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Common agronomic adaptation strategies to climate change may increase soil greenhouse gas emission in Northern Europe

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ABSTRACT

Climate change poses a significant threat to agriculture, highlighting the need for adaptation strategies to reduce its impacts. Agronomic adaptation strategies, such as changes in planting dates, fertilization, and irrigation, might sustain crop yield. However, their impact on soil greenhouse gas (GHG) emission is unknown under future climate scenarios. Using the LandscapeDNDC model, we assessed the effect of agronomic adaptation strategies (early sowing, increased fertilization dose, and increased irrigation amount) on soil GHG emission, yield, and yield-scaled GHG emission. A diversified crop rotation (potato – winter wheat – spring barley – faba bean) of a long-term experiment in Denmark was used for model validation. The adaptation practices to climate change were implemented for two representative concentration pathways (RCPs; 4.5 and 8.5) and five coupled global circulation and regional climate models. The adaptation scenarios were contrasted against a baseline scenario under current management practices. Soil-related variables showed better model fit (refined index of agreement $\geq$ 0.38) and lower errors (mean absolute error $\leq$ 8.18) than crop-based outputs for model validation. A total yield of ~29 (± 3) t DW ha^{-1}, and soil GHG emission of ~3.02 (± 1.39) t CO_2e ha^{-1} (RCP8.5) were obtained for the crop rotation system under the baseline for 2071–2100. Early sowing and its combination with increased fertilization decreased the yield compared to the baseline by 6.1 and 4.8 %, respectively (RCP8.5). Conversely, early sowing with increased irrigation, and early sowing with increased fertilization and irrigation, produced higher yields by 2.3 and 4.0 %, respectively (RCP8.5). All the agronomic adaptation strategies increased soil GHG emissions (ranging from 4.1 to 17.8 %) as well as yield-scaled GHG emissions (varying from 3.0 to 12.9 %) (RCP8.5). The highest soil GHG emission was simulated for early sowing in combination with increased fertilization and irrigation. Our study indicates that soil GHG emission will increase in the coming decades and that the agronomic adaptation strategies needed to sustain food production may further exacerbate this emission.

1. Introduction

Climate change is one of the greatest threats to agricultural production (Lesk et al., 2022, 2021; Zhu et al., 2022). Emission scenarios project that atmospheric CO_2 concentration ([CO_2]) will increase in the coming decades, potentially reaching around 650 to 1370 ppm by 2100, based on radiative concentration pathways (RCP) 4.5 and 8.5, respectively (IPCC, 2021; Van Vuuren et al., 2011). Additionally, global temperature is projected to increase by approximately 2.5–3 °C (RCP4.5) or ~5 °C (RCP8.5), while precipitation patterns and rates will change differently in different geographical settings (IPCC, 2021; Pielke et al., 2022). These daunting climatic and atmospheric variations will alter agroecosystems functioning and associated services, and therefore, adequate adaptation strategies are a prerequisite to ensure appropriate crop productivity and quality (Asseng et al., 2019).

To determine appropriate crop management adaptation strategies, it is necessary to consider the interactions between crop growth, environmental conditions, and management practices (Müller et al., 2014). Many agronomic adaptation practices have been proposed for maintaining regional and global crop production under climate change, such as introducing new cultivars or crop rotations, modifying the sowing date, precision farming, fine-tuning irrigation, and adjusting

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fertilization practices (Olesen et al., 2011; Wiréhn, 2018; Zhao et al., 2022b; Wakatsuki et al., 2023). Among them, manipulating sowing date and rates of fertilizer and irrigation application represent some of the main farm-based adaptation strategies without requiring high technological development or cost and have promising implementation opportunities (Dobor et al., 2016; Wiréhn, 2018; Wakatsuki et al., 2023). For example, planting date adjustments may be needed to cope with accelerated phenological development due to increasing temperatures and to improve crop resilience (Dobor et al., 2016; Minoli et al., 2022). Irrigation practices must be tailored to increase water use efficiency and account for the increased potential evapotranspiration during the growing seasons, depending on region-specific and management conditions (Iglesias and Garrote, 2015; Zhao et al., 2015). Moreover, increased fertilization rates may be required to support plant growth and productivity under elevated [CO_2], avoiding the dilution effect of crop tissue (i.e., preserving the quality of harvested products) (Asseng et al., 2014, 2019; Raymundo et al., 2018; Zhao et al., 2022a).

Studies on agronomic adaptation strategies have primarily focused on crop production responses (Wakatsuki et al., 2023; White et al., 2011). However, the consequences of these strategies for the greenhouse gas (GHG) balance of agricultural soils have been largely ignored (Wakatsuki et al., 2023). This is a significant knowledge gap since soil GHG emissions from agroecosystems are expected to increase under future climate conditions (Reay et al., 2012; Van Dijk et al., 2021). For example, rising temperatures may increase the decomposition of soil organic carbon (SOC; Conant et al., 2011; Davidson and Janssens, 2006) and enhance N_2O production (Reay et al., 2012) due to the stimulation of abiotic and biological processes (e.g., mineralization and denitrification). Changes in precipitation intensity and frequency will affect soil moisture, with wetter conditions resulting possibly in 1) higher SOC because increased net primary production (and associated litter) may offset the potential increases in soil respiration (Falloon et al., 2011) and 2) higher N_2O emissions due to increased nitrogen (N) turnover rates and anaerobicity (Smith et al., 2018). As a climate change adaptation practice, and depending on climatic conditions and crop type, early sowing could increase or decrease yield due to erratic weather events (Dobor et al., 2016; Huang et al., 2020). The influence of climate change on crop biomass development may also affect soil GHG emissions as plant nutrient uptake and associated quantity and quality of aboveground and belowground residues affect agroecosystem C and N fluxes and soil GHG emissions (Abalos et al., 2022). Improving irrigation and fertilization under climate change conditions will likely affect N_2O emissions due to changed soil environmental conditions (e.g., soil moisture) and (de-)nitrification substrate availability (Olesen et al., 2004). However, literature assessing the impacts of agronomic adaptation strategies to climate change on soil GHG emissions using process-based models (i.e., a Tier 3 approach) is scarce (Wakatsuki et al., 2023) and constrained to the N cycle (Ma et al., 2018; Zimmermann et al., 2017) or C dynamics (Liu & Basso, 2020) separately.

Process-based models are powerful tools to estimate soil GHG emissions and crop productivity by integrating soil-plant-atmosphere mechanisms. Several models have been developed with varying levels of complexity to simulate plant growth and development, and soil microbial and physicochemical processes (Del Grosso et al., 2012; Gilhespy et al., 2014; Keating et al., 2003). LandscapeDNDC is a model framework integrating terrestrial ecosystems processes and biogeochemical C—N cycling (Haas et al., 2013; Kraus et al., 2015). The modeling framework has been tested worldwide for various agroecosystems under current and future climate conditions (Ehrhardt et al., 2018; Kasper et al., 2019; Petersen et al., 2021; Zhang et al., 2015) and at different scales (Haas et al., 2022; Smerald et al., 2022; Kim et al., 2015; Molina-Herrera et al., 2016), proving to be a robust option for evaluating climate adaptation strategies and estimating soil GHG balances.

