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Regenerative practices reduce global warming impact and intensity of maize systems in north-central Italy

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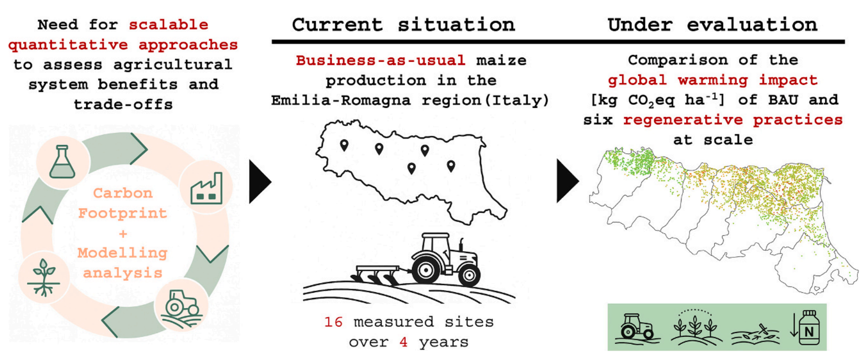
HIGHLIGHTS

- BAU maize practices emit 5.6 Mg CO_2-eq ha^{-1} yr^{-1}, due to SOC loss and N fertilizers.
- Regenerative management reduces GWI by up to 87 % compared to conventional BAU.
- Combining no-till, crop rotation, and lower N rate leads to a near C neutral GWI.
- The N_2O contribution from crop residues, roots and SOM mineralized N was determined.
- Hybrid LCA dynamic modeling and regional emission factors used to scale GHG impacts.

GRAPHICAL ABSTRACT



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ABSTRACT

Agriculture significantly contributes to global climate warming, accounting for up to one-third of anthropogenic greenhouse gas (GHG) emissions. One of the key strategies to mitigate these emissions is through adopting regenerative agricultural practices. This study quantified the global warming impact (GWI) and its intensity (GWI-I) associated with conventional and regenerative maize production systems in Emilia Romagna in the center of the Po Valley region, Italy. Using detailed field-level producer data and a hybrid quantification framework that combines process-based crop modeling with carbon footprint analysis, we compared a business-as-usual (BAU) management scenario—characterized by intensive tillage, frequent irrigation, and high agro-chemical inputs—with six regenerative strategies. Results from the 16 measured sites over four years (2019–2022) showed an average GWI of 5594 kg CO_2-eq ha^{-1} yr^{-1} under BAU, primarily driven by GHG emissions from soil organic carbon (SOC) loss and synthetic nitrogen (N) fertilizer inputs. When scaled regionally, regenerative practices substantially reduced GWI and GWI-I, with reductions ranging from 35 % to

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87 % compared to BAU. The most climate mitigating management scenario involved a combination of no-tillage, diversified crop rotation, and N rate reduction. These practices enhanced SOC gain by 0.38 Mg C ha^{-1} yr^{-1}, reduced nitrous oxide (N_2O) emissions by 35 %, while maintaining crop yields. Our findings highlight that adopting regenerative agricultural practices offers climate mitigation potential without sacrificing productivity.

CONTEXT: Agriculture is a major contributor to climate change, responsible for up to one-third of global anthropogenic greenhouse gas (GHG) emissions. There is an urgent need to identify scalable strategies that mitigate these emissions without compromising productivity. Regenerative agriculture has emerged as a promising solution, but field-scale data combined with robust modeling approaches are needed to assess its effectiveness.

OBJECTIVE: To quantify the global warming impact (GWI) and its intensity (GWI-I) of conventional (business-as-usual, BAU) versus regenerative maize management practices in the Emilia Romagna region of northern Italy, while identifying the best scenarios that offer the greatest climate mitigation potential without reducing crop yield.

METHODS: We applied a hybrid quantification framework that integrated field-level measurements, carbon footprint (CF) life cycle assessment (LCA) based, and process-based crop modeling (CSM) to evaluate GWI and GWI-I under BAU and six regenerative management scenarios. Data from 16 maize fields over four years (2019–2022) were collected and regionally upscaled to 3509 maize fields using soil datasets. Scenarios included variations in tillage, crop rotation, cover cropping, and nitrogen fertilizer application. GHG emissions were estimated from both off-site and on-site sources, including soil organic carbon (SOC) change.

RESULTS AND CONCLUSIONS: Under BAU, the average GWI was 5594 kg CO_2-eq ha^{-1} yr^{-1}, primarily due to SOC loss (47 % of GWI) and synthetic nitrogen use. Regenerative scenarios reduced GWI by 35–87 %, with the most effective involving no-till, diversified rotation with soybean and rye cover crops, and a 25 % nitrogen rate reduction. This scenario increased SOC by 0.38 Mg C ha^{-1} yr^{-1}, reduced N_2O emissions by 35 %, and maintained yields, resulting in near carbon-neutral or even negative GWI-I values. SOC accrual and lower N_2O emissions were the primary drivers of reduced climate impact.

SIGNIFICANCE: This study demonstrates that regenerative maize systems can significantly reduce agricultural GHG emissions while sustaining productivity. The hybrid CF-CSM approach provides a replicable, high-resolution framework for evaluating and scaling regenerative agricultural practices. The findings offer actionable insights for policy and land management strategies to meet climate neutrality targets.

1. Introduction

Agriculture is both at risk from and a large contributor to climate warming (IPCC, 2021). Depending on the extent of the accounting boundaries, globally 'agriculture' has been shown to contribute between about one tenth to one-third of all anthropogenic greenhouse gas (GHG) emissions. When, as is frequent, crop and livestock production activities within the farm gate are solely considered, emissions estimates are at the lower end of the range (e.g., Mbow et al., 2019), whereas when associated land-use change (LUC), and GHG producing activities along the food supply chain are added, values at the higher range are obtained (e.g., Rosenzweig et al., 2020; Crippa et al., 2021; Tubiello et al., 2021).

Measures to mitigate agricultural GHG emissions are of major global importance providing the second largest share of mitigation potential in managed ecosystems. They can both deliver carbon dioxide (CO_2) removal and substitute for fossil fuels, thereby enabling emissions reductions in other sectors (Nabuurs et al., 2022). Carbon sequestration in cropland soil is a major component of this mitigation potential. Management that minimizes soil disturbance, diversifies crop type and increases the number of crops in rotation, and maintains ground cover, can help build soil organic carbon (SOC) stock and contribute to this mitigation (Chenu et al., 2019). This includes reduced tillage or no-till, planting cover crops, and introducing perennial plants into crop rotations (Lessmann et al., 2022), management types that from a process-based perspective are some of the most commonly adopted practices associated with regenerative agriculture (Newton et al., 2020). However, climate mitigation only occurs when the accrual of SOC is from a net gain of atmospheric C (Powlson et al., 2011), and as such management that increases C inputs from photosynthesis into plant biomass with subsequent incorporation into the soil via above and below ground crop residues is the most reliable approach.

Globally, cropland has been estimated to store about 140 Pg C in the top 30 cm of soil with potential to accrue between 0.9 and 1.85 Pg C annually (Zomer et al., 2017). However photosynthetic constraints likely render this value closer to 0.2 Pg C (Janzen et al., 2022).

Management changes in SOC dynamics also impact the soil nitrogen (N) cycle. From the viewpoint of GHG budgeting, increases in emissions of the potent and long-lived GHG (IPCC, 2021) nitrous oxide (N_2O), produced primarily from the biological processes of nitrification and denitrification (e.g., Butterbach-Bahl et al., 2013) can under certain, but common conditions, largely neutralize or even outdo the climate benefit brought about by any SOC gain (e.g., Liu and Greaver, 2009; Guenet et al., 2021; Basso et al., 2025).

Croplands are the largest anthropogenic source of N_2O (e.g. Reay et al., 2012), with direct agricultural emissions close to 4 Tg N annually, a near doubling in the last four decades (Tian et al., 2024). Within the farm gate, global crop production contributes about three quarters of all anthropogenic N_2O emissions (FAO, 2021) and is fundamentally and primarily tied to the magnitude of N inputs, particularly in the form of synthetic fertilizers (Xu et al., 2020). Management to reduce N additions is therefore an important strategy to mitigate N_2O emissions (Yao et al., 2024).

Accounting for both longer-term changes in SOC (Smith et al., 2020) and the high spatial and temporal variability in N_2O emissions (Zhang et al., 2024) is a measurement challenge. Few long-term empirical data sets exist of both under different land management changes (LMCs), i.e., where a permanent change in land cover is not involved. Therefore, process-based crop system models (CSM) individually (Campbell and Paustian, 2015) or in an ensemble approach (Basso et al., 2025) are often used to simulate the impacts of various management practices on GHG budgets.

While CSMs are useful for determining the within farm gate GHG budget associated with changes in SOC and field emissions of N_2O, they do not consider GHG emissions associated with energy inputs used for field operations, such as fuel to power agricultural machinery and irrigation pumps, or those from pre-production activities, such as agrochemical (e.g., fertilizers and herbicides) or equipment manufacture.

While essential for better analyzing how agricultural production contributes to climate change and identifying land areas and supply chain intervention points for targeted mitigation efforts, these substantial emissions have often been 'overlooked' as a component of agriculture's contribution, for example being reported as part of the 'energy', 'industry', or 'transport' sectors in GHG inventories (UNFCCC, 2025). More recently, studies that have combined these sectors into an integrated global food system GHG approach (Rosenzweig et al., 2020) have shown that pre-and post-production services dominate emissions (Tubiello et al., 2022) and that the agri-food sector contributes around one-third of all anthropogenic emissions (e.g., Crippa et al., 2021).

More research and data are needed on the benefits and tradeoffs for countries with agriculturally productive regions to tackle their food system GHG emissions (Rosenzweig et al., 2021), through the adoption of more site-specific and scalable quantitative methods.

Life cycle assessment (LCA) is a common approach that helps account for the environmental impacts, including GHGs of crop production systems (Goglio et al., 2014). Carbon 'footprint' (CF) analysis is a single-impact LCA that considers the global warming potential of the GHGs as the sole category (ISO, 2018). However, many LCA studies in crop-based systems do not assess the changes in SOC dynamics, and where done, methods have been inconsistent and include (most commonly) generalized emissions factors (EFs), but also simple soil carbon models, dynamic CSMs, and (often considered the highest quality approach) direct field-specific observations (Goglio et al., 2015). In a comparison of these methods, Goglio et al. (2018), found that while all gave comparable CO_2 and N_2O emissions estimates for perennial and legume crops, only the CSM gave similar results to the direct observations (field measurements) for annual and cereal crops. The use of higher IPCC Tiers, corresponding to disaggregated regional or country-specific EFs (Tier 2) and CSMs (Tier 3) has also been shown to improve the accuracy of calculations of the CF of agricultural products (Peter et al., 2016).

