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Climate change impacts on European arable crop yields: Sensitivity to assumptions about rotations and residue management

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ABSTRACT

Most large scale studies assessing climate change impacts on crops are performed with simulations of single crops and with annual re-initialization of the initial soil conditions. This is in contrast to the reality that crops are grown in rotations, often with sizable proportion of the preceding crop residue to be left in the fields and varying soil initial conditions from year to year. In this study, the sensitivity of climate change impacts on crop yield and soil organic carbon to assumptions about annual model re-initialization, specification of crop rotations and the amount of residue retained in fields was assessed for seven main crops across Europe. Simulations were conducted for a scenario period 2040–2065 relative to a baseline from 1980 to 2005 using the SIMPLACE[1] modeling framework. Results indicated across Europe positive climate change impacts on yield for C3 crops and negative impacts for maize. The consideration of simulating rotations did not have a benefit on yield variability but on relative yield change in response to climate change which slightly increased for C3 crops and decreased for C4 crops when rotation was considered. Soil organic carbon decreased under climate change in both simulations assuming a continuous monocrop and plausible rotations by between 1% and 2% depending on the residue management strategy.

1. Introduction

Warmer temperatures and more frequent extreme weather events under climate change are expected to lead to yield losses for current crop varieties in large parts of Europe (Webber et al., 2018). The negative impact of warmer temperatures has already been detected for European crops, with average production-weighted continent-wide yield reductions of 2.5% and 3.8% for wheat and barley, respectively, over a 20 year period from 1989 (Moore and Lobell, 2015). However, elevated atmospheric CO_2 concentrations can be expected to offset some yield losses and even lead to yield increases for C3 cereals like wheat in temperate regions like Europe (Kimball, 2016; Makowski et al., 2020). Similarly, warmer temperatures may extend the growing season of maize in parts of Northern Europe (Olesen et al., 2011). At European level, climate impact studies have projected yield increases in autumn-sown C3 cereals due to CO_2 fertilization, while yields were projected to decrease in spring-sown crops due to shortened growth duration and intensified drought under future climate (Webber et al., 2018).

Most large-scale climate impact studies on crop yields in Europe have made a number of simplifying assumptions regarding crop management which may lead to large uncertainties in projected impacts (Olesen et al., 2007). Foremost, likely adaptations of the crop growing season duration and sowing date in response to gradually warming temperatures have not been considered in many studies, though farmers are very likely to make these adaptations. Zimmermann et al. (2017) demonstrated that

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[1] SIMPLACE is the shortened name for SIMPLACE <Lintul5,SlimwaterModified,NPKDemandSlimNitrogen,CanopyT,HeatStressHourly,soilCN>.

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not considering these adaptations leads to overly pessimistic crop yield projections for a number of crops in Europe. These results were largely corroborated at the global scale as shown by Minoli et al. (2019) who demonstrated that by adapting season duration, global production losses can compensate for up to 2 °C temperature increase in continental and temperate regions. Zhao et al. (2015) investigated the sensitivity of projected yield changes to assumptions about irrigation, and concluded that simulated impacts considering only rainfed conditions were negatively biased as compared to considering the actual irrigated production, with the largest error for spring sown crops in Mediterranean countries where irrigated production is widespread. Similarly, Webber et al. (2015) investigated how sensitive simulated impacts were to the consideration of nitrogen (N) fertilization and limitation. This study demonstrated that in spring-sown crops, projected climate-change impacts did not depend on whether or not N limitation was considered, whereas simulated impacts for autumn-sown crops (winter barley, winter rapeseed and winter wheat) were sensitive to assumptions about the timing of nitrogen application.

Studies have also been simplified by assuming monocrop systems, with re-initialization of soil water and nitrogen contents each year (Webber et al., 2015; Zhao et al., 2015). In reality, crops are grown in rotations, in response to market factors, livestock feed and fodder production needs, to manage pests, weeds, soil borne diseases, soil nutrients and organic matter, and to reduce soil erosion (Basso et al., 2015). Reckling et al. (2016b) reported that diversified rotations with legumes had positive phytosanitary effects. Similarly, assumptions about post-harvest management of crop residues is an important consideration that has not been investigated for climate impact studies. In many cases, cereal residues are harvested for use as straw bedding, directly harvested for feed in the case of silage maize and are increasingly considered as a source of biomass for bioenergy production. In other cases, residues are retained on the soil surface in either no-tillage systems or incorporated with tillage (Kaye and Quemada, 2017; Stella et al., 2019).