We aimed to improve the current understanding of sustainability aspects of adaptation strategies by simultaneously evaluating soil GHG and crop production effects, thereby reconciling environmental and food production perspectives. We investigated the effects of key agronomic adaptation strategies for climate change (i.e., sowing date, fertilization, and irrigation) on crop productivity and soil GHG emissions using a validated LandscapeDNDC model. A diversified crop rotation system was analyzed as a case study using data from a long-term experiment in Denmark. The conditions represent temperate regions in Northern Europe, characterized by relatively mild winters, surplus winter precipitation, and the predominance of light-textured soils.

2. Material and methods

2.1. Long-term experiment and measurements for model validation

We used data from a long-term crop rotation experiment started in 1997 on loamy sand soil at Aarhus University, Campus Foulum, Denmark (56° 30′ N, 9° 34′ E). This soil is classified as a MollicLuvisol according to FAO World Reference Base, and the climate at the study site is temperate oceanic (Cfb in the Köppen classification). The experiment was established to compare the agronomic and ecosystem effects of conventional and organic crop rotation systems. The site, soil properties, and experimental design have been described previously (Chirinda et al., 2010; Olesen et al., 2000a; Pugesgaard et al., 2017). Our study focused on a subset of the experiment representing a cycle of the 4-year conventional rotation system between 2006 and 2009: potato (*Solanum tuberosum* L.) – winter wheat (*Triticum aestivum* L.) – spring barley (*Hordeum vulgare* L.) – faba bean (*Vicia faba* L.). This treatment was represented in two replicates (i.e., same cycle of crop rotation sequence) and four pseudoreplicates (i.e., different entries of the crop rotation sequence) for every year. Synthetic fertilizers (calcium ammonium nitrate, phosphorus, and potassium) were used, along with conventional tillage practices. Weeds, pests, and diseases were controlled following conventional practices applying agrochemicals.

A comprehensive campaign was conducted to measure a range of soil physicochemical features, crop productivity, and soil GHG fluxes. Briefly, soil N_2O fluxes were measured weekly and biweekly during the 2008 – 2009 growing seasons using the static chamber method (Chirinda et al., 2010); N_2O concentrations were determined by gas chromatography (Brozyna et al., 2013; Pugesgaard et al., 2017); N_2O measurements outside of the growing seasons were performed monthly. Soil temperature was measured with thermocouples contact sensors at 0–10 cm in 2007 – 2008, simultaneously with gas sampling. Soil moisture was recorded from 2007 to 2008 at 0–30 cm using a time domain reflectometer sensor (Chirinda et al., 2010). Total soil carbon (C) and nitrogen (N) content were measured in 2004 and 2008 at 0–20 cm by dry combustion (De Notaris et al., 2021). Dry weight (DW) yield was determined from plant material dried at 80 °C for 24 h and N uptake by near-infrared spectroscopy and the Dumas method (Büchmann et al., 2001; Hansen, 1989) for the 2006 – 2009 growing seasons (Pandey et al., 2018; Shah et al., 2017).

2.2. LandscapeDNDC

2.2.1. Model overview

LandscapeDNDC (v.1.35.2) is a model library for terrestrial ecosystem models focusing on biogeochemical C—N cycling (Haas et al., 2013). This study uses the following models: CanopyECM, PlaMo^x, MeTr^x, and WatercycleDNDC. Briefly, CanopyECM simulates the distribution of solar radiation, air temperature within the canopy, and soil temperature (Grote et al., 2009). PlaMo^x simulates plant physiology and growth using the photosynthesis equations of Farquhar et al. (2001) and Ball et al. (1987). Species-specific parameters allow to model plant phenological stages defined by cumulative growing degree days and C assimilation; the Rubisco enzyme activity regulates photosynthesis depending on [CO_2], temperature, drought, and N availability; for further details, see Petersen et al. (2021). MeTr^x simulates the soil C and N turnover and transport based on soil physicochemical features and plant litter decomposition. Specific modeled soil processes include humification, mineralization, nitrification, denitrification, immobilization, leaching, and gas transport (Kraus et al., 2015; Molina-Herrera et al., 2017). WatercycleDNDC models evapotranspiration and soil water transport, calculating potential evapotranspiration using the Penman method and actual evapotranspiration using the gross primary productivity and species-specific water use efficiency. Soil water transport is estimated using a tipping bucket approach based on soil physical properties (i.e., field capacity, wilting point, and saturated hydraulic conductivity); further details can be found in Kiese et al. (2011).

2.2.2. Description of model inputs

2.2.2.1. Historical and projected air chemistry. We obtained site-specific daily atmospheric deposition of nitrate (NO_3) and ammonium (NH_4) from the Danish Ammonia Modelling System (Ellermann et al., 2018). We used average values from 1996 to 2009 for all simulations, with NO_3 at 0.016 and NH_4 at 0.0295 kg ha^{-1} d^{-1}. We used the average annual historical [CO_2] from the National Oceanic and Atmospheric Administration - Global Monitoring Laboratory (https://gml.noaa.gov/), which ranged from 361 ppm in 1996 to 387 ppm in 2009. To project the [CO_2] for climate change scenarios, we assumed transient yearly increases for two radiative concentration pathways (RCP), RCP4.5 and RCP8.5, from Meinshausen et al. (2011).

2.2.2.2. Historical and projected climate data. Climate information for Foulum (Denmark) was obtained from a local weather station (56° 29′ N, 9° 34′ E), including daily values of maximum, average, and minimum air temperature (°C), precipitation (mm), and solar radiation (W m^{-2}). The climate variables during the evaluated growing cycles are depicted in Figure S1.

We used the projected climate data from the RCP4.5 and RCP8.5 from the Danish Meteorological Institute (DMI, Thejll et al. (2021)), representing the most commonly assessed scenarios (Wakatsuki et al., 2023). We employed an ensemble of Global Circulation Models (GCM) and Regional Climate Models (RCM) with complete daily information on maximum, average, and minimum air temperature, precipitation, and solar radiation. We selected subsets of coupled GCM-RCM with consistent climate sensitivity to [CO_2] and bias-corrected future periods (2011–2100). The specific coupled GCM-RCMs for the climate change scenarios are shown in Table S1 and Figure S2.

2.2.2.3. Soil properties. The initial soil conditions were measured in 1996, as described by Djurhuus & Olesen (2000) and Olesen et al. (2000a). We estimated the saturated hydraulic conductivity based on Vereecken et al. (1989). The initial soil physicochemical parameters are shown in Table S2.

2.2.2.4. Agronomic management. We considered plot-specific management practices from 1996 to 2009 to represent the historic field management effects on soil C and N pools. The management practices included tillage (plowing, rolling, and harrowing), sowing, fertilizer application, irrigation, and harvesting time. The N annual fertilizer rate (ammonium nitrate) for each crop was as follows: potato (140 kg N ha^{-1}), winter wheat (167 kg N ha^{-1}), spring barley (130 kg N ha^{-1}), and faba bean (0 kg N ha^{-1}); the fertilizer was incorporated into the soil. The annual irrigation amount ranged from 25 mm to 104 mm, depending on weather conditions during crop growth. Spring crops were planted in April and harvested in August/September, while winter wheat was sown in September and harvested in August. Tillage was performed one to two weeks before sowing. For detailed information on field operations during the monitoring period, refer to Chirinda et al. (2010), De Notaris et al. (2021), Pandey et al. (2018), Pugesgaard et al. (2017), and Shah et al. (2017) or consult the supplementary files of our model implementation.

2.2.3. Model performance

We used goodness-of-fit statistics to assess model performance. The selection of statistical indicators followed the recommendations of Willmott et al. (2015) and Yang et al. (2014).