Therefore, combining site-specific CF with a CSM and higher tier EFs to provide regional scaling provides a robust approach to estimate overall GHG budgets of varying LMC scenarios, and is in strong agreement with the quantification preferences detailed in Goglio et al. (2018) and Pelaracci et al. (2025).

Moreover, while GHG emissions budgets estimates are relatively common, intensity metrics for crop production, where within farm gate GHG emissions are expressed in terms of e.g., crop yield (e.g., Mosier et al., 2006; Linquist et al., 2012) or calories (Carlson et al., 2017), are less investigated, and studies that expand the accounting boundary beyond the farm gate rarer still (Bai et al., 2024). However, doing so will better target mitigation efforts towards locations, crops, and management where both emissions and emissions intensity values are high, a more comprehensive strategy than those that focus on high emissions alone.

To our understanding there are very few studies that use small to regional scale combined CF-CSM modeling approaches with site specific observations to estimate the global warming impact (GWI), defined by Robertson (2014) as the balance of all the GHG sources and sinks of different management practices.

Here, we conduct such an analysis in the European Union, a 27-country zone committed to become climate-neutral by 2050 (European Commission and Directorate General for Climate Action, 2019), where the aim is to reduce agricultural emissions by at least 55 % by 2030, by for example reducing fertilizer and pesticide use and promoting carbon farming (European Environment Agency, 2023). Specifically, we focus on the Po Valley in northern Italy, an area where agricultural GHG emissions are among the highest in a country where farmlands are responsible for 75 % of these emissions (Romano et al., 2025).

Using field-level site specific data and farming records, regionally specific emissions factors, and process-based crop system modeling, our objectives are to 1) estimate the global warming impact (GWI) and intensity (GWI-I) of maize production in the region under conventional, business-as-usual (BAU) management and six alternative regenerative management strategies, and 2) determine the management practices and cropping system scenarios that offer most opportunity for GHG mitigation while maintaining crop productivity.

2. Materials and methods

2.1. Study area

Our study sites are located in the Po Valley in north-central Italy, a highly fertile alluvial plain and essential water source for northern Italy, as well as a crucial economic area and one of the most important agricultural zones in Europe. The Emilia-Romagna region, where the majority of the field sites are located, constitutes about half of the Po Valley (more than 22,000 km^2), and contains more than one million hectares of farmland, about 80 % of which are in arable cropping, with maize and wheat as major crops alongside rice, fruits and vegetables. About one third of farms have irrigation, and of the more than 200 typological soil units described (Regione Emilia Romagna, 2024), Eutric Vertisols are most common in the alluvial plain valleys. The climate is characterized as dry (Antolini et al., 2017) with a mean annual temperature of 13.1–13.8 °C (Nistor, 2016) and mean annual precipitation of 889 mm (Aepae, 2025).

2.2. Data collection

2.2.1. Measured sites

Sixteen fields were identified within the "Conserve Italia" producer consortium. Ten of these fields (63 %) were located within Emilia-Romagna where the consortium is based, with the remainder in the nearby provinces of Cremona, Lodi, and Mantova. For each field, four years of data (2019 to 2022) were collected, including information on crop yield and management activities, such as type and frequency, equipment fuel consumption, and the agrochemicals used and their quantity (Table 1; full dataset in supplemental material). The management at these sites is historically typical of the region, representing the business-as-usual (BAU) practices of conventional tillage, frequent irrigation, and routine application of fertilizers and agrochemicals at generous rates (Borrelli et al., 2014; Negri et al., 2024).

2.2.2. Regional upscale

To compare the measured conventional management practices at the field sites with alternative management strategies, we conducted an upscaling of all practices from the field scale to the regional (Emilia Romagna) scale, where the majority of the measured sites are located and are representative of the other field locations within the Po Valley. To identify individual fields across the region, we used two publicly available datasets: (1) the WorldCereal database (Van Tricht et al., 2023) to provide maize cultivation data at 10 m resolution, and (2) the Land Use and Cover Area frame Statistical survey (Ugalde et al., 2022), to provide cropland soil properties (i.e., soil texture, soil organic carbon percentage and bulk density) at 30 cm depth. These datasets were interpolated to identify fields where maize was planted as a primary crop and where all required soil properties for analysis were available. As a result, 3509 individual fields were identified as representative of maize farming within the region, with each field assigned a unique identifier (UID). To better align with the dominant maize production practices in the region, a grain maize cultivar typically used for animal feed was selected, in contrast to the sweet maize cultivar grown at the measured sites. Given the broad applicability of conventional maize management practices regardless of final crop use, the average business-as-usual (BAU) management scenario identified from the measured sites was scaled up to the entire region. During upscaling we increased the management parameter for nitrogen fertilization rate, to reflect the higher nutritional demand of grain maize when compared to sweet maize.

To gain insight and information about management practices that were not conducted at the measured field sites (hereafter, termed regenerative practices) but that were feasible and had potential to lower the environmental impact of the cropping system, we conducted a survey with technical experts from the region. As a result, six alternative

Table 1
Average frequency of management events (tillage, irrigation, and agrochemical application), N fertilization, total water and fuel consumption, and sweet maize crop yield. Values are annual, averaged over four years (2019–2022) at each of the 16 sites. Tillage at each site is considered conventional, and activities can include plowing, subsoiling, disc harrowing, harrowing, rotary hoeing, crust breaking, rolling or hoeing. Irrigation types include traveling gun, furrow or pivot. Agrochemicals applications include herbicide and-or pesticide. Nitrogen fertilizer types include urea, ammonium nitrate and/or NPK fertilizer. Total water use includes water from irrigation, herbicide, and pesticide applications. Total fuel use includes all field-based operations (i.e., tillage, agrochemical application) excluding irrigation. Production is the dry matter (DM) production of the maize grain. For more details, see Supplemental material.

Site ID	Soil type	Average value						
		Tillage frequency	Irrigation frequency	Agrochemical applications	N fertilization (kg N ha^{-1})	Total water use (m^3 ha^{-1})	Total fuel use (l ha^{-1})	Crop yield (Mg DM ha^{-1})
1	Clay-Loamy	4	4	4	162	1276	205	4.1
2		5	4	4	183	1277	228	5.8
3		4	4	4	169	1201	217	5.0
4		4	5	4	168	1351	230	4.7
5		5	4	4	168	1201	232	5.2
6		5	3	4	148	976	233	4.7
7		5	4	3	171	1276	232	4.0
8	Sandy	5	4	4	150	3601	200	4.3
9		5	5	4	172	1051	226	4.2
10		6	3	4	141	2476	219	5.2
11		4	5	4	141	951	192	4.5
12		5	6	4	134	1101	201	4.2
13		5	4	3	155	1126	194	4.1
14		5	4	3	144	1126	193	3.6
15	Clay-Loamy	5	4	3	155	1126	220	4.7
16	Sandy	5	5	4	121	1501	202	4.2

regenerative scenarios were chosen alongside the conventional business-as-usual measured practices, to be upscaled across all the identified UIDs in the Emilia Romagna region (Table 2 and Table S1). Simulations for all scenarios were run for 23 years between 2000 and 2022, and data processing and analysis was conducted using RStudio software 2023.12.1.402 (Posit Team, 2025).

2.3. *Carbon footprint*

Estimation of the Carbon Footprint (CF) of the crop production systems at the measured sites and across the regional upscale is based on Life Cycle Assessment (LCA) principles. We use the current global ISO standard (14067; ISO, 2018) that builds upon LCA outlined in ISO 14040 (ISO, 2006a) and ISO 14044 (ISO, 2006b) and break down the process into four steps: 1) Goal and Scope definition, 2) Life Cycle Inventory (LCI) analysis, 3) Life Cycle Impact Assessment (LCIA), and 4) interpretation and integration with model outputs. As part of the first step, we defined functional units (FU) as GHG emissions (CO_2-eq) per hectare (ha) of cultivated land (Li et al., 2020) and per kilogram (kg) of harvested product. The system boundary is defined as cradle to farm-gate, including the off-site and on-site emissions associated with the inputs used and the field operations carried out in relation to crop production (Fig. 1).

2.3.1. *Life cycle inventory*

In the LCI analysis phase, we compiled the off-site (background system) and on-site (foreground system) input data associated with crop production (Supplemental file S1 and Table S1 for measured sites and upscaled scenarios respectively). The off-site emissions include those from the extraction of raw materials as well as the production and transportation of agricultural inputs and to facilitate operations, such as equipment and machinery, irrigation water, fuel, fertilizers, seeds, and agrochemicals. These values, determined from emission factors (EF) were derived from the background datasets in the Ecoinvent database (version 3.9.1, FitzGerald and Sonderegger, 2022), where the most relevant National, European, or Global datasets were selected as appropriate (Table S2). The on-site GHG emissions include those from fuel use for equipment and machinery that perform operations related to land preparation, planting, fertilization, irrigation, pest and disease management, and harvesting. These were estimated following the recommendations of Nemecek and Kägi (2007). Emissions from on-site nitrous oxide (N_2O) were categorized into direct or indirect. Direct emissions (eq. 1) occur directly from the soil surface of the field (e.g., from nitrification and denitrification in the soil), while indirect emissions (eq. 2) occur beyond the field site as result of N fertilizer volatilization and re-deposition and N leaching and runoff (IPCC, 2019) followed by subsequent transformation to N_2O. Direct and indirect N_2O emissions were determined from N inputs, with values sourced from field activities or from modeling outputs, along with a combination of disaggregated Tier 1 EFs (IPCC, 2019), and sub-regionally specific EFs (Cui et al., 2021) (Table 3). The approach estimates direct emissions including N from synthetic fertilizers (F_{SN}), aboveground and belowground crop residues (F_{CR}), and mineralized from soil organic matter (SOM) (F_{SOM}). No organic N fertilizer was used or assumed to be applied

Table 2
Major characteristics of the management scenarios and their identification throughout this study, used for the regional upscale. For more details see Table S1.

