	**-22.4**	*(-26.2, -11.0)*	**-23.8**	*(-35.4, -12.5)*	**-22.3**	*(-37.2, -9.6)*
		R50	**-20.4**	**-18.9**	*(-35.3, -11.0)*	**-21.9**	*(-27.3, -10.9)*	**-24.7**	*(-34.6, -12.8)*	**-22.3**	*(-36.7, -8.5)*
		R100	**-19.5**	**-17.5**	*(-34.7, -10.0)*	**-19.2**	*(-26.2, -9.9)*	**-23.0**	*(-33.3, -11.9)*	**-20.4**	*(-34.4, -7.0)*
	Oats	R10	**28.8**	**36.6**	*(21.7, 52.2)*	**38.6**	*(23.1, 48.8)*	**45.0**	*(31.0, 59.4)*	**44.6**	*(27.7, 73.7)*
		R50	**30.2**	**36.2**	*(24.0, 49.4)*	**35.5**	*(23.7, 48.4)*	**45.2**	*(28.8, 62.6)*	**46.0**	*(27.4, 75.8)*
		R100	**28.8**	**35.4**	*(23.0, 48.6)*	**32.3**	*(22.2, 43.3)*	**42.7**	*(27.5, 63.7)*	**39.9**	*(26.1, 78.4)*
WWB	Wheat	R10	**3.9**	**5.7**	*(-1.9, 14.0)*	**9.4**	*(1.5, 17.8)*	**11.1**	*(-3.7, 18.0)*	**15.2**	*(-2.0, 25.8)*
		R50	**3.1**	**3.7**	*(-3.7, 13.1)*	**8.4**	*(-1.0, 18.0)*	**8.6**	*(-6.6, 16.2)*	**12.2**	*(-3.9, 23.9)*
		R100	**0.9**	**0.9**	*(-6.7, 8.4)*	**4.1**	*(-4.5, 14.2)*	**2.7**	*(-9.8, 11.1)*	**6.5**	*(-6.7, 17.7)*
	Barley	R10	**11.8**	**14.1**	*(2.7, 30.1)*	**14.0**	*(6.8, 29.8)*	**19.2**	*(5.5, 35.0)*	**21.0**	*(7.0, 44.6)*
		R50	**11.9**	**12.6**	*(-0.5, 26.5)*	**14.4**	*(4.1, 24.5)*	**15.8**	*(4.6, 31.1)*	**12.9**	*(3.4, 35.1)*
		R100	**12.3**	**12.1**	*(-1.7, 24.1)*	**10.7**	*(3.3, 23.2)*	**11.6**	*(2.6, 28.4)*	**11.3**	*(-1.0, 26.6)*
WWC	Wheat	R10	**5.7**	**8.1**	*(1.0, 17.6)*	**11.3**	*(4.3, 21.3)*	**14.8**	*(-1.3, 21.2)*	**16.6**	*(-0.3, 28.3)*
		R50	**1.2**	**1.9**	*(-4.3, 10.1)*	**5.6**	*(-1.8, 13.0)*	**6.4**	*(-8.4, 12.0)*	**8.0**	*(-6.9, 18.1)*
		R100	**-1.9**	**-2.6**	*(-7.6, 4.5)*	**0.3**	*(-6.2, 8.0)*	**0.7**	*(-12.3, 5.9)*	**1.6**	*(-10.3, 11.4)*
	Canola	R10	**-3.4**	**-3.0**	*(-10.2, 6.2)*	**-2.6**	*(-9.6, 9.8)*	**-2.5**	*(-8.7, 7.2)*	**2.2**	*(-14.3, 14.8)*
		R50	**-2.2**	**-1.8**	*(-10.2, 6.3)*	**-1.6**	*(-9, 9.8)*	**-1.7**	*(-7.8, 7.6)*	**0.9**	*(-13.7, 12.9)*
		R100	**-2.7**	**-2.1**	*(-11.6, 4.0)*	**-2.7**	*(-10.6, 6.3)*	**-5.0**	*(-10.4, 4.1)*	**-1.7**	*(-15.9, 6.7)*
WWO	Wheat	R10	**4.0**	**5.9**	*(-0.8, 14.6)*	**9.6**	*(1.2, 16.7)*	**10.9**	*(-3.2, 17.9)*	**14.6**	*(-1.5, 24.4)*
		R50	**2.0**	**3.7**	*(-2.8, 10.8)*	**5.7**	*(-2.1, 14.2)*	**6.4**	*(-6.6, 13.4)*	**11.7**	*(-4.8, 19.5)*
		R100	**-1.0**	**-0.5**	*(-6.7, 5.7)*	**0.8**	*(-5.9, 9.5)*	**1.1**	*(-10.1, 7.5)*	**4.3**	*(-9.7, 11.9)*
	Oats	R10	**26.8**	**32.2**	*(19.7, 45.3)*	**34.2**	*(23.6, 46.2)*	**39.6**	*(23.6, 57.4)*	**40.8**	*(23.1, 71.9)*
		R50	**29.6**	**31.8**	*(19.6, 46.6)*	**36.4**	*(22.7, 48.7)*	**37.2**	*(20.6, 55.2)*	**40.1**	*(20.5, 68.9)*
		R100	**26.4**	**27.2**	*(15.4, 40.4)*	**31.1**	*(13.9, 41.9)*	**28.1**	*(14.8, 44.4)*	**28.0**	*(11.1, 55.4)*

Table S4-2. The change (%) in simulated gross margins with cover crop (CC) compared to no cover crop (NC). The ranges indicate the 10th (left) and 90th (right) percentiles of simulations based on 27 GCMs.

Scenario	**Period**	**Residue**	**WC**	**WFWC**	**WFWO**	**WWB**	**WWC**	**WWO**
Historical period		R10	-4.1	-8.7	-12.8	**2.3**	-3.5	-0.6
		R50	-6.0	-9.9	-14.2	**1.7**	-5.6	-2.9
		R100	-9.1	-12.4	-18.5	-0.2	-8.0	-6.7
SSP245	Near future	R10	-0.9	-7.7	-14.4	**5.7**	-0.4	**3.2**
		Range	*(-10.1, 11.7)*	*(-16.9, 2.8)*	*(-25.8, 1.0)*	*(-5.5, 15.0)*	*(-10.5, 8.7)*	*(-11.1, 17.9)*
		R50	-5.2	-10.5	-16.1	**2.7**	-4.9	-0.4
		Range	*(-13.3, 7.0)*	*(-18.9, 0)*	*(-28.8, -1.0)*	*(-7.7, 13.4)*	*(-13.2, 4.8)*	*(-14.0, 13.3)*
		R100	-10.0	-13.6	-22.2	-1.0	-8.5	-5.8
		Range	*(-17.3, -0.7)*	*(-21.8, -4.0)*	*(-34.2, -7.3)*	*(-10.2, 10.2)*	*(-15.8, 0)*	*(-20.0, 5.6)*
	Far future	R10	**3.6**	-4.6	-12.8	**10.5**	**1.4**	**10.1**
		Range	*(-8.7, 14.9)*	*(-17.2, 5.6)*	*(-28.4, 4.3)*	*(-4.7, 23.9)*	*(-9.2, 14.1)*	*(-14.9, 20.9)*
		R50	-2.8	-7.8	-16.0	**8.6**	-3.3	**5.9**
		Range	*(-13.5, 6.9)*	*(-20.4, 1.5)*	*(-30.5, 1.4)*	*(-7.6, 20.1)*	*(-13.6, 8.3)*	*(-18.3, 16.1)*
		R100	-8.3	-11.7	-21.9	**3.9**	-8.4	-3.0
		Range	*(-19, 0.3)*	*(-22.9, -4.3)*	*(-37.6, -7.4)*	*(-11.5, 13.0)*	*(-17.6, 1.6)*	*(-23.5, 9.5)*
SSP585	Near future	R10	**0.6**	-5.7	-12.1	**9.8**	**1.9**	**7.2**
		Range	*(-8.5, 10.1)*	*(-15.2, 2.2)*	*(-23.1, -0.9)*	*(-3.6, 17.2)*	*(-9.3, 10.0)*	*(-6.6, 21.8)*
		R50	-3.1	-8.5	-11.9	**7.1**	-1.5	**4.5**
		Range	*(-11.4, 5.5)*	*(-16.8, -0.6)*	*(-24.1, -0.7)*	*(-5.1, 15.2)*	*(-12.2, 5.8)*	*(-10.6, 18.4)*
		R100	-7.7	-12.9	-16.5	**2.7**	-5.5	-1.6
		Range	*(-15.4, 0.4)*	*(-19.3, -4.9)*	*(-28.5, -5.2)*	*(-7.9, 11.1)*	*(-15.3, 0.9)*	*(-15.7, 11.4)*
	Far future	R10	**8.6**	-1.7	-3.7	**16.3**	**8.1**	**16.4**
		Range	*(-10.2, 22.3)*	*(-17.9, 13.3)*	*(-28.1, 8.4)*	*(-3.7, 36.0)*	*(-8.5, 22.5)*	*(-11.8, 35.2)*
		R50	**1.8**	-5.6	-6.5	**11.7**	**2.7**	**13.4**
		Range	*(-15.3, 12.4)*	*(-20.4, 7.6)*	*(-31.3, 2.0)*	*(-7.8, 30.2)*	*(-13.1, 15.3)*	*(-16.1, 29.6)*
		R100	-5.7	-9.9	-17.2	**5.6**	-3.6	**3.9**
		Range	*(-20.4, 4.0)*	*(-23.8, 0.4)*	*(-36.5, -6.5)*	*(-11.4, 22.2)*	*(-17.3, 7.5)*	*(-20.9, 17.1)*

Table S4-3. Simulated responses to cover crop (CC) relative to no cover crop (NC) in comparison with values found in previous studies.

Simulated values	Literature estimate	Literature type	Literature location	Literature source
Soil water storage on the day of sowing the next cash crop reduced by CC compared to NC (mm or %)				
- 25-51 mm	- 20-50 mm	Model	France	Meyer et al. (2020)
- 17-30 %	- 13-18 %	Meta	Global	Wang et al. (2021a), Garba et al. (2022)
SOC sequestration rate increased by CC compared to NC (0-30 cm, t C ha^{-1} $year^{-1}$)				
0.05-0.10 t	0.14 t (0-20 cm)	Experiment	Denmark	Jensen et al. (2021a)
	0.12 t (0-22 cm)	Meta and Model	Global	Poeplau and Don (2015)
Nitrogen leaching reduced by CC compared to NC (%)				
- 57-77 %	- 39-54 %	Model	Global	Porwollik et al. (2022)
	- 60%	Experiment	Denmark	Notaris et al. (2018)
	- 49-73 %	Experiment	Netherlands	Elhakeem et al. (2023)
	- 21-47 %	Model	New Zealand	Teixeira et al. (2021)
Nitrogen uptake in grain changed by CC compared to NC (%)				
-29 to +55 %	+16 %	Meta	Global	Abdalla et al. (2019)
+2 to +55 % for cereals	+2 to +41 % for cereals	Experiment	Europe	Rinnofner et al. (2008), Małecka and Blecharczyk (2008), Doltra and Olesen (2013)
Cash crop total nitrogen uptake changed by CC compared to NC (%)				
-26 to +60 %	+ 0-26 %	Experiment	United States	Adeyemi et al. (2020)
	+ 15-40 %	Experiment	Poland	Małecka and Blecharczyk (2008)

Table S4-4. The median values of sowing and harvesting DOY (the day of year) of cash crops changed from no cover crop to with cover crop. Positive values represent the delayed days caused by cover crops, and vice versa.

Scenario	Residue retention	Period	Changed DOY		Shortened days of crop growth
			Sowing	Harvesting	
SSP245	R10	Historical	+ 13	- 1	14
		Near future	+ 14	- 1	14
		Far future	+ 15	0	15
	R50	Historical	+ 13	- 1	14
		Near future	+ 13	- 1	14
		Far future	+ 14	0	14
	R100	Historical	+ 12	- 1	13
		Near future	+ 12	- 1	14
		Far future	+ 13	0	13
SSP585	R10	Historical	+ 13	- 1	14
		Near future	+ 14	0	14
		Far future	+ 17	+ 1	16
	R50	Historical	+ 13	- 1	14
		Near future	+ 13	0	14
		Far future	+ 16	0	16
	R100	Historical	+ 12	- 1	13
		Near future	+ 12	- 1	13
		Far future	+ 14	0	15

4.6.3 Supplementary figures

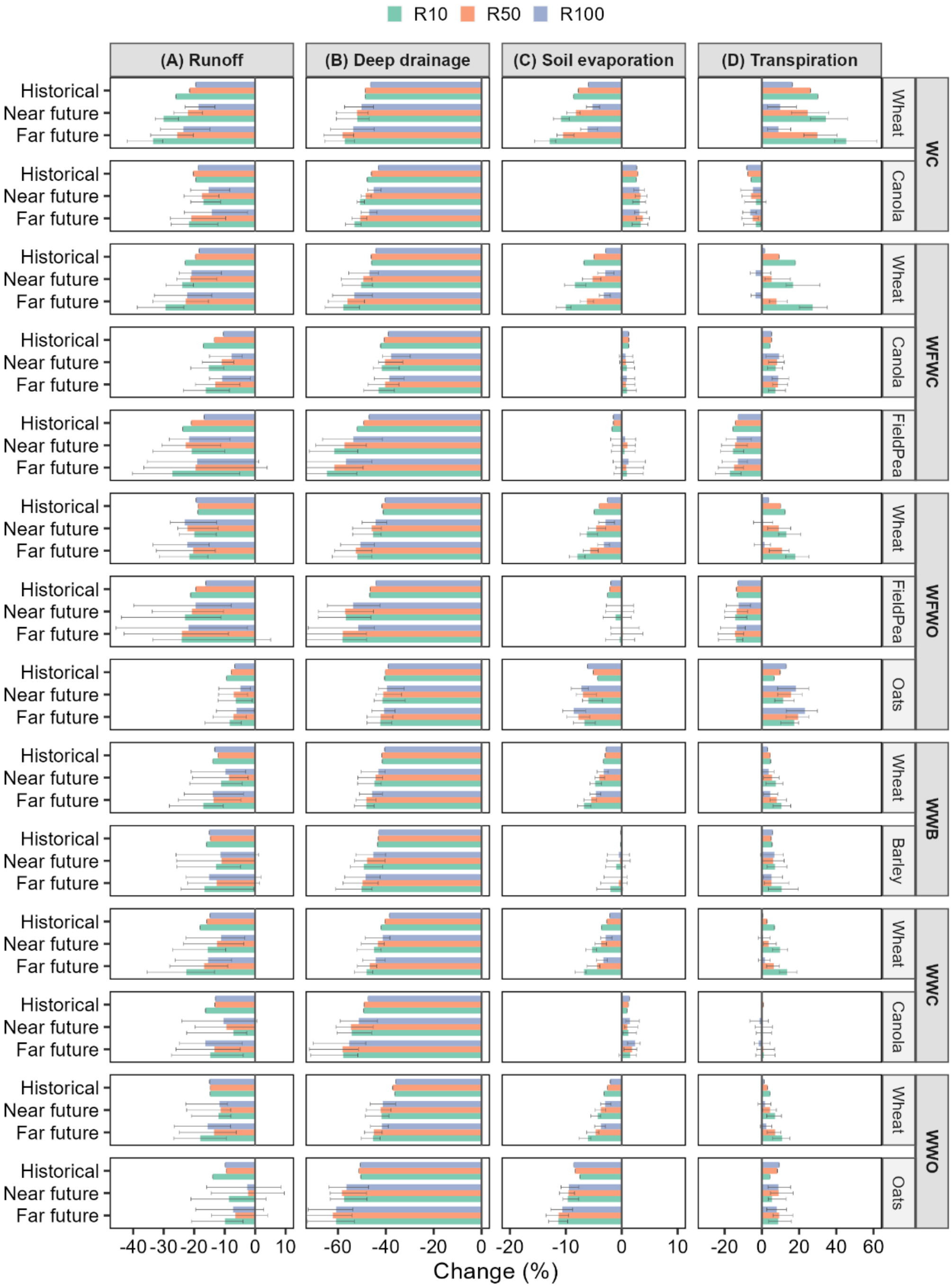

Fig. S4-2 The change (%) in simulated runoff (A), deep drainage (B), soil evaporation (C) and transpiration (D) with cover crop (CC) compared to no cover crop (NC) for each crop species in six rotations during three periods under SSP245. The bars represent the median values with 25th and 75th percentiles based on APSIM simulations using 27 GCMs.

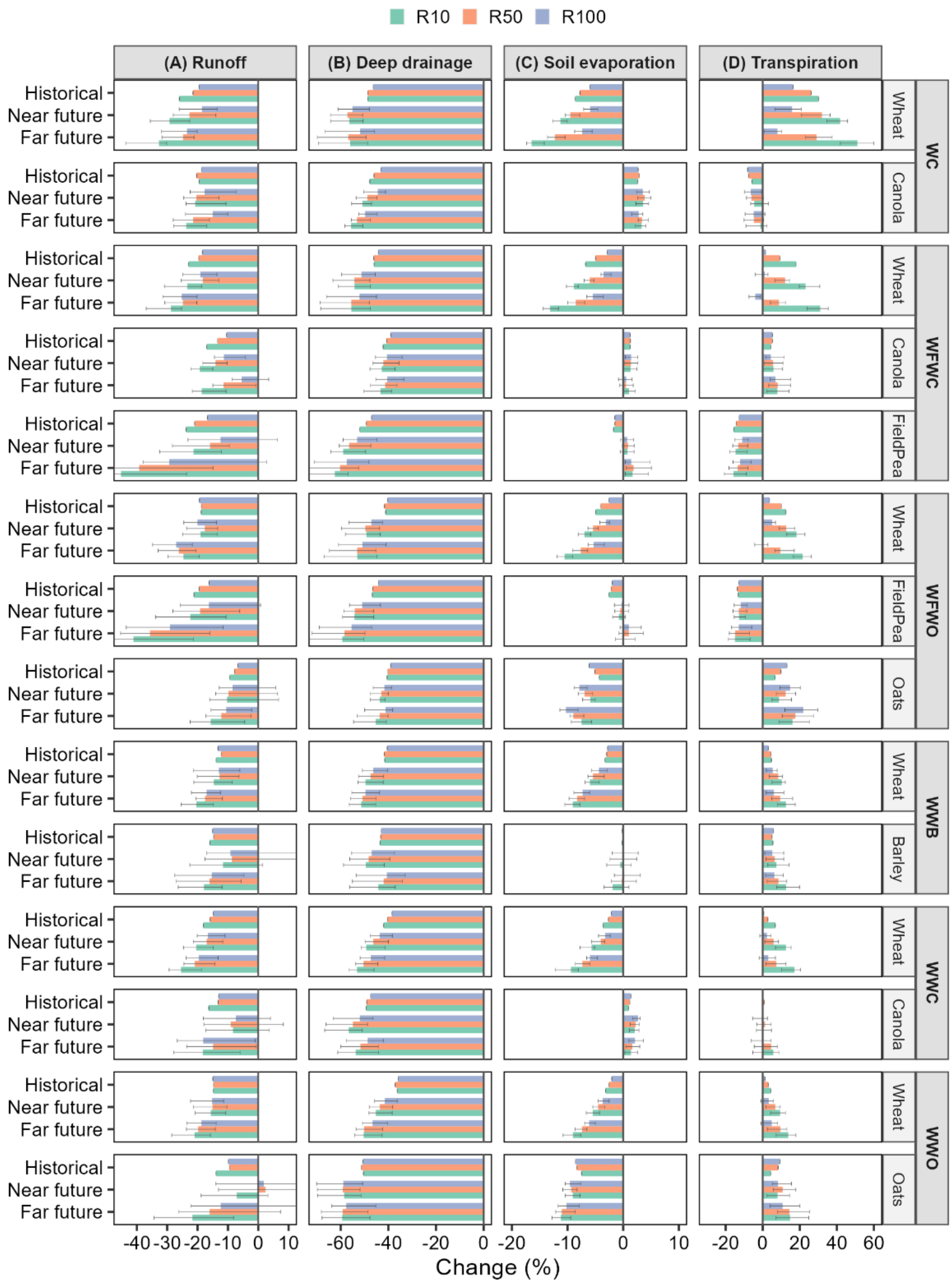

Fig. S4-3 The change (%) in simulated runoff (A), deep drainage (B), soil evaporation (C) and transpiration (D) with cover crop (CC) compared to no cover crop (NC) for each crop species in six rotations during three periods under SSP585. The bars represent the median values with 25th and 75th percentiles based on APSIM simulations using 27 GCMs.

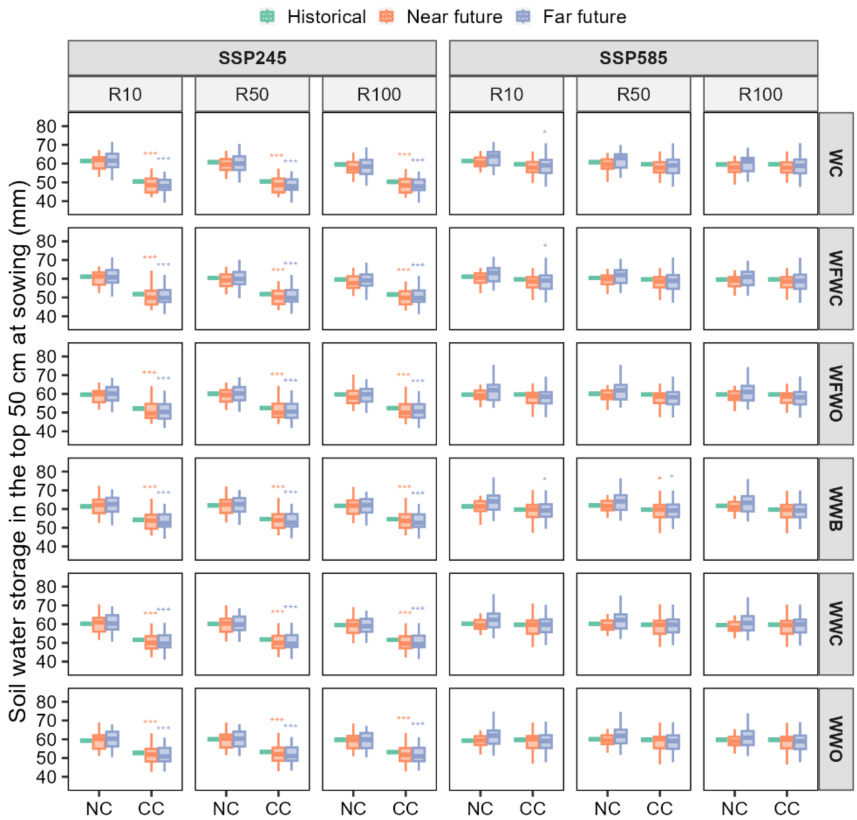

Fig. S4-4 Simulated soil water storage (0-50 cm) on the day of sowing the next cash crop with cover crop (CC) and without cover crop (NC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats) during three time periods (historical period: 1985-2020, near future: 2021-2056, and far future: 2057-2092) under SSP245 and SSP585. The boxplots for the historical period and future periods are based on the simulations with observed climate data and 27 GCMs, respectively. Asterisks represent significant differences between CC and NC for each treatment with 27 GCMs using paired t-test (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

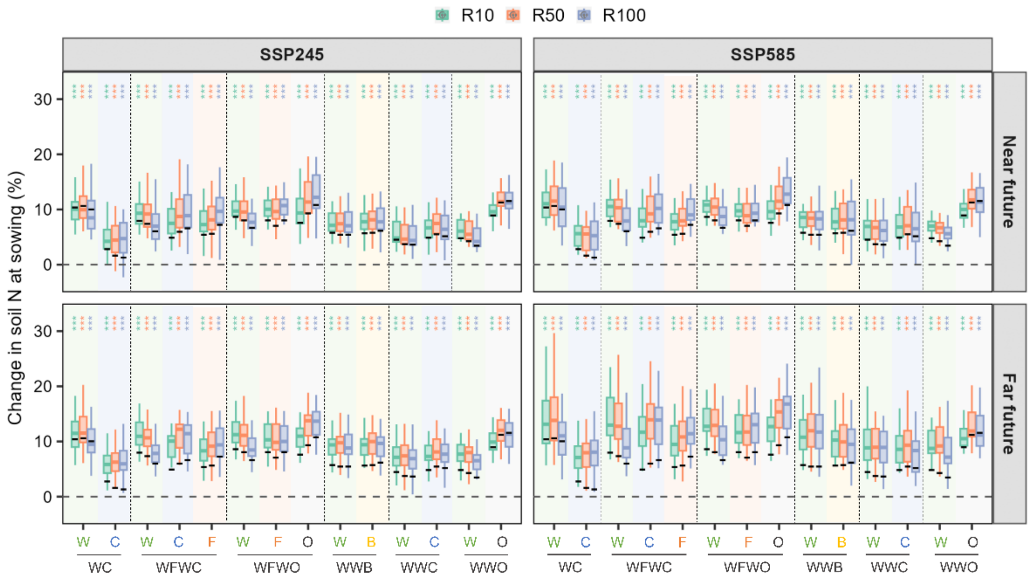

Fig. S4-5 The change (%) in simulated soil nitrogen content on the day of sowing the next cash crop with cover crop (CC) compared to without cover crop (NC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats). The black lines represent historical simulations based on observed climate data. The boxplots for two future periods are based on the simulations from 27 GCMs. Asterisks represent the significant differences between CC and NC for each treatment using paired t-test (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