We calculated the mean absolute error (*MAE*) and root mean square error (*RMSE*) to estimate the model error. The model fit was assessed based on the refined index of agreement d_r ($d_r \approx 1$ represents a perfect fit, while $d_r \approx$ -1 indicates that the averaged observed value is a better estimate than the simulated values; Willmott et al. (2012)).

We elaborated a graphical representation of model performance integrating the model error and fit based on Coucheney et al. (2015). This graphic is grounded on the geometrical relation between the *RMSE*, the systematic error ($RMSE_s$) and the unsystematic error ($RMSE_u$) defined by Willmott (1981): $RMSE^2 = RMSE_s^2 + RMSE_u^2$.

$$RMSE_s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{S}_i - O_i\right)^2} \tag{1}$$

$$RMSE_u = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(S_i - \widehat{S}_i\right)^2} \tag{2}$$

where $\widehat{S}_i$ is the predicted value calculated from linear regression of the observed versus simulated values: $\widehat{S}_i = a + bO_i$. For every specific variable of evaluation, the model performance is represented by a point whose coordinates are proportional to $RMSE_s$ and $RMSE_u$, normalized by the standard deviation of the observed values (σ_O). The distance from the origin to this point is proportional to *RMSE* normalized by σ_O, with points closer to the origin representing smaller errors. Normalizing with the standard deviation allows us to account for the variable variation and to compare the performance of different variables on heterogeneous datasets comprehensibly (Coucheney et al., 2015). The point size was scaled by d_r to incorporate the model fit. The figure was divided by the 1:1 identity line, where $RMSE_s$ (model bias) prevails above the diagonal and $RMSE_u$ (model dispersion) below the diagonal (Coucheney et al., 2015). This visualization has been previously used for several models (e.g., Grados et al., 2020; Morissette et al., 2016).

2.3. Scenarios definition and soil GHG balance

2.3.1. Baseline scenario

The baseline scenario (BS) simulations started in 2010 and lasted until 2100, assuming the same crop sequence as the crop rotation experiment. One irrigation event of 30 mm was adopted for each crop during the plant vegetative stage. Nitrogen fertilizer doses were adjusted to current Danish regulation (2021–2022) for the specific soil type (without correction for the succeeding crop), representing conventional and contemporary rates, and resulting in more realistic simulations: potato (227 kg N ha^{-1}), winter wheat (202 kg N ha^{-1}), spring barley (159 kg N ha^{-1}) and faba bean (0 kg N ha^{-1}). Crop residues were left on the field and incorporated following the practices of the long-term experiment. The timing and specific field practices represent standard management and were assumed to remain constant for BS (cf. Olesen et al., 2000; Zhao et al., 2015; Zimmermann et al., 2017).

2.3.2. Scenarios of agronomic adaptation strategies

We simulated three different agronomic adaptation practices (i.e., early sowing, increased fertilization dose, and increased irrigation amount) implemented in four scenarios for each climate change projection. The scenarios are described in Table 1.

2.3.3. Calculation of soil GHG balance

We calculated the soil GHG balance at the field level for each growing season ($GHG_{balance}$; t CO_2e ha^{-1} growing season^{-1}) according to Autret et al. (2019) and Launay et al. (2021):

Table 1
. Description of agronomic adaptation strategies.

Scenario	Adaptation practice	Description
ES	Early sowing	Sowing occurred when the 10-day moving average of daily mean temperature[a] was equal to the emergence temperature for each crop (potato[b] 5 °C, winter wheat[c] 12 °C, spring barley[c] 5 °C, and faba bean[c] 10 °C). Sowing dates were confined to the beginning of meteorological spring or autumn, given the possible negative impact of increased pests and diseases and unsuitable soil conditions [d,e,f,g]. The timing of other agronomic management events was adjusted to the new crop calendars based on the BS.
ES-IF	Early sowing with increased fertilization	Early sowing, including a transient increase dose of N fertilization by 5 % (2011–2040), 15 % (2041–2070), and 25 % (2071–2100) for each crop compared to the BS.
ES-II	Early sowing with increased irrigation	Early sowing, including an extra irrigation event of 30 mm during the plant reproductive stage (~30 days after the first irrigation event), compared to the BS.
ES-IF-II	Early sowing with increased fertilization and irrigation	A combination of the three agronomic adaptation practices (early sowing, increased fertilization, and increased irrigation) as defined previously.

[a] Olesen et al. (2012).
[b] Struik (2007).
[c] Waha et al. (2012).
[d] Dobor et al. (2016).
[e] Lindblad & Waern (2002).
[f] Olesen et al. (2011).
[g] Wiréhn (2018).

$$GHG_{balance} = 273\text{x}\frac{44}{28}(direct\ N_2Oe) - \frac{44}{12}\Delta SOC \tag{3}$$

where *direct N_2Oe* represents the soil N_2O emissions (t N_2O—N ha^{-1} growing season^{-1}) and ΔSOC the soil organic carbon (SOC) change in the topsoil (30 cm).

Direct N_2O emissions were estimated daily and accumulated for the growing season. We used the global warming potential factor of N_2O emissions (273) for a 100-year timeframe from IPCC (2021). We quantified the SOC change in the topsoil (30 cm) as the difference between the initial and final SOC content for each growing season. $GHG_{balance}$ was aggregated at the crop rotation system level. Methane emissions were not considered in the $GHG_{balance}$ because they are negligible in upland soils.

Combining the aggregated DW yield of the crop rotation system (t DW ha^{-1}) and $GHG_{balance}$ (t CO_2e ha^{-1} growing season^{-1}), we calculated the yield-scaled GHG emission (t CO_2e t DW^{-1}) (Mosier et al., 2006; Van Groenigen et al., 2010). We considered in-season N_2O emissions due to the minor contribution of off-season emissions to the total annual emissions (Pugesgaard et al., 2017; Brozyna et al., 2013), the difficulty of disaggregating background emissions from crop-specific effects from crop residues and management, and the dynamic implementation of the agronomic adaptation strategies scenarios. Accordingly, our approach ensured consistent data analysis and scenario comparisons (see Section 2.4).

2.4. Data analysis

We constructed univariate kernel density estimations (KDE) for yield, $GHG_{balance}$, and yield-scaled GHG emission to assess the baseline and adaptation strategies scenarios for three-time periods (2011–2040, 2041–2070, and 2071–2100). KDE is a non-parametric statistical technique that allows to estimate the probability density function of a variable without any underlying assumption of the density function (Chen, 2017). A histogram was built to assess the distribution of the sowing dates and a KDE for the duration of the growing seasons of ES scenario. The effect on yield, soil $GHG_{balance}$, and yield-scaled GHG emission of the adaptation strategies was estimated against the BS by calculating the relative change (%). Bivariate KDE (yield and $GHG_{balance}$) was used to evaluate the overall effect of the adaptation strategies. Data processing, analysis, and figure generation were executed using R v.4.2.2 (R Core Team, 2022) and the R-packages tidyverse v. 2.0.0 (Wickham et al., 2019) and ggplot2 v. 3.4.1 (Wickham, 2016).