Scenario ID	Abbreviation	Management - tillage	Crop rotation	Nitrogen rate
1	BAU	Conventional (Business-as-usual)	Maize monocropping	100 %
2	MZ MT	Minimum tillage		
3	MZ ST	Strip tillage		
4	MZ NT	No-till		
5	MZ-SB NT	No-till	Maize - soybean	
6	MZ-SB NT + CC	No-till, cover crops	Maize – rye - soybean - rye	
7	MZ-SB NT + RN + CC	No-till, reduced nitrogen, cover crops	Maize – rye - soybean - rye	75 %

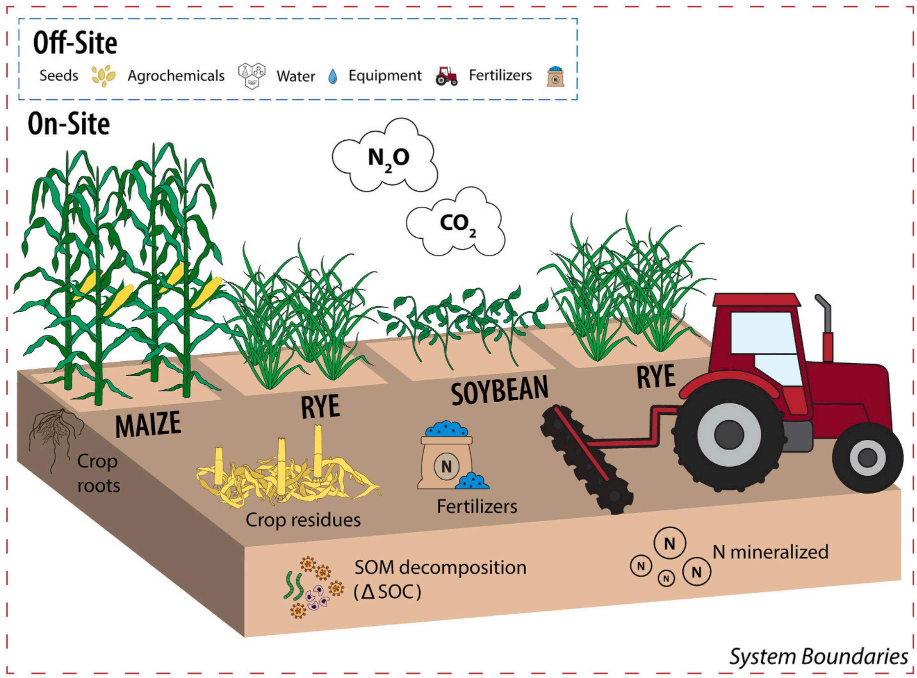

Fig. 1. Carbon footprint system boundaries.

Table 3
Breakdown of components of the greenhouse gas (GHG) emissions budget for all scenarios with their source of (activity) data, corresponding emission factor (EF), crop that they are applicable to, and the reference source.

Component	Data source	GHG	Crop	Emissions factors		Reference
				Direct	Indirect	
Synthetic N fertilizers (F_{SN})	Field measured	N_2O & CO_2	Maize	$EF_1 = 0.6–0.9$ %	EF_2 [N volatilization/redeposition] = 0.5 % $Frac_{GASF}$ *- Urea = 15 %* *- Ammonium-nitrate-based = 5 %* *- NPK-based = 5 %* EF_3 [leaching/runoff][1] = 1.1 % $Frac_{LEACH}$ = 24 % EF_4 [CO_2 from Urea] = 20 %	Direct: Cui et al., 2021 EF_4: IPCC, 2006 Others: IPCC, 2019
Above and below ground crop residue biomass (F_{CR})	Modeled	N_2O	Maize Soybean Rye	$EF_1 = 0.6–0.9$ % $EF_1 = 0.5$ % $EF_1 = 0.5$ %	EF_3 [N leaching/runoff][1] = 1.1 % $Frac_{LEACH}$ = 24 %	Direct: Cui et al., 2021 Indirect: IPCC, 2019 IPCC, 2019
Mineralized N from SOC loss (F_{SOM})	Modeled	N_2O		$EF_1 = 0.5$ %	EF_3 [N leaching/runoff][1] = 1.1 % $Frac_{LEACH}$ = 24 %	IPCC, 2019
Product manufacture	Measured	N_2O & CO_2		EFs from Ecoinvent database (v. 3.9.1)		Frischknecht and Rebitzer (2005)
Farming practices	Field measured	N_2O & CO_2		EFs from Ecoinvent database (v. 3.9.1)		Nemecek and Kägi (2007)

[1] Under the dry climate of Po Valley region, the indirect N_2O emission component for leaching/runoff is only determined when irrigation is present.

in our study.

$$N_2O_{direct} - N = (F_{SN} + F_{CR} + F_{SOM})^*EF_1 \quad (1)$$

$$N_2O_{indirect} - N = N_2O_{ATD} - N + N_2O_L - N \quad (2)$$

where N_2O_{ATD} is the annual amount of N_2O–N produced from the atmospheric deposition of N volatilized from managed soil, (kg N_2O–N yr^{-1}; eq. 3, Table 3) and N_2O_L is the annual amount of N_2O–N produced from leaching/runoff of the N additions to managed soil in locations where it occurs (kg N_2O–N yr^{-1}, eq. 4, Table 3).

$$N_2O_{ATD} - N = (F_{SN}{}^*Frac_{GASF})^*EF_2 \quad (3)$$

$$N_2O_L - N = (F_{SN} + F_{CR} + F_{SOM})^*Frac_{LEACH}{}^*EF_3 \quad (4)$$

For the crop residue and root biomass component of direct N_2O emissions:

$$F_{CR} = (AGR^*N_{AG}) + (BGR^*N_{BG}) \quad (5)$$

where AGR is the above ground dry matter crop residue biomass, BGR is the below ground (roots) dry biomass, and N_{AG} and N_{BG}, the N concentrations of the respective biomass. Specific N_{AG} and N_{BG} values were: above-ground (0.6 %, maize; 0.8 %, soybean; 0.5 %, rye) and below-ground (0.7 %, maize; 0.8 %, soybean; 1.1 %, rye) (IPCC, 2019). Values and details of the EFs and fractions used to determine direct and indirect N_2O emissions are found in Table 3.

2.3.2. *Impact assessment and integration with modeling outputs*

Each off-site and on-site emissions component was expressed as kg

CO_2-eq ha^{-1} yr^{-1}, using the global warming potential (GWP) for the 100-year time horizon (GWP100) for CO_2 (1) and N_2O (273) (IPCC, 2021):

$$GHG_{emission} = E*C*GWP \tag{6}$$

where E is the emission value (as N_2O-N or CO_2-C; kg ha^{-1} yr^{-1}), C the corresponding conversion factor from N to N_2O (44/28) or C to or CO_2 (44/12), and GWP the 100-year time horizon global warming potential.

Then, using a combined approach, where individual off-site or on-site GHG emission values were either derived from the CF framework or the process-based modeling (see Section 2.4) we can define the final global warming impact (GWI, Robertson, 2014; Sainju, 2020) of maize production:

$$GWI = \left(GHG_{off-site} + GHG_{on-site}\right) - \Delta SOC \tag{7}$$

where GWI per unit area (kg CO_2-eq ha^{-1} yr^{-1}) was calculated by summing off-site and on-site emissions and adjusting for changes in soil organic carbon (ΔSOC). A GWI value per unit of yield (Mosier et al., 2006), normalized to maize grain yield equivalents (kg CO_2-eq kg^{-1}, eq. 9) was also determined and termed as GWI intensity (GWI-I):

$$\mathrm{GWI-I} = \frac{GWI}{Grain_{yield}} \tag{8}$$

To enable GWI-I comparisons across the different scenarios with varying crop rotations, we normalized by converting soybean yields to maize grain yield equivalents using the maize equivalent yield (MEY, eq. 9).

$$MEY = \frac{Avg\ production_{soybean}}{Avg\ production_{maize}} * Yield_{soybean} \tag{9}$$

where the two production values are the average productivity for maize and soybean in the Emilia Romagna region from 2015 to 2023 (ISTAT, 2025), and Yield$_{soybean}$ the annual crop grain production estimated by the CSM.

The CF evaluation was conducted using SimaPro software (version 9.5; SimaPro, 2025), which includes access to the Ecoinvent database, while SALUS a process-based CSM was used to estimate dynamic on-site emissions from the crop residues, roots, SOM mineralized N, and SOC change.

2.3.3. Statistical analysis

A linear mixed-effects model was applied to assess the relative contribution of the different GHG sources (combining off and on-site emissions) to the overall GWI across the 64 measured site years (16 sites over 4 years). The analysis was conducted using the 'lmerTest' package (Kuznetsova et al., 2017) in R, with the GHG source category as a fixed effect. Random intercepts were included for the site and year to account for spatial and temporal variation. An ANOVA was performed to test the significance of the fixed effect. Post hoc pairwise comparisons among GHG source categories were conducted using estimated marginal means ('emmeans' package), with p-values adjusted using the 'Sidak' method. Data processing and analysis was conducted using RStudio software 2023.12.1.402 (Posit Team, 2025).

2.4. Process-based crop system modeling

The `System Approach for Land Use Sustainability` (SALUS), a process-based, crop system model (CSM) (Basso and Ritchie, 2015; Basso et al., 2018b) was used to determine annual SOC stock change and total above and below ground crop residue biomass. SALUS is designed to investigate the effects of the interactions between soil, climate, genetics, and agronomic management on crop growth and yield, SOM, N dynamics, and heat balance, and can be used to simulate different practices and their varying management, such as tillage, planting, irrigation, fertilization, harvest, and crop residue handling. The model has been extensively used to evaluate soil carbon dynamics in many systems (e.g., Senthilkumar et al., 2009; Basso et al., 2018a; Basso et al., 2025).

2.4.1. Model structure

The SALUS model has three main modules: i) crop growth, ii) SOM and nutrient cycling, and iii) soil water balance and soil temperature. The environmental variables (e.g., growing degree days and photoperiod) control plant development, while C assimilation and dry matter (DM) production are a function of maximum potential rates (controlled by light interception and parameters defining the variety-specific growth potential) which are then moderated according to water and/or N limitations.

The SOM and N modules simulate the processes of organic matter decomposition and N mineralization/immobilization across three distinct SOM pools (active, slow, and passive), each characterized by unique turnover rates and C:N ratios. To enhance the representation of conservation tillage systems (minimum, strip, and no-till in our study), a surface-active SOM pool associated with surface residue was incorporated. Soil carbon inputs originate from fresh organic matter (FOM) sources, including non-harvested aboveground or incorporated belowground plant residues, root biomass, and organic amendments. Fig. S1 illustrates the flow of carbon through the SOC model component for a hypothetical soil. Although the kinetic parameters for each SOM pool remain constant, the composition of organic material entering the soil influences its decomposition dynamics and allocation among the three SOM pools.