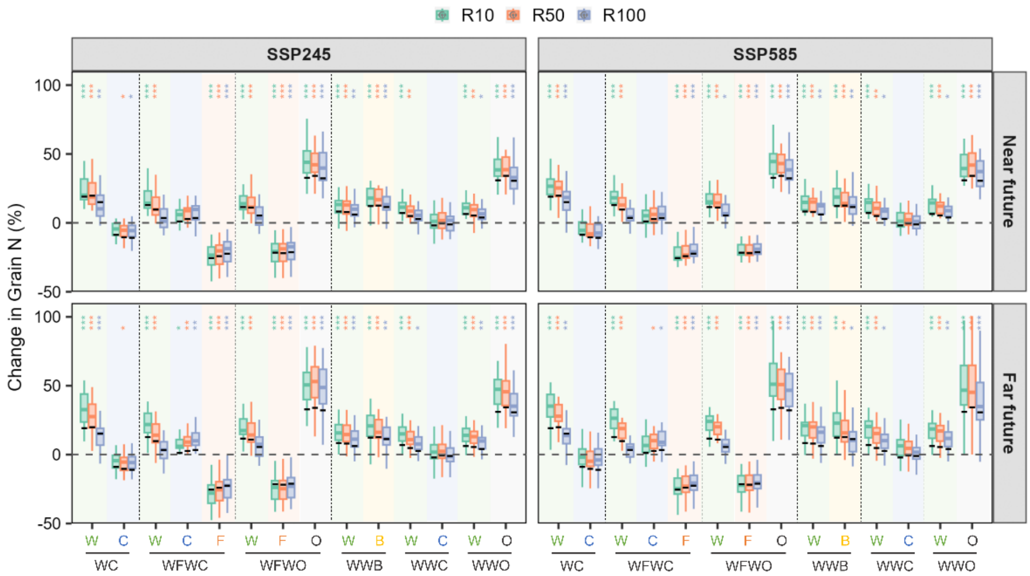

Fig. S4-6 The change (%) in simulated total grain N with cover crop (CC) compared to without cover crop (NC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats). The black lines represent historical simulations based on observed climate data. The boxplots for two future periods are based on the simulations from 27 GCMs. Asterisks represent the significant differences between CC and NC for each treatment using paired t-test (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

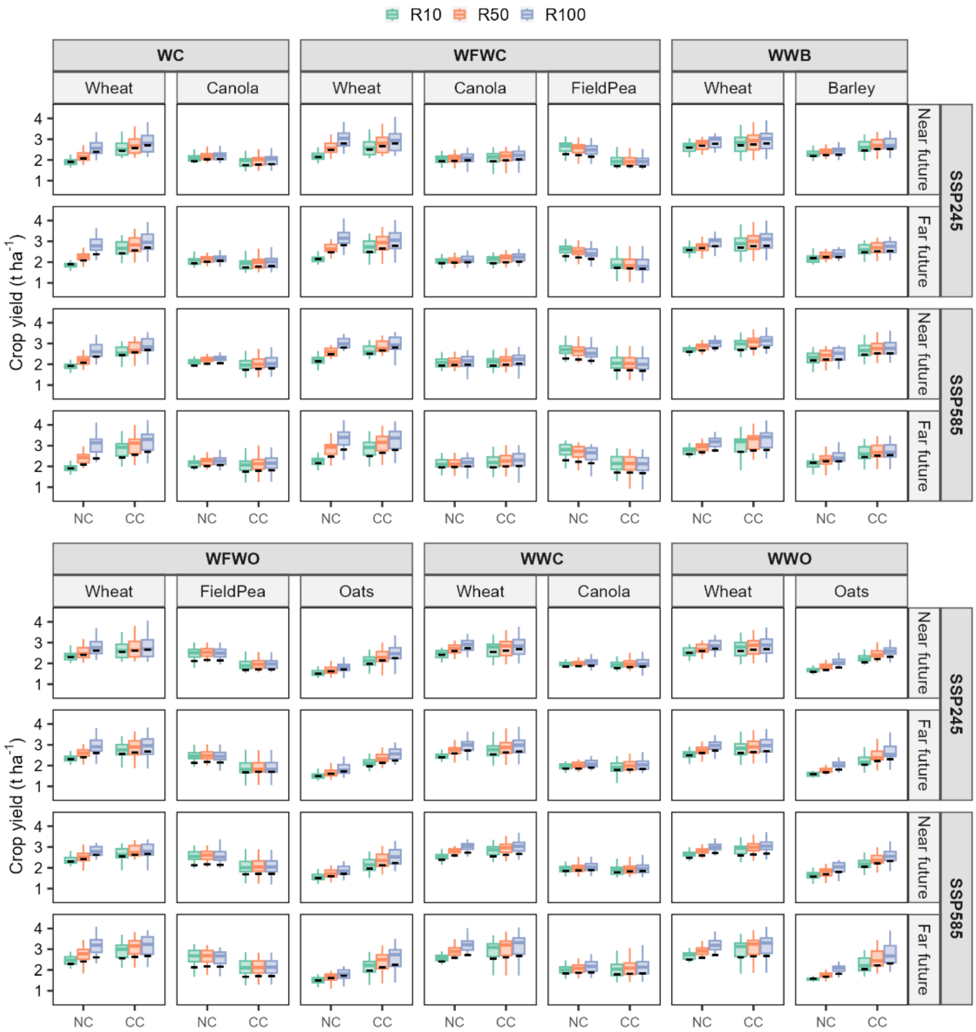

Fig. S4-7 Simulated crop yield with cover crop (CC) and without cover crop (NC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats). The black dashes represent historical simulations based on observed climate data. The boxplots are based on the simulations from 27 GCMs.

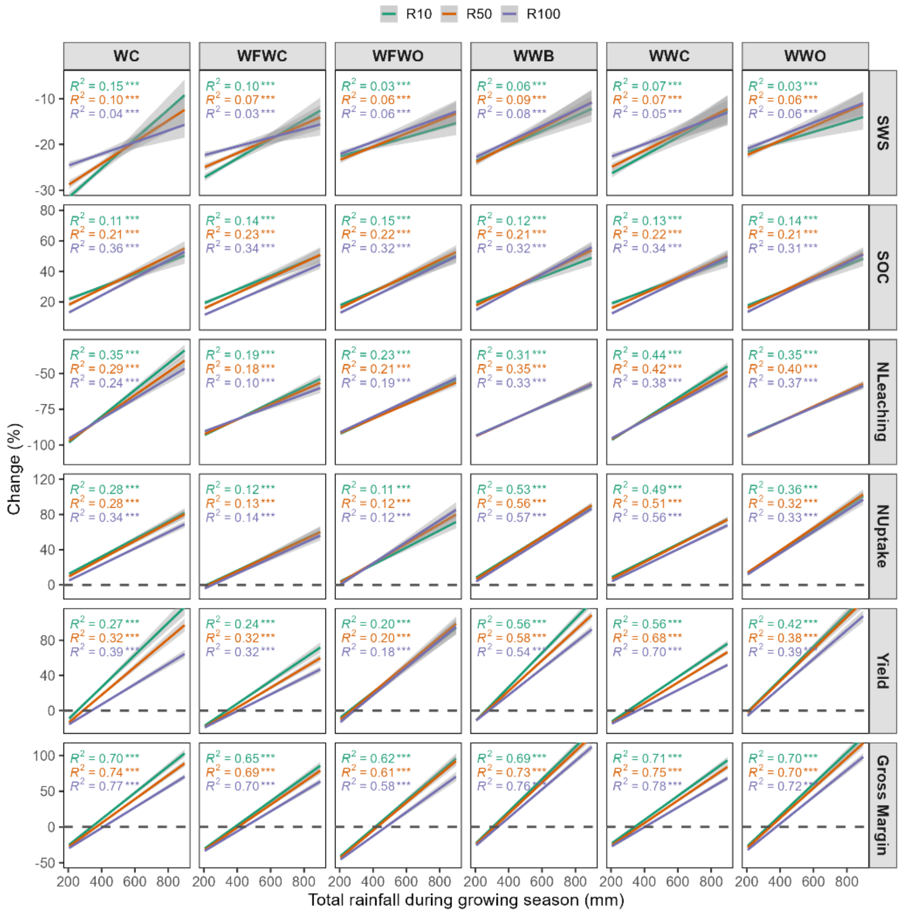

Fig. S4-8 The relationship between total rainfall during growing season (April to November) and change (%) induced by cover crop (CC) compared to no cover crop (NC) for simulated soil water storage on the day of sowing the next cash crop (SWS), soil organic carbon (SOC), N leaching (NLeaching), crop N uptake (NUptake), crop yield, and gross margin. Median values of changes (as shown in Fig. 4-3 to Fig. 4-8) and rainfall projected from 27 GCMs under SSP585 were averaged over three periods (1985-2020, 2021-2056, and 2057-2092). The linear regression with 95% confidence interval used simulations across 204 sites (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

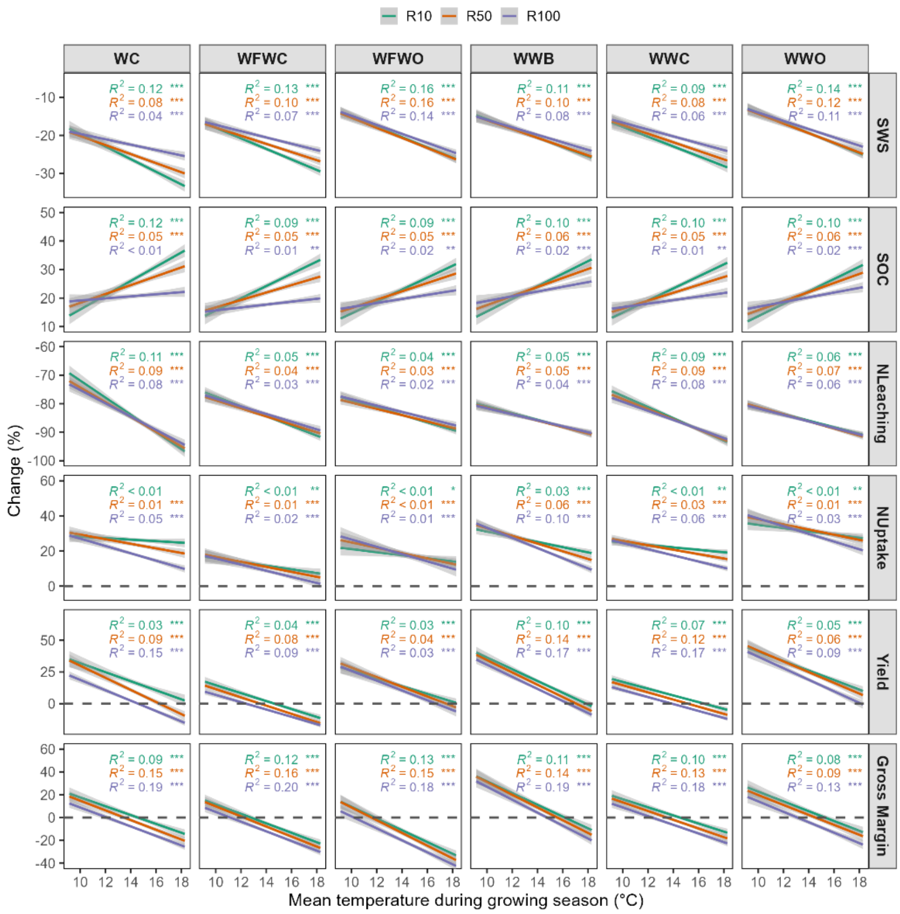

Fig. S4-9 The relationship between mean temperature during growing season (April to November) and change (%) induced by cover crop (CC) compared to no cover crop (NC) for simulated soil water storage on the day of sowing the next cash crop (SWS), soil organic carbon (SOC), N leaching (NLeaching), crop N uptake (NUptake), crop yield, and gross margin. Median values of changes (as shown in Fig. 4-3 to Fig. 4-8) and temperature projected from 27 GCMs under SSP585 were averaged over three periods (1985-2020, 2021-2056, and 2057-2092). The linear regression with 95% confidence interval used simulations across 204 sites (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

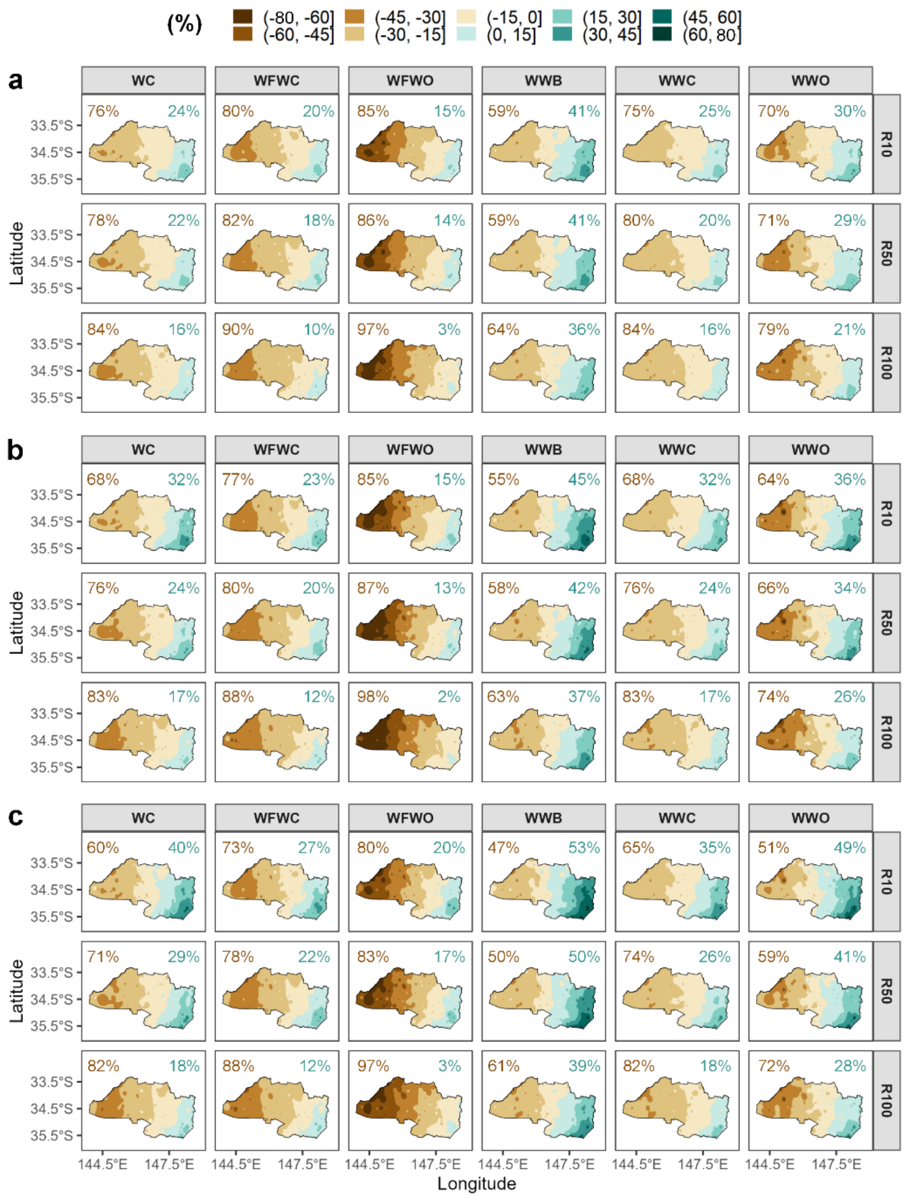

Fig. S4-10 Spatial pattern of gross margin change (%) from NC (no cover crop) to CC (with cover crop) during historical period (a), near future (b), and far future (c) under SSP245. The median values simulated by APSIM using 27 GCMs were interpolated with inverse distance weighting (IDW) method. The left and right labels represent the areas of negative and positive changes, respectively.

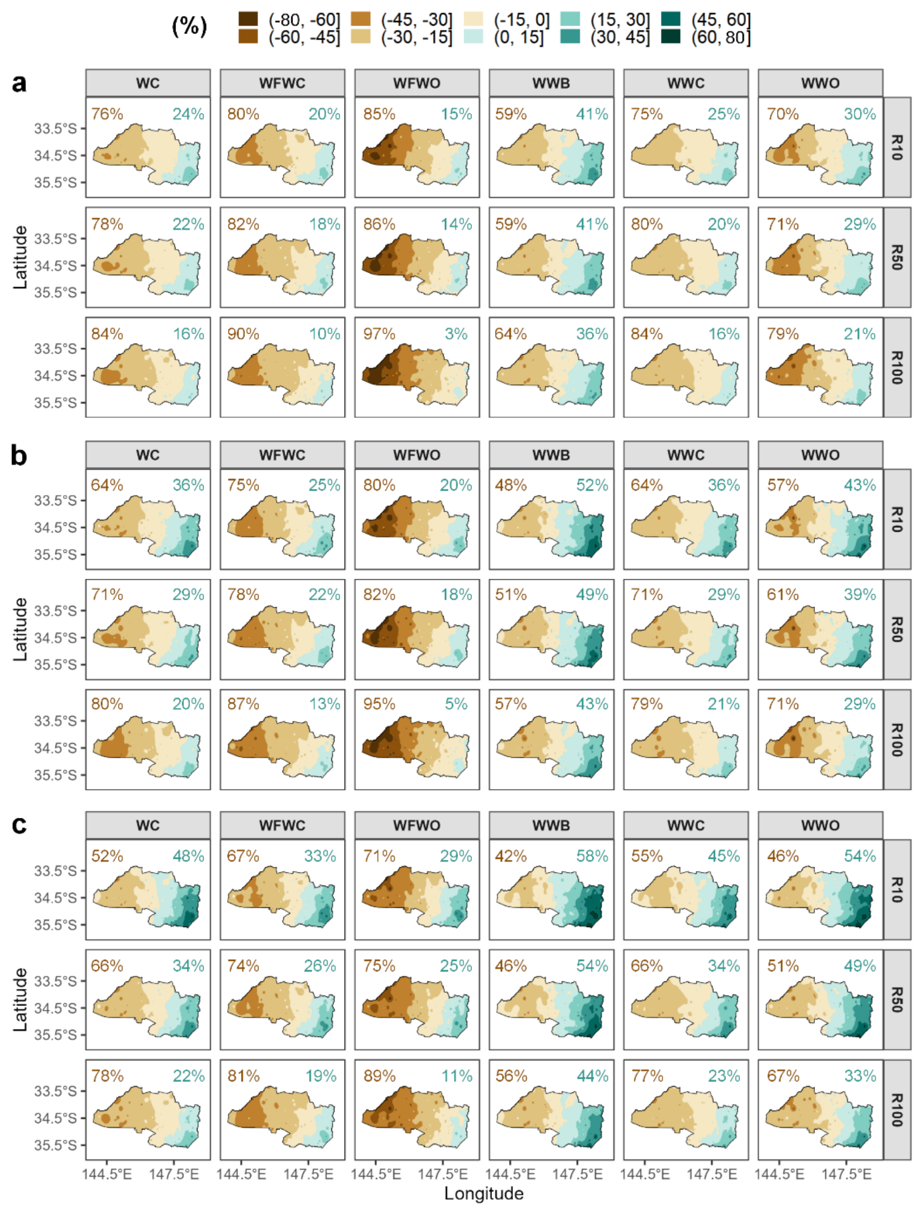

Fig. S4-11 Spatial pattern of gross margin change (%) from NC (no cover crop) to CC (with cover crop) during historical period (a), near future (b), and far future (c) under SSP585. The median values simulated by APSIM using 27 GCMs were interpolated with inverse distance weighting (IDW) method. The left and right labels represent the areas of negative and positive changes, respectively.

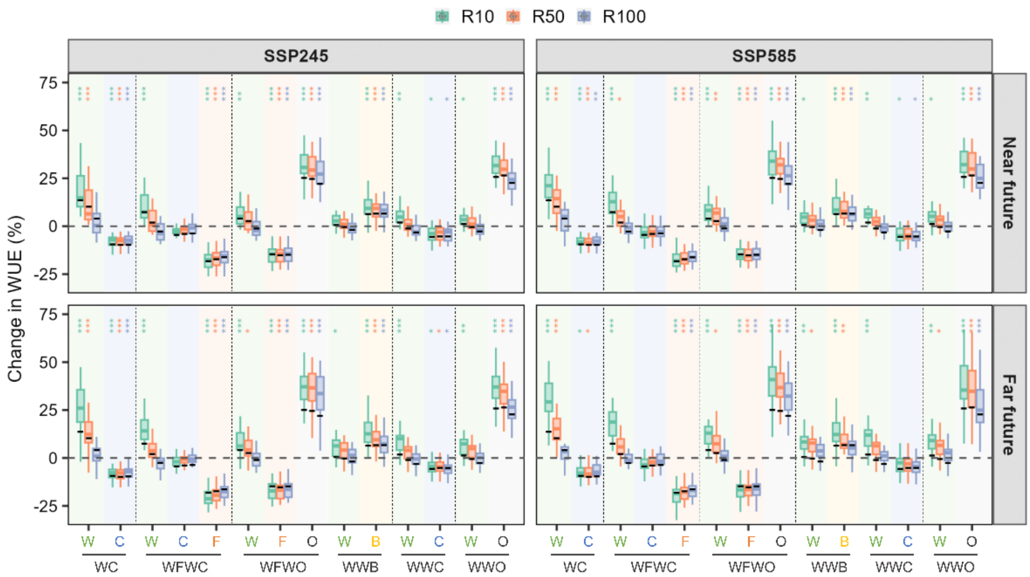

Fig. S4-12 The change (%) in simulated crop water use efficiency (the ratio of yield and evapotranspiration) with cover crop (CC) compared to no cover crop (NC) for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats). The black lines represent historical simulations based on observed climate data. The boxplots for two future periods are based on the simulations from 27 GCMs. Asterisks represent the significant differences between CC and NC for each treatment using paired t-test (*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$).

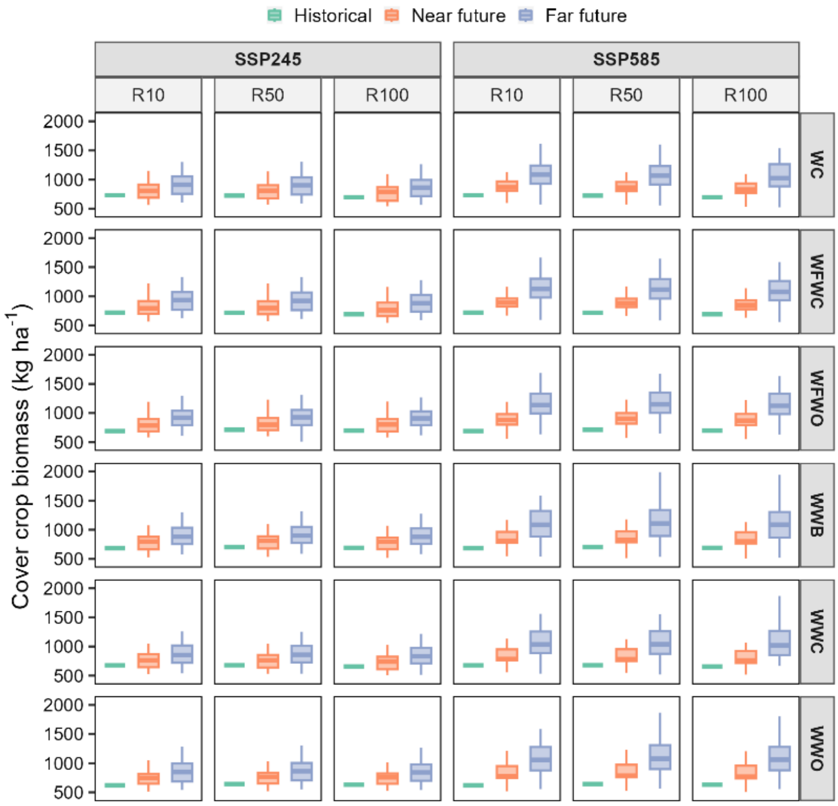

Fig. S4-13 Simulated cowpea cover crop biomass for three residue retention (R10: 10%, R50: 50%, and R100: 100%), and six rotations (WC: wheat-canola, WFWC: wheat-field pea-wheat-canola, WFWO: wheat-field pea-wheat-oats, WWB: wheat-wheat-barley, WWC: wheat-wheat-canola, and WWO: wheat-wheat-oats). The boxplots for the historical period and future periods are based on the simulations with observed climate data and 27 GCMs, respectively.