3. Results

3.1. Evaluation of model performance

Based on the soil and crop parameters of the long-term crop rotation experiment, soil-related variables showed better model fit ($d_r \geq 0.38$) and lower model errors ($MAE \leq 8.18$) than crop-based outputs (Fig. 1 and Table S3). Model simulations followed the temporal dynamics of observed values (Figures S3 - S6). Most of the crop-related variables (dry weight (DW) yield and nitrogen (N) uptake) laid within the systematic error (Fig. 1), where $RMSE_s$ is preponderant (Table S3). The model fit and model errors were superior for the DW yield and yield N uptake of potato, winter wheat, and faba bean than for spring barley (Fig. 1 and Table S3). Yield N uptake was better modeled compared to DW yield, with the highest d_r values for potato (0.62) and winter wheat (0.41) (Fig. 1 and Table S3).

Soil temperature and volumetric moisture showed good model fit (d_r values of 0.89 and 0.93) with low *MAE* and *RMSE* (Table S3) and unsystematic *RMSE* (Fig. 1). Soil organic carbon (SOC) and total N obtained $d_r \sim 0.5$ and *MAE* of 8.18 and 0.49, respectively (Table S3). The simulation accuracy of N_2O emission was placed in the unsystematic error region (i.e., predominant $RMSE_u$ - Fig. 1), with a d_r value of 0.38, *RMSE* of 10.75, and standardized *RMSE* of 2.03.

3.2. Baseline scenario (BS) – yield and soil GHG balance

Model simulations showed that crop yields of the rotation system will increase in the future, although the degree of productivity gain for each crop is variable (Fig. 2A). The median yield increase (for RCP4.5 and RCP8.5, respectively) was predicted to be 12 and 27 % for potato, 21 and 19 % for winter wheat, 8 and 3 % for spring barley, and 17 and 75 % for faba bean (2071–2100 compared to 2011–2040). The yield of potato and spring barley is expected to become highly variable compared to winter wheat and faba bean, as shown by the high dispersion of the kernel density estimation (Fig. 2A).

Total soil greenhouse gas (GHG) emissions of the crop rotation system are estimated to increase under climate change (Fig. 2B). The soil GHG balance transitioned from about neutral (~0 t CO_2e ha^{-1} for both RCPs) in 2011–2040 to a source (2.33 and 3.02 t CO_2e ha^{-1} for RCP4.5 and RCP8.5) in 2071–2100. For 2071–2100, LandscapeDNDC simulated losses of topsoil (0–20 cm) SOC stocks due to increased mineralization and a concomitant increase of N_2O emissions (Fig. 2B).

A steady increase in yield-scaled GHG emission was simulated under both RCPs scenarios for the crop rotation system (Fig. 2C). Starting with median values of ~0 t CO_2e t DW^{-1} for both RCPs in 2011–2040, the estimates increased to 0.09 (RCP4.5) and 0.11 (RCP8.5) by 2071–2100.

3.3. Adaptation strategies – cropping period, yield, and soil GHG balance

Sowing dates for the early sowing (ES) scenario tended to antecede the static sowing dates of the BS for all crops of the rotation system in the future (Fig. 3A). While the planting dates for potato and spring barley predominantly happened at the start of the meteorological spring

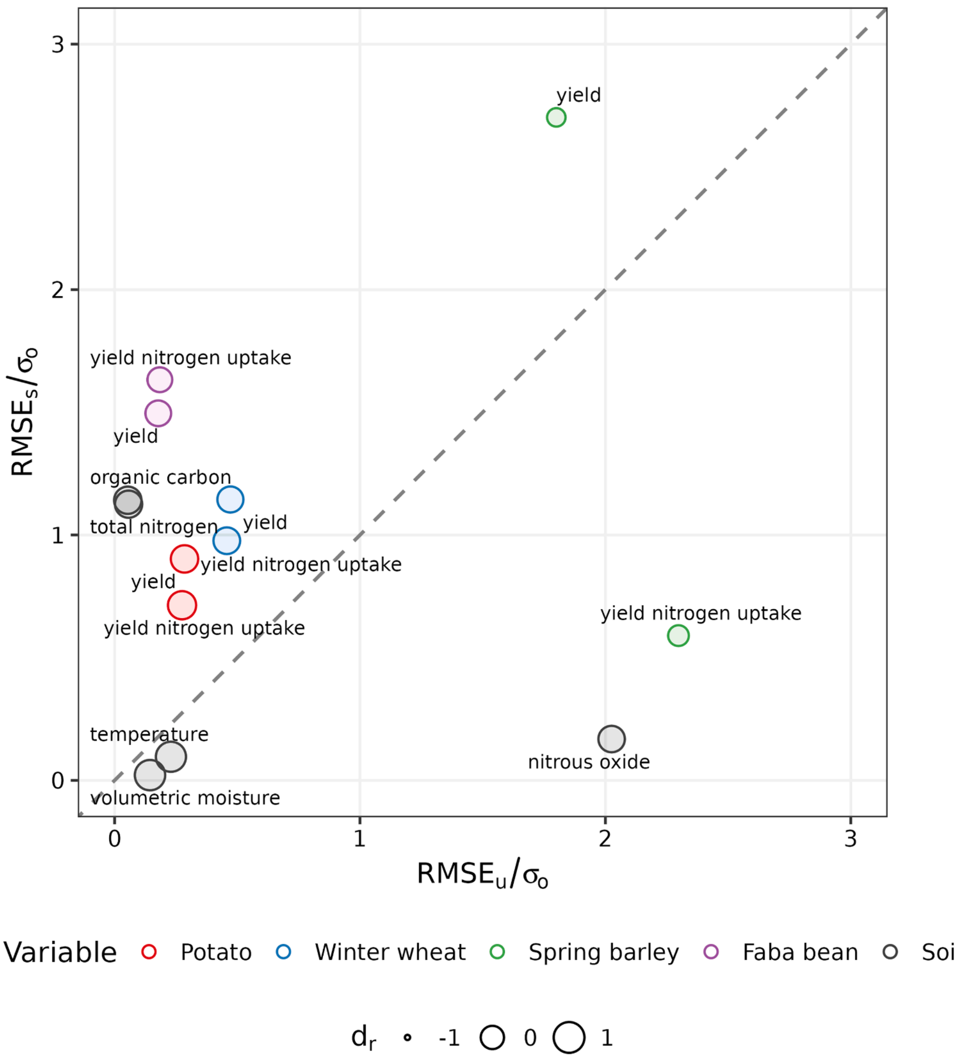

Fig. 1. Graphical representation of the model performance for plant and soil variables in the long-term field experiment. The root mean square error (RMSE) normalized by the standard deviation of the observed values (σ_O) is read as the distance from the origin to the point coordinates. The coordinates represent the unsystematic RMSE ($RMSE_u$) and the systematic RMSE ($RMSE_s$) normalized by σ_O. Circles size is proportional to the redefined index of agreement (d_r). The dotted line represents 1:1 reference identity line.

seasons under both RCPs, the planting dates for faba bean became more variable, as shown by the wider histogram range for this crop. Sowing dates of winter wheat occurred mainly during the first days of autumn (Fig. 3A). The cropping period was shortened for each crop, with higher reductions under RCP8.5 scenario (Fig. 3B). Spring crops were subject to a reduction of the median number of cropping days (for RCP4.5 and RCP8.5), potato (~7 and ~20 days), and spring barley (~8 and ~16 days) when comparing 2071–2100 to 2011–2140. Similarly, the cropping period of winter wheat was expected to shorten by ~11 days (RCP4.5) and ~23 days (RCP8.5) by 2071–2100 relative to 2011–2040 (Fig. 3B).