SALUS predicts the influence of crop residue cover and tillage events on soil surface properties and plant development. After a tillage event, soil conditions dynamically change to represent the altered bulk density, saturated hydraulic conductivity, and water content at saturation. SALUS operates on a daily time increment, simulating all the key components noted above for a chosen time period when weather data are available. Several different management strategies can be run simultaneously under the same weather conditions. Further details of SALUS are reported in Basso and Ritchie (2015).

2.4.2. Model inputs

SALUS requires a minimum set of inputs to operate. These include initial soil properties (i.e., texture, OC concentration, bulk density and water limits), daily weather data (i.e., solar radiation, maximum and minimum temperature and precipitation) and management details for each scenario. For each of the measured sites, we used available producer data for soil texture, and the type and timing of all management practices between 2019 and 2022. For additional soil metrics we used publicly available LUCAS datasets (Ugalde et al., 2022). Hydraulic soil water property inputs were determined using the approach of Ritchie et al. (1999), and daily weather variables were retrieved from the NASA POWER database (NASA, 2024). To allow for deep root growth, each soil profile was simulated to 130 cm depth, with soil texture maintained throughout, attenuating for SOC content using an exponential density distribution algorithm and readjusting bulk density according to Manrique and Jones (1991). The regional upscale data inputs for the 3509 UIDs were retrieved for soil properties from LUCAS and daily weather variables from NASA POWER.

2.4.3. Model parametrization and validation

A single common sweet maize cultivar was calibrated to represent all measured sites. Only crop (not soil) related parameters were calibrated against measured sweet maize yields, to identify a single common maize cultivar representing all the sites under study. Calibration performance was evaluated using the relative root mean square error (RRMSE, eq. 10, Fig. S2):

$$RRMSE(\%) = 100^{*}\frac{\sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}}{\overline{O}} \tag{10}$$

where P_i and O_i are predicted and observed data respectively, n the number of P/O pairs and $\overline{O}$ the mean of observed data.

For the regional upscaling, a grain maize cultivar commonly used for animal feed was selected to represent the dominant maize cropping system in the area. Grain yield was calibrated to achieve a productivity range of 10–14 Mg ha^{-1} of fresh grain biomass at harvest, consistent with the regional Integrated Production Guidelines (Regione Emilia Romagna, 2025a), which recommend a blanket nitrogen fertilization rate of 240 kg N ha^{-1}. To accurately simulate crop growth and development, the calibration process also involved parameterizing the harvest index and root-to-shoot ratio (Table 4).

For the measured sites and the regional upscale, a 10-year spin-up period was implemented to stabilize the model's SOM pool fractions prior to simulating the various management practice scenarios.

SALUS has been previously validated to reproduce SOC dynamics using only crop yield calibration, as annual crop residues returned to the soil are known to have a major influence on SOC dynamics (Poeplau and Don, 2015; Meurer et al., 2018). Therefore, no soil-related parameters were calibrated or altered from their defaults. Nevertheless, to further (re)validate SALUS's ability to accurately and independently reproduce SOC stock change over time, model's simulations were tested against four external independent long-term datasets from experimental sites located in Northen Italy (Table S3). To ensure consistent, high quality measured datasets, sites from the scientific literature were selected only if five (data) conditions were met: [1] initial soil conditions, including measured SOC stock, [2] multiple years of crop yield data, [3] a SOC time series' (with either SOC stock values or BD and C% available for SOC stock calculation), [4] detailed management descriptions, and [5] the presence of maize, grown either continuously, or in a two-year rotation, or within an extended rotation with other crops (e.g., wheat and alfalfa). Sites were also prioritized to include as many management types as possible. SALUS performance in reproducing SOC change was tested using the root mean square error (RMSE) index (eq. 11, Table S4).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{11}$$

3. Results

3.1. GWI and its intensity under business-as-usual management at the measured sites

Across the 16 measured fields between 2019 and 2022, the average global warming impact (GWI) under conventional, business-as-usual (BAU) management was 5594 (± 1166) kg CO_2-eq ha^{-1} yr^{-1} (Fig. 2a). The GWI intensity (GWI-I) calculated using maize equivalent grain yields was 1.28 kg CO_2-eq kg^{-1} (Fig. S3).

Using the linear mixed-effects model, we identified the GHG contributions of specific components to the total GWI of the BAU management, by partitioning into off-and on-site domains and further subdividing into constituent GHG sources for seeds, agrochemicals, fertilizers, machinery operations, and irrigation, as well as crop residues and roots, mineralized soil N, and SOC change (Fig. 2b). The analysis revealed that emissions source (as the sum of off and on-site contributions) had a highly significant effect on GWI ($p < 0.001$, Table S5), indicating strong differentiation among contributions, all of which were 'positive' GHG sources.

The change (loss) in SOC stock was the dominant contributor, contributing nearly half (47 %) of the total GHG source strength for the BAU scenario. At all our measured sites in all years there was a net loss of SOC stock. This ranged from a small (436 kg CO_2-eq ha^{-1} yr^{-1}) to a very large (5498 kg CO_2-eq ha^{-1} yr^{-1}) source, with a mean GWI of 2644 kg CO_2-eq ha^{-1} yr^{-1}—substantially higher than all other contributions. Pairwise comparisons confirmed that SOC change was statistically distinct from all other emission sources, with N fertilizer (21 % of total) ranked second (1200 kg CO_2-eq ha^{-1} yr^{-1}), followed by machinery operations (845 kg CO_2-eq ha^{-1} yr^{-1}, 15 %), and mineralized N (329 kg CO_2-eq ha^{-1} yr^{-1}, 6 %). Agrochemicals, crop residues and roots, and irrigation were all lower (<3.6 %) and statistically identical, ranging from 135 kg CO_2-eq ha^{-1} yr^{-1} to 203 kg CO_2-eq ha^{-1} yr^{-1}, whereas seeds (0.8 %) showed on average the lowest contribution of 45 kg CO_2-eq ha^{-1} yr^{-1}. The model explained 81 % of the variance in GWI through fixed effects alone and was only marginally improved upon when random effects for site and year were included (82 %), again highlighting the primary role of emission source category in driving overall GWI, as opposed to spatial or inter-annual differences.

3.2. GWI and its intensity at the regional scale

We compared our measured, conventional (BAU) management scenario with the six producer-proposed alternative regenerative management scenarios (Table 2) at 3509 sites across the Emilia-Romagna region. All of the regenerative scenarios showed lower GWI values than the BAU scenario, ranging between 829 kg CO_2-eq ha^{-1} for a no-till, reduced N fertilized, maize-soybean rotation with cover crops (MZ SB-NT + RN + CC) to 3496 kg CO_2-eq ha^{-1} for minimally tilled monocropped maize (MZ MT) (Table S6). The GWI-I values also vary with scenario and field location (Fig. 3), similar to GWI due to the consistent yield across the scenarios (see below and Fig. S4), but again all show a substantially lower median GWI-I value than the BAU scenario (0.63 kg CO_2-eq kg^{-1}), ranging from 35 % lower (0.40 kg CO_2-eq kg^{-1}) with MZ MT (Fig. 3a) to 87 % lower (0.08 kg CO_2-eq kg^{-1}) with MZ SB-NT + RN + CC (Fig. 3f).

Reducing the intensity of the tillage in a maize monocrop reduces GWI-I, with strip-till (MZ ST, 0.32 kg CO_2-eq kg^{-1}) and no-till (MZ NT, 0.29 kg CO_2-eq kg^{-1}) values, 48 % and 53 % lower than conventionally tilled (BAU) maize, respectively. The sequential 'addition' of regenerative practices (e.g., the addition of soybean in the crop rotation or the introduction of a cover crop) shifts the GWI-I to the left of the BAU impact line, indicating a reduced intensity as the number of regenerative practices increases at a location. For the 'best-performing' scenario 7, when all site location data are averaged the GWI-I value is close to zero (0.08 kg CO_2-eq kg^{-1}), with sites in the North-West of the region particularly low, and often below zero (−0.43 kg CO_2-eq kg^{-1} being the lowest value). The two 'most regenerative' scenarios 6 and 7 show the broadest uncertainty range around their median values, with values across both ranging from −0.43 to 0.93 kg CO_2-eq kg^{-1}.

As with the measured sites, the two major contributing factors to the lowering of the GWI and therefore GWI-I in the regional regenerative scenarios (Fig. S4) were the changes in SOC and N_2O emissions, and their relative tradeoffs. Under the maize monocrop scenarios only BAU (scenario 1) showed a (large) loss of SOC (~1.5 Mg CO_2-eq ha^{-1} yr^{-1}), whereas in the other tillage regimes (scenarios 2, 3, and 4), there were increases in SOC stock between 39 kg CO_2-eq ha^{-1} yr^{-1} (MZ MT) and

Table 4
Range of values (Mg ha^{-1}) for grain yield (maize and soybean) or above ground biomass (rye cover crop), harvest index, and root-to-shoot ratios used in the upscaled simulation scenarios.

Variable	Crop			References[1]
	Maize	Soybean	Rye	
Yield / biomass	10–14	2–4	1.2–3.1	1–6
Harvest index	~ 0.55	~ 0.4	–	6
Root-to-shoot ratio	0.07–0.27	0.12–0.23	0.42–0.56	7–9

[1] References: 1 Regione Emilia Romagna, 2025a; 2 Regione Emilia Romagna, 2025b; 3 Fiorini et al., 2020; 4 Corti et al., 2024; 5 Raimondi et al., 2023; 6 Boselli et al., 2020; 7 Ordóñez et al., 2020; 8 Patel et al., 2024; 9 IPCC, 2019.