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Chapter 5. A food-energy-water-carbon nexus framework informs region-specific optimal strategies for agricultural sustainability

This chapter is based on the following manuscript:

Qinsi He, De Li Liu, Bin Wang, Zikui Wang, Annette Cowie, Aaron Simmons, Zhenci Xu, Linchao Li, Yu Shi, Ke Liu, Matthew Tom Harrison, Cathy Waters, Alfredo Huete, Qiang Yu. A food-energy-water-carbon nexus framework informs region-specific optimal strategies for agricultural sustainability. Resources, Conservation and Recycling, 203, 107428, 2024.

Highlights

- Conservation agriculture practices are assessed from a food-energy-water-carbon perspective.
- Cover cropping reduces greenhouse gas emissions but consumes more energy and water per hectare.
- Legume-inclusive rotations are generally more sustainable than other rotations.
- Residue retention with cover cropping is more sustainable in northern NSW.
- The nexus approach reveals region-specific optimal strategies to achieve agricultural sustainability.

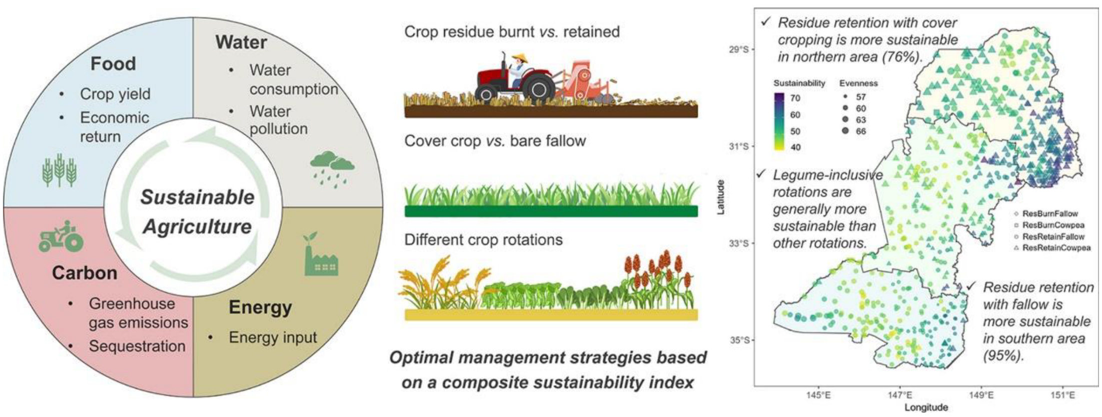
Abstract

Agricultural sustainability is threatened by pressures from water scarcity, energy crises, escalating greenhouse gas (GHG) emissions, and diminishing farm profitability. Practices that diversify crop rotations, retain crop residues, and incorporate cover crops have been widely studied for their impacts on soil organic carbon and crop production. However, their associated usage of natural resources and economic returns have been overlooked. Here, we employed a food-energy-water-carbon (FEWC) nexus framework to assess the sustainability of crop rotations plus various management strategies across three sub-regions of New South Wales (NSW) in Australia. We found that compared with residue burning and fallowing, residue retention and cover

cropping contributed to GHG abatement, but the latter consumed more energy and water per hectare. The composite sustainability scores, calculated with the FEWC framework, suggested that legume-inclusive rotations were generally more sustainable. Furthermore, in northern NSW (with existing sorghum/wheat/chickpea/wheat rotation), residue retention with cover cropping was the most suitable combination, while the use of residue retention with fallow yielded greater benefits in southern NSW (with existing wheat/field pea/wheat/canola rotation). Regional disparities in climate, soil, cropping systems, and on-farm costs prompted region-specific strategies to address the unbalanced distribution among FEWC domains. Our study provides assessments for identifying feasible management practices to advance agricultural sustainability.

Key words: Food-energy-water-carbon nexus, Greenhouse gas emissions, Resource consumption, Soil carbon, Profitability

Graphical abstract



5.1 Introduction

Meeting the mounting demands for nutritious food, amidst a growing population, degrading soil, and changing climate, poses an unprecedented challenge for global food systems (Xie et al., 2023). Yet the promotion of input-intensive agriculture to boost crop growth has led to serious compromises for natural resources and the environment (Gu et al., 2023; Pellegrini and Fernández, 2018). Major threats, such as the water scarcity, energy crisis, global warming, and their likely linked social, economic and political consequences, underscore the need to shift towards more sustainable agriculture (Chaudhary et al., 2018; Gustafson et al., 2021). The United Nations, therefore, explicitly included sustainable agriculture as one of the Sustainable Development Goals (SDGs) in 2015, especially as SDG 2.4.1: "*Proportion of agricultural area under productive and sustainable agriculture practices*". Moving forward, although the SDGs are globally applicable, their achievement requires specific measures customized to local conditions (Chaudhary et al., 2018).

Notwithstanding the fact that effects of climate cannot be influenced by landholders, long-term sustainability can be shaped by management and land stewardship (Muleke et al., 2022). Sustainable intensification (SI) has been proposed as a framework focusing on increasing yields with fewer inputs and without cropland expansion (Muleke et al., 2023; Pretty, 2008); climate-smart agriculture (CSA) is often put forward as an integrated approach for securing productivity under climate change and curbing greenhouse gas (GHG) emissions (Lipper et al., 2014). Both concepts are closely linked, and are aligned with conservation agriculture (CA) – an operational strategy that aims to sustain crop production while also building the health of the agroecosystem (Hobbs, 2007; Prestele et al., 2018). Practices applied under CA include zero or reduced tillage (Nouri et al., 2021), crop rotation (Gao et al., 2022; Hochman et al., 2021), residue return (Liu et al., 2023), cover crops (Quemada et al., 2020), biochar application (Huang et al., 2023), and nitrogen management (Parihar et al., 2022). Adoption of CA to improve sustainability of crop production has implications for water (SDG 6), energy (SDG 7) and climate change (SDG 13), due to the deep interconnections between these domains. Specifically, water is essential for plant growth and must be supplied through rainfall or irrigation; energy is required in the whole process of crop production including mechanical operations, fertilization and irrigation (Pellegrini and Fernández, 2018); and crop products can be converted into energy resources (Xing et al., 2022). Meanwhile, all these processes are associated with GHG emissions (Sándor et al., 2020; Zou et al., 2022). Few studies, however, have undertaken a holistic assessment of the impacts of CA practices on food, energy, water and GHG emissions on a regional scale to provide comprehensive solutions to inform landscape-scale resource management. Indeed, transdisciplinary work focusing on systems has shown that prospective adaptations differ much when multiple objectives are factored in (Bilotto et al., 2023).

The nexus approach has been developed to address cross-sectoral integration for simultaneously achieving multiple SDGs (Liu et al., 2018). Recent applications in the natural resource realm have explored the food-energy-water nexus with the addition of issues like GHG emissions in the context of carbon neutrality (He et al., 2022a; Saray et al., 2022; Yadav et al., 2021; Yoon et al., 2022; Zhu et al., 2023). The focus of these studies is on simple cropping systems. Comparatively, nexus research on multiple rotational systems with various management practices lags behind. Moreover, heterogeneity in environmental conditions and economic considerations have seldom been taken into account, despite calls to tailor management strategies based on region-specific context (Amelung et al., 2020; Prestele and Verburg, 2020).

Australia holds a prominent position on the global stage as a major exporter of agricultural products, but its production systems are associated with high levels of GHG emissions, water extractions and habitat loss (Hatfield-Dodds et al., 2015). There is an increasing interest in CA practices due to industry and government policies aimed at motivating Australia's farmers to improve sustainability (ABARES, 2023a). Australia is one of the world leaders in the adoption of zero/reduced tillage (ABARES, 2023b), and efforts are being made to promote residue return, diversifying crop rotations, and incorporating cover crops for soil carbon sequestration to support the national net-zero GHG emissions target for 2050 (Feron et al., 2022). Furthermore, adoption of CA practices will support climate change adaptation, which is particularly crucial as Australian agriculture is uniquely vulnerable to climate change (Phelan et al., 2015; Wood et al., 2021). Reaping the win-win between sustained crop yields and emission abatement where and when possible using CA practices is laudable (He et al., 2022b). However, water and energy consumption are also influenced by these practices, but often tend to be overlooked (Li et al., 2019; Zhang et al., 2022). Here, our aim is to fill gaps in the research linking economics (i.e., crop production and farm income), environment (i.e., GHG emissions), and resource use (i.e., energy and water) in Australian cropping systems.

In this study, we defined sustainable farming systems from a food-energy-water-carbon nexus perspective as a system that allows for minimal resource consumption and environmental costs while maintaining food production and ensuring adequate income. We seek to investigate the following three questions: (1) How do food production and profitability, energy, water and carbon footprints change under different management practices? (2) How sustainable are these farming systems based on a composite food-energy-water-carbon index? (3) What are the differences in sustainability performance across different sub-regions? To answer the above questions, a footprint method based on a set of data from relevant literature was developed to evaluate the energy footprint (EF), water footprint (WF) and carbon footprint (CF) from the production of crops in different rotations under multiple scenarios. To accurately reflect the footprint dynamics, a biophysical process-based model called APSIM, was used to provide data related to crop growth and soil processes. We aimed to examine farming practices based on local realities and provide a preliminary evaluation to support decision-makers to manage cropland in a more sustainable way.

5.2 Materials and methods

5.2.1 Study area

The study area is located in the state of New South Wales (NSW) in south-eastern Australia, covering three adjacent Local Land Services (LLS) regions: North West, Central West, and Riverina (Fig. 5-1). LLS is a regional-focused NSW Government agency, which aims to deliver quality customer services for agricultural production and natural resource management relevant to local needs (https://www.lls.nsw.gov.au/). These three LLS regions were selected as they are main NSW cropping zones, and provide a profile of diverse agricultural operations (Wang et al., 2022a). The pattern of rainfall shifts from summer-dominant rainfall in the north to more even rainfall distribution in the south, and transitions from high rainfall in the east to low rainfall in the west (Table S5-2). Agriculture is an important enterprise in these three LLS regions, with cropping systems occupying 26%, 23%, and 50% of the land area for North West, Central West, and Riverina, respectively (NSW, 2018). These LLS regions accounted for about half of NSW total gross value of agricultural production (DPI, 2020), making it an important area for the study of suitable crop management options in the context of sustainable agriculture.

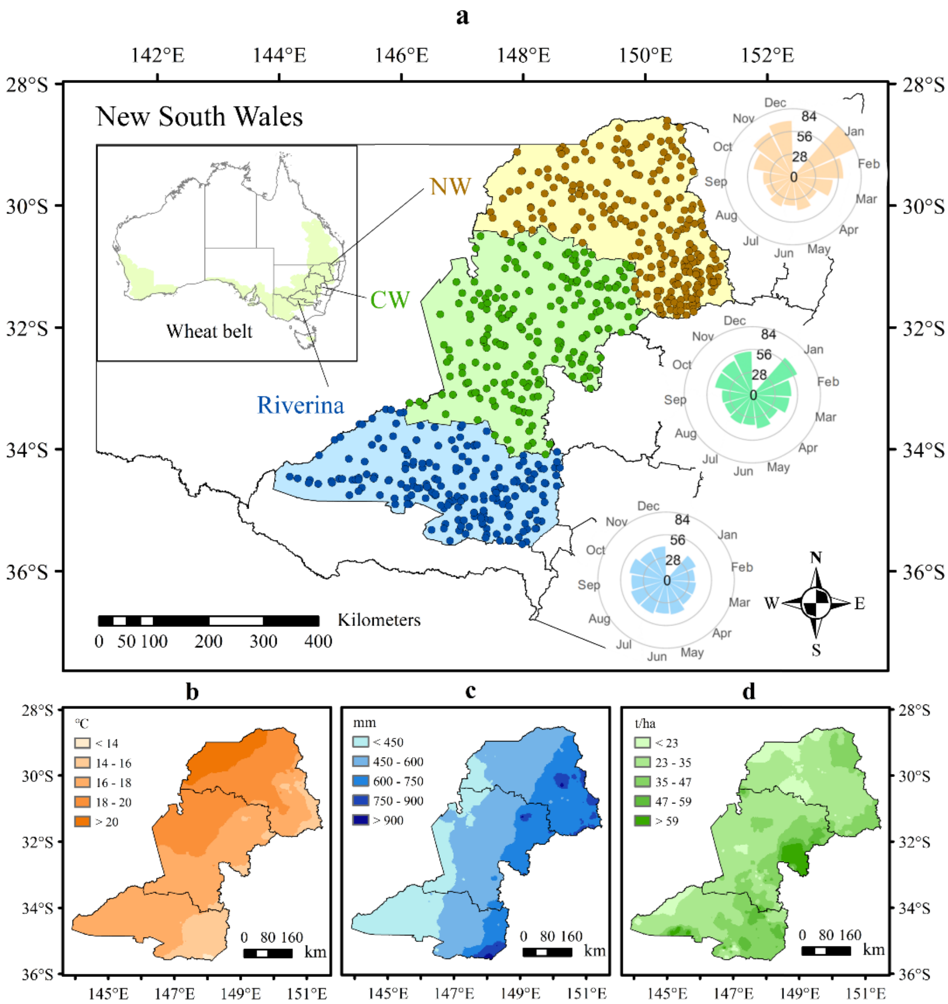


Fig. 5-1. (a) Locations of three regions and the study sites of each region; (b-c) annual mean temperature and rainfall during 1961-2020; (d) initial soil organic carbon stock in topsoil 0-30 cm before scenario set in the APSIM model. The monthly average rainfall of each region is shown as radial charts in (a).

5.2.2 Scenarios

From discussions with farmer groups and research staff, several crop rotations reflecting local farming practices were selected for the three regions, in which winter cereals (wheat, barley, and oats) were rotated with summer cereal (sorghum), and/or oilseed crop (canola), and/or pulse crops (chickpea and field pea) (Table 5-1). These rotations are representative of the cropping sequences used in each region. For each rotation, the following four scenarios were modelled to investigate the effects of residue retention and cover cropping on farming systems:

1 ResBurnFallow – cash crop residues were burnt after harvest, followed by a fallow period before the sowing of cash crop in the next year.
2 ResBurnCowpea – cash crop residues were burnt after harvest, followed by a cowpea cover crop before the sowing of cash crop in the next year.
3 ResRetainFallow – cash crop residues were fully retained in field, followed by a fallow period before the sowing of cash crop in the next year.
4 ResRetainCowpea – cash crop residues were fully retained in field, followed by a cowpea cover crop before the sowing of cash crop in the next year.

Table 5-1. Crop rotations selected for each region.

Region	Rotation	Year1	Year2	Year3	Year4	Year5
North West	WWB	Wheat	Wheat	Barley	…[1]	…
	SWW	Sorghum	#[2]	Wheat	Wheat	…
	SWKW	Sorghum	#	Wheat	Chickpea	Wheat
Central West	WWB	Wheat	Wheat	Barley	…	…
	WWO	Wheat	Wheat	Oats	…	…
	WC	Wheat	Canola	Wheat	Canola	…
	WWC	Wheat	Wheat	Canola	…	…
	WFWC	Wheat	Field pea	Wheat	Canola	…
	WKWC	Wheat	Chickpea	Wheat	Canola	…
Riverina	WWB	Wheat	Wheat	Barley	…	…
	WWO	Wheat	Wheat	Oats	…	…
	WC	Wheat	Canola	Wheat	Canola	…
	WWC	Wheat	Wheat	Canola	…	…
	WFWC	Wheat	Field pea	Wheat	Canola	…
	WFWO	Wheat	Field pea	Wheat	Oats	…

[1]Start of subsequent rotation cycle same as the first.

[2]In the North West, no crop is sown in the first year after sorghum because soil moisture is depleted, and growing season rainfall may be insufficient to sustain winter crops (Serafin et al., 2019b).

Therefore, a total of 245 (sites) × 3 (rotations) × 4 (scenarios) = 2940 cases for North West, 199 × 6 × 4 = 4776 cases for Central West, and 204 × 6 × 4 = 4896 cases for Riverina, were investigated from 1961 to 2020 using annual climate data at each site in this study.

5.2.3 Evaluation indicators

The evaluation framework is shown in Fig. 5-2. Site-level carbon footprint, energy footprint, water footprint, and economic value of each scenario were calculated. Considering the uneven spatial distribution of sites, all average values of each region were calculated by inverse distance weighted average method. Specific APSIM modelling processes are presented in Supplemental Information.

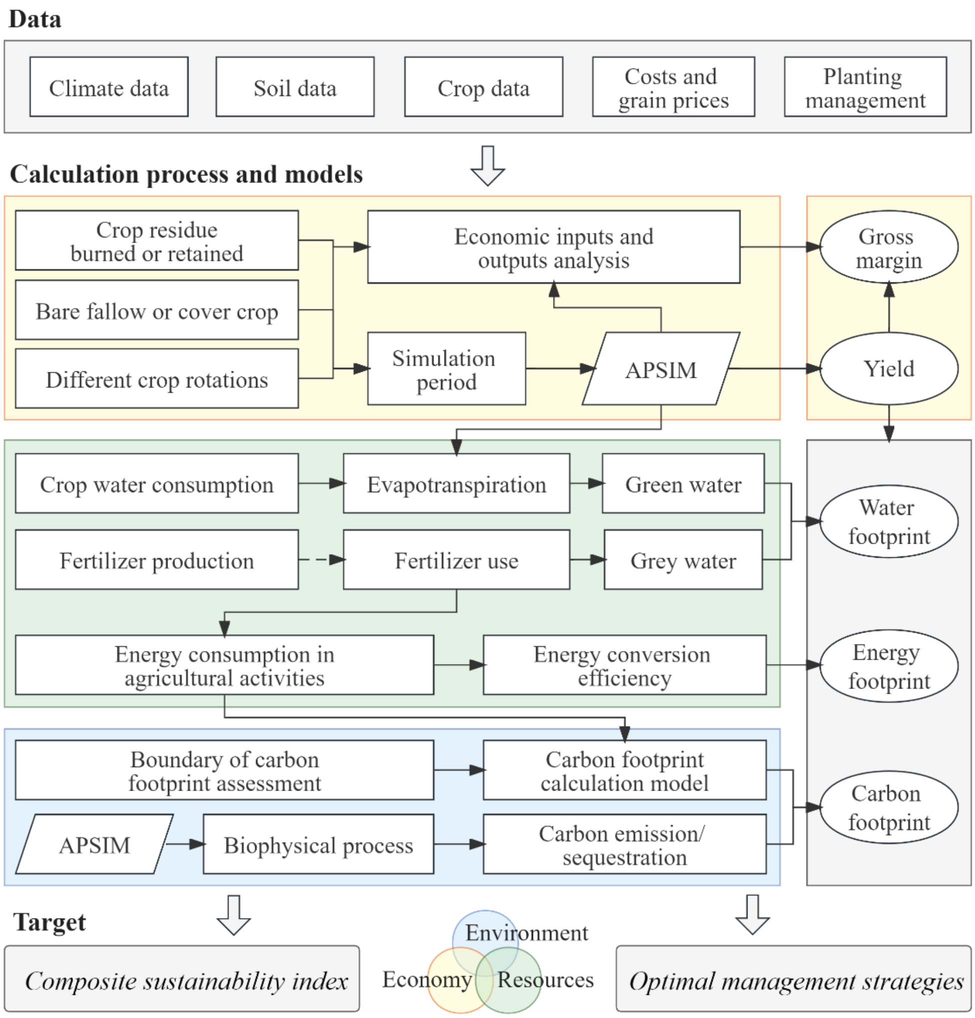


Fig. 5-2. Framework for sustainability evaluation based on resource consumption, environmental impact, and food economic benefit.

(I) Carbon footprint

The GHG emissions associated with tractor use for on-farm operations were calculated using data and assumptions from (Simmons et al., 2020; 2019). Emissions from diesel used for sowing, spraying, spreading, tilling, harvesting and grain collection were calculated by multiplying fuels use by the relevant emission factors. Lime was applied once every 10 years, so its emission was averaged over a 10-year period. Where GHG emissions were dependent on dynamic biophysical processes, the outputs from APSIM were used. For example, we used the amount of N leaching simulated by APSIM multiplied with the emission factor from NIR (2020) to estimate N_2O emission from N leaching, as described in our earlier work (He et al., 2022b). In addition, the annual SOC changes simulated from APSIM can be positive or negative, which indicate that the soil is a net sink or source of atmospheric CO_2, respectively. The details of emission calculations are shown in Fig. S5-1. Finally, total GHG emissions were estimated by converting specific emissions of CO_2, N_2O, and CH_4 to CO_2-eq by multiplying the estimated values with their respective 100-year global warming potential (GWP) factors (IPCC, 2014):

$$GHG = 265 \times [N_2O] + 28 \times [CH_4] + 1 \times [CO_2] - \frac{44}{12} \times \Delta SOC_{d30} \quad (5\text{-}1)$$

where $[N_2O]$, $[CH_4]$ and $[CO_2]$ represent the amounts of flux in kg mass ha^{-1} yr^{-1}; ΔSOC_{d30} is SOC change in 30 cm topsoil (kg C ha^{-1} yr^{-1}); -44/12 is the factor to convert the ΔSOC_{d30} to CO_2 emissions (kg CO_2-eq ha^{-1} yr^{-1}). The GWP conversion factors for CO_2, N_2O and CH_4 are 1, 265 and 28, respectively.

The carbon footprint (CF) was estimated based on the boundary established at the field level. Upstream emissions such as emissions from fertilizer manufacture, are excluded as the focus of the study was on-farm emissions. Calculations of the CF for various rotation systems were made based on the annual emissions and corresponding crop yields, which were used to evaluate the GHG emitted per unit of grain produced (Yadav et al., 2021):

$$CF_j = \frac{\sum_{i=1}^{n} GHG_{i,j}}{Yield_j} \quad (5\text{-}2)$$

where $GHG_{i,j}$ $(i = 1, 2, \dots, 10)$ represent the total GHG emissions (kg CO_2-eq ha^{-1} yr^{-1}) from different agricultural activities and biophysical processes of the year j (Table S5-3); $Yield_j$ $(j = 1, 2, \dots, 60)$ is the crop yield in t ha^{-1} from 1961 to 2020.

(II) Energy footprint

The material input in the above-mentioned crop production process is not only accompanied by GHG emissions, but also energy inputs (He et al., 2022a). These energy inputs were computed by multiplying the quantity of inputs with their respective energy equivalent coefficients, as reported in several studies (Table S5-3 and Table S5-4). Then, the energy footprint (EF) was calculated as follows (Jiang et al., 2022):

$$EF_j = \frac{\sum_{i=1}^{n} EI_{i,j}}{Yield_j} \tag{5-3}$$

where $EI_{i,j}$ $(i = 1, 2, \dots, 9)$ are the energy inputs (MJ ha^{-1} yr^{-1}) for crop seeds, nitrogen fertilizer and lime application, and diesel used for sowing, spraying, spreading, tilling, harvesting and grain collection of the year j.

(III) Water footprint

The water footprint (WF) introduced by Hoekstra et al. (2011) is expressed as the water consumption (green and blue water) and the degree of pollution (grey water) per unit of product. In the case of rain-fed crops, blue water use is zero, and green water use is calculated by summing the daily values of actual evapotranspiration (ET) over the length of the growing period (Mekonnen and Hoekstra, 2011). Because the cover crop consumed water during the fallow period, the ET of cover crop and soil evaporation (E) of fallow were also considered for the comparison between scenarios. Therefore, the water consumption of the whole year was taken into the WF calculation:

$$WF_j = WF_{Green,j} + WF_{Grey,j} \tag{5-4}$$

$$WF_{Green,j} = \frac{10 \times \sum_{i=1}^{n} ET_{i,j}}{Yield_j} \tag{5-5}$$

$$WF_{Grey,j} = \frac{(\alpha \times AR_j)/(C_{max} - C_{nat})}{Yield_j} \tag{5-6}$$

where $ET_{i,j}$ $(i = 1, 2, 3)$ are the water used by cash crop, cover crop, and fallow (mm, modelled by APSIM), 10 is the factor that converts water depth (mm) into water volume per unit area (m^3 ha^{-1}); α is the percentage of nitrogen fertilizer lost through leaching, and AR_j is the application rate of nitrogen fertilizer of the year j. We used the nitrogen leaching modelled by APSIM instead of a constant ratio to represent the dynamic nitrogen loss in this study. C_{max} is the allowable maximum level of nitrogen in fresh water, following the standard of 10 mg L^{-1} of nitrate-nitrogen in Australia (https://www.dcceew.gov.au/environment/); C_{nat} is the natural level of nitrogen in water bodies, which was assumed to be zero in Australia (Hossain et al., 2021).