The agronomic adaptation strategies had contrasting impacts on the total yield of the crop rotation system (Fig. 4A). The scenarios of ES and early sowing with increased fertilization (ES-IF) consistently reduced total yield compared with BS (Fig. 4A). A median yield of 29.1, 26.6, and 27.3 t DW ha^{-1} for the crop rotation system was simulated for BS, ES, and ES-IF by 2071–2100 (RCP8.5), respectively. Towards 2071–2100 and for RCP8.5, the yield for early sowing with increased irrigation (ES-II) and early sowing with increased fertilization and irrigation (ES-IF-II) was lower than the BS by 3.0 and 0.7 % (Fig. 4A). A median total yield of 25.7, 26.1, and 26.8 t DW ha^{-1} for the crop rotation system was simulated for BS, ES-II, and ES-IF-II by 2071–2100 (RCP4.5), respectively.

The crop rotation system was a net sink of soil GHG until ca. 2040, irrespective of the agronomic adaptation scenario (Fig. 4B). ES, ES-IF, and ES-IF-II scenarios increased median cumulative soil GHG emission compared to BS by 15.6, 32.2, and 29.6 % (RCP8.5) and 3.9, 21.4, and 17.6 % (RCP4.5), respectively. The ES-II scenario produced higher median cumulative soil GHG emission than BS (13.5 %) for RCP8.5 and a similar value (31.2 t CO_2e ha^{-1}) for RCP4.5 (Fig. 4B).

Similar to the soil GHG emission (Fig. 4B), the cumulative yield-scaled GHG emission of the crop rotation system represented a source of CO_2e per DW for all the agronomic adaptation scenarios after ca. 2040 (Fig. 4C). ES-IF, ES, and ES-IF-II generated higher cumulative yield-scaled GHG emissions than BS (Fig. 4C). Final cumulative values for ES-IF, ES, and ES-IF-II were 1.72, 1.59, and 1.59 t CO_2e t DW^{-1} (RCP8.5). ES-II produced higher yield-scaled GHG emission than BS for RCP8.5 but not for RCP4.5 (Fig. 4C).

Fig. 5 depicts the relative changes in yield and soil GHG emission across the adaptation strategies and climate change projections. It can be seen that the ES and ES-IF scenarios tended to reduce yield overall from 2011 to 2100; however, high variability was found under both RCPs (Fig. 5). The median yield decrease was 6.1 and 4.8 % (RCP8.5) for ES and ES-IF, respectively. In contrast, ES-II and ES-IF-II increased yield relative to BS (Fig. 5). ES-II improved median yield by 2.3 and 1.8 % for

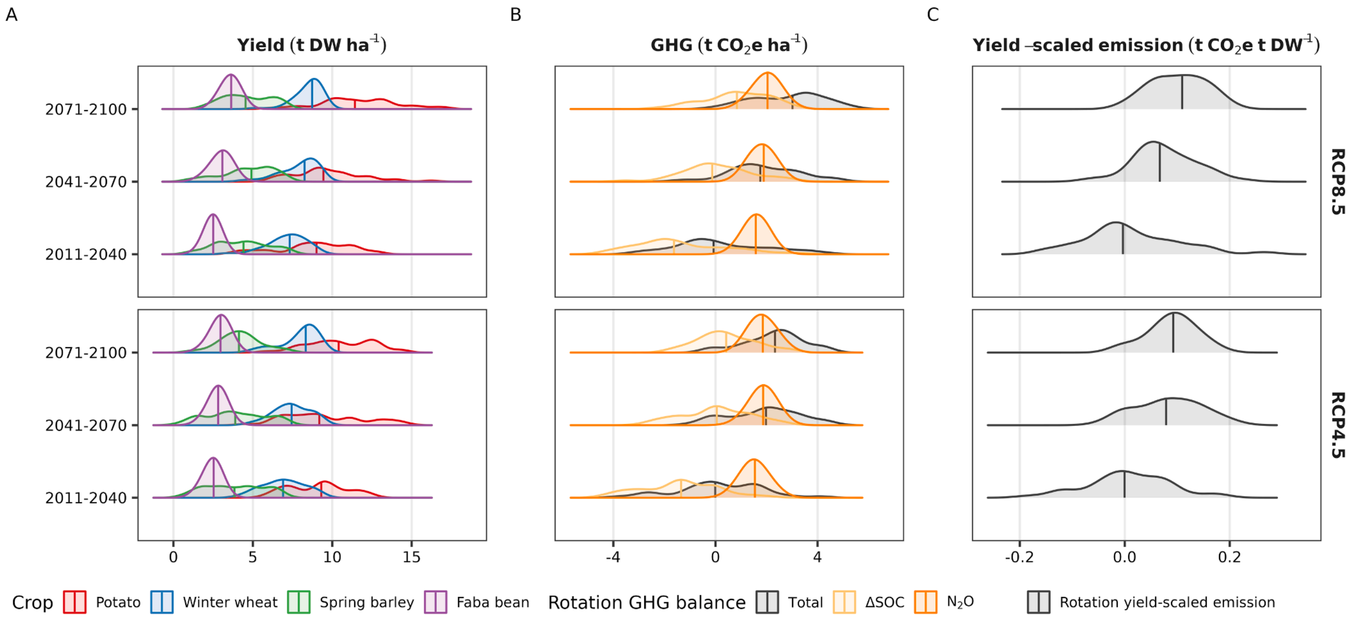

Fig. 2. Kernel density estimation of metrics for the baseline scenario across three periods (2011–2040, 2041–2071, and 2071–2100). Panel A shows the dry weight (DW) yield (in t DW ha^{-1}), Panel B the soil greenhouse gas (GHG) emission (in t CO_2e ha^{-1}), and Panel C the yield-scaled GHG emission (in t CO_2e t DW^{-1}). The vertical lines within the distributions represent the median values.