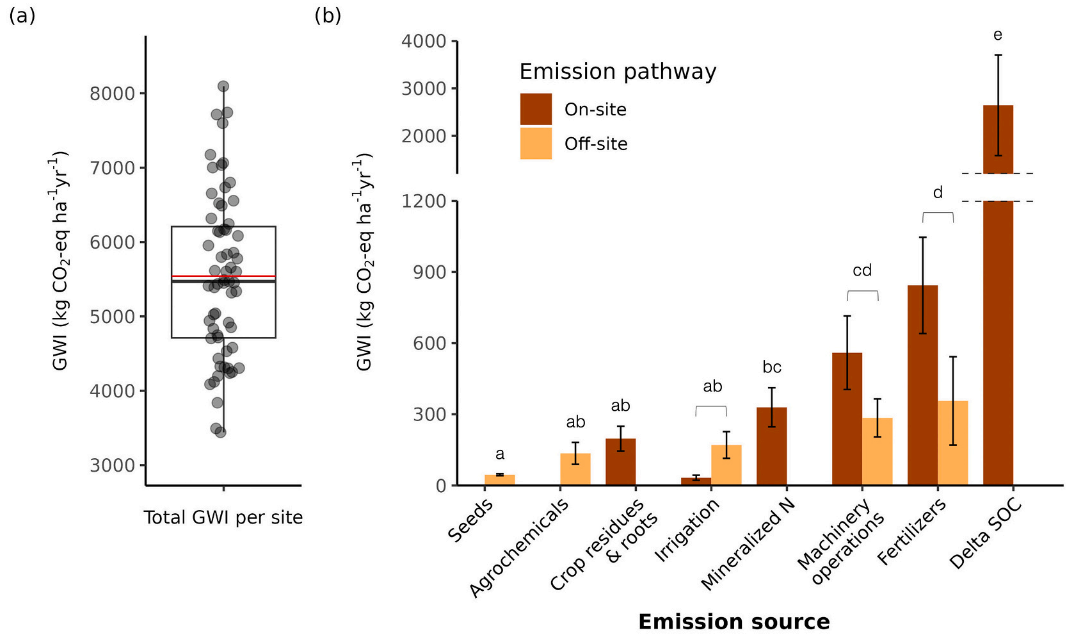

Fig. 2. (a) Data distribution of the total Global Warming Impact (GWI) across 16 measured sites over four years (2019–2022), expressed as kg CO_2-eq ha^{-1} yr^{-1}. Each dot indicates a single site-year combination, and the red line represents the overall mean. (b) Average contribution of different greenhouse gas (GHG) emission sources to the total GWI across the 16 sites from 2019 to 2022. The x-axis labels indicate individual GHG source, while bar colors differentiate between on-farm (red) and off-farm (yellow) emission pathway. Positive values indicate net CO_2-equivalent emissions sources. Error bars indicate standard deviations. Different letters above the bars indicate statistically significant differences between emission sources ($p < 0.001$), based on the total emissions (on-site plus off-site combined) for each category. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

602 kg CO_2-eq ha^{-1} yr^{-1} (MZ NT) (Table S6). When soybean was added to the maize monoculture under no-till (MZ-SB NT), the GWI-I (0.19 kg CO_2-eq kg^{-1}, Fig. 3d) was 34 % lower than MZ NT (Fig. 3c). The associated reduction in N fertilizer rate (i.e., soybean did not receive any fertilizer) primarily contributed to the fertilizer emissions reductions from 2300 kg CO_2-eq ha^{-1} yr-1 (MZ NT) to 1151 kg CO_2-eq ha^{-1} yr^{-1} (MZ-SB NT), a 49 % reduction. When a cover crop was added to the maize-soybean rotation (MZ-SB NT + CC) the GWI-I was lowered to 0.15 kg CO_2-eq kg^{-1} from 0.19 kg CO_2-eq kg^{-1} and associated with a larger SOC gain (1422 kg CO_2-eq ha^{-1} yr^{-1}, about 390 kg C ha^{-1} yr^{-1}) compared to no cover crop (589 kg CO_2-eq ha^{-1} yr^{-1}, about 160 kg C ha^{-1} yr^{-1}). When N_2O sources are summed together, adding a cover crop in the rotation translates into an increase in total N_2O emissions (1822 kg CO_2-eq ha^{-1} yr^{-1}) compared to no cover crop (1528 kg CO_2-eq ha^{-1} yr^{-1}). When the N fertilizer rate to maize was reduced (25 %) in the maize-soybean cover crop rotation (MZ-SB NT + RN + CC) the GWI-I was reduced from 0.15 kg CO_2-eq kg^{-1} to 0.08 kg CO_2-eq kg^{-1}. This N rate reduction was accompanied by a reduction in total N_2O emissions from 1822 kg CO_2-eq ha^{-1} yr^{-1} to 1499 kg CO_2-eq ha^{-1} yr^{-1}.

Beyond the GWI-I scenario differences attributable to SOC change and N_2O emissions, other sources of difference were typically smaller. Of the remainder, GHG (CO_2) emissions from machinery operations (combined on-and off-site) were the largest, contributing 893 kg CO_2-eq ha^{-1} yr^{-1} in the BAU scenario, reduced in the MZ MT by 135 kg CO_2-eq ha^{-1} yr^{-1} (15 %), 332 kg CO_2-eq ha^{-1} yr^{-1} in MZ ST (37 %), and 356 kg CO_2-eq ha^{-1} yr^{-1} in MZ NT (40 %), almost all due to the lowering of the intensity and number of tillage operations throughout the respective maize cropping seasons (Table S6). When soybeans were added to the rotation (scenario 5 vs. 4) there was a 16 % reduction in the GWI from machinery operations, mainly due to less emissions associated with irrigating soybeans (104 kg CO_2-eq ha^{-1} yr^{-1}) as opposed to maize (259 kg CO_2-eq ha^{-1} yr^{-1}). The addition of cover crops increased the GHG emissions compared to no cover crops in the maize-soybean rotations by 11 %, due to machine operations associated with rye sowing and termination.

4. Discussion

4.1. Global warming impact under conventional management at the measured sites

The extensive data collected from farmer fields provides us with a robust evaluation of the practices and inputs associated with conventional maize management in the Po Valley region, with the business-as-usual (BAU) scenario characterized by multiple, intensive tillage and soil disturbance operations, irrigation events, and agrochemical applications during each crop growing season (Table 1). Results from our approach that combines carbon footprint analysis with crop system modeling (CF-CSM) to determine GWI and GWI-I from cradle to farm gate, has few direct comparisons in the literature in the region under investigation, but below we evaluate similar approaches and provide assumptions to enable better matching between the studies.

Prior analyses conducted in the Po Valley have used 'standard' life-cycle assessments, with similar climate change impact contributions included. Fantin et al. (2017) found a maize GWI-I of 0.41 kg CO_2-eq kg^{-1} grain for the cultivation phase, and Noya et al. (2015) a range of 0.38 to 0.63 kg CO_2-eq kg^{-1} depending on maize cultivar and yield. Comparative GWI's were 3690 kg CO_2-eq ha^{-1} (Fantin et al., 2017) and 3599 to 4756 kg CO_2-eq ha^{-1} (Noya et al., 2015). These GWI values are substantially lower than in our study, however they do not include a contribution from SOC stock change, which in many LCAs is assumed to be constant over time and therefore not considered (Goglio et al., 2015), despite for example, large amounts of organic digestate being used in Noya et al. (2015). In addition, values from Fantin et al. (2017), included transport to and processing at a cooperative's facility beyond the farmers gate, which for maize contributed 8.2 % of the total GWI. Remaining differences may be attributed to the lower synthetic N fertilization rates (typically a large GHG impact source, see below) applied at our measured sites (average of 155 ± 36 kg N ha^{-1} with 91 % as urea) compared to the higher rates of 230 kg N ha^{-1} as urea, reported in Fantin et al. (2017), and 280 kg N ha^{-1} (160 kg N from organic

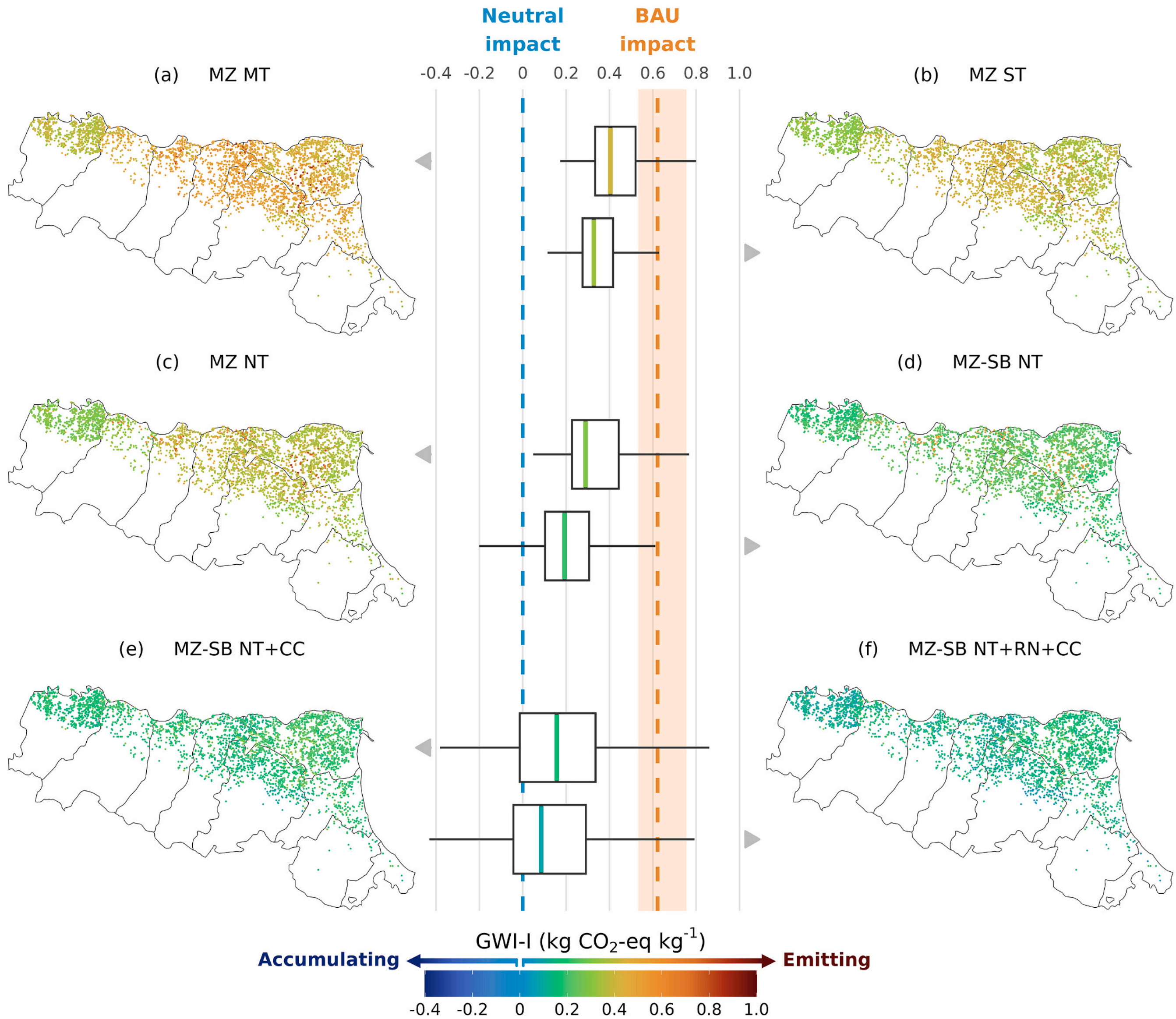

Fig. 3. Impact of the conventional, business-as-usual (BAU) measured management scenario compared to six regenerative management practice scenarios (a–f) on global warming impact intensity (GWI-I) across the Emilia Romagna region. Positive GWI-I values (green to red) represent net positive greenhouse gas emissions ("Emitting"), whereas negative values (light to dark blue) indicate net-zero or net-negative emissions ("Accumulating"). Boxplots represent the 23-year GWI-I data distribution across all locations (n = 3509). Boxplot medians are colored according to the legend, while outliers are omitted for visual clarity. The orange dashed vertical "BAU impact" line indicates the median GWI-I of the BAU scenario, with the surrounding orange shaded area depicting the 25th and 75th percentiles. Each point on the maps represents the 20-year average for an individual location. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

digestate and 120 kg N ha^{-1} separately applied in equal measure as ammonium nitrate and urea) noted in Noya et al. (2015).