(IV) Gross margin

The economic analysis was performed by multiplying the crop price by its yield, less the variable costs associated with growing the crop, to give a gross margin (GM), which can be used to represent the profitability of food production. Input costs and grain prices were obtained from NSW Department of Primary Industries across the three regions (Table S5-5). The calculation was similar to He et al. (2023):

$$GM_j = (GI_j - \sum_{i=1}^{n} CO_{i,j}) \times (1 - L) \tag{5-7}$$

where GI_j is the grain income (AU\$ t^{-1}) of the year j; $CO_{i,j}$ $(i = 1, 2, \ldots, 6)$ are the costs for cultivation, sowing, pest control, harvest, tilling, and fertilizer; additional cowpea costs are also considered under cover cropping scenarios; and L is the government levy that funds research and development, assumed to be 1.02%.

5.2.4 Agricultural sustainability assessment framework

To assess the four domains – food production profitability (that is gross margin in this study), energy footprint, water footprint, and carbon footprint – hereafter referred as food-energy-water-carbon (FEWC), we computed a composite sustainability index based on the FEWC nexus framework as developed in recent studies (Hua et al., 2020; Jiang et al., 2022; Nhamo et al., 2020; Simpson et al., 2022), following steps below:

(1) Normalization. For the comparison between these indicators measured in different units, their values were first normalized to transform them into a uniform scale from 0 to 100. Because a lower value of footprint is better, but a higher value of

gross margin is more favourable, two min-max methods were utilized for the normalization of footprint and profitability indicators, respectively:

$$S_{EWC} = \frac{S_{max} - S_i}{S_{max} - S_{min}} \tag{5-8}$$

$$S_F = \frac{S_i - S_{min}}{S_{max} - S_{min}} \tag{5-9}$$

where S_{EWC} and S_F are the normalized values of energy, water, carbon, and food, respectively. S_{max} and S_{min} are the maximum and minimum values of each indicator. Thus, the higher values of S represent higher sustainability.

(2) Aggregation. The sustainability score was then calculated using the arithmetic average of the four normalized indicators. Equal weighting was used such that each domains has equal importance:

$$S_{FEWC} = (S_F + S_E + S_W + S_C)/4 \tag{5-10}$$

where S_{FEWC} is the composite sustainability index ranged from 0 to 100.

(3) Evenness. Given that uneven FEWC indicators may lead to the same composite sustainability value, an improved radar chart method (from polygon to sector radar) was used to assess the evenness score from the four normalized indicators (eq.8 and eq.9) following Liu et al. (2020):

$$ES = \frac{A_i}{\pi \times (L_i/2\pi)^2} \times 100 \tag{5-11}$$

$$A_i = \sum_{i=1}^{n} \pi w_i r_i^2 \tag{5-12}$$

$$L_i = 2(r_{i,max} - r_{i,min}) + \sum_{i=1}^{n} 2\pi w_i r_i \tag{5-13}$$

where ES is the evenness score, which refers to the ratio between the total area A_i ($i = 1, 2, 3, 4$) of the radar chart formed by four indicators and the area of a circle with the same perimeter L_i (the evenest distribution of the four indicators). ES ranges from 0 to 100, and decreases as unevenness among four indicators increases. w_i represents the weight, and is 1/4 for each indicator in this study. r_i represents the value of each indicator which was used as the radius. The doubled value of the difference between r_{max} and r_{min} represents the part of the perimeter other than the total length of all arcs formed by $2\pi w_i r_i$, as detailed described in Wang et al. (2022b).

5.3 Results

5.3.1 Greenhous gas emissions and energy & water consumption per unit area

For all three regions, only ResRetainCowpea achieved negative emissions of 199-487 kg CO_2-eq ha^{-1} yr^{-1} (North West), 232-367 kg CO_2-eq ha^{-1} yr^{-1} (Central West), and 180-296 kg CO_2-eq ha^{-1} yr^{-1} (Riverina) across various rotations, in which the increases in SOC offset the emissions mainly from N_2O and liming (Fig. 5-3a, d, g). This contrasted with the scenario of ResBurnFallow where residues were burnt, emitting a large amount of non-CO_2 GHG (N_2O and CH_4), and SOC decreased substantially, leading to total emissions of 836-966 CO_2-eq ha^{-1} yr^{-1} (North West), 905-982 CO_2-eq ha^{-1} yr^{-1} (Central West), and 848-919 CO_2-eq ha^{-1} yr^{-1} (Riverina) across various rotations. Additionally, residue retained with no cover crop (ResRetainFallow) produced low or zero GHG emissions, but cover cropping with residue burned (ResBurnCowpea) still generated high GHG emissions almost without SOC change.

The total energy inputs were mainly contributed by nitrogen fertilizer, contributing 56-78% (North West), 58-76% (Central West), and 54-78% (Riverina) across all rotations and scenarios (Fig. 5-3b, e, h). The second contributor was the seed, with 7-20% (North West), 7-19% (Central West), and 6-22% (Riverina), in which seed inputs of cover cropping scenarios (ResRetainCowpea and ResBurnCowpea) were higher than others. Notably, although seed inputs of legume-included rotations, such as WKWC and WFWC (Central West), and WFWO and WFWC (Riverina), were relatively higher than those of WC and WWC, their fertilizer inputs were lower, leading to the lowest total energy inputs. This was similar for North West, where SWKW showed the lowest energy inputs.

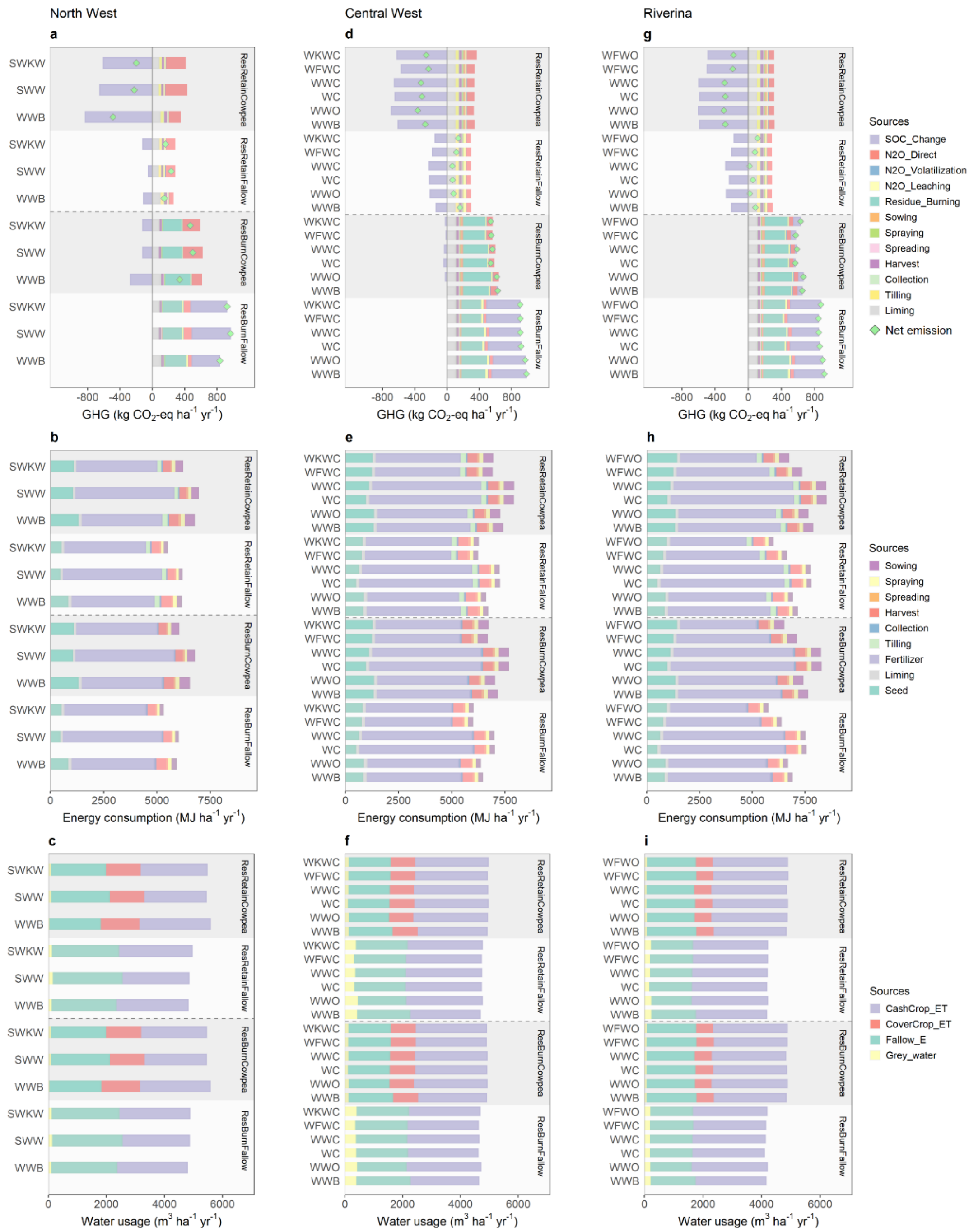


Fig. 5-3. Average values of GHG emission, energy input, and water consumption for North West **(a-c)**, Central West **(d-f)**, and Riverina **(g-i)** from 1961 to 2020. Negative GHG emissions sourced from SOC change mean increased SOC, and negative net emissions (green diamond) mean net carbon sequestration. The meanings of rotation abbreviations are shown in Table 5-1.

Compared with fallow scenarios (ResRetainFallow and ResBurnFallow), additional water used by cover crops in ResRetainCowpea and ResBurnCowpea caused a larger total water consumption (Fig. 5-3c, f, i). The evapotranspiration during cover cropping ranged between 1188-1327 m^3 ha^{-1} (North West), 836-876 m^3 ha^{-1} (Central West), and 561-607 m^3 ha^{-1} (Riverina). Meanwhile, soil evaporation during fallow was reduced by two cover cropping periods in North West, but not obviously affected by the single cover cropping in Riverina. The amounts of grey water were negligible, and always close to zero under ResRetainCowpea and ResBurnCowpea. There was little difference in the cash crop evapotranspiration between rotations and scenarios.

5.3.2 Food-energy-water-carbon footprints and productivity

With respect to the carbon footprint, the WWB showed the highest GHG emission under ResBurnFallow (311 CO_2-eq t^{-1}), and moderate carbon sequestration under ResRetainCowpea (-118 CO_2-eq t^{-1}) in North West (Fig. 5-4a). The WWO had both the highest carbon footprint under ResBurnFallow (407 CO_2-eq t^{-1} and 366 CO_2-eq t^{-1}) and the lowest carbon footprint under ResRetainCowpea (-183 CO_2-eq t^{-1} and -185 CO_2-eq t^{-1}) for Central West and Riverina, respectively (Fig. 5-4d, g). However, the energy footprint of ResRetainFallow was always lower than those of other scenarios in Central West and Riverina, but was comparable with others in North West (Fig. 5-4b, e, h). Within ResRetainFallow, the legume-included rotations consistently had the lowest energy footprint across all regions, with values of 1416 MJ t^{-1} for SWKW (North West), 2096 MJ t^{-1} for WFWC (Central West), and 2160 MJ t^{-1} for WFWO (Riverina). Similarly, ResRetainFallow had a lower water footprint especially in Riverina, and those of sorghum-included rotations were notably lower than others (Fig. 5-4c, f, i).

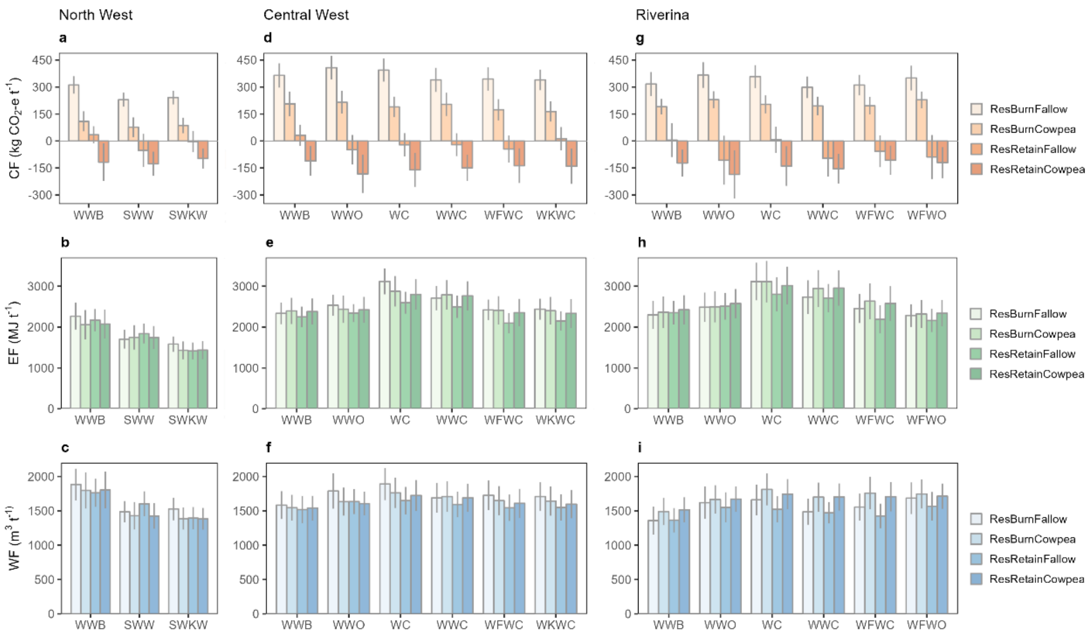


Fig. 5-4. Average values of carbon footprint (CF), energy footprint (EF), and water footprint (WF) for North West **(a-c)**, Central West **(d-f)**, and Riverina **(g-i)** from 1961 to 2020. The error bars represent the standard deviation across different study sites. The meanings of rotation abbreviations are shown in Table 5-1.

The average yields increased slightly or remained unchanged in residue retained scenarios (ResRetainFallow and ResRetainCowpea) compared to residue burning scenarios (ResBurnFallow and ResBurnCowpea). However, cover cropping (ResRetainCowpea and ResBurnCowpea) increased most cereal yields but reduced the yields of canola and legume relative to fallow (ResRetainFallow and ResBurnFallow), and the benefits were more evident in North West than in Central West and Riverina (Fig. S5-2). Accordingly, gross margins were enhanced by ResRetainCowpea and ResBurnCowpea for cereal rotations in North West, but in Central West and Riverina, the ResRetainFallow exhibited the highest gross margins across most rotations (Fig. 5-5). Given that the different grain prices and on-farm costs of various crops, our results showed that SWKW (509-556 AUD ha^{-1} yr^{-1}), WKWC (599-724 AUD ha^{-1} yr^{-1}), and WC (565-658 AUD ha^{-1} yr^{-1}) were the highest-return rotations in North West, Central West and Riverina, respectively (Fig. 5-5).

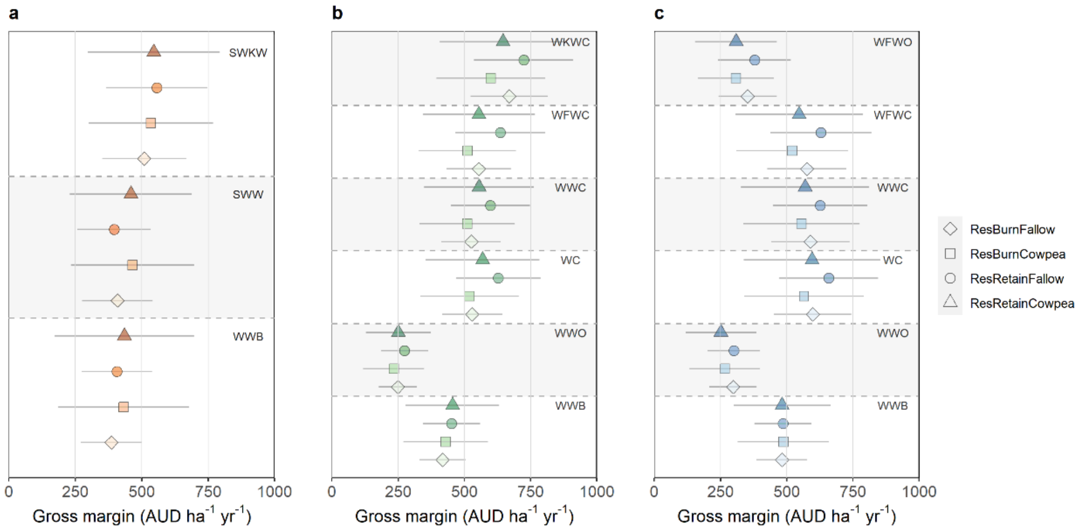


Fig. 5-5. Average values of gross margin for North West **(a)**, Central West **(b)**, and Riverina **(c)** from 1961 to 2020. The error bars represent the standard deviation across different study sites. The meanings of rotation abbreviations are shown in Table 5-1.

5.3.3 Food-energy-water-carbon composite sustainability and evenness

Based on the FEWC index, the sustainability score exhibited different patterns in the three regions. For North West, it is evident that ResRetainCowpea had the highest score and SWKW was the optimal rotation (Fig. 5-6a). In contrast, ResRetainFallow had the highest score across most rotations in Central West and all rotations in Riverina, and the canola and legume included rotations (WFWC and WKWC) performed better than others (Fig. 5-6b-c). Moreover, although composite sustainability scores of these scenarios were moderately high (scores over 50), most rotations cannot reach a balanced improvement regarding the four sustainability domains. For example, ResRetainFallow was more beneficial with respect to water and energy, but weaker in carbon compared to ResRetainCowpea. Considering both sustainability and evenness, aforementioned rotations and scenarios with high sustainability in each region also had relatively high evenness (Fig. 5-6d). Note that, the score only denotes relative sustainability, and a score closer to 100 does not mean that the farming system is definitely sustainable.

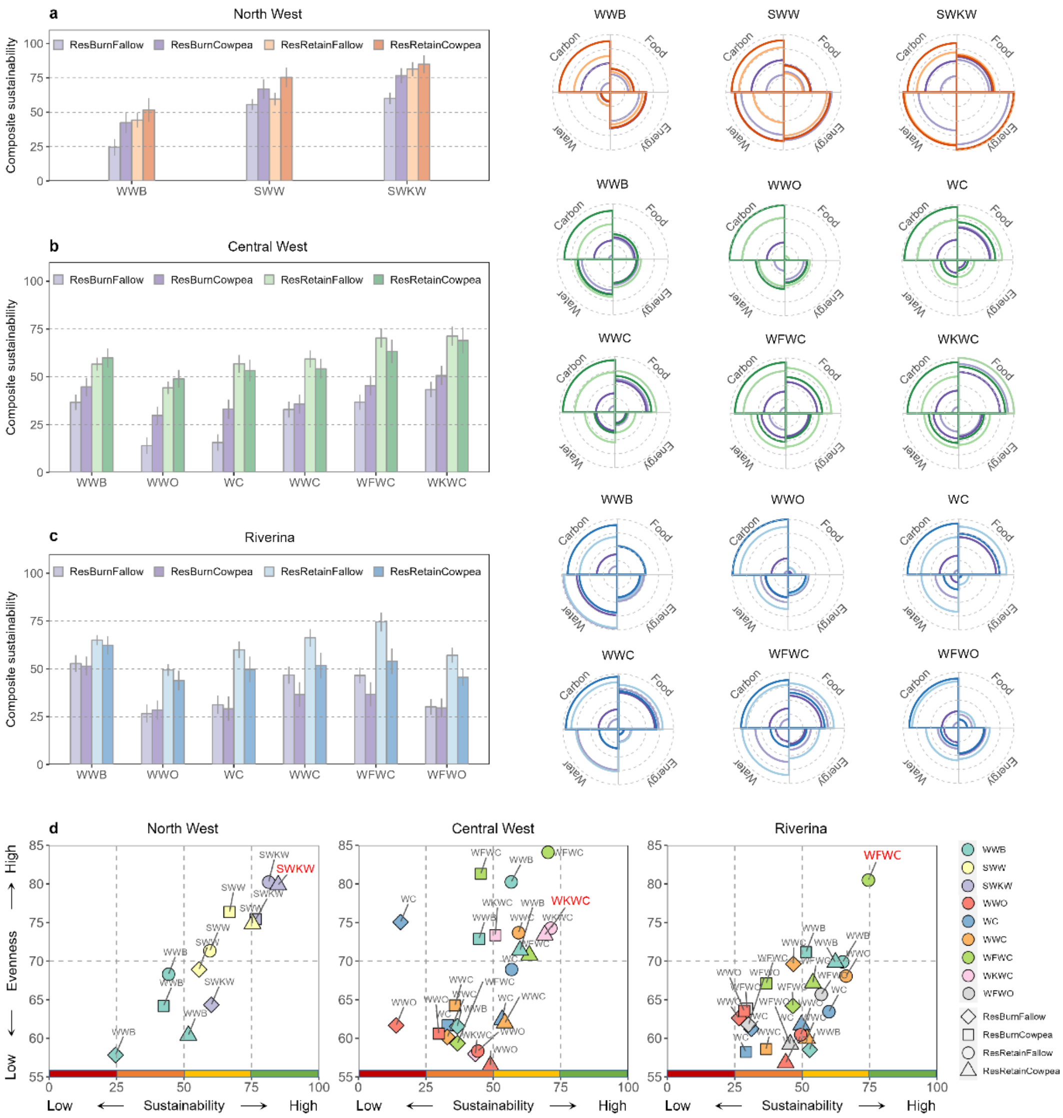


Fig. 5-6. The composite sustainability with error bars (the standard deviation across different study sites), and performance for each sustainability domain (the inner-to-outer rings represent scores of 0, 25, 50, 75, and 100, respectively) for each rotation in North West **(a)**, Central West **(b)**, Riverina **(c)**, and the distribution of both sustainability and evenness for all rotations in each region **(d)**. The meanings of rotation abbreviations are shown in Table 5-1.

5.3.4 Optimization across sub-regions

Based on the above comparison of rotations over each sub-region, we selected the optimal rotation which had the highest sustainability and high evenness score for North West (SWKW), Central West (WKWC), and Riverina (WFWC) to further investigate the spatial pattern. The map of the best scenario for each location demonstrated that

ResRetainCowpea was the optimal strategy at most sites in North West (76%), while ResRetainFallow was dominant in Riverina (95%) (Fig. 5-7a). The advantage of ResRetainCowpea in North West was mainly from the improvement in the carbon domain, but ResRetainFallow in Riverina was generally superior in energy and water domains (Fig. 5-7b). In addition, the best performance of ResRetainCowpea was concentrated in the east of North West, and sustainability scores were always higher in the east over all regions (Fig. 5-7a). Considering the climate differences from east to west (Fig. 5-1b-c), four quantiles of sustainability score of the selected rotations within each optimal scenario were displayed. The results showed that higher sustainability interval (Q4, above 75th percentile) occurred at sites with higher rainfall and lower temperature, and this pattern was the most evident in North West (Fig. 5-7c).