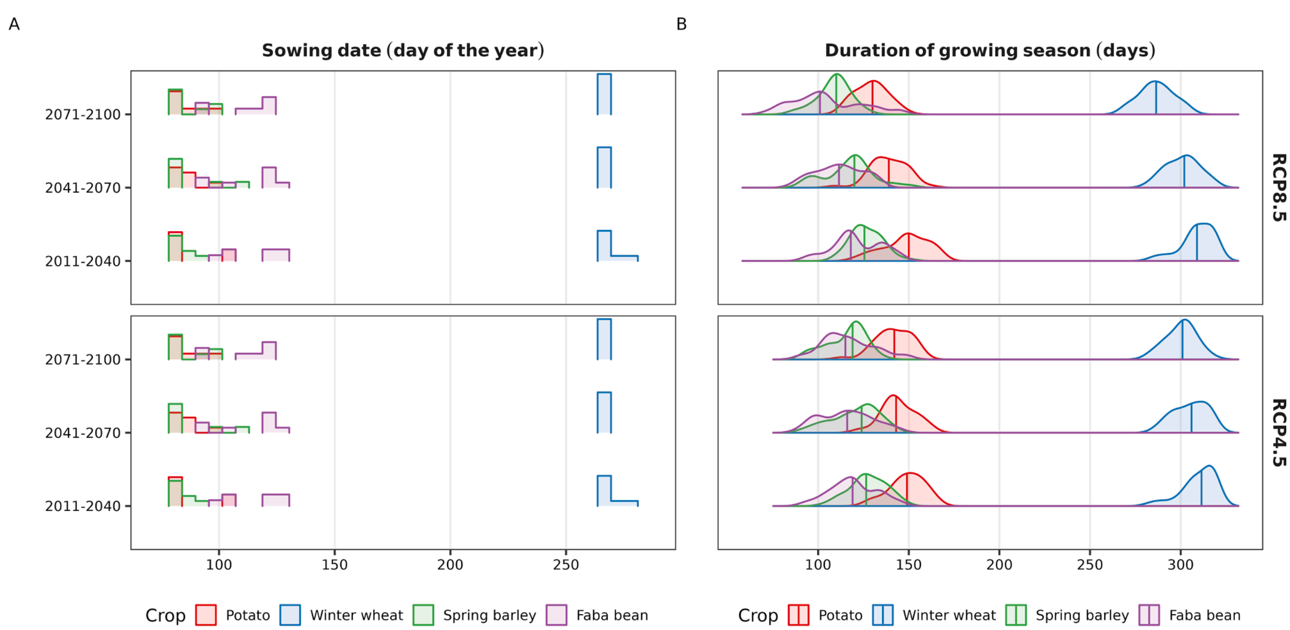

Fig. 3. Histogram of sowing dates (Panel A) and kernel density estimation of the duration of the growing seasons (Panel B) for the early sowing scenario across three-time periods (2011–2040, 2041–2071, and 2071–2100). The vertical lines within the distributions represent the median values in Panel B.

RCP8.5 and RCP4.5; ES-IF-II enhanced yield twice as much as ES-II independently of the RCP. Although the relative change of soil GHG emission for the rotation system was highly variable (Fig. 5), ES slightly increased soil GHG compared to BS overall (4.1 and 1.0 % for RCP8.5 and RCP4.5). ES-IF, ES-II, and ES-IF-II tended to increase soil GHG by 9.3, 6.9, and 17.8 % in contrast to BS for RCP8.5 (Fig. 5). The yield-scaled GHG emission followed the same trend of the soil GHG relative change in relation to BS, with increases of 4.1 (ES), 12.9 (ES-IF), 3.0 (ES-II), and 12.0 % (ES-IF-II) (RCP8.5).

4. Discussion

4.1. Model performance

The predictive capability of LandscapeDNDC was satisfactory overall, providing confidence for its application to climate change scenarios. LandscapeDNDC reproduced the dynamics of soil environmental conditions with comparable quality to other modeling studies using the same model framework (Houska et al., 2021; Molina-Herrera et al., 2016). Although yield DW and N uptake simulations had acceptable goodness-of-fit statistics (particularly for potato and winter wheat) and adequate multiyear temporal trends, their prediction errors were

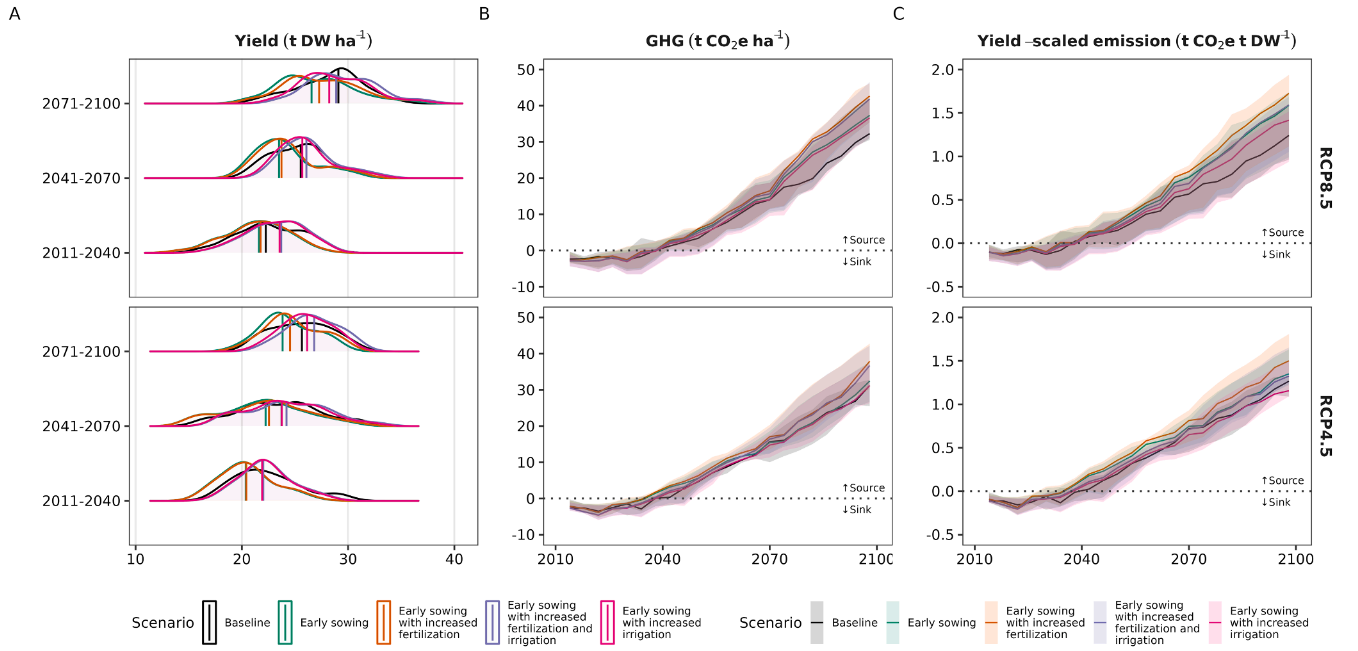

Fig. 4. Distribution and cumulative time series of metrics for the baseline and adaptation practices scenarios. Panel A shows the kernel density estimation of dry weight (DW) yield (in t DW ha^{-1}) across three time periods (2011–2040, 2041–2071, and 2071–2100), Panel B the time series of cumulative soil greenhouse gas (GHG) emission (in t CO_2e ha^{-1}), and Panel C the time series of cumulative yield-scaled GHG emission (in t CO_2e t DW^{-1}). The vertical lines within the distributions represent the median values in Panel A. The shaded areas show the maximum and minimum values in Panels B and C.