Likewise, our average GWI-I value for the measured sites (1.28 kg CO2-eq kg^{-1}; Fig. S3) was approximately two to three times higher than noted in the above LCA studies. This can be explained by the differences in crop cultivar; we used measured grain yield values for the sweet maize grown by the producers (but not for the regional scaling) that ranged from 2.7 to 6.8 Mg DM ha^{-1}, with an average of 4.5 Mg DM ha^{-1} (see Supplemental Material S1) that is approximately 50 % (Fantin et al., 2017) and 36–79 % (Noya et al., 2015) of the yields used in the LCA studies for food grain maize.

Other European studies in conventional maize monocropping systems under similar climate and management also show comparable results. For example, Zugasti-López et al. (2024) found an average GWI value of 2261 kg CO_2-eq ha^{-1} yr^{-1} in the Ebro Valley, Spain, and Willaume et al. (2025) across five sites in southwestern France, determined a GWI range of between 1440 and 5519 kg CO_2-eq ha^{-1} yr^{-1}, although four of the sites showed a narrower range (1440 to 1846 kg CO_2-eq ha^{-1} yr^{-1}), with the much higher value of the remaining site almost exclusively due to direct N_2O emissions. Although Zugasti-López et al. (2024) measured SOC in their system, they found no change over time, and therefore no SOC contribution to overall GWI, unsurprising as the interval between their successive measurements was only three years and (any) SOC change typically takes a decade or more to be reliably detected by measurement (Córdova et al., 2025). Removing the SOC contribution from our study generates a GWI of 2950 kg CO_2-eq ha^{-1} yr^{-1}, similar to Zugasti-López et al. (2024). Willaume et al. (2025) modeled SOC and found GWI contributions that ranged from a small GHG source (161 to 349 kg CO_2-eq ha^{-1} yr^{-1}) to a small sink (479 to 652 kg CO_2-eq ha^{-1} yr^{-1}). In the absence of these variable SOC contributions, our values for the remaining components of the LCA show good agreement with these studies but clearly highlight the variation in GWI brought about by different accounting boundaries, and the necessity of including accurate SOC stock change over extended time in CF determinations (e.g., Goglio et al., 2018; De Feudis et al., 2022). To ensure robust values, external and independent validation of SOC changes predicted by the CSM model being used is strongly recommended (Tables S3–S4), particularly when the impact of varying agricultural management practices on SOC sequestration is being investigated.

4.1.1. Soil organic carbon

While mono-cropped maize has the potential to gain SOC due to the high amounts of above and below ground residue being returned to the soil (Wu et al., 2025), soil tillage and other soil disturbance events are known to decrease SOC content (e.g., Man et al., 2021; Yu et al., 2020), through oxidation and decomposition, as well as accelerating soil erosion through greater exposure to wind and rain. In the case of our measured sites these events, particularly deep tillage, likely were the driving force for, in some cases dramatic SOC loss. Historically, large amounts of SOC have been lost from the Emilia Romagna region, due primarily to agricultural intensification and mechanization that resulted in deep soil tillage becoming widespread from the 1960s onwards (Pezzi, 2005). An estimation of regional SOC loss between 1937 and 2022 found an average loss of 208 Mg CO_2-eq ha^{-1}, corresponding to 2.45 Mg CO_2-eq ha^{-1} yr^{-1} (Salani et al., 2024), very similar to our average losses of 2.64 Mg CO_2-eq ha^{-1} yr^{-1}.

4.1.2. Nitrous oxide emissions

In our study, off-site emissions of N_2O due to fertilizer manufacture are considered minor, as most of the N fertilizer applied (91 %) is in the form of urea, which does not require nitric acid, the production of which is an anthropogenic source of N_2O (IPCC, 2006). Also, while N_2O is produced during fuel combustion, the total GWI of vehicle exhaust (either from transportation of fertilizer and other inputs to the farm gate, or machinery use on the field sites) is dominated by CO_2 emissions, with contributions from N_2O, only 1–2 % (Hoekman, 2020). In contrast, biological emissions of N_2O from the soil are much more consequential, but within crop-based LCAs are often inadequately quantified and poorly harmonized across studies (Goglio et al., 2024). Total on-site N_2O emissions across our measured sites averaged 2.95 kg N_2O-N ha^{-1} yr^{-1}. This includes direct and indirect emissions associated with synthetic N fertilizers, above ground crop residues, below ground roots, and SOM N mineralization, and is equivalent to 1266 kg CO_2-eq ha^{-1} yr^{-1}, very close to half that of the average SOC source contribution (2644 kg CO_2-eq ha^{-1} yr^{-1}). With the assumption that all N_2O-N emitted is ultimately derived from newly created reactive N (Crutzen et al., 2008), we find an overall EF value of 2.0 %, in good agreement with estimates of this contribution to atmospheric N_2O (Davidson, 2009). Below we discuss the individual contributions to these total on-site emissions, highlighting their importance and the need for them all to be included in crop-based CF-LCAs.

Very few LCA studies consider N_2O emissions associated with N mineralized from SOM, despite it being a major source of available N (Reid et al., 2025). Most N in the soil is stored in organic form, associated with C in soil organic matter (SOM). Changes in SOC and N mineralization rates from SOM are therefore closely coupled (Cotrufo et al., 2021), and an increase in N cycling may result from SOM decomposition, leading to a potential trade-off between SOC storage and N availability (e.g., Janzen, 2006; Palmer et al., 2017; Averill and Waring, 2018), and the resulting N_2O emissions.

Indeed, the average modeled rate of mineralized N across our measured sites was 100 kg N ha^{-1} yr^{-1} (about two-thirds of the N applied from synthetic N fertilizer). This aligns closely with Chiriac et al. (2025), who estimated 96 kg N ha^{-1} yr^{-1} was mineralized from SOM in maize cropping systems in northwestern Italy, based on crop, agrometeorological, and soil data spanning nearly three decades. Applying emission factors (IPCC, 2019, Table 3), we can estimate direct N_2O emissions from the N mineralized from SOM as 215 kg CO_2-eq ha^{-1} yr^{-1}, and indirect N_2O emissions of 114 kg CO_2-eq ha^{-1} yr^{-1}, in total more than one-third of a metric ton of CO_2-eq ha^{-1} yr^{-1}, a considerable, but often overlooked contribution to the overall GWI (Fig. 2).

Returning crop residues to the soil provides several benefits for soil health, such as maintaining or increasing SOM content (e.g., Powlson et al., 2008). However, they also contribute to N_2O emissions through addition of organic N and impact on the microbial processes that produce N_2O (Olesen et al., 2023). Predicting crop residue impact on N_2O emissions is challenging due to multiple interactions between crop type, environmental conditions, and soil properties (Chen et al., 2013). Factors such as the timing of residue incorporation and plant C:N ratios, as well as other quality indicators are known to strongly impact emissions (Abalos et al., 2022a), and the amount of N in crop residues is used in national GHG emissions inventories to estimate agricultural N_2O emissions (Romano et al., 2025). Given that crop residue incorporation can increase N_2O emissions by on average 40–50 % compared to scenarios where they are fully removed from the field (Abalos et al., 2022b), a more detailed knowledge of crop residue biomass and N content as it varies spatially and temporally is needed. In our study, calibration of the model for crop yields (Table 4) allowed for accurate estimation of the annual crop residue and root biomass produced at the different sites. This along with the regionally disaggregated EF value for maize (Cui et al., 2021, see N fertilizer section below), provided for a more robust estimate of N_2O emissions over time and helped avoid potential confounding issues associated with the varying longevity of crop residue influence on both short-term and longer-term background emissions (Kim et al., 2013).

Across our measured sites, the average total N_2O emissions from above and belowground crop biomass was 0.46 kg N_2O-N ha^{-1} yr^{-1} or 198 kg CO_2-eq ha^{-1} yr^{-1}, contributing about 16 % to total N_2O emissions, in excellent agreement with the 17 % of direct N_2O emissions from agricultural soils attributable to crop residues across the EU (EEA, 2024). The contribution of N_2O from crop residues and roots to the total GWI of the measured sites, while relatively low on average (3.5 %), was as high as 10 % at some sites in certain years. Including residue- and root-derived N_2O emissions is therefore essential for GWI accounting and ideally should be carried out using dynamic modeling to better reflect the spatial and temporal variability associated with the underlying mechanisms.

The substantial contribution of synthetic N fertilizers in cropping systems on GWI, primarily via their impact on N_2O emissions following field application, is well known (FAO, 2021). Given the challenges of long-term measurements of N_2O, few LCA studies employ them directly, particularly when multiple management practices and sites are being compared, but see Gelfand et al. (2013). Other than field site measurement, CSMs are seen as an accurate quantification approach (e.g., Goglio et al., 2018) but again may not be suitable for studies with multiple sites and management, given the expertise required to run them appropriately (Goglio et al., 2024). Beyond these, the use of EFs is the most used method (Andrade et al., 2021). Given their apparent simplicity, it is important to recognize that GHG emissions values can be strongly influenced by the choice of EF and the GWI conversion factor. The use of country-specific or localized EFs, corresponding to Tier 2 methods as opposed to Tier 1 ‘default’ values (IPCC, 2019) can improve the accuracy of calculations of the CF of agricultural products (Peter et al., 2016). For direct N_2O emissions from maize, our approach uses crop-specific, spatially disaggregated EF values for the Emilia Romagna region, as developed by Cui et al. (2021), ranging between 0.6 and 0.9 %, in conjunction with the field measured N inputs from synthetic fertilizers, and the modeled N inputs from above and below ground plant biomass (Table 3). Across our measured sites, the average total N_2O emissions from synthetic N fertilizers was 1.73 kg N_2O-N ha^{-1} yr^{-1}, comprised of 1.21 kg N_2O-N ha^{-1} yr^{-1} from direct and 0.52 kg N_2O-N ha^{-1} yr^{-1} from indirect emissions, contributing 59 % of all N_2O emissions sources. These values are consistent with measurements from conventionally tilled, continuous maize cropping systems elsewhere. For example, in the US Midwest, Ussiri et al. (2009) in rainfed systems, found direct emissions of 1.82 kg N_2O-N ha^{-1} yr^{-1} with 200 kg N applied as urea (184 kg N) and NPK (16 kg N), and Liu et al. (2005) in irrigated systems in the semi-arid, temperate US, found direct emissions of 2.33 kg N_2O-N ha^{-1} yr^{-1} with 224 kg N, and 1.55 kg N_2O-N ha^{-1} yr^{-1} with 134 kg N, applied as UAN.