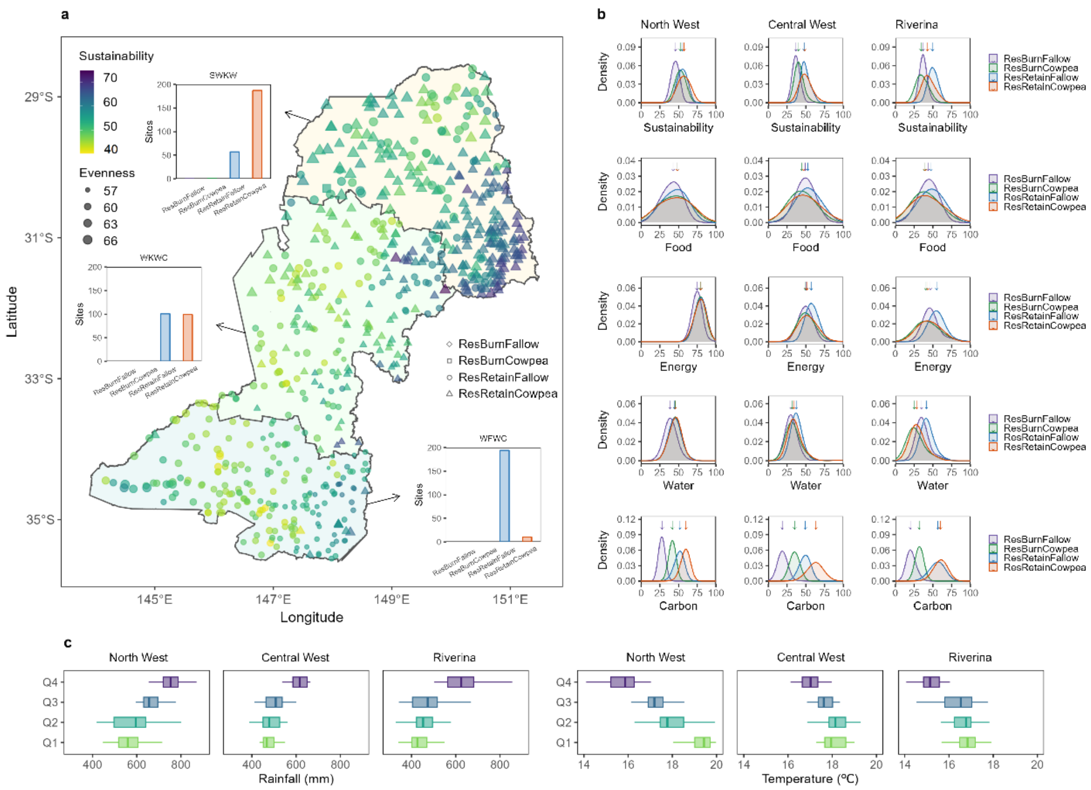


Fig. 5-7. (a) Map of the highest sustainability score within four scenarios for the selected optimal rotations in North West (SWKW), Central West (WKWC), and Riverina (WFWC) at each study site; **(b)** kernel density distributions of scores for sustainability and four contributing domains for the optimal rotations across all sites of each region under four scenarios; **(c-d)** distribution of annual mean rainfall and temperature (from 1961 to 2020) among different sustainability quantiles (Q1: < 25^{th}, Q2: 25-50^{th}, Q3: 50-75^{th}, and Q4: > 75^{th}) based on the optimal combinations generated from **(a-b)** in North West (SWKW with ResRetainCowpea), Central West (WKWC with ResRetainFallow), and Riverina (WFWC with ResRetainFallow). The meanings of rotation abbreviations are shown in Table 5-1.

5.4 Discussion

5.4.1 A nexus perspective to optimize management strategy

The FEWC analysis provides quantitative assessment of agricultural sustainability for different management strategies. Results reveal that the overall sustainability was improved by residue retention and cover cropping especially in terms of carbon domain (Fig. 5-6a-c). Both residues from cash crops and cover crops contributed to soil carbon sequestration, but direct N_2O emissions were doubled with the inclusion of cover crops (Fig. 5-3a, d, g). The input of organic carbon from crop residues is the key contributor to the increased stock of SOC (Paustian et al., 2016; Yang et al., 2018). N_2O production in soils – which is modelled by nitrification and denitrification processes in APSIM (Thorburn et al., 2010) – occurs readily when stimulated by the amendment of N-rich crop residues. This is more evident in North West where rainfall is higher and sorghum harvesting is followed by a gap year with two cover cropping periods (Fig. 5-3a). Enhanced N_2O emissions by legume residues have also been reported in previous meta-analysis (Basche et al., 2014; Muhammad et al., 2019) and modelling studies (Lugato et al., 2018; Quemada et al., 2020). The decomposition of legume residues with a low C/N ratio probably resulted in less immobilization of N in soils, leading to more N available for nitrification and denitrification and therefore the production of N_2O (Xia et al., 2018).

Although the inclusion of cover cropping increased soil carbon sequestration, it consumed more energy and water resources. Additional seed input and diesel use for sowing cover crops were the main reasons for the greater energy consumption compared to the fallow scenarios (Fig. 5-3b, e, h). Nitrogen fertilizer always contributed the most to energy consumption (Farine et al., 2010; Yadav et al., 2020), and was lower in legume-included rotations due to the lower nitrogen requirement of leguminous crops. Interestingly, the grey water induced by nitrogen fertilizer was close to zero under all cover cropping scenarios but not negligible when there was no cover crop, especially in Central West, suggesting a larger amount of nitrogen leaching in this region (Fig. 5-3c, f, i). Cover cropping has been well recognized as an option to reduce nitrogen leaching through N uptake of excess N remaining in soils after the cash crop harvesting (Abdalla et al., 2019; Nouri et al., 2022; Porwollik et al., 2022; Teixeira et al., 2021). However, the reduced grey water was small and unable to balance the water usage from cover crops, and soil evaporation showed little difference from fallow because one cover crop only lasted for about one month, resulting in larger amounts of water consumption under cover cropping scenarios, as reported by some studies (Garba et al., 2022a; Qin et al., 2021; Shackelford et al., 2019).

Combined with the crop yield and profitability, large inequalities appear to exist among the four domains regarding food, energy, water and carbon (Fig. 5-6a-c). All rotation systems achieved negative carbon footprints when using both residue retention and cover cropping, but nexus trade-offs occurred and influenced the goals of improving resource use efficiencies and economic benefits. That is, most rotations in Central West and Riverina had higher water and energy footprints but lower gross margin under ResRetainCowpea compared to ResRetainFallow (Fig. 5-4 and Fig. 5-5). This result can be complementary to the findings of He et al. (2022a), in which classical optimal planting patterns were found to be beneficial to water use and profitability, but not to the carbon neutrality. Xu et al. (2020) also reported that supply-oriented management may boost food production at the expense of environmental burdens and resource consumption. Collectively, although conflicts within the FEWC cannot be completely resolved by the implementation of residues or cover crops in this study, we have demonstrated the benefits of applying the nexus perspective to inform identification of optimal management strategies.

5.4.2 Comparison of sustainability across different regions

Based on the integrated FEWC framework, an optimal rotation system exhibiting a relatively high sustainability across all domains was selected for each region to investigate the spatial performance (Fig. 5-6d). The scenario with the highest sustainability score at each site was presented on a map which revealed divergent optimal solutions among the three regions (Fig. 5-7a). ResRetainCowpea was optimal in North West, but ResRetainFallow performed the best in Riverina. The Central West, situated between North West and Riverina, had approximately half each of the sites scoring the highest under ResRetainFallow or ResRetainCowpea. This could be due to that the sorghum within SWKW rotation in North West was followed by a gap year, during which two cover cropping periods benefited both SOC and gross margin, without incurring additional energy consumption (Fig. 5-7b). The stored soil water from the gap year could also be used by the following cash crops (Chen et al., 2023; Oliver et al., 2010). In addition, the yields of sorghum were double those of wheat, consistent with Stephens et al. (2012). Consequently, when considering the annual average yields of sorghum within the two-year period, they were comparable to wheat yields but had lower energy and water consumption per unit of yield. However, in water-limited conditions, cover crops may compete for soil water resources (Deines et al., 2023; Garba et al., 2022b; Rose et al., 2022). It is evident that ResRetainCowpea scored a little higher in carbon but much lower in energy, water and gross margin domains than ResRetainFallow across most sites in Riverina, leading to a lower composite sustainability score (Fig. 5-7b). Therefore, adopting cover cropping in the generally wetter North West region is feasible, but not suitable in the intensive rotation systems of Riverina.

Residue retention was beneficial for all regions, as it provided a positive feedback loop that enhanced both SOC and yield, as has been widely reported in Australia (Page et al., 2020), and globally, including in China (Berhane et al., 2020; Han et al., 2018), and Europe (Haas et al., 2022; Sándor et al., 2020). Our study complemented these findings by indicating that residue retention also resulted in lower energy and water footprints compared to residue burning (Fig. 5-4). Residue retention may therefore play a key role for enhancing sustainability of agriculture (Xiao et al., 2021). Furthermore, the composite sustainability score displayed a clear decreasing trend from east to west across all regions (Fig. 5-7a). The four quantiles of sustainability scores in relation to rainfall and temperature revealed that the wetter and cooler sites always had higher sustainability scores in this study (Fig. 5-7d). The site-specific performance highlighted the importance of climate conditions in determining the final outcomes of optimal management strategies (Sun et al., 2020).

5.4.3 Policy implications and limitations of this study

Integrated thinking and analysis, as simply exemplified in this study, highlighted relationships among different but interconnected FEWC domains. This nexus approach can help to optimize agricultural management strategies in alignment with the SDGs, revealing synergies and trade-offs for potential implications to decision makers.

First, reducing the dependency on nitrogen fertilizer should be a priority for both research and government policy. Nitrogen fertilizer was the most energy intensive input, and also affected the GHG emissions and water usage (Rawnsley et al., 2019). Legume-included rotations were found to use less nitrogen per hectare farmed each year. Rotations with nitrogen-fixing crops can reduce the fertilizer requirement of the subsequent crops, thus alleviating environmental burdens and improving profitability (Li et al., 2021; Xing et al., 2017; Zhao et al., 2022). Reducing N inputs after legumes, in combination with nitrogen adjustment, specifically precision fertilization, should be further considered to better contribute to the various goals of sustainable agriculture.

Second, well-targeted incentives are needed to promote the adoption of cover crops in NSW in areas where they are beneficial. Cover cropping is widely promoted as a management practice for supporting the goal of net zero GHG emissions by sequestering SOC (Abdalla et al., 2019; Muhammad et al., 2019; Tribouillois et al., 2018), but was found to increase water and energy footprints, and decrease profitability in drier regions of this study. This means that cover cropping is not a sustainable option for regions with less rainfall. Our study did not assess different cover cropping scenarios (e.g., crop species, planting and terminating time), which may lead to different water and energy footprints. Furthermore, the possible yield penalties would discourage growers (Deines et al., 2023), and current financial incentives (e.g., carbon credits) for cover crops may not be sufficient to cover the economic costs (Qin et al., 2023). Cover cropping should be adapted to local conditions, and its adoption necessitates increased economic incentives and technical assistance.

Finally, holistic sustainability assessment, in conjunction with emerging technologies (e.g., satellite observation), should be integrated to provide a decision support tool to optimize agricultural management strategies. Our study only focused on the FEWC components of cropping systems, more environmental impacts, such as land footprint and biodiversity footprint, could be included in this nexus framework (Liu et al., 2015). Some statistical indicators, like employment and population, could also be incorporated to better represent the social sustainability dimension (Ren et al., 2023). To guide policymaking effectively, context-specific management strategies should be formulated for different regions. We hope that our agricultural-centered FEWC nexus approach can inform optimal strategies to support the sustainable development.

5.5 Supporting information

5.5.1 Supplementary methods

(I) Simulation model

The APSIM (Agricultural Production Systems sIMulator) is a comprehensive process-based model that produces predictions of yields, crop transpiration, soil evaporation, soil organic carbon dynamics, and N_2O emissions within a farming system according to the climate, soil, and management inputs (Holzworth et al., 2014; Keating et al., 2003). In this study, the pre-validated APSIM version 7.10 was used, by linking crop modules (crop growth and development), soil modules (soil water, carbon and nitrogen dynamics) and the manager module (a set of management rules) in the APSIM interface (https://www.apsim.info/).

(II) Climate and soil data

Daily observed climate data including solar radiation, rainfall, maximum and minimum temperature at each study site from 1961 to 2020 were downloaded from SILO (https://www.longpaddock.qld.gov.au/silo/). Soil data were obtained from the APSoil database (https://www.apsim.info/apsim-model/apsoil/) – a repository of soil information developed for use in the APSIM toolbox. The database focuses on the physical and chemical soil characteristics that drive crop production, and covers many cropping regions of Australia (Dalgliesh et al., 2012). Soil data that were closest to each study site were finally used in the modelling.

(III) Model initialization

APSIM can project the long-term effects of agricultural management practices on SOC stocks by assuming that SOC is near steady state at the beginning of simulation. However, the SOC recorded in the APSoil database at each site represents different cropping histories and farming management at the time of the data collection. Given that the SOC pools require many decades to re-stabilize after a land use change, APSIM was run for a continuous wheat cropping system from 1920 to 1960 as a spin-up phase to reach a steady state before scenarios were simulated (O'Leary et al., 2016). Therefore, the SOC values in 1960 were considered the baseline for initial SOC, with subsequent changes simulated under different management practices.

(IV) Simulation setup

Simulation of different crop rotations, residue retention and cover cropping scenarios commenced in 1961. The pre-validated crop varieties in each crop module released by APSIM were used following the sowing guidelines of the NSW Department of Primary Industries (Matthews et al., 2015; Serafin et al., 2019b). To avoid the failure of cash crop establishment under the widely varied soil and climate conditions across sites, specific sowing dates were adjusted by site-level soil water content and rainfall (Ren et al., 2024). The cowpea cover crop was sown between four days after the cash crop harvesting and 50 days before the next cash crop sowing, and the specific date depended on soil moisture and temperature. More details about the sowing rules for cash crop and cover crop can be found in our previous work (He et al., 2023). To avoid excessive soil water used by cover crops during the fallow period, the cowpea cover crop was allowed to grow until the flowering initiation stage, and then assumed to be terminated mechanically, with residues left on the field. The growth of cowpea after winter crops (wheat, barley, oats, canola, field pea, and chickpea) lasted for about one to two months in the summer. Because there was a one-year gap after summer sorghum, the cowpea cover crop was grown in both summer and winter of the gap year. No irrigation was applied in the modelling as cropping systems are mainly rainfed in NSW (Shen et al., 2018). The fertilizer application was determined to align with local farming practices across the study area. Considering the yield potential is strongly correlated with rainfall in rainfed area, we calculated site-specific fertilizer inputs as a function of rainfall, using the following empirical formula (He et al., 2022b; Simmons et al., 2022):

$$N = \frac{(WU - A) \times C}{WU - B} \tag{S5-1}$$

where N is the nitrogen input. WU is the sum of the rainfall during the cropping season and one quarter of the rainfall in the remaining months. The total N amounts are calculated by A = 150 and B = 90 for all crops except legumes, and C = 108, 130, 80, 64.8 and 260 for wheat, canola, barley, oats and sorghum, respectively. The total N was split into two applications. The amount of N applied at sowing was calculated by using A = 150, B = 10 and C = 25, respectively. The remaining N was applied at APSIM stage 5 (flowering initiated) for each crop. N application for field pea and chickpea was only 10 kg N ha^{-1} at sowing, and no fertilizer was used for cover crops. The amounts of N application across the three regions are shown in Table S5-1.

Cash crop residues were either burnt or retained as set in the Surface Organic

Matter module of APSIM. The residues were retained on the surface through the fallow period, and the tillage occurred prior to the next cash crop sowing. We specified a disking tillage operation with an incorporation depth of 10 cm for residue retained scenarios. Shallow disking, as an example of a reduced tillage practice, mixes crop residues into the topsoil to favour microbial decomposition (Rowen et al., 2020). Through tillage, the surface organic matter was added to the fresh organic matter pool of APSIM, and then decomposed following an exponential decay function (Thorburn et al., 2001). To mimic the long-term effects of management practices, simulations were conducted without resetting any APSIM state variables, thereby preserving the continuity of soil water, nitrogen and organic carbon from the preceding crop year.

(V) Scenarios design

More diversified crop rotations that include legumes and canola as break crops are often used for alleviating the yield decline in wheat monoculture in Australia (Hochman et al., 2020). Typical crop rotations are based on wheat (winter) and sorghum (summer) cereals in NSW (Serafin et al., 2019a). Here we used an interview process with local agricultural consultants and extension agronomists to select crop rotations. We selected six, six and three rotations for Riverina, Central West and North West regions, respectively. In the North West, leaving fields fallow for 12-15 months is common during the transition from summer to winter crops. Summer sorghum is harvested in autumn, followed by wheat that sown in the winter of the next year. In other all-winter crop rotations, each crop was cultivated within a given year. For the cover crop, cowpea can be suitable for a wide range of soil textures and environments (Simmons et al., 2022), and has proved able to grow during the hot and dry summer in Australia (McNee et al., 2022). The effects of different cover crop species are not the concern in this study. Considering the diverse soil and climate conditions across the three regions, cowpea cover crops were selected as a suitable crop that could be used throughout the entire study area.

5.5.2 Supplementary tables

Table S5-1. Management rules applied to individual crops.

Crop	Sowing window	Nitrogen fertilizer
Wheat	15 March to 30 June	54 - 84 kg N ha^{-1} (North West); 56 - 93 kg N ha^{-1} (Central West); 65 - 100 kg N ha^{-1} (Riverina)
Barley	15 April to 15 July	39 - 61 kg N ha^{-1} (North West); 41 - 69 kg N ha^{-1} (Central West); 48 - 74 kg N ha^{-1} (Riverina)
Canola	8 April to 15 June	66 - 112 kg N ha^{-1} (Central West); 78 - 121 kg N ha^{-1} (Riverina)
Oats	1 May to 22 June	41 - 57 kg N ha^{-1} (Central West); 39 - 60 kg N ha^{-1} (Riverina)
Field pea	1 May to 30 June	10 kg N ha^{-1}
Chickpea	12 May to 27 June	10 kg N ha^{-1}
Sorghum	19 September to 17 January	127 - 198 kg N ha^{-1}

Table S5-2. The three Local Land Service (LLS) regions used in this study. The mean temperature and annual rainfall indicate the mean values from 1961 to 2020, with the averages (outside the brackets) and ranges (in the brackets) across all sites in each region.

LLS region	Area (km^2)	Mean temperature (°C)	Annual rainfall (mm)	Climate type	Soil attribute
North West	82,443	18 (14-21)	627 (418-981)	Warm and temperate climate with summer rainfall.	Soils are red, brown and yellow duplex soils, fertile brown gradational soils and large areas of cracking clays.
Central West	91,619	18 (14-20)	543 (388-964)	Warm and temperate climate with evenly spread winter and summer rainfall.	Soils are red, grey and yellow duplex soils and fertile brown gradational soils.
Riverina	67,083	16 (12-18)	510 (328-1136)	Semi-arid to temperate climate with reliable winter rainfall.	Soils are red, grey and yellow duplex soils, fertile brown gradational soils and small areas of cracking clays.

Table S5-3. Data source of each calculation parameter.

Item	Value	Source
Greenhouse gas emissions		
Soil organic carbon change	/	APSIM output
Direct and indirect N_2O emissions	/	APSIM output, NIR (2020)
Residue burning*	/	APSIM output, NIR (2020)
Lime application	2.5 t ha^{-1} every 10 years	Simmons et al. (2020), NIR (2020)
Diesel used for sowing	6.2 L ha^{-1}	Eady et al. (2017)
Diesel used for spraying	0.7 L ha^{-1}	Eady et al. (2017)
Diesel used for spreading	2.3 L ha^{-1}	Eady et al. (2017)
Diesel used for harvesting	12.0 L ha^{-1}	Eady et al. (2017)
Diesel used for grain collection	2.1 L ha^{-1}	Eady et al. (2017)
Diesel used for tilling	13.7 L ha^{-1}	Eady et al. (2017)
Energy equivalent		
Diesel fuel	38.6 MJ L^{-1}	Chen et al. (2015)
Nitrogen	65.0 MJ kg^{-1}	O'Halloran et al. (2008)
Lime	0.6 MJ kg^{-1}	O'Halloran et al. (2008)
Seed (cereals and pulses)	14.0 MJ kg^{-1}	Jackson et al. (2010)
Seed (canola)	26.0 MJ kg^{-1}	Farine et al. (2010)
Water consumption		
Evapotranspiration (cash crop)	/	APSIM output
Evapotranspiration (cover crop)	/	APSIM output
Evaporation (fallow)	/	APSIM output
Grey water	Change with nitrogen use	APSIM output, Hossain et al. (2021)

/ Values varied with biophysical processes simulated in model.

* CO_2 emissions from the burning of crop residues are not included since an equivalent amount of CO_2 was removed by the growing crop, therefore only the GHGs (CH_4 and N_2O) released during combustion were included.

Table S5-4. Sowing rate used to calculate the energy input from crop seeds.

Seed	Density set in APSIM (plants m^{-2})	1000 seed weight* (g)	Sowing rate** (kg ha^{-1})
Wheat	120	40	63.2
Oats	120	36	56.8
Barley	130	30	51.3
Canola	50	4.5	3.0
Field pea	35	180	82.9
Chickpea	35 (20 for NW)	200	92.1 (52.6 for NW)
Sorghum	6	30	2.4
Cowpea	35	76	35.0

* Data are from Serafin et al. (2019b) and Matthews et al. (2015) for summer and winter crops, respectively.

** $\text{Sowing rate} = (\text{Density} \times 1000\ \text{seed weight}/100)\ /\ (0.8 \times 0.95)$.

Table S5-5. Economic input costs and prices used to calculate the gross margin.

Variable	Grain price (AU\$ t^{-1})	Cultivation (AU\$ ha^{-1})	Sowing* (AU\$ ha^{-1})	Pest control (AU\$ ha^{-1})	Harvest (AU\$ ha^{-1})	Tilling (AU\$ ha^{-1})	Fertilizer (AU\$ t^{-1})
North West							
Wheat	247	0	48	43	64		
Barley	237	0	56	77	70	0 for RB;	660
Chickpea	542	0	87	185	81	20 for RR	
Sorghum	237	0	41	136	76		
Central West							
Wheat	247	0	51	70	52		
Barley	237	0	58	76	58		
Canola	510	0	56	95	130	0 for RB;	660
Oats	217	5	51	25	58	20 for RR	
Chickpea	542	0	138	187	50		
Field pea	350	0	145	44	50		
Riverina							
Wheat	247	23	30	67	37		
Barley	237	0	29	68	37		
Canola	510	17	47	62	90	0 for RB; 20 for RR	660
Oats	217	38	34	30	37		
Field pea	350	0	101	91	49		
Cowpea	0	0	34	0	14	0	0

* Seed cost is based on farmer's own seed.

Data are from DPI gross margin budgets of summer crop and winter crop in 2012 (https://archive.dpi.nsw.gov.au/).

5.5.3 Supplementary figures

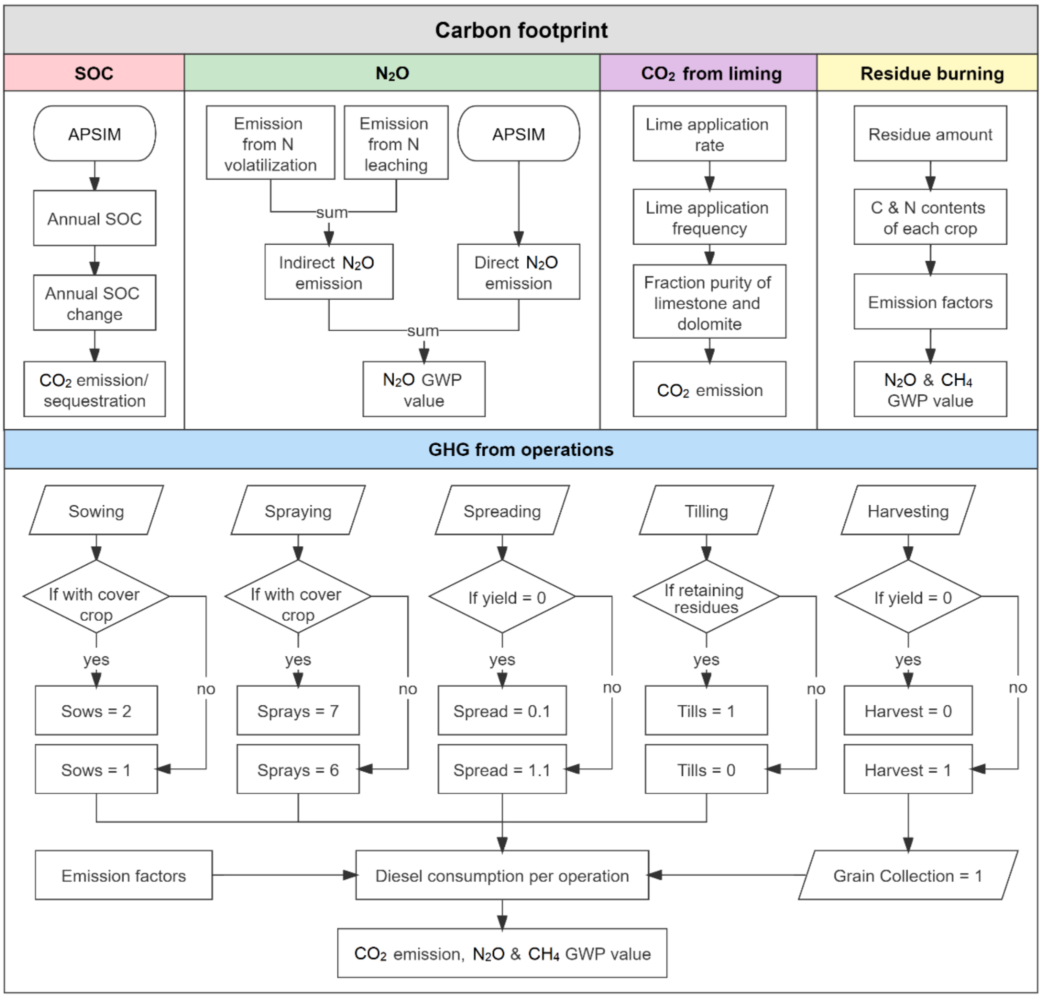


Figure S5-1. Calculation process of each GHG component.