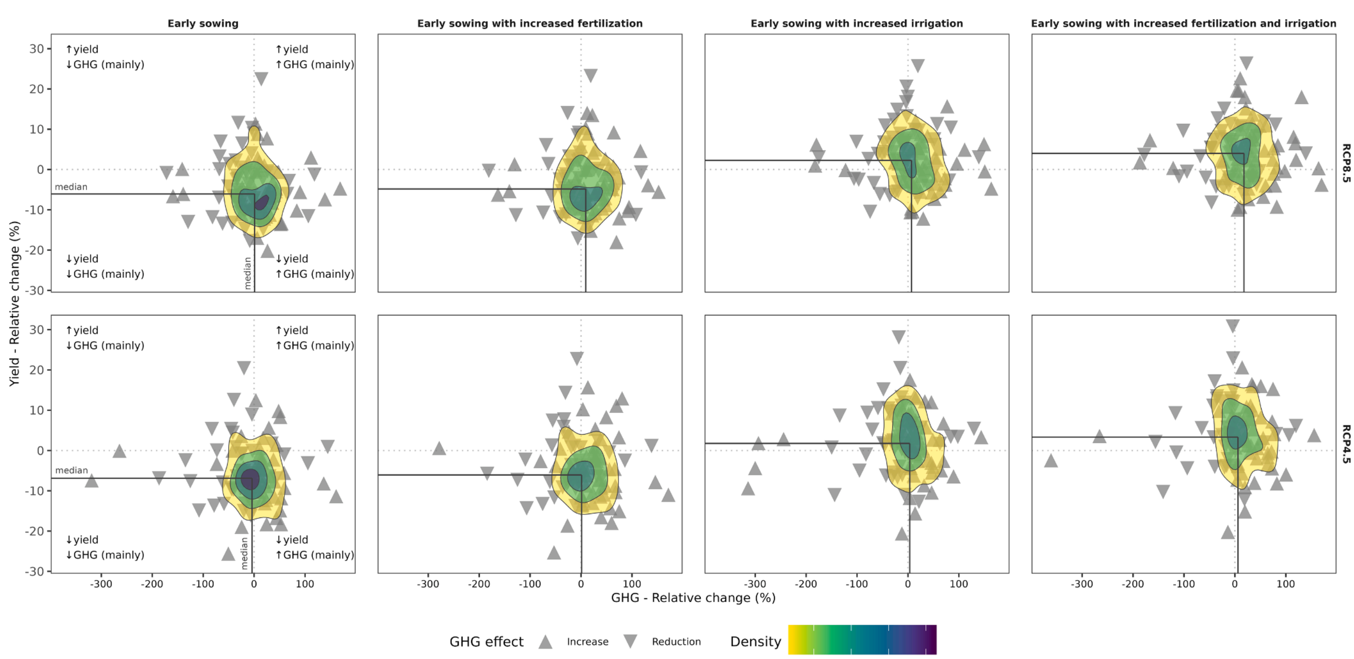

Fig. 5. Bivariate kernel density estimation of the relative change (compared to the baseline scenario in%) of the agronomic adaptation practices for crop yield and soil greenhouse gas (GHG) emission. Triangles represent the comparisons of the aggregated values of crop yield and soil GHG emission for the crop rotations from 2011 to 2100. *x*-axis is limited to 5–95 % quantiles to increase the visualization readability.

defined mainly by systematic error. The reasons can be that the relatively low number of samples limited the observed-simulated comparisons, and that the lack of crop-specific phenological mechanisms affected the simulated plant biomass accumulation and N uptake. However, the RMSE of yield DW and N uptake were in the same order of magnitude as that of other models which considered more phenological stages for each crop: potato (Raymundo et al., 2017), winter wheat (Montesino-San Martín et al., 2014), spring barley (Cammarano et al., 2019), and faba bean (Boote et al., 2002).

The simulated errors for topsoil C stocks and total N content were primarily systematic, which might be influenced by the infrequent sampling time and limited replications (often the case for long-term agroecosystems experiments; Rasmussen et al., 1998). This potential shortcoming affected the SOC and total N model comparison. The horizontal and vertical spatial variability of these variables has been documented as an important source of uncertainty (Schrumpf et al., 2011). However, recent studies have shown that the model is suitable for long-term simulations of topsoil C and N dynamics in Denmark (Haas et al., 2022; Kollmer, 2023). Furthermore, the results of our SOC and total N simulations are consistent with similar trends observed with other process-based models under similar pedoclimatic conditions in Denmark (e.g., Autret et al., 2020), further supporting the suitability of our model simulations.

The sampling strategy adopted for N_2O emissions provided reliable N_2O fluxes for the crop rotation system (Chirinda et al., 2010; Pugesgaard et al., 2017). The N_2O model performance showed unsystematic error preponderantly caused by the dynamic daily emission pattern (e.g., short-term legacy effects, intricate N processes, and hotspots) and the high spatial variability of measured N_2O fluxes. The spatial heterogeneity of soil physicochemical properties influences the variability of N_2O fluxes (Venterea et al., 2020), seldom captured with manual chamber measurements in cropland agroecosystems (Charteris et al., 2020), which contrasts with the homogenous average site conditions considered by models (Del Grosso et al., 2020; Giltrap et al., 2020). Nevertheless, most of the simulated N_2O peaks and overall trends were comparable to field observations, and calculated model errors of observed-simulated values were similar to previous studies (Houska et al., 2017; Molina-Herrera et al., 2016).

4.2. Implications of the baseline scenario for yield and the soil GHG balance

The effect of the $[CO_2]$ increase (5.5 ppm y^{-1}) inducing higher photosynthetic activity and air temperature (0.04 $^{\circ}C$ y^{-1}) accelerating crop phenology under RCP8.5, led to increases in crop yield for the baseline scenario, especially for winter wheat (cf. Olesen et al., 2000b). This result contrasts with Ozturk et al. (2017), who reported decreased winter wheat yield in the future but agrees with Montesino-San Martín et al. (2014), reporting a slight yield improvement (0.3–1.2 Mg ha^{-1}) in the medium-term (2030–2050) under current management practices in Denmark. Similar effects have been reported for temperate climate regions; for example, Alexandrov et al. (2002) in Austria and Trnka et al. (2004) in the Czech Republic found that climate change might result in yield gains for winter wheat when elevated $[CO_2]$ was considered. Yawson et al. (2016) also showed yield increases for spring barley in the UK for future scenarios.

There is limited evidence of the impact of future climatic conditions on the yield of spring barley and faba bean (Knox et al., 2016). Crops with high heat and drought stress sensitivity might experience high yield variability (e.g., faba bean, potato, and spring barley; Falconnier et al., 2019; Raymundo et al., 2018; Rezaei et al., 2022) or even crop failure (Trnka et al., 2014). Similarly, while we used 5 GCM-RCM models, the choice and variability of particular GCM-RCM models (Knutti and Sedláček, 2012) and whether it is used in isolation or ensemble can impact the climate prediction and, thus, the yield estimates (Challinor et al., 2009; Knox et al., 2016; Woldemeskel et al., 2014).

We found an increase in soil GHG emissions of agroecosystems under future climate scenarios, which is consistent with previous research (Li et al., 2005; Lugato et al., 2018). After 30 years (ca. 2040), the increase in N_2O emissions dominated the soil GHG balance, and the topsoil C stock started to deplete (cf. Ozturk et al., 2018). In contrast to the short-term soil GHG balance (2011–2040), the importance of changes in topsoil C stock for the total and cumulative soil GHG emission tends to decrease for long-term periods (2041–2100) in our study. The C stock dynamic is controlled by the C input type, decomposition, and mineralization rate (Liu et al., 2014; Maillard and Angers, 2014), and the simulated C stock depletion reflects that the increase in soil respiration and associated CO_2 loss caused by warming was higher than the increase in C inputs from the greater plant biomass.

Two mechanisms might explain the important role of soil N_2O emission under climate change. First, the warmer temperatures promote higher microbial activity and, at the same time, greater availability of labile C and N compounds, providing substrates for (de)nitrification (Butterbach-Bahl and Dannenmann, 2011; Smith, 1997). Second, increased $[CO_2]$ and soil moisture stimulate higher plant biomass (Xia et al., 2021), which may serve as an N source after crop residue incorporation, boosting N_2O-producing processes (Abalos et al., 2022; Xia et al., 2018). Considering $[CO_2]$ and global temperatures are rising unequivocally, implementing N_2O mitigation strategies should represent an urgent priority in policy agendas (Grados et al., 2022).