4.2. Global warming impact under regenerative management at the regional scale

Agriculture faces increasing pressure from unsustainable practices and the effects of climate change. Small- to medium-scale farms, prevalent in Italy (Rivaroli et al., 2016), are highly vulnerable, with the ability to maintain production quality standards across the value chain impaired (Pulighe et al., 2024). Adaptive management at the farm level is essential to effectively address future climate scenarios (Reidsma et al., 2010). Practices associated with regenerative agriculture such as the use of cover crops, reducing or eliminating tillage, reducing chemical inputs, and increasing crop diversity in rotations (e.g., Newton et al., 2020; Giller et al., 2021) provide opportunities for mitigating climate change by reducing GHG emissions and enhancing SOC accrual. Despite this, studies investigating climate change impacts from these regenerative practices embedded within LCAs are rare in Italy, where conducted they focus on conventional crop management practices at the field to cooperative scale (e.g., Noya et al., 2015; Fantin et al., 2017). Therefore, to compare our BAU management scenario with the six regenerative practices, we upscaled all seven scenarios to cover the Emilia-Romagna region.

4.2.1. Tillage intensity

Tillage practices are typically distinguished by the type of equipment used, resulting in varying degrees of soil disturbance and incorporation of surface plant C into deeper layers. Full inversion tillage (here referred to as conventional tillage [CT], BAU), often involving a moldboard plow, turns the soil to a depth of at least 15 cm leaving a small percentage of the surface covered with crop residue. Reduced tillage (here minimum tillage [MT] and strip tillage [ST]) disturbs the soil without inversion, using tools such as chisels, sweeps, or discs, whereas no-till (NT) eliminates inversion altogether, with crops directly seeded into undisturbed soil, typically maintaining a larger percentage of surface residue cover. With maize as a monocrop, a lowering of the tillage intensity (MT, ST, and NT; scenarios 2, 3, and 4, respectively) and a concomitant reduction in the frequency of soil disturbance events, substantially lowers the overall GWI-I (Fig. 3) by 35 % (MZ MT), 48 % (MZ ST), and 53 % (MZ NT), when compared to BAU (MZ CT). These reductions are primarily due to variation in the rate of SOC gain or loss. In MZ CT (BAU) there was a decrease in regional SOC stock (a GHG source) at a mean rate of 1.5 Mg CO_2-eq ha^{-1} yr^{-1} (0.41 Mg C ha^{-1} yr^{-1}), whereas in all maize monoculture regenerative scenarios (the varying tillage regimes), there were increases in mean regional SOC stock (a GHG sink), at rates of 39 kg CO_2-eq ha^{-1} yr^{-1} (MZ MT), 435 kg CO_2-eq ha^{-1} yr^{-1} (MZ ST), and 602 kg CO_2-eq ha^{-1} yr^{-1} (MZ NT), the latter equivalent to an 0.57 Mg C ha^{-1} yr^{-1} increase in SOC gain when compared to MZ CT. This high value is consistent with the results of Mazzoncini et al. (2016) who found mean annual SOC gain of 0.40 Mg C ha^{-1} yr^{-1} at 0–30 cm depth under no-till management after 28 years in Italy. Although all the regenerative tillage practices decrease the GWI and therefore GWI-I (because maize grain yields equivalent were similar across all scenarios, Fig. S5) relative to BAU, these amounts were insufficient to generate a net neutral or negative impact intensity, with regional medians of 0.33 kg CO_2-eq kg^{-1} (MZ ST), 0.40 kg CO_2-eq kg^{-1} (MZ MT), and 0.29 kg CO_2-eq kg^{-1} (MZ NT) (Fig. 3). These positive values differ from Dachraoui and Sombrero (2020) who for irrigated maize monocultures in Spain found GWI-I values of between −0.3 and − 0.2 kg CO_2-eq kg^{-1} under no-till. This is mainly due to differences in the SOC rates of change, yield variability between the tillage treatments (NT was significantly higher than CT), as well as different accounting boundaries –off-farm emission sources were omitted in their assessment.

The magnitude of N_2O emissions can be impacted by multiple factors, including soil aeration and moisture content, soil temperature, bulk density, and microbial community composition, all of which can be altered by varying tillage practice. This complexity is reflected in the inconsistent results found in literature compilations, where NT or RT have been shown to decrease (Van Kessel et al., 2013; Li et al., 2023) or increase (Shakoor et al., 2021; Huang et al., 2018) N_2O emissions to varying degrees when compared to CT. In our study, there were small, consistent reductions in overall N_2O emissions from MZ MT (2 %), MZ ST (4 %), and MZ NT (5 %) when compared to BAU (MZ CT), due primarily to lower amounts of available N mineralized from SOM, consistent with our understanding of long-term N mineralization dynamics in maize (e.g., Pecci Canisares et al., 2021), and with Forte et al. (2017) who found that MT reduced annual emissions of N_2O by 23 % when compared to CT in mono-cropped, drip-irrigated maize systems in southern Italy. Other small contributions to the lower GWI-I of the RT and NT scenarios compared to CT, include the lower GHG emissions associated with reduced fuel consumption from the smaller number of machine operations on the field.

4.2.2. Crop rotation and cover crop adoption

In our study, scenarios with maize monoculture (1 through 4) have higher GWI-Is than scenarios with a maize-soybean rotation (5 through 7; Fig. 3). We can, however, only directly compare scenario 4 (MZ NT) with scenario 5 (MZ-SB NT) to show that under no-till, planting soybean into a maize monoculture changes the regional GWI-I from 0.29 kg CO_2-eq kg^{-1} to 0.19 kg CO_2-eq kg^{-1}, a substantial 34 % reduction. Unlike tillage variation under maize monocultures, this reduction is not associated with differences in the rate of SOC change, with both showing very similar gains – 602 kg CO_2-eq ha^{-1} yr^{-1} (MZ NT) and 589 kg CO_2-eq ha^{-1} yr^{-1} (MZ-SB NT). Here, the major contribution to the lower GWI and GWI-I values is from a reduction in the average amount of synthetic N fertilizer input, i.e., 50 % of MZ NT due to half of the crop years being planted to soybean, an N fixing legume that does not receive any N fertilizer input. Total N_2O emissions are 1561 kg CO_2-eq ha^{-1} yr^{-1} (MZ NT) and 982 kg CO_2-eq ha^{-1} yr^{-1} (MZ-SB NT), a 37 % reduction fully accounting for the GWI-I difference.

Cover crops can increase levels of SOC by adding more C from their shoots and roots and reducing C loss from soil erosion (Van Eerd et al., 2023). They have an impact on many of the factors and processes that influence N_2O production and emissions, including the amount of mineralizable N and easily decomposable C, soil microbial communities, soil moisture content, and soil physical properties.

In our study we can compare the absence and presence of a rye cover crop in the maize-soybean rotation under no-till. We find that overall GWI-I is lower with a cover crop (0.15 kg CO_2-eq kg^{-1}) compared to no cover crop (0.19 kg CO_2-eq kg^{-1}), with no negative impact from the cover crop on cash crop yield. This reduction is primarily driven by the substantially larger SOC gain with cover crop (1422 kg CO_2-eq ha^{-1} yr^{-1}) compared to no cover crop (589 kg CO_2-eq ha^{-1} yr^{-1}), a difference of 833 kg CO_2-eq ha^{-1} yr^{-1} that is only partially offset (about 35 %) by the increase in total N_2O emissions from the cover crop addition (1275 kg CO_2-eq ha^{-1} yr^{-1}) compared to no cover crop (982 kg CO_2-eq ha^{-1} yr^{-1}), and driven by large increases in N_2O emissions from SOM N mineralization (103 %) and N from the above ground crop residues (32 %) and roots (139 %) in the cover crop scenario.

As such our SOC increase (0–30 cm) with cover crops (0.23 Mg C ha^{-1} yr^{-1}) is in reasonable agreement with long-term studies in the USA (0.40 Mg C ha^{-1} yr^{-1}, 0–30 cm, Blanco-Canqui, 2022; 0.24 Mg C ha^{-1} yr^{-1}, 0–15 cm, Peng et al., 2023) and Europe (0.40 Mg C ha^{-1} yr^{-1}, 0–30 cm, Petersson et al., 2025), and estimates from global meta-analyses (e.g., 0.32 Mg C ha^{-1} yr^{-1}, 0–22 cm, Poeplau and Don, 2015). The increase in total N_2O emissions we found with cover crop addition (approximately 0.7 kg N_2O-N ha^{-1} yr^{-1} or 30 %) also agrees very well with two recent global meta-analyses who found 26–30 % increases in N_2O emissions with cover crops (Qiu et al., 2024; He et al., 2025), but given the variables and complexity of interactions, differs from other analyses that found an overall decrease (Muhammad et al., 2019) or no effect (Basche et al., 2014; Abdalla et al., 2019). The large contribution from increased crop residue N and N from SOM mineralization is also consistent with Haas et al. (2022) who in European croplands found that with 100 % crop residue return to the soil, N_2O emissions increased by 17–30 %.

There was large variability in the GWI-I values in the cover crop (rye) scenarios, ranging from −0.4 to 0.85 kg CO_2-eq kg^{-1} in MZ-SB NT + CC, a function of the intra- and inter-annual variability that cover crops experience and introduce (during 23 years of simulations, see Fig. S6). The variable weather conditions during cover crop establishment and growth, particularly when planted after both cash crops (maize and soybean), are reflected in the wide variability of resulting biomass. This biomass is subsequently incorporated into the soil as above-ground residues or retained as roots in these no-till systems. This variability is clearly illustrated in Fig. S6, where certain years (e.g., 2001, 2007, 2015) show lower biomass production (~1.5 Mg DM ha^{-1}), while others (e.g., 2002, 2004, 2008, 2012) exhibit substantially higher biomass (between 3 and 4 Mg DM ha^{-1}).