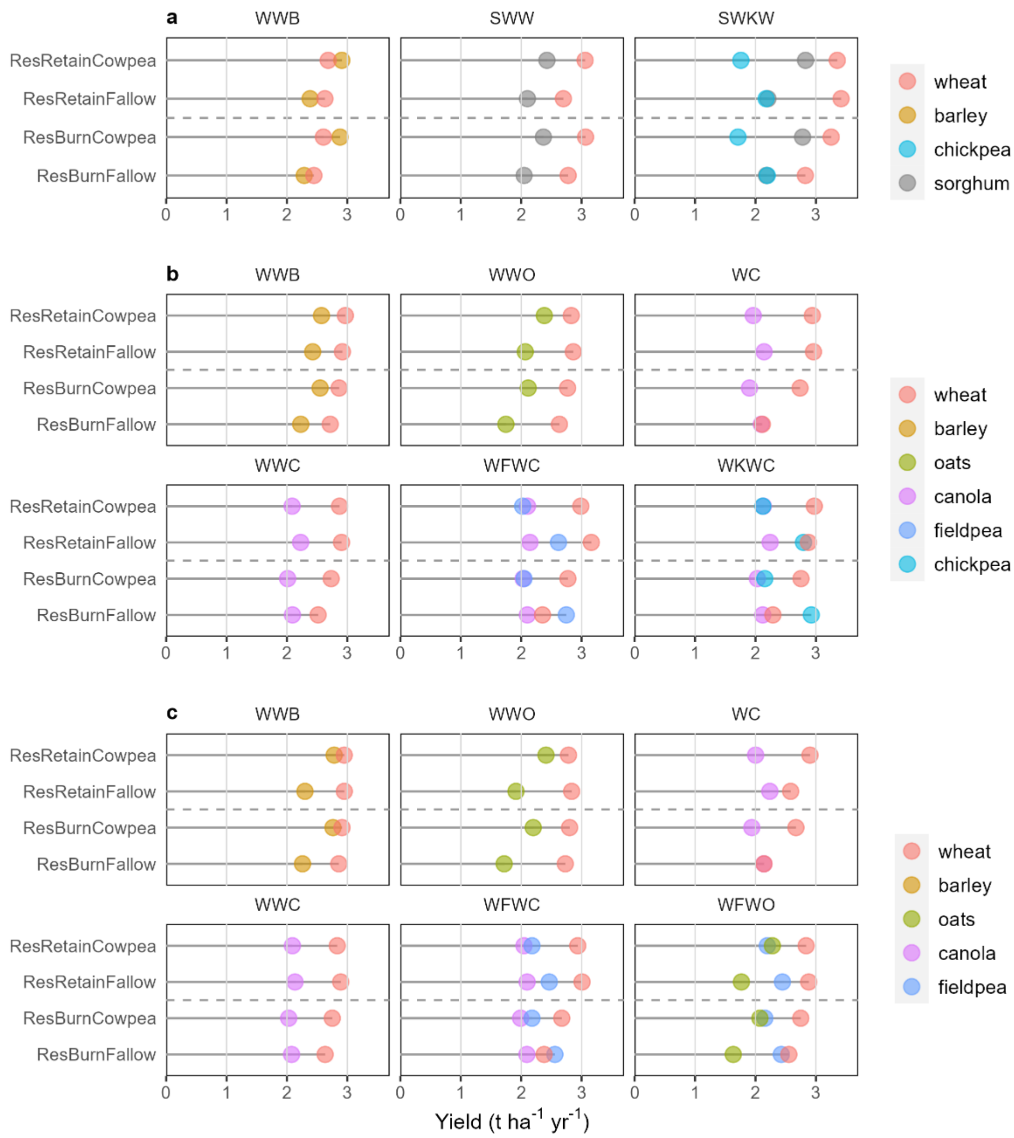


Figure S5-2. Average crop yields within each rotation for North West **(a)**, Central West **(b)**, and Riverina **(c)** from 1961 to 2020. The sorghum were harvested followed by a gap year, so their yields were averaged across the two year for the comparison with annual yields of other crops. The meanings of rotation abbreviations are shown in Table 5-1.

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Chapter 6. Optimizing cover cropping application for sustainable crop production

This chapter is based on the following manuscript:

Qinsi He, Chaoqun Lu, Annette Cowie, Shuaixiang Zhao, De Li Liu, Bo Yi, Lijie Shi, Shengwei Zhang, Kadambot H.M. Siddique, Qiang Yu, Linchao Li (Under review).

Abstract

Cover cropping is a key strategy in sustainable agriculture, gaining traction in many farming regions. However, farmers worldwide hesitate to adopt cover crops due to concerns about the potential yield loss and uncertain environmental benefits. In this study, we conducted a global meta-analysis of 3,160 observations from 271 studies to assess the impacts of cover crops on soil organic carbon (SOC), crop yield, and nitrous oxide (N_2O) emissions. Our findings revealed that legume and non-legume cover crops significantly increased SOC content by 5.9% and 4.0%, respectively, with SOC change mainly influenced by mean annual temperature. Legume cover crops enhanced yield by 16.0% but also increased N_2O emissions by 36.2%, and these emissions can be mitigated by combining cover cropping with other practices, such as no-tillage, deficit irrigation, and diversified crop rotations. The greatest benefits in SOC and yield from legume cover crops were observed in farming systems with low nitrogen fertilizer inputs, low crop diversity (especially cereal-dominated systems), and low initial SOC, under humid and warm climates. Data-driven models showed that incorporating legume cover crops into continuous cereal systems for three years can significantly benefit low-input environments (such as many parts of Africa), enhancing both SOC and yield. This study highlights the potential of integrating legume cover crops for sustainably advancing global food production and provides suggestions to support broader adoption.

Keywords: Legume, Non-legume, Cover crop types, Crop yield, Greenhouse gases, Co-benefit and trade-off

6.1 Introduction

The growing demand for food to sustain an increasing global population will lead to significant environmental costs unless more sustainable agricultural practices are adopted (Foley et al., 2011). Over the past decade, conservation agriculture has gained considerable attention as a strategy for sustainable intensification (Jat et al., 2020; MacLaren et al., 2022). Cover crops (CCs), the non-cash crops grown between the harvest and next planting of main crops, are considered a key component of conservation agriculture (Deines et al., 2023). Replacing bare fallow periods with CCs offers multiple benefits for soil health such as suppressing weeds, reducing soil erosion, and improving biodiversity (Garland et al., 2021; Shackelford et al., 2019). However, the specific impacts of CCs vary depending on field management, climatic zones, and soil properties (Lamichhane and Alletto, 2022). Therefore, despite strong recommendations from government and private organizations, and significant funding such as over USD$155 million dollars budgeted by USDA's Environmental Quality Incentives Program in 2018 alone for the promotion of CCs (Wallander et al., 2021) — to grow or not to grow CCs remains a confusing question for many farmers around the world due to concerns about yield loss and uncertain environmental benefits (Eerd et al., 2023; Rose et al., 2022).

The choice between legume and non-legume CC is crucial, as it directly affects the ecosystem services provided by CCs (Daryanto et al., 2018). Legume CCs are able to biologically fix nitrogen (N), and thus to provide additional N inputs for subsequent main crops (Griffiths et al., 2022). While non-legume CCs can better capture surplus N after the main crop harvest (Nouri et al., 2022). Some studies found that non-legume CCs commonly produce more biomass than N-fixing legume CCs due to the energy cost of N fixation in legumes (Iannetta et al., 2016), and the residues of non-legume CCs decompose more slowly than those of legume CCs because of their lower C: N ratio (Blanco-Canqui et al., 2015), so non-legume CCs could be expected to enhance SOC to a greater extent. However, other studies found that legume CCs provide the organic N required to stabilize an additional amount of SOC, and the supplied N can help increase biomass production of the subsequent crops to contribute to more carbon inputs, which show a greater potential to increase SOC than non-legume CCs (Jian et al., 2020; Vendig et al., 2023). Therefore, there is considerable uncertainty over the comparative effectiveness of legume and non-legume CCs in enhancing SOC. Quantifying the type-specific SOC benefits from legume and non-legume CCs is needed to improve SOC sequestration potential estimates (Qin et al., 2023).

The influence of CCs on SOC can affect nitrous oxide (N_2O) emissions, as the C and N biogeochemical cycles are closely coupled in cropland ecosystems (Lugato et al., 2018). A low C: N ratio of CC residues can increase the availability of soil N for nitrification and denitrification, whereas a high ratio may result in N immobilization (Guenet et al., 2021). Consequently, N_2O emissions are generally negatively correlated with the C: N ratio of CC residues, increasing in the presence of legume CCs and decreasing with non-legume CCs (Muhammad et al., 2019). However, when considering the CC growth period and the main crop growing season separately, results have been inconsistent, showing either increased or decreased N_2O emissions compared to no CC (Basche et al., 2014; Han et al., 2017). Therefore, the effects of legume and non-legume CCs on N_2O emissions are not yet fully understood and may be highly site-specific. Accurate quantification is critical to avoid overestimating the climate change mitigation benefits of CCs by neglecting additional N_2O emissions (Lugato et al., 2018).

Whether farmers adopt cover cropping hinges on more than its potential for climate change mitigation or improving soil health. A primary concern lies in understanding to what extent the yields of main crops are affected by CCs (Deines et al., 2023; Lobell and Villoria, 2023). A review by Daryanto et al. (2018) reported increases in main crop yield of 27% under legume CCs and 6% under non-legume CCs. In contrast, Abdalla et al. (2019) found that both legume and non-legume CCs decreased main crop yield by 4%, although this drawback could be avoided by using mixed legume/non-legume CCs which increased yield by 13%. Another meta-analysis reported opposite effects of legume CCs (+16%) and non-legume CCs (-7%) on main crop yield in Mediterranean climates (Shackelford et al., 2019). Evidence shows that the exact impacts of CCs on yield are context-dependent (Garba et al., 2022; He et al., 2023; Rose et al., 2022). For example, negative effects on yield could be as high as 20% in water-limited situations where CCs compete with main crops for soil water (Lobell and Villoria, 2023). However, the interactive impacts of CCs with site conditions and management practices on main crop yield remain poorly understood, raising many questions about the possible consequences of widespread CC adoption.

This study aims to fill these knowledge gaps using a meta-analysis of published data on the responses of SOC, yield and N_2O emissions to legume and non-legume CCs compared to fallow. These variables are closely aligned to soil health, food security, and climate change mitigation, critical to achieving the UN Sustainable Development Goals. By using a data-driven approach, our objectives are to address three key questions: (a) Do the effects of legume and non-legume CCs on SOC, yield, and N_2O emissions differ? (b) How do climatic, soil, and management drivers influence the CC effects on SOC, yield, and N_2O emissions globally? and (c) When do CCs offer the greatest benefits, and what are the magnitude of those benefits?

6.2 Materials and methods

6.2.1 Data collection

To gather data for analysis, we began by reviewing study lists of two recent meta-analyses on cover cropping (Muhammad et al., 2019; Vendig et al., 2023). We subsequently conducted an extensive literature survey using Google Scholar and the Web of Science to search the relevant peer-reviewed papers published before December 2023. The search keywords included ‘cover crop’, ‘catch crop’ or ‘green manure’ in combination with ‘soil organic carbon (SOC)’, ‘nitrous oxide (N_2O)’, ‘crop yield’ or ‘productivity’. Then, we applied several criteria to screen the papers: (i) the experiment was implemented with a pairwise design, including a clear control (i.e. bare fallow or spontaneous off-season regrowth) and a cover cropping treatment (i.e. non-harvested crop grown between productive seasons); (ii) the experiment must contain at least one of the target response variables, and report at least two replicates;

(iii) growing conditions and other agronomic management in the control and cover cropping treatments had to be identical; (iv) the experiment must cover at least one full growing season, and data had to be used only once if the same data appeared in several studies. When more than one cover crop treatment was conducted in the same experiment, the control treatment was compared to each cover cropping system separately. Laboratory experiments and modelling studies were not included in our dataset. We also excluded papers published in languages other than English. Finally, a total of 271 articles spanning six continents and 35 countries were winnowed, including 260 peer-reviewed journal papers, seven master's theses, one dissertation, two conference proceedings, and one book chapter. In two instances, three publicly available datasets were used to supplement additional data and/or information for the corresponding journal papers.

For each study, we extracted the means, the number of replications and sampling variances for the control and cover cropping treatments. The treatment value was matched to the control value only if both groups were sampled at the same time and differed in no other respect than the use of CCs (e.g., same fertilizer input, tillage practice, irrigation amount and residue management). In addition to the response variables, our dataset also included site characteristics including experimental location, climate conditions, soil properties and management details, which we used to explain the variation among studies. Data presented in tables were directly extracted, and data from graphs were obtained using the software GetData Graph Digitizer (version 2.25). If latitude and longitude were not reported, we used Google Maps (https://www.google.com/maps) to estimate this information based on the name and location of the experimental sites. In some studies, the climate and soil information that might have affected the impacts of CCs were lacking. Those climate factors, including mean annual air temperature (MAT), mean annual precipitation (MAP) and aridity index (AI) of the MAP divided by potential evapotranspiration, were derived from Climate Research Unit (CRU) database (http://www.cru.uea.ac.uk/data); missing soil characteristics, including initial SOC, soil pH, bulk density, sand, silt and clay content, were extracted from Harmonized World Soil Database (HWSD) (Wieder et al., 2014) according to the latitude and longitude coordinates of the site.

6.2.2 Data processing

For cover crop type, studies were divided into non-legume and legume (including the mixtures of legume and non-legume) to test the differences in SOC, yield and N_2O responses. To explore possible factors that affect the effects of the two types of CCs, factors were grouped into different categories. Geographic regions were grouped into Africa, Asia, Europe, Oceania, North America, and South America. MAT was classified into cool (≤ 10 °C per year), warm (10-18 °C per year) and tropical (> 18 °C per year). MAP was classified into arid (≤ 500 mm per year), semi-arid (500-1000 mm per year) and humid (> 1000 mm per year) (Li et al., 2024). Soil texture was categorized as fine, medium and coarse, following the classification previously described (Li et al., 2023). Experimental duration was grouped into short (≤ 3 years), medium (3-10 years) and long (> 10 years) following Zhao et al. (2022b). Due to limited long-term observations of N_2O emissions, durations for N_2O responses were classified as 1 year (short), 1-3 years (medium), and > 3 years (long). Main crop types were grouped into cereals, leguminous crops, vegetables, fibre and others according to the crop classification in FAO (2017). Tillage practices for the main crop were treated as a binary variable (CT/NT), where 'CT' indicated that the main crop was tilled by conventional tillage, including moldboard plough, chisel plough, rotary tillage, and 'NT' contained no tillage and reduced tillage, including no-till, strip-till and ridge-till (Zhao et al., 2022a). Residue management was also treated as a binary variable (return/removal), representing that main crop residues were returned to the field or removed (e.g., physically removed or burned) following harvest. Irrigation practice was recorded as yes or no. When information on these variables was not clearly defined, the cells were left blank.

To quantify the effects of CCs, the natural log of response ratio (RR) was calculated by pairwise comparing SOC, yield and N_2O emissions following Hedges et al. (1999):

$$\ln RR = \ln\left(\frac{\bar{X}_t}{\bar{X}_c}\right) \quad (6\text{-}1)$$

where $\bar{X}_t$ and $\bar{X}_c$ denote the mean values of target variables (i.e., SOC, yield and N_2O emissions) for the cover crop treatment and control, respectively. The effect size $\ln RR$ for each study was weighted by the level of replication. Some studies contained more extractable observations than others, which might contribute a disproportionate amount to the final model. To avoid giving more weight to individual studies, we used the formula following Pittelkow et al. (2015) and Vendig et al. (2023):

$$W = \frac{n_t \times n_c}{n_t + n_c} \times \frac{1}{N} \quad (6\text{-}2)$$

where n_t and n_c denote the number of replicates for the cover crop treatment and control, respectively. N is the total number of observations contributed by a given study. In order to directly show the changes induced by CCs, the meta-analysis results were back-transformed and reported as percentage changes as:

$$\text{Change} = \left(e^{\ln RR} - 1\right) \times 100\% \quad (6\text{-}3)$$

where a significant positive percentage change indicated an increase, and a negative change suggested a decrease in the target variables as an effect of CCs.

A weighted mixed-effects model was performed to generate the mean effect sizes with corresponding 95% confidence intervals (CIs) for each subgroup, using the '*rma.mv*' function in the R package '*metafor*' with the method of restricted maximum likelihood (REML). To ensure the independence of each study, 'study site' was set as a random factor in the mixed-effects models. Mean effect sizes were considered significant if the 95% CIs did not include 0, and effect sizes between grouped categories were considered as significant if their 95% CIs did not overlap. All calculations were performed using R software (version 4.3.2).

6.2.3 Boosted regression tree analysis

Boosted regression tree (BRT) analyses were conducted to quantify the relative importance of climate (MAT, MAP and AI), soil (initial SOC, soil pH, bulk density and clay content), and management (experimental duration, N input, tillage, rotation diversity and main crop type) in predicting the $\ln RR$ of SOC and yield for legume and non-legume CCs, respectively. Due to the limited observations of N_2O emissions (only 130 and 151 observations for legume and non-legume CCs, respectively), we did not apply BRT for the $\ln RR$ of N_2O emissions. Other management factors such as residue and irrigation practices were not included in our BRT analyses because of the large proportions of missing data, which would bias the results. Except for tillage and main crop type, which were classified as discrete variables, the remaining factors were continuous variables.

As tree-based models that use recursive partitioning of datasets, BRT uses large numbers of relatively simple tree models to generate improved predictive performance. Thus, BRT is an ensemble method that combines the strengths of regression trees and boosting algorithms (Elith et al., 2008). For the tree number, tree complexity and learning rate, we used a grid-search procedure to select the best hyperparameter combinations of BRT models which resulted in the lowest cross-validation root mean square error (Table S6-1) (Ren et al., 2024). Other parameters were set following previous studies (Hou et al., 2020; Zhao et al., 2022b), i.e. the number of cross validations as 10 and bag fraction as 0.75. The relative importance of each factor denoted a percentage of the total variation explained by the BRT models. The BRT analyses were performed using the '*gbm*' package, and additional functions from Elith et al. (2008).

Finally, the data-based BRT models were applied to global gridded data of above predictors to estimate the changes in SOC and yield due to CCs at a 0.5×0.5 degree resolution, using existing global datasets of: (1) climate data from CRU (http://www.cru.uea.ac.uk/data), (2) soil properties from HWSD (Wieder et al., 2014), (3) N inputs by fertilizer and manure from Tian et al. (2022), (4) cropland distribution from Hurtt et al. (2020), and (5) tillage practices from Porwollik et al. (2019). Uncertainties in the predicted SOC and yield changes were given by calculating the 95% bootstrap CIs (You et al., 2023).

6.3 Results

6.3.1 Cover crop effects at a global scale

Across all observations, CCs significantly increased SOC by an average of 5.2% (95% CI: 3.5% to 6.8%), main crop yield by 9.1% (5.9% to 12.4%), and N_2O emissions by 25.7% (7.4% to 47.0%) (Fig. 6-1b). Among different CC types, legume CCs significantly increased SOC by 5.9% (3.8% to 8.0%), yield by 16.0% (12.2% to 19.9%), and N_2O emissions by 36.2% (15.5% to 60.7%). In contrast, non-legume CCs increased SOC by 4.0% (1.5% to 6.7%) but had no significant effect on yield (p = .69) or N_2O emissions (p = .06).

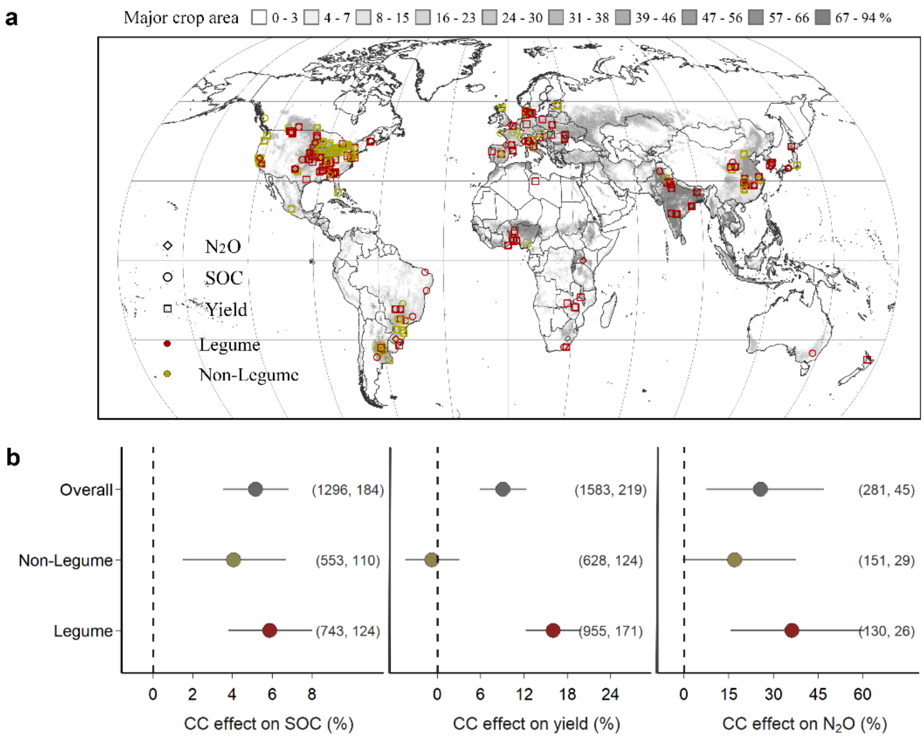

Fig. 6-1. World map showing the locations of the 271 primary studies included in this study (**a**). Overall effects of legume and non-legume cover crops (CCs) on SOC, yield, and N_2O emissions compared to no cover crop (**b**). Numbers in parentheses are observations in each grouping, followed by the number of corresponding unique sites. Center dots indicate mean effect sizes, and error bars indicate 95% confidence intervals.

6.3.2 Drivers affecting the cover crop effects

On a regional scale, the effects of both CC types on SOC increased with increasing MAT, showing non-significant effects in cool regions to positive impacts in tropical regions (7.7% for legume CCs and 6.0% for non-legume CCs on average) (Fig. 6-2a). A similar pattern was also found for yield and N_2O emissions, for example, the effects of legume CCs on yield increased from 9.8% (4.7% to 15.1%) in cool regions to 28.0% (18.7% to 38.0%) in tropical regions (Fig. 6-2b). Moreover, both CC types increased SOC significantly in humid regions (5.6% for legume CCs and 4.0% for non-legume CCs), and legume CCs increased yield the most in humid regions (23.0%, 17.1% to 29.2%) compared to arid and semi-arid regions. In Asia, main crop yields significantly increased with legume CCs by 19.8% (11.1% to 29.2%), and non-legume CCs by 9.9% (0.8% to 19.8%). However, in South America, CCs did not significantly affect yield but increased N_2O emissions by as much as 118.7% in legume CCs (69.8% to 181.7%) and 112.8% in non-legume CCs (20.9% to 274.8%) (Fig. 6-2c).