Yield-scaled GHG emission increased under future climate conditions after ca. 2040. Therefore, the increases in soil GHG emission will be greater than the potential yield gains obtained in the coming decades. Overcoming this challenge will require both increases in crop production and reductions in soil GHG emissions. Yield increases can be obtained by including sensitive crops to elevated $[CO_2]$ with reduced stomatal conductance and transpiration rates (Faye et al., 2023), thereby improving water use efficiency or optimizing the timing and placement of fertilizer application (Gu et al., 2023). Reducing soil GHG emissions can be achieved by adopting practices enhancing the permanence of topsoil SOC stock while decreasing N_2O emissions, such as biochar amendment (Bai et al., 2019; Grados et al., 2022).

4.3. Productivity under agronomic adaptation strategies

Food security is expected to rely on increases in crop production under sustainable intensification and adaptation of agroecosystems for future climate conditions (Cassman and Grassini, 2020; Ray et al., 2013). Under future climate scenarios, planting dates have been documented to occur earlier due to the temperature increase, especially in regions with similar temperate climates (Olesen et al., 2011) as our study site. However, crops requiring high germination temperatures for longer periods might experience considerable sowing date variability caused by seasonal weather fluctuations (e.g., faba bean in our analysis). Although a temperature-based planting event has been proposed for regions with temperate climates (Waha et al., 2012), such as Denmark, rainfall conditions might also define future sowing days. Early sowing and accelerated crop growth and development altered the crop calendars in our study case, shortening the growing seasons. Similar trends have been documented in Finland (up to ~21 days with early sowing by 2031–2050) (Appiah et al., 2023). Early planting, together with the effect of accelerated crop growth and development, could allow the inclusion of short-term and fast-growing crops. However, the degree to which the time window within the crop rotation system will be enough for appropriate crop development is prone to further study.

The scenarios of early sowing solely and in combination with increased fertilization decreased yield compared to the baseline scenario. Conversely, scenarios including increased irrigation had higher yields for the rotation system. Yield reductions in the early sowing scenario were thus primarily caused by enhanced drought stress, showing that supplementary adaptation practices are required. The early sowing enhanced the period of increased evapotranspiration and occasionally increased stress with reduced yield, which was compensated through irrigation. Such effects may vary between soil types (Olesen et al., 2000b). Although there was a yield gain when increased fertilization was included with early sowing (compared to the early sowing alone scenario), the yield effect was marginal; however, the additional N supply could become crucial in the future to maintain the quality of the harvested yield without negating the positive effect of increased $[CO_2]$ (Asseng et al., 2019). Although solar radiation is expected to decrease slightly in our study region (12 W m^{-2} y^{-1}, RCP8.5), increasing temperatures will outweigh its effect on evapotranspiration, and irrigation will still be needed to cope with higher evapotranspiration rates. By including an extra irrigation event (30 mm) in our simulations, the impact of potential water limitation was attenuated, promoting higher yields for water-sensitive crops such as potato and faba bean (Wagg et al., 2021; Khan et al., 2010). However, greater or more frequent irrigation amounts will still be required to reduce drought stress in any scenario. Given the median ratio of evapotranspiration and water input (rainfall plus irrigation) during the growing seasons for ES (~1.6 for RCP8.5), periods of water stress could have been lessened with precision irrigation practices. Similar to our study, Olesen et al. (2000b) found increased yield for winter wheat under increased irrigation for similar soil and management conditions. Contrary to the findings of Zhao et al. (2015) for winter wheat in Northern-temperate regions, our study showed that increased irrigation might be needed in future climate scenarios to sustain or increase yields; similarly, higher water requirements for potato under future climate projections will be necessary (Zhao et al., 2015).

4.4. Reconciling the effect of agronomic adaptation strategies on soil GHG balance

The agronomic adaptation strategies increased soil GHG emission in absolute terms and when scaled to yield, particularly under warmer climate scenarios (RCP8.5). Therefore, sustaining or enhancing yield in the coming decades might come at the cost of increased soil GHG emissions. Early sowing was affected by heavier rainfall (~50 mm in March for RCP8.5) after planting compared to the baseline scenario (~40 mm in March for RCP8.5), resulting in increased soil anaerobicity, especially for spring crops. This factor and the shift of field activities, such as the initial fertilization coinciding with low N demand at early plant stages, increased soil N_2O and GHG emissions. Increased fertilization and irrigation exacerbated N_2O emissions by adding N sources and promoting soil anaerobicity (Butterbach-Bahl and Dannenmann, 2011; Lu et al., 2021; Zhang et al., 2021). Although increased N fertilization and irrigation could have helped enhance topsoil C stock (Yang et al., 2022; Emde et al., 2021), the gain was insufficient to keep the rotation system as a soil GHG sink, due to global warming-induced increases in soil respiration and N_2O emissions. A primary factor leading to decreased (until ca. 2040) and increased (from ca. 2040 onwards) soil GHG emission is soil C accumulation from crop residues and posterior decomposition (i.e., soil legacy effects). The amount of residues produced and returned to the soil in the scenarios considering fertilization and irrigation surpassed the baseline and early sowing scenarios, thus also contributing to the higher soil GHG emission with fertilization and irrigation.

To our knowledge, our study is the first assessment reconciling the effect of climate change adaptation strategies on soil GHG emission and yield. This work contributes to benchmarking future soil GHG emissions, representing an essential initial step toward an integrated climate-smart soil and agriculture (Paustian et al., 2016). Future research should explore the potential genetic improvement of crop cultivars (i.e., genotypic adaptation with low photoperiodism, long reproductive phases, and late maturity cultivars; Montesino-San Martín et al., 2014; Olesen et al., 2011) to take advantage of the extended growing seasons and its influence on the soil GHG balance. Complementary studies should explore how to fine-tune N and water management strategies for increased input efficiency (e.g., timing and frequency; Adu et al., 2018; Xia et al., 2017) and their impact on yield-scaled GHG emissions, including the effect of extreme weather events. Similarly, assessments of the environmental sustainability of adaptation strategies should include their impact on other crucial issues, such as nitrate leaching and soil erosion (Doltra et al., 2014).

5. Conclusions

We assessed the impact of agronomic adaptation practices to climate change on soil GHG emission and yield, using a diversified crop rotation system in Northern Europe as a study case. The predictive capability of LandscapeDNDC was satisfactory overall, especially for soil-related variables. We found that climate change projections increased crop yield and, to a greater extent, soil GHG emissions. Early sowing and its combination with increased fertilization decreased yield compared to the baseline scenario of current management practices. In contrast, early sowing with increased irrigation and early sowing with increased fertilization and irrigation increased yields. The agronomic adaptation strategies increased the cumulative and overall soil GHG balance and the yield-scaled GHG emission. Our results indicate that agronomic management practices must be adjusted to comply with goals related to yield and soil GHG emissions as the climate evolves, or agriculture will become an even larger source of GHG emissions.

CRediT authorship contribution statement

Diego Grados: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing, Validation. **David Kraus:** Software, Writing – original draft, Writing – review & editing, Validation. **Edwin Haas:** Software, Validation. **Klaus Butterbach-Bahl:** Writing – original draft, Writing – review & editing. **Jørgen Eivind Olesen:** Writing – original draft, Writing – review & editing. **Diego Abalos:** Conceptualization, Formal analysis, Funding acquisition, Project administration, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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

Data availability

The simulation data and code that support the main findings of this study are openly available at the following URL/DOI: https://doi.org/10.17605/osf.io/hqs84.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2024.109966.

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