The amount of biomass a cover crop can accumulate is directly linked to the amount of C it can return to the soil, with greater biomass linked to a higher likelihood of more SOC gain (e.g., Joshi et al., 2023). Across all sites over the simulation period, cover crop above ground biomass for the MZ-SB NT + CC scenario was between 0.9 and 5.4 (mean of 3.0) Mg DM ha^{-1} and for the MZ-SB NT + RN + CC between 0.0 and 5.1 (mean of 2.8) Mg DM ha^{-1}. These average values are relatively high, being more than the thresholds where SOC gain is typically observed (Blanco-Canqui, 2022). Rarely considered in LCAs due to lack of observational data, the root biomass input can be more critical than above ground biomass for SOC gain (Berhongaray et al., 2019; Xu et al., 2021) and can contribute up to 75 % of all SOC gain (e.g., Gale et al., 2000). Here, the cover crop root biomass yield from the MZ-SB NT + CC scenario was between 0.5 and 2.9 (mean of 1.3) Mg DM ha^{-1} and the MZ-SB NT + RN + CC between 0.0 and 2.8 (mean of 1.2) Mg DM ha^{-1}. These values are in excellent agreement with a review by Blanco-Canqui et al. (2020) who found average cover crop root biomass to be 1.33 ± 0.98 Mg ha^{-1} in 0–30 cm soil depth, but lower than the rye root biomass (5.1 ± 2.4 Mg ha^{-1}) found by Raimondi et al. (2023) in Northeast Italy. Finally, the variability of GWI driven by SOC across the cover crop scenarios, can also in part be due to the absence of tillage events, by which an annual `reset` of the SOC content in the topsoil is brought about due to the loss of the C accumulated in the prior year being driven off as CO_2. Finally, variability in soil texture (Fig. S6) clearly explains part of the GWI variability. Within a given year, GWI values can vary by up to 0.2 kg CO_2-eq kg^{-1} due to differences in soil texture, as observed in 2007, 2015, 2017, and 2021.

Stacking regenerative practices through the addition of a leguminous cash crop and a cereal cover crop to increase the rotational complexity, reduces the impact intensity by almost half from 0.29 kg CO_2-eq kg^{-1} (MZ NT) to 0.15 kg CO_2-eq kg^{-1} (MZ-SB NT + CC). This is due primarily to a more than doubling of the rate of SOC accrual alongside a reduction in total N_2O emissions of around 18 %, a win-win scenario, and in agreement with prior studies on the impacts of diversified crop rotations (e.g., Lehman et al., 2017; Yang et al., 2024). The requirement for increased rotational complexity is already required in Europe as part of the latest European Union Common Agriculture Policy (EU CAP; European Parliament and Council, 2021) to support commitments to reduce GHG emissions. For example, in Italy, farmers are now required to implement a two-year rotation plan that includes at least one of the following as the main crop: leguminous crops, forage crops or renewal crops such as maize or soybeans (European Parliament and Council, 2024). Moreover, crop rotation is already part of the most recent regional Integrated Production Guidelines (Regione Emilia Romagna, 2025a). Our maize-soybean-cover crop rotation meets these requirements and shows that implementing this management at broad scale benefits the environment through climate mitigation while maintaining stable productivity.

4.2.3. Reduced nitrogen fertilization

The contribution of N fertilizers through their on-field emissions and off-site manufacture and transport is often one of the largest contributors to the overall GWI of maize-based cropping systems (e.g., Zhang et al., 2018; Eranki et al., 2019; Dachraoui and Sombrero, 2020). Therefore, reducing synthetic N fertilizer rate is well established as a management practice to reduce N_2O emissions. Here, to investigate this, we reduced the synthetic N fertilizer rate applied to maize by 25 % in our no-tilled maize-soybean-cover crop rotation (MZ-SB NT + RN + CC) and found a near halving of the overall GWI-I, from 0.15 kg CO_2-eq kg^{-1} to 0.08 kg CO_2-eq kg^{-1}. Not unexpectedly this was primarily brought about by a reduction in N_2O emissions directly associated with reduced N fertilizer input (442 kg CO_2-eq ha^{-1} yr^{-1} vs. 331 kg CO_2-eq ha^{-1} yr^{-1}), but also by small reductions in N_2O emissions associated with SOM N mineralization (8 %), crop residue N (2 %) and root N (3 %). Maize crop yields were not negatively impacted by the N rate reduction (see Fig. S4), and there was still a large gain in SOC (1407 kg CO_2-eq ha^{-1} yr^{-1}), nearly identical to the full N scenario (1422 kg CO_2-eq ha^{-1} yr^{-1}). While N fertilizer inputs can increase soil C stocks by increasing crop growth and associated rates of crop residue production, evidence suggests that excess N can speed decomposition (Gill et al., 2022) and thereby lower (Khan et al., 2007) or maintain (Russell et al., 2009) C stocks that might otherwise increase. Elsewhere, optimizing N input by reducing N rate has been shown to maintain or increase crop biomass while maintaining or increasing SOC content and reducing N pollution, including N_2O emissions (Grandy et al., 2006; Xia et al., 2020; Pan et al., 2022; Wang et al., 2025).

4.2.4. Machinery operations

The GHG emissions associated with machinery operations include those from the production and use of diesel as well as the manufacture, use, and maintenance of the equipment. Operations on site include sowing, plowing, harrowing, hoeing, irrigation, fertilization, herbicide control, and harvesting. Of these, the differences in total GWI from equipment use primarily arise from the different soil disturbance practices carried out under conventional, minimum, strip, and no-till for the maize monoculture scenarios (1 through 4), and from different irrigation requirements for soybeans when compared to maize in the more rotationally complex scenarios (5 through 7). While overall, in the absence of a substantial SOC sink (scenarios 1 and 2), machinery operations contribute no more than 22 % of the total GHG sources (Table S6), their role in the attribution of GWI changes (i.e., mitigation) between scenarios is relatively small compared to that of changes in SOC change and N_2O emissions. For example, the largest contribution to GHG mitigation across the scenarios from machinery is a 441 kg CO_2-eq ha^{-1} yr^{-1} reduction between MZ CT and MZ-SB NT (Table S6). However, this represents only about 21 % of the difference in GWI that results from the change in SOC between these scenarios, not negligible, but relatively minor.

4.3. Hybrid modeling framework: advantages, limitations, and opportunities

Our methodology integrates process-based, dynamic crop-system modeling that leverages disaggregated and high Tier (IPCC, 2019) emissions factors with a carbon footprint evaluation that uses a life-cycle analysis approach. This hybrid framework allows us to both examine small-scale operations in detail from measured data at our conventionally managed farmer field sites and enables scaling of these results alongside simulated regenerative management practices to overcome the spatial and temporal limitations of individual field trials. In doing so, we capture the weather variability over an extended period of time (23 years) and the soil spatial heterogeneity across more than 3500 sites in the Emilia-Romagna region.

Although process-based modeling approaches represent the most practical and accurate way to investigate long-term SOC changes at large scale (Basso et al., 2025), their ability to capture N_2O dynamics is less reliable and is still receiving much ongoing effort. For this reason, and relatedly due to the lack of in situ N_2O measurements for model calibration, we used spatially sensitive emission factors (Cui et al., 2021) to estimate components of the N_2O contribution to the GWI. While their use is an advanced method for large-scale N_2O estimation in LCA studies, they are not temporally sensitive to changes in agricultural practices, and thus remain disconnected from farm management feedbacks. Owing to the absence of national or regional datasets that quantify the adoption rates of regenerative management systems, we were also unable to provide an overall quantitative assessment of the GWI based on the total area under conventional versus regenerative practices.

The major contributions to the GWI-I of all seven management scenarios are from changes in SOC, either gains or losses, and emissions of N_2O associated with N fertilizer inputs and other available N sources. Field-scale experimental trials using a traditional CF LCA approach are usually unable to capture these contributions adequately as they are typically conducted over short time periods with limited resources (Goglio et al., 2018). As such they are unable to detect changes in SOC, that are typically manifested only after a decade or more following new management practice adoption (e.g., Córdova et al., 2025) or directly measure N_2O fluxes from the site, due to a lack of measurement expertise and equipment access. Therefore, for greater accuracy and standardization of the calculations for these important GWI contributions, recent LCA guidelines have recommended at least a 20-year time-frame to establish reliable SOC dynamics (Goglio et al., 2015), and the use of calibrated and validated, dynamic models and Tier 2 EFs for accurate N_2O emissions estimation (Goglio et al., 2024; Pelaracci et al., 2025), all of which are carried out here.

These requirements are particularly relevant and timely for countries in Europe, where standardized tools for evaluating agricultural GHG emissions are lacking, despite the EU CAP incorporating 'eco-schemes' designed to incentivize farmers to reduce GHG emissions, maintain existing C stores, and enhance SOC sequestration (European Parliament and Council, 2021). Moreover, discussions about future EU strategic agricultural investments increasingly emphasize the comprehensive quantification of farming's environmental impacts, enabling farmers to monetize their sustainable practices through direct governmental support and market recognition. Therefore, analogous to small-scale (farm to county based) GHG and carbon intensity-based evaluation tools in the USA (e.g., Plastina et al., 2024; Basso et al., 2025), a standardized, tailored, and accurate quantification framework for European countries could help connect farmers to carbon market programs and support broader sustainability objectives.

5. Conclusions

Conventionally tilled, maize monocrop systems in the Po Valley region of Italy are a large GHG emissions source, primarily due to the loss of SOC from frequent and deep soil tillage events, but also from emissions of N_2O mostly associated with high synthetic N fertilizer amounts. Farmers who adopt reduced tillage or no-till practices and include regenerative management practices that increase rotational complexity and reduce N inputs, will gain rather than lose SOC, converting their soil from a GHG source to a GHG sink, while lowering GHG emissions at and beyond their field sites from fertilizer, agrochemicals, and machinery operations. They can do so without any yield penalty such that the GWI intensity of their cropping systems can be reduced more than sixfold, bringing about substantial environmental benefit.

CRediT authorship contribution statement

Tommaso Tadiello: Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Diego Armando Arellano Vazquez:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. **Neville Millar:** Writing – review & editing, Investigation, Formal analysis. **Mariarita Cammarata:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Giampaolo Oliviero:** Writing – review & editing, Data curation. **Prateek Sharma:** Writing – review & editing, Software, Formal analysis. **Michela Gallo:** Writing – review & editing, Supervision, Resources, Funding acquisition, Data curation. **Adriana Del Borghi:** Writing – review & editing, Data curation. **Bruno Basso:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Bruno Basso is a cofounder of CIBO Technologies. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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Data availability

Data used are provided as supplemental material.

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