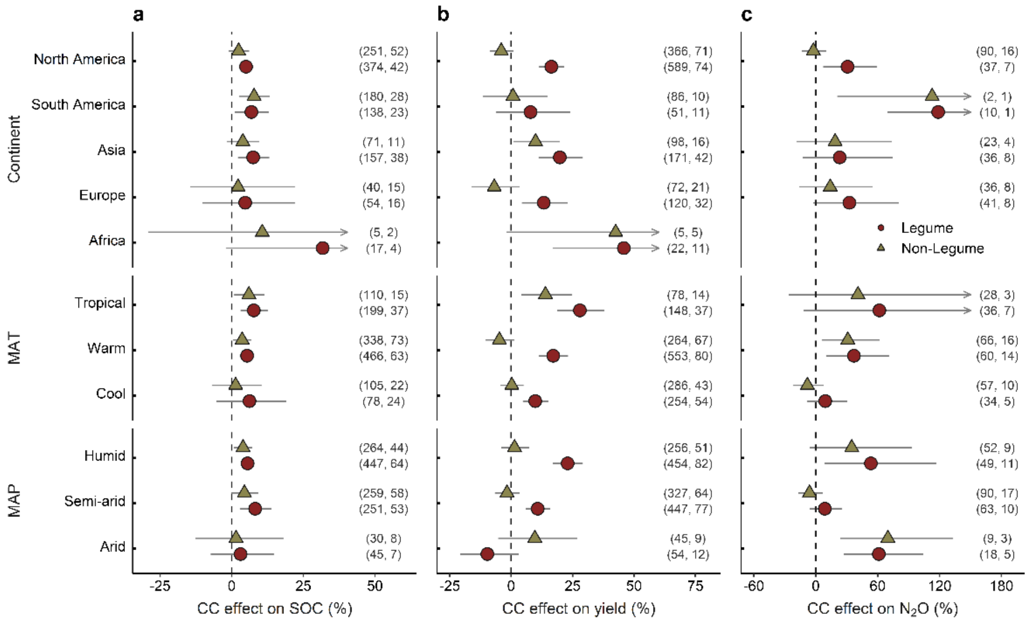

Fig. 6-2. Regional effects of legume and non-legume CCs on SOC (**a**), yield (**b**) and N_2O emissions (**c**) compared to no cover crop. Numbers in parentheses are observations in each grouping, followed by the number of corresponding unique sites. Center dots indicate mean effect sizes, and error bars indicate 95% confidence intervals. No comparison for N_2O emissions in Africa due to the insufficient observations.

For management practices, SOC increases were negatively associated with crop diversity, with significant SOC increases in continuous cropping systems (7.0% for legume CCs and 4.6% for non-legume CCs), but not in more diversified rotations (Fig.

6-3a). This pattern was more evident for yield and N_2O responses, especially yield responses to legume CCs which ranged from 22.5% ($p < .001$) in continuous cropping to 3.6% ($p = .21$) in rotations with three or more main crop species (Fig. 6-3b). Interestingly, N fertilizer also influenced yield responses to legume CCs, with yields increasing by 42.5% (31.7% to 54.2%) under no N fertilizer, but by 7.9% (4.2% to 11.6%) with N fertilizer. However, legume CCs also generated more N_2O emissions under no N fertilizer (103.3%, 30.7% to 216.3%) than with N fertilizer (25.3%, 6.9% to 46.7%) (Fig. 6-3c). Moreover, the effects of legume CCs on N_2O emissions shifted from positive (46.7%, 16.5% to 84.7%) under no-tillage to non-significant under conventional tillage.

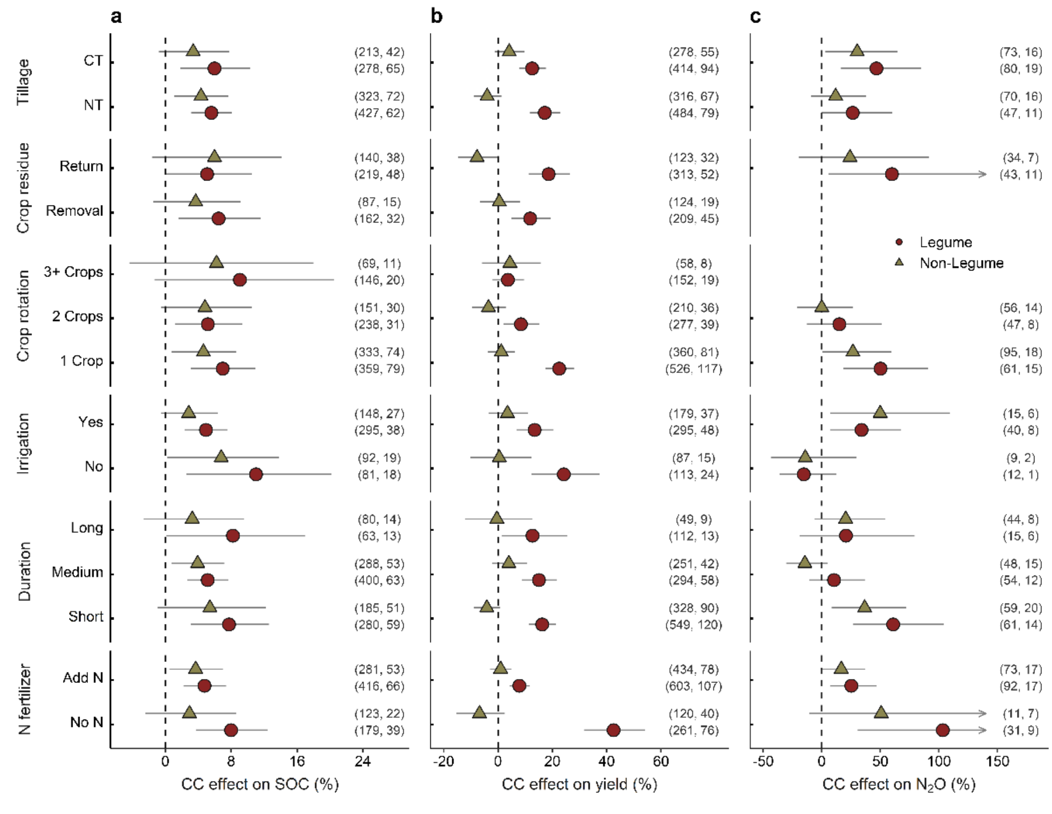

Fig. 6-3. Management effects of legume and non-legume CCs on SOC (**a**), yield (**b**) and N_2O emissions (**c**) compared to no cover crop. Numbers in parentheses are observations in each grouping, followed by the number of corresponding unique sites. Center dots indicate mean effect sizes, and error bars indicate 95% confidence intervals. No comparison for N_2O emissions in residue removal and 3+ crop rotation groups due to the insufficient observations.

Legume CCs increased yield more and generated fewer N_2O emissions in soils with low initial SOC, while initial SOC levels did not affect yield and N_2O emissions for non-legume CCs. Specifically, yield responses to legume CCs increased from 7.5% (0.6% to 14.8%) with initial SOC greater than 16 g kg^{-1} to 22.1% (16.3% to 28.2%) with initial SOC below 10 g kg^{-1} (Fig. 6-4b). Meanwhile, N_2O responses to legume CCs decreased from 58.9% (16.9% to 115.9%) under high initial SOC to 28.2% (1.7% to 61.5%) under low initial SOC (Fig. 6-4c). In addition, legume CCs increased SOC the most (8.7%, 2.0% to 16.0%) but did not significantly affect N_2O emissions in soils with high bulk density (i.e. > 1.4 g cm^{-3}). Non-legume CCs were consistently less effective than legume CCs at increasing SOC, yield and N_2O emissions (Fig. 6-4).

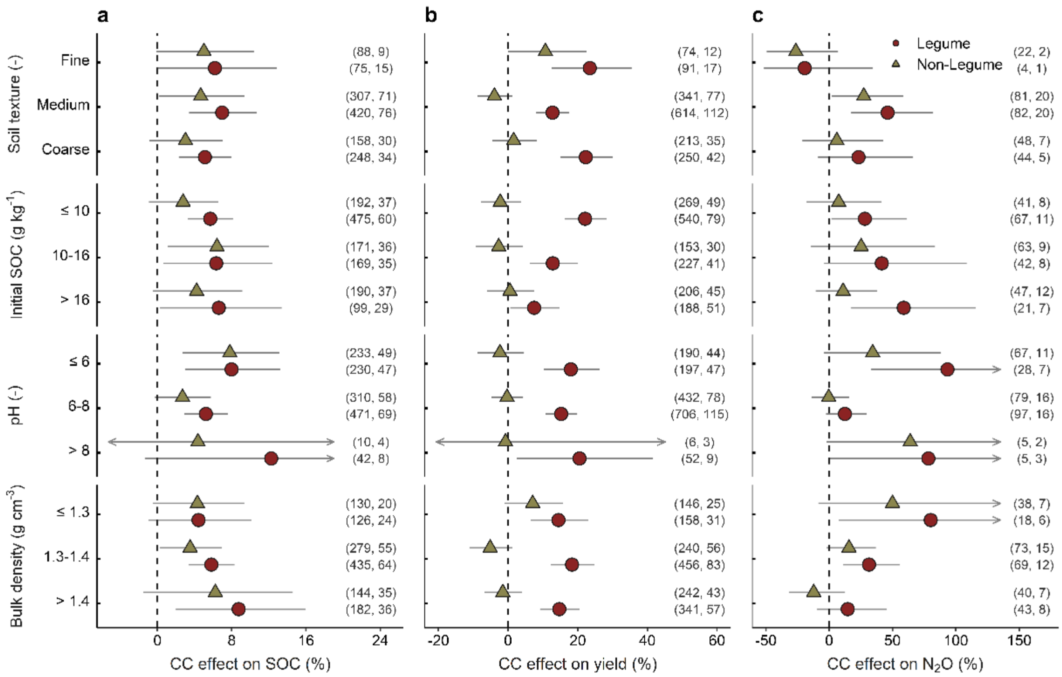

Fig. 6-4. Soil effects of legume and non-legume CCs on SOC (**a**), yield (**b**) and N_2O emissions (**c**) compared to no cover crop. Numbers in parentheses are observations in each grouping, followed by the number of corresponding unique sites. Center dots indicate mean effect sizes, and error bars indicate 95% confidence intervals.

6.3.3 Predictors of cover crop effects and scaling up

Based on the empirical relationships between CC effects and climate, soil, and management predictors, we developed BRT models that could explain 51-73% of the variability in SOC and yield across different sites for both CC types (Fig. 6-5). Among the 12 predictors considered, MAT was the most important factor in explaining variations in SOC at 0-30 cm soil depth, with importance values of 26% for legume CCs and 21% for non-legume CCs (Fig. 6-5a-b). N fertilizer emerged as the primary variable determining yield, contributing 23% for legume CCs and 17% for non-legume CCs (Fig. 6-5d-e). Initial SOC and MAT came second in explaining yield variability for legume CCs (22%) and non-legume CCs (13%), respectively.

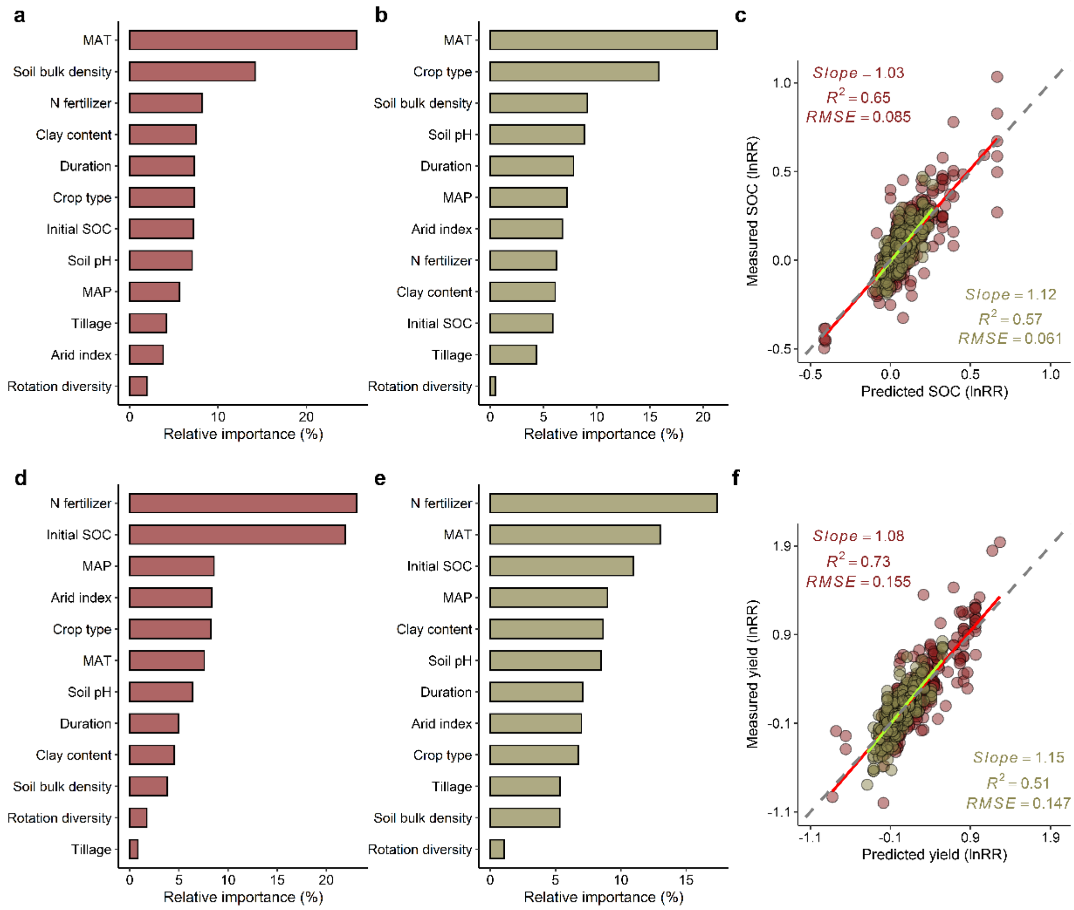

Fig. 6-5. Variable importance of 12 predictors of the effects of CCs on SOC at 0-30 cm depth (**a, b**) and yield (**d, e**), and the relationship between the model's predicted and measured response ratios for SOC at 0-30 cm depth (**c**) and yield (**f**). The relative importance in **a** and **d** is quantified based on legume CC effects, and **b** and **e** is based on non-legume CC effects. The red and yellow lines in **c** and **f** represent the fitted function, and dashed gray line is the 1:1 line.

We used BRT models to predict the potential average effects of CCs over a 3-year adoption period for continuous cereal cropping systems on SOC and yield across global croplands (Fig. 6-6), along with its associated uncertainties (standard deviations, and the lower and upper limits of 95% CIs) (Fig. S6-1-S6-2). The results indicated overall mean annual increases in SOC of 7.4% (95% CI: 0.9% to 17.0%) for legume CCs and 5.0% (0.5% to 9.8%) for non-legume CCs. The impacts of CCs on SOC varied considerably with latitude, showing higher values in tropical regions and lower values in the northern and southern high latitudes (Fig. 6-6a-b). In terms of yield, legume CCs increased cereal yields by an average of 19.8% (4.9% to 39.2%) compared to fallow, with the most significant increases in West and Central Africa, Brazil, and Southeast Asia. Conversely, non-legume CCs decreased crop yields for about half of the global croplands, with an average change of 0.7% (-8.8% to 11.3%) (Fig. 6-6c-d).

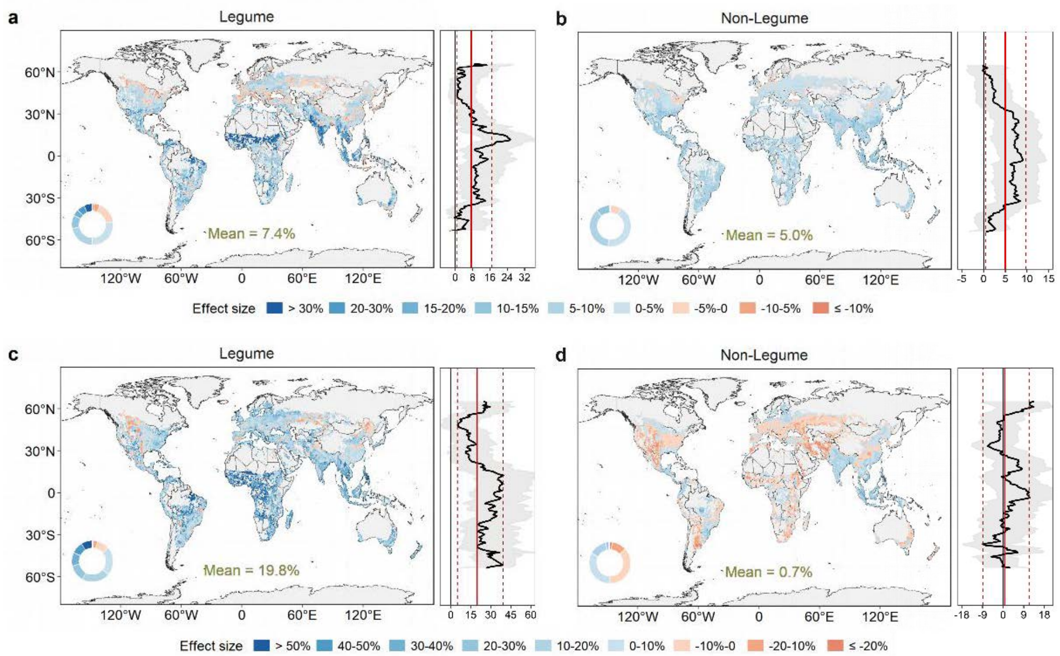

Fig. 6-6. Predicted spatial variation in effects of CCs on SOC at 0-30 cm depth (**a, b**) and yield (**c, d**) in global cropland. Grid-level changes were predicted using BRT models combining a spatial dataset with 12 predictors. Experimental duration, main crop type and rotation diversity were fixed as three years, cereals, and one (continuous cropping), respectively, and other 9 predictors sourced from datasets at a 0.5° resolution. The black lines and gray shading indicate the predicted values and 95% confidence intervals respectively, with red lines representing the averages. The inset donut plots represent the area proportion of each classified change from the total cropland area.

6.4 Discussion

6.4.1 When do cover crops increase yield?

Nitrogen fertilizer emerges as the primary factor driving the effect of CCs on main crop yield (Fig. 6-5d-e). We identified that including legume CCs results in significant yield advantages under unfertilized conditions, while non-legume CCs showed greater yield improvements with fertilization (Fig. 6-3b). The main reason for this contrasting relationship (Fig. S6-3) is that higher N fertilizer can fulfill crop demands, thereby negating the N benefits derived from the preceding legume CCs' N-fixation but stimulating the residue decomposition of non-legume CCs (Bourgeois et al., 2022; Islam et al., 2022; Tonitto et al., 2006). One of the main advantages of non-legume CCs is their ability to immobilize soil N and reduce N losses. However, this can also cause some N stress for subsequent main crops, so results tend to show larger effects on fields with higher fertilizer inputs. Moreover, it has been reported that legume nodulation and biological N-fixation are inhibited under high soil mineral N levels (Ma et al., 2022; Zahran, 1999). Thus, legume CCs as a N source can increase yield more effectively under low N fertilization (White et al., 2017). Furthermore, the yield changes induced by legume CCs depend significantly on the main crop types, with large yield increase in cereals (e.g., corn, 24.9% with $p < .001$) and small decline in leguminous crops (e.g., soybean, -6.4% with $p = .10$) (Fig. S6-4), aligning with previous field experimental results (Qin et al., 2021; Singh et al., 2020).

Notably, greater effects of legume CCs on yield were observed in continuous cropping systems (Fig. 6-3b). Two possible causes may account for the negative relationship between legume CC effects on yield and crop rotation diversity (i.e. the number of crop species in a rotation). First, the yield advantages of diversified cropping systems, which have been well documented (Ponisio et al., 2015; Smith et al., 2023; Yang et al., 2024), potentially rendered the N addition effects of legume CCs redundant, as noted by Vendig et al. (2023). Second, the positive yield response to legume CCs may not solely be attributed to N benefits but also to the break-crop effect, such as disrupting disease and insect cycles in cereal monocultures (Fageria et al., 2005). More complex rotations tend to include legumes, with 78.6% of systems in our dataset featuring over three crop species incorporating legumes. Thus, our results highlight that legume CCs can boost cereal yields, especially in farming systems with low N fertilizer input and low crop diversity.

Another major driving factor that regulates yield responses to CCs is initial SOC (Fig. 6-5d-e). Legume CCs had a stronger impact on main crop yield when initial SOC is below 10 g kg^{-1} (median value) (Fig. 6-4b). SOC has long been considered a key soil quality indicator (Lal, 2004), being a major constituent of soil organic matter (SOM). Higher SOM levels provide more essential macro- and micro-nutrients, enhancing crop yields (Oldfield et al., 2019). Ma et al. (2023b) found that there are threshold levels of SOC beyond which further increases do not provide any additional yield benefit. In soils with low initial SOC, a greater yield increase induced by legume CCs is understandable, as legumes can perform better than non-legumes in infertile conditions (Velásquez Ramírez et al., 2021; Wang et al., 2009). Precipitation also plays an important role in moderating CC effects on crop yield (Rose et al., 2022; Wang et al., 2021). In drier conditions, soil water consumed by CCs is less likely to be replenished through precipitation, leading to non-significant yield responses when MAP is below 500 mm (Fig. 6-2b). In contrast, in wetter environments, CCs tend to produce more biomass without competing for soil water with the subsequent main crops, thereby resulting in greater yield increases (Sun et al., 2020). The positive relationship between yield responses and precipitation (Fig. S6-3) is consistent with the findings from Garba et al. (2022) and He et al. (2023).

6.4.2 Co-benefit and trade-off between yield with soil organic carbon and N_2O

One of the key goals of cover cropping is to build soil carbon and mitigate climate change (Poeplau and Don, 2015). Mean annual temperature is, not surprisingly, the primary predictor of SOC changes for both CC types (Fig. 6-5a-b), and there is a strong positive relationship between MAT and CC effects on SOC (Fig. S6-3). In humid regions, winter cover crop biomass production can increase with rising temperatures to enhance the carbon inputs to soils (Ruis et al., 2019). Another study also reported that CCs increased microbial necromass accumulation for SOC accrual in humid and warm climates (Zhou et al., 2023). Improved SOC induced by CCs also has positive repercussions for yield by providing better soil structure and enhanced nutrient retention, suggesting a win-win outcome (Moinet et al., 2023). However, co-benefits to SOC and yield are evident only in regions where temperature and precipitation do not limit CC growth and biomass decomposition (Sun et al., 2020). Furthermore, our data presented that, contrary to legume CCs, non-legume CCs are more likely to achieve increases in both SOC and yield with higher N fertilizer (Fig. 6-3a). We therefore suggest that considering the constraints for different CC types, such as temperature, water and fertilizer shown here, will be more beneficial for concurrently achieving SOC accrual and yield advantage (Lin et al., 2023). In this study, while CC effects on SOC are detectable in short-term experiments (< 3 years), long-term trials (> 10 years) have large variations. Increasing the availability of long-term data is crucial for better understanding CC-induced SOC stabilization (Liang et al., 2023; Nouri et al., 2019).

Although legume CCs generally provide co-benefits between SOC and yield, trade-offs also exist as the legume CCs significantly increase soil N_2O emissions (Fig. 6-1b). Some meta-analyses report that legume CCs increase N_2O emissions by adding N to the soil, while non-legume CCs decrease N_2O emissions by scavenging surplus N (Li et al., 2024; Muhammad et al., 2019). Our data points show significant increases in N_2O emissions during the main crop growing season for both CC types, while non-growing season and full-year measurements have non-significant N_2O changes (Fig. S6-5a). This is similar to the results of Basche et al. (2014), but we additionally provide evidence that no-tillage, no-irrigation, diversified crop rotations, and long-term CC implementation can be used as essential strategies to mitigate the N_2O emissions associated with CCs (Fig. 6-3c). By exposing residue surfaces to microorganisms, tillage can enhance aeration and microbial activity, and thus increase residue mineralization and N_2O emissions (Muhammad et al., 2019); irrigation events can trigger a pulse in N_2O flux due to low oxygen availability, so deficit irrigation is suggested to reduce soil N_2O emissions (Li et al., 2024). To attenuate the increase in N_2O emissions, these practices can be combined with CCs application. Nevertheless, N_2O emissions generated by legume CCs require careful examination, and more concurrent observations are needed to assess overall net greenhouse gas balances with cover cropping, and to understand the underlying processes responsible (Abdalla et al., 2019).

6.4.3 Global potential of cover crops to increase soil organic carbon and yield

Based on the sub-group analyses, we envisage a scenario with the most responsive combination of management – continuous cereal systems with three-year CC implementation, to investigate the global potential of CCs to increase SOC and yield. Our results suggest that cereal yields have the risk of decreasing under non-legume CCs in nearly half of global cropland (Fig. 6-6d) but yield gains can be achieved by adding legume cover crops, giving an average increase in cereal yield of 19.8% (Fig. 6-6c). Given the variation in site conditions and management practices, the effects of CCs on yield strongly differ across the continents. For instance, non-legume CCs increased cereal yields in Southeast Asia (e.g., India and Indonesia), where both N fertilization and precipitation are high. Conversely, these crops have decreased yields in most temperate regions, such as the Midwestern United States and Southern Australia. One mechanism contributing to these yield decreases, as previously mentioned, is the N immobilization caused by non-legume CCs. Additionally, soil water competition with subsequent main crops, as highlighted by Garba et al. (2022), is another crucial factor. Our estimated mean yield loss of -3.1% in the United States is consistent with the simulation study by Qin et al. (2021) which found a yield loss of -3.9%, and the satellite data analysis by Deines et al. (2023) which reported a yield loss of -5.5% for maize following non-legume CCs in US Corn Belt.

Regions with lower N fertilizer inputs (e.g., West Africa and Central Africa) benefit especially from planting legume CCs. Enhancing N fertilizer use to an optimal level has been a key priority in sub-Saharan Africa, where nutrient-depleted soils coupled with low levels of N input significantly contribute to persistently low crop yields (Vanlauwe et al., 2014; Vitousek et al., 2009). However, due to the limited available data, there are larger variations in legume CC effects on yield in Africa (average standard deviation of 14.4%) compared to other continents (average standard deviation of 10.4%) (Fig. S6-2b). Thus, the estimates should be interpreted cautiously, especially considering the extra economic cost and technical overhead of CCs which may pose challenges for local adoption (Jennings et al., 2024). In most mid-latitude regions of the northern hemisphere, the increases in yield from legume CCs are below the global average. For example, yield benefits are 15.0% in Europe, 6.2% in China, and 12.2% in North America. These benefits are comparable to the 16% increase reported in California and the Mediterranean (Shackelford et al., 2019), and the 12% increase reported in China (Fan et al., 2021) in plots that used legumes as CCs. Cereals, especially corn, show significant potential for yield benefits by incorporating legume CCs (Alvarez et al., 2017; Marcillo and Miguez, 2017; Peng et al., 2024), highlighting an opportunity to benefit both food security and climate.

Further, co-benefits of yield and SOC from legume CCs are apparent in humid tropical regions, varying considerably with latitude (Fig. 6-6a, c). This pattern can be attributed to the significant positive relationships between yield and SOC with MAT and MAP (Fig. S6-3). The effects of CCs on SOC are consistently higher in the tropical zone between 23.5° N and 23.5° S (mean effect sizes are 13.3% for legume CCs and 7.3% for non-legume CCs), but lower in high latitudes (mean effect sizes close to 0) (Fig. 6-6a-b). Our findings align with those of Olin et al. (2015) and Porwollik et al. (2022), who reported the highest C sequestration potential of CCs in tropical regions using global modeling. However, estimates of surface SOC changes by CCs in humid tropics may be overestimated, as SOM turnover in these environments is very rapid (Fromm et al., 2024). Soils in humid tropics are often characterized by high C inputs and fast microbial decomposition and, consequently, are likely to have a limited potential for long-term SOC stabilization (Georgiou et al., 2022; Reichenbach et al., 2023). Conversely, the smaller increases in SOC due to CCs in northern temperate climate regions can be attributed to the low temperatures, resulting in slow SOM decomposition and slow N releases throughout the year (Ma et al., 2023a; Olin et al., 2015), which partly explains the smaller (legume CCs) and negative (non-legume CCs) effects on yield in these regions (Deines et al., 2023; Garba et al., 2022).

6.4.4 Limitations and perspectives

Our meta-analysis systematically quantifies the effects of different types of CCs on SOC, yield and N_2O emissions, however, there are some unavoidable limitations. First, in under-studied regions like Oceania, we collected only three observations for yield with different CCs. Consequently, not all soil types, climatic zones, and agronomic practices are represented equally, calling for more paired field studies of CCs in the future. Second, only 12.5% of measurements in our dataset span over ten years, but SOC accumulation is a continuous and slow process (Lehmann and Kleber, 2015; Poeplau et al., 2011). Soil improvement through long-term cover cropping will impact crop yield and N_2O emissions, necessitating more long-term observations to capture the legacy effects of CCs. Third, we divided the CC types into two broad categories, legume and non-legume, but the effectiveness of CCs may vary across species and genera (Nouri et al., 2022). Moreover, farmers' selection of CC species should consider local context, for example, rye is widely used as the winter CC in the United States due to its relatively low seed costs and ability to be sown later in the fall (Lobell and Villoria, 2023). Last, our machine learning models were built based on the limited information provided by the field studies, so we cannot explain the variability in outcomes caused by some unincluded factors like the termination date, resulting in uncertainties in predicting SOC and yield changes due to cover cropping.

Given the wide variability in cover crop management, soil conditions, and climate, the success of cover crops in building up SOC and increasing yield is highly variable. In addition, the associated stimulated N_2O emissions should not be neglected. Future work should combine data-driven black-box models with process-based modeling approaches to generate robust bottom-up estimations (Rahimi et al., 2024). The practice of cover cropping contributes to multiple ecosystem services beyond those explored here, such as erosion control (Chen et al., 2022), water quality regulation

(Elhakeem et al., 2023), and pest control (Bowers et al., 2020), underscoring the significant potential of cover crops in advancing sustainable agriculture.

6.5 Conclusion

This meta-analysis reveals that (1) both legume and non-legume CCs increase SOC. Legume CCs increase main crop yield and N_2O emissions, whereas non-legume CCs have a non-significant effect on average; (2) the effectiveness of CCs in enhancing SOC is mainly associated with mean annual temperature, exhibiting a positive correlation. Nitrogen fertilizer input is the primary factor influencing the impact of CCs on yield, with higher nitrogen levels increasing the yield response to non-legume CCs but decreasing the response to legume CCs; (3) legume CCs show greater benefits in terms of SOC and yield in farming systems with low nitrogen input, low crop diversity, and low initial SOC content, especially in humid and warm environments. Despite the increased N_2O emissions, growing legume CCs has the potential to reduce nitrogen fertilizer without yield penalty, and no-tillage, deficit irrigation, and diversified crop rotations can be combined with legume CCs to help mitigate the N_2O emissions. Upscaling of cover cropping effects suggests that incorporating legume CCs into cereal-dominated cropland can be a win-win strategy for enhancing both SOC and yield. The greatest co-benefits are achievable in regions with humid and warm climates, particularly those currently struggling with nitrogen deficiencies.

6.6 Supporting information

Table S6-1. The best hyperparameter combinations for BRT models. Tree numbers were set from 50 to 2,000 with a step size of 50, tree complexity were set as 1, 2, 3, and learning rates were set as 0.005, 0.01, 0.1 in the grid-search procedure.

Variables	Cover crop	Tree complexity	Learning rate	Tree number	$RMSE_{cv}$
SOC	Legume	2	0.10	1100	0.587
	Non-Legume	3	0.01	2000	0.557
Yield	Legume	3	0.10	400	0.713
	Non-Legume	3	0.01	1850	0.555

Table S6-2. Comparison of this study with previous meta-studies. The 95% confidence intervals are presented in brackets. LCC and NLCC represent legume and non-legume cover crops, respectively.

	SOC (%)		Yield (%)		N_2O (%)		Region	Source
	LCC	NLCC	LCC	NLCC	LCC	NLCC		
Meta-studies	—	—	**6** (2, 11)	**-3** (-8, -1)	—	—	Nordic countries	Valkama et al. (2015)
	9		**27**	**6**	**49**		Worldwide	Daryanto et al. (2018)
	6 (5, 7)		—	—	—	—	Worldwide	Bai et al. (2019)
	—	—	—	—	**61** (30, 97)	**-46** (-36, -26)	Worldwide	Muhammad et al. (2019)
	9 (4, 15)		**17** (8, 26)	**-7** (-11, -3)	—	—	California and Mediterranean	Shackelford et al. (2019)
	—	—	**14.6,** (10.6, 18.6)	**7.9,** (4.2, 11.6)	—	—	China	Fan et al. (2021)
	12		—	—	—	—	Worldwide	Hu et al. (2023)
	—	—	—	—	**3.3** (-14.8, 25.2)		Worldwide	Li et al. (2023)
	6.1 (3.4, 8.8)		—	—	—	—	Worldwide	Wooliver and Jagadamma (2023)
This study	**5.9** (3.8, 8.0)	**4.0** (1.5, 6.7)	**16.0** (12.2, 19.9)	**-0.8** (-4.4, 3.0)	**36.2** (15.5, 60.7)	**17.0** (-0.5, 37.6)	Worldwide	—

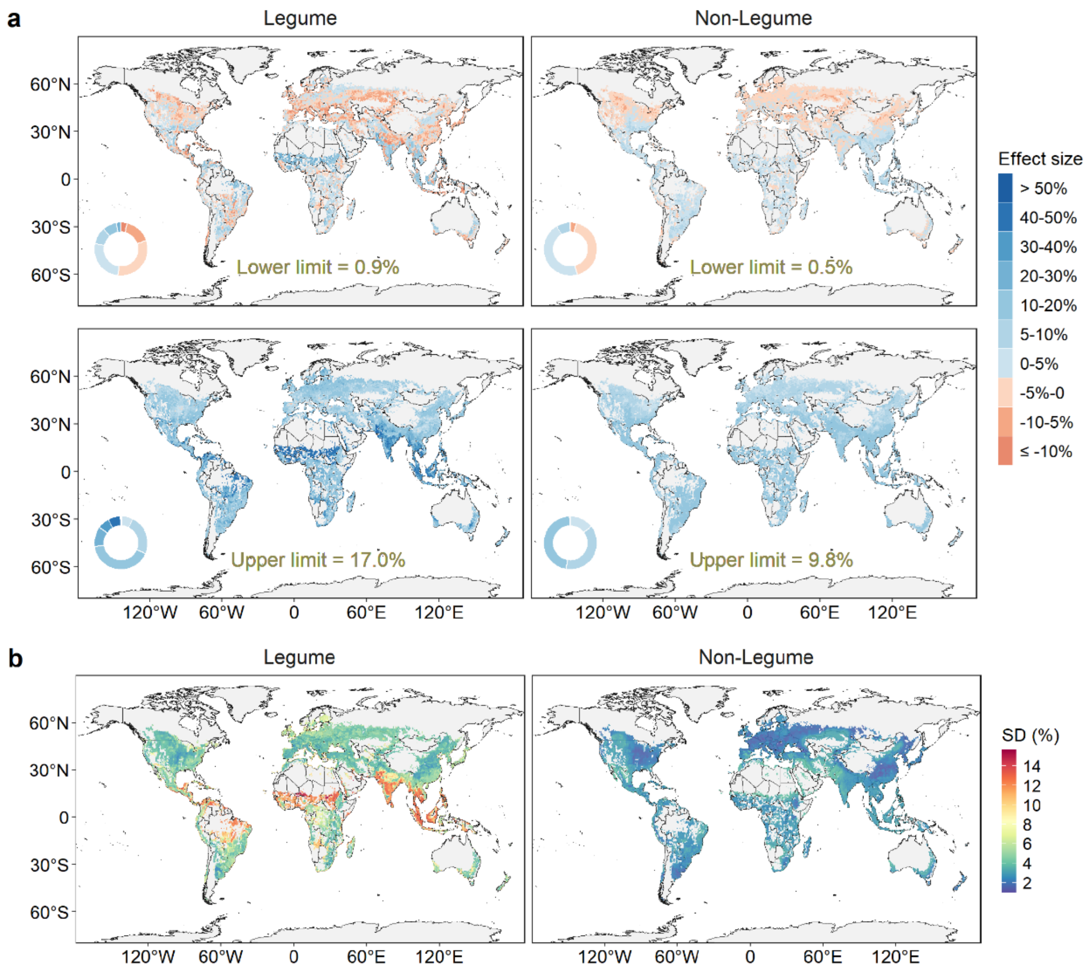

Fig. S6-1. Lower and upper limits of the 95% confidence intervals (a) and standard deviations (b) for predicted spatial variation in effects of CCs on SOC at 0-30 cm depth.

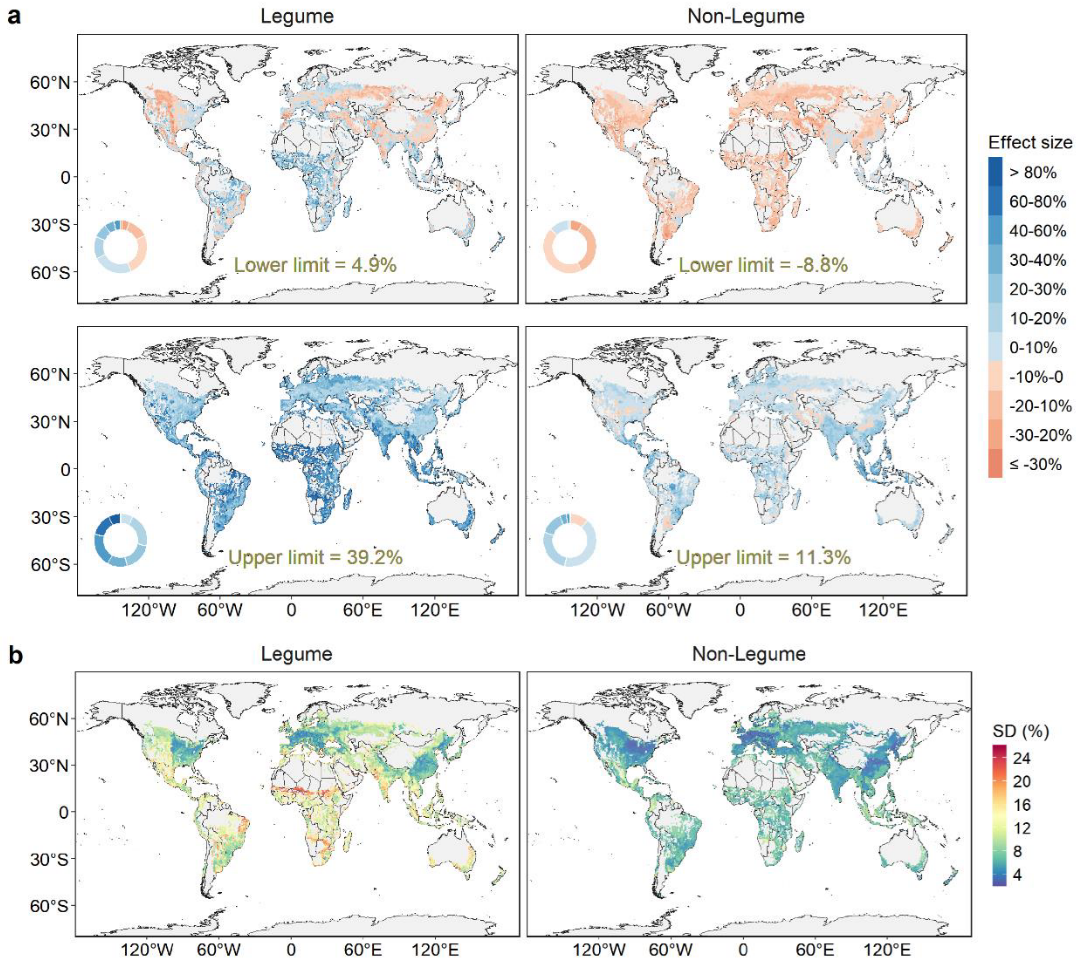

Fig. S6-2. Lower and upper limits of the 95% confidence intervals (a) and standard deviations (b) for predicted spatial variation in effects of CCs on cereal yield.

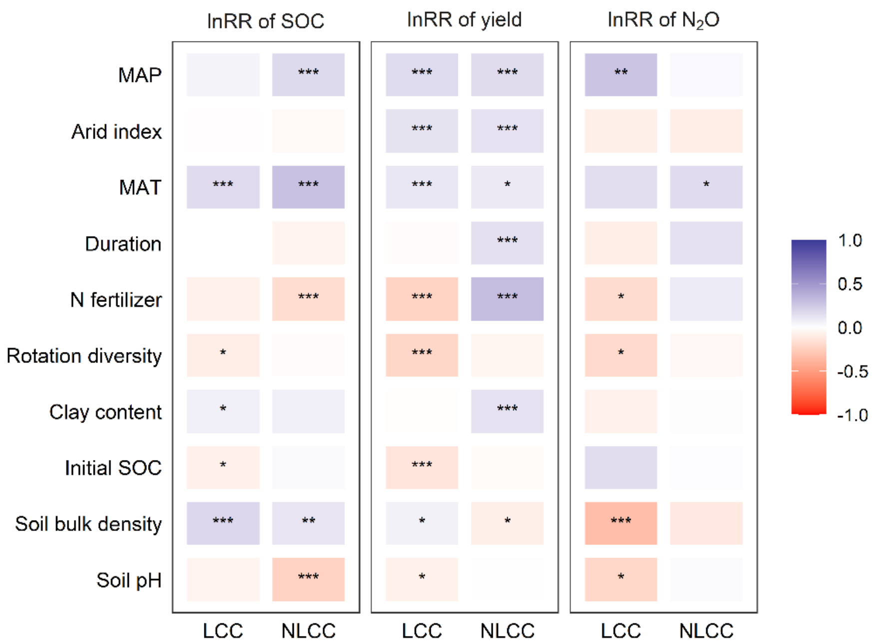

Fig. S6-3. Pearson's correlation (* $p < .05$, ** $p < .01$, *** $p < .001$) between *lnRR* and climate, soil, and management variables for legume cover crop (LCC) and non-legume cover crop (NLCC), respectively.

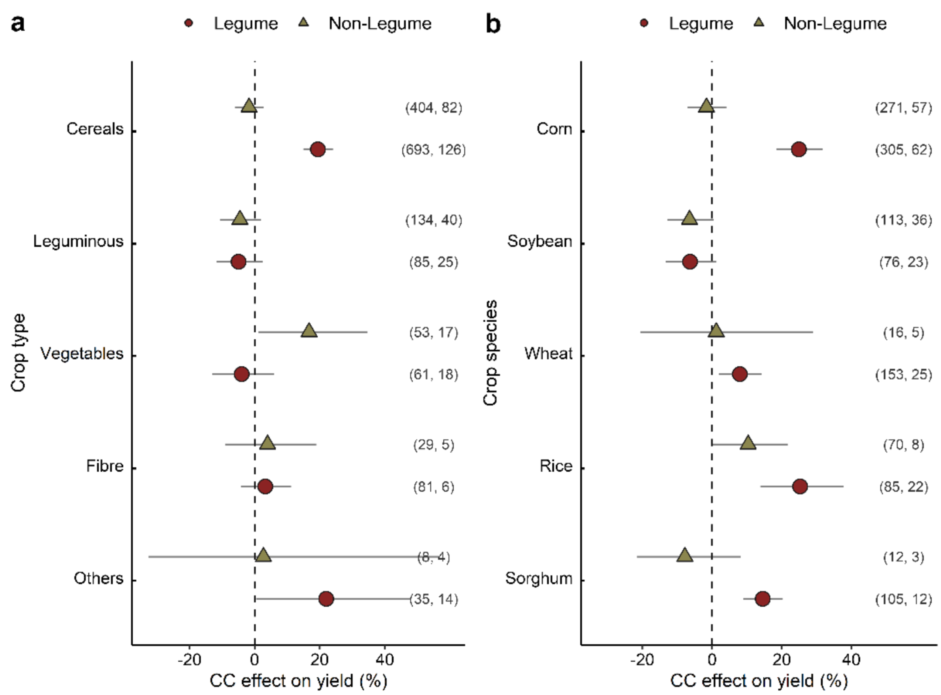

Fig. S6-4. Effects of legume and non-legume CCs on the yields of different crop types (**a**) and main crop species (**b**) compared to no cover crop. Numbers in parentheses are observations in each grouping, followed by the number of corresponding unique sites. Center dots indicate mean effect sizes and error bars indicate 95% confidence intervals.

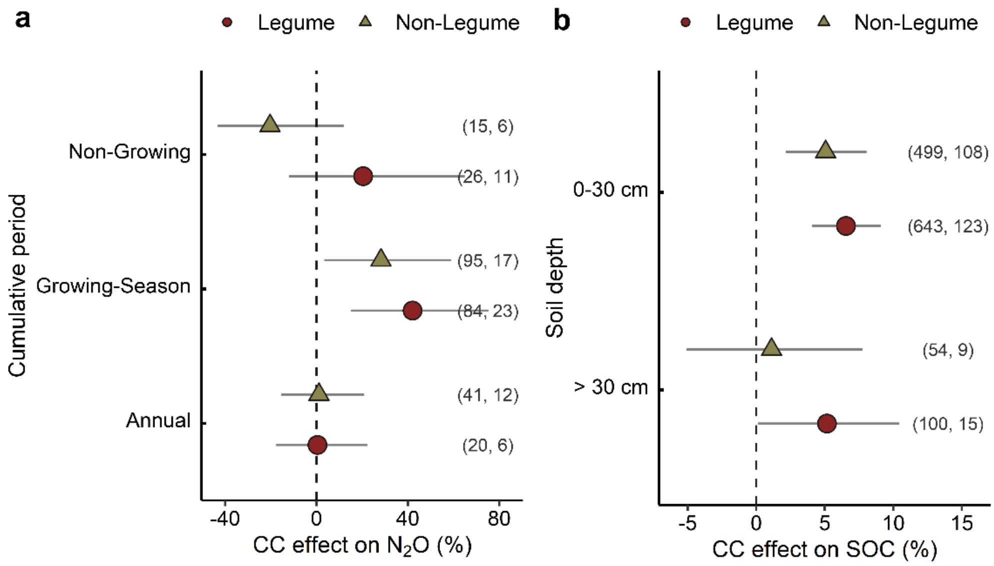

Fig. S6-5. Effects of legume and non-legume CCs on N_2O emissions (**a**) and SOC (**b**) compared to no cover crop. Numbers in parentheses are observations in each grouping, followed by the number of corresponding unique sites. Center dots indicate mean effect sizes and error bars indicate 95% confidence intervals.

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Chapter 7. Final conclusions and future research

7.1 Final conclusions

This study systematically examined the effects of conservation practices, including crop rotation, residue retention, and cover crops, on crop production and profitability, soil carbon sequestration, nitrous oxide emissions, and other related environmental factors. By using crop modelling and meta-analysis, the findings presented herein offer insights into the potential of conservation practices to promote sustainable agriculture amid both present conditions and future climate change scenarios.

In the Riverina region of NSW, retaining all crop residues in cropland turned the soil from a carbon source to a carbon sink, although this benefit was partly offset by the concomitant increase in N_2O emissions. Among the various crop rotations studied, the wheat-wheat-canola rotation with full residue retention achieved a win-win solution. It not only provided significant GHG abatement but also boosted a high gross margin compared to other rotations. Furthermore, cover crops decreased soil moisture but enabled greater sequestration of SOC and reduced nitrogen loss through leaching. The benefits derived from cover crops in terms of yield and gross margin were more pronounced in regions with higher rainfall and lower temperatures. Consequently, the long-term implementation of cover crops showed promise in improving existing crop rotations and sustaining crop productivity with reduced environmental impacts, particularly under wetter conditions in the study region.

Across three sub-regions of NSW, residue retention and cover cropping contributed to GHG abatement, but the latter consumed more energy and water per hectare. The composite sustainability scores, calculated with the food-energy-water-carbon framework, suggested that legume-inclusive rotations were generally more sustainable. Furthermore, in northern NSW (with an existing sorghum/wheat/chickpea/wheat rotation), residue retention with cover cropping was the most suitable combination, while the use of residue retention with fallow yielded greater benefits in southern NSW (with an existing wheat/field pea/wheat/canola rotation). Regional disparities in climate, soil, cropping systems, and on-farm costs prompted region-specific strategies to address the unbalanced distribution among food-energy-water-carbon domains.

Globally, both legume and non-legume cover crops significantly increased SOC content, with the increases dominated by mean annual temperature, exhibiting a positive correlation. Legume cover crops benefited yield but also increased N_2O emissions, which can be mitigated by combining with other practices, such as no-tillage, deficit irrigation, and diversified crop rotations. Greater SOC and yield advantages of legumes were observed for farming systems with low nitrogen fertilizer inputs, low crop diversity (especially where cereals dominate), low initial SOC, and for humid and warm climatic conditions. Thereby, incorporating legume cover crops into continuous cereal systems can benefit most low-input environments (e.g. many parts of Africa) to achieve a win-win outcome of enhanced SOC and yield.

7.2 Limitations and future research

Despite the overall contributions of this study presented above, there are a number of limitations which require further investigation in the future.

(1) Nitrogen optimization. Nitrogen fertilizer was found to be the most energy intensive input, and also affected the GHG emissions and water usage. However, the reduced nitrogen amount by using legume-included rotations and legume cover crops had not been considered. Reducing N inputs after legumes, in combination with nitrogen adjustment, specifically precision fertilization, should be further considered to better contribute to the various goals of sustainable agriculture.

(2) The hybrid models. The APSIM model could effectively simulate crop production, nutrient cycling, and environmental impacts as influenced by management interventions and climate change. However, its application at a large scale was limited by computational cost, model uncertainty, and data availability. In contrast, machine learning techniques could generate large-scale simulations quickly but lacked the ability to interpret underlying processes. Therefore, coupling crop models with machine learning should be further investigated to facilitate regional predictions of various management practice.