Both the specification of crop rotations and postharvest residue management have implications for evolution of soil organic carbon (SOC), greenhouse gas emissions, surface soil water evaporation and climate change mitigation efforts (Huang et al., 2018). The 4 per 1000 Initiative was launched in that perspective to counteract the effect of anthropogenic emissions of greenhouse gases. Indeed, over the past century climate and land-use changes have led to a sharp decrease of SOC stocks, dramatically overwhelming the simulated effects associated with elevated atmospheric [CO_2] and nitrogen deposition (Tian et al., 2015). However, it is difficult to generalize over observational studies as SOC dynamics depend on climate, soil type, land management, residue quantity and quality (Kong et al., 2005), and on initial SOC values, as described by Corbeels et al. (2019) for the case of Sub-Saharan Africa. Residue retention in fields, often coupled with reduced tillage systems, have the potential to increase storage of SOC and constitute an important option to mitigate climate change in agricultural land use (Lipper et al., 2014; Powlson et al., 2014; Paustian et al., 2016; Huang et al., 2018) as well as limit surface soil water evaporation. Nash et al. (2018) estimate that crop rotations have greater potential to influence SOC stocks than tillage systems. Beyond its role in climate change mitigation (Poeplau and Don, 2015), SOC levels are essential for agricultural soil (Lehtinen et al., 2014), as SOC can be an important source of nutrients and contributes to improving the physical, chemical and biological properties of soil (Page et al., 2020). Increases in SOC increase subsequent crop water availability through increasing water holding capacities (de Moraes Sá et al., 2017; Zdruli et al., 2017). As SOC and crop yields influence each other, but each responds individually to changing temperature, soil moisture, elevated [CO_2] and crop and soil management (Lugato et al., 2007), one can expect that projected climate change impacts on crop yields depend on consideration of crop management affecting SOC (Prior et al., 2005; Marhan et al., 2008). However, datasets to allow a more comprehensive understanding of the complex interactions between tillage, cropping system and fertilization related to greenhouse gases emissions and SOC sequestration from croplands (Johnson et al., 2005) and models representations of these complex interactions are subject to considerable uncertainties (Lutz et al., 2019). SOC dynamics themselves are expected to be affected by climate change. Warmer temperatures are expected to increase mineralization rates and thus decrease SOC. However, interactions between temperature, precipitation and crop biomass input are critical to consider (Wang et al., 2014). Elevated atmospheric [CO_2] can be expected to increase organic matter inputs (if water is not limiting) and offset higher soil respiration rates, as projected for northern Europe (Lugato et al., 2014b). Indeed, long term losses of soil carbon due to increased respiration may even be exacerbated with an increase in soil heterotrophic activity with warmer temperatures (Black et al., 2017). Feedbacks of soil organic carbon and nitrogen on crop yields under climate change were explored by Basso et al. (2018) in eight locations across the globe.

For European agriculture, SOC dynamics have been widely investigated with crop or land-use models at field (Lugato and Berti, 2008; Luo et al., 2014), regional (Stella et al., 2019) and continental scales (Lugato et al., 2014a, 2014b). While most crop models will not capture the effects of rotations or residues on pathogens and disease cycles, many can capture effects on surface soil water evaporation as well as, on soil organic carbon and nitrogen dynamics (Ewert et al., 2015). At the field scale in New Zealand, Teixeira et al. (2015) demonstrated the sensitivity of simulated soil related variables (SOC, mineral soil nitrogen and soil water content) and limiting growth conditions to the consideration of various rotation combinations for four crops (winter wheat, green-feed wheat, forage kale and silage maize). Regarding crop yields, Kollas et al. (2015) showed that continuous simulation of multi-year crop rotations can improve model skill slightly compared to simulations for single years with re-initialization of initial conditions. However, in predicting grain N, continuous simulation did not lead to improvements in reproducing observations as compared to re-initialization each year (Yin et al., 2017). Nevertheless, to the best of our knowledge, no studies for Europe have investigated how sensitive simulated climate-change impacts are to assumptions on initialization strategies, crop rotations or residue management. The study of Basso et al. (2015) was an important step in this direction, investigating the importance of soil re-initialization for simulated climate change impacts, though it was limited to only maize systems in Nebraska, USA and did not consider the importance of rotations or residue management.

In this context, the overarching objective of this study was to assess the sensitivity of simulated climate change impacts on major crop yields across Europe to assumptions about re-initialization of simulations for soil conditions, crop rotations and crop residue management. We conducted a simulation experiment to evaluate the sensitivity of relative crop yield changes to:

a. different assumed model initialization and crop rotation strategies (3 levels: no rotation with annual model re-initialization of soil water and nitrogen status; monocrop with continuous model simulations; or crop rotations with continuous model simulations
b. crop residue retention strategy (3 levels: 0%, 50% and 100% retention) for each level of a).

We conducted the study for winter wheat, winter barley, winter rapeseed, potato, sugar beet, silage maize and grain maize across Europe with crop model simulations at 25 km spatial resolution. Simulations were conducted for three representative concentration pathway scenarios (RCP 2.6, 4.5 and 8.5) for the period 2040–2065 relative to a reference period of 1980–2005.

2. Materials and methods

2.1. Model description

This study used a crop model solution in the SIMPLACE modeling framework (www.simplace.net), combining the Lintul5 crop growth model (Wolf, 2012), a modified version of the soil water balance Slimwater (Addiscott et al., 1986; Addiscott and Whitmore, 1991) model, the FAO-56 dual crop coefficient procedure for calculating crop evapotranspiration (Allen et al., 1998), the NPKDemandSlimNitrogen module (Addiscott and Whitmore, 1991; Porter, 1993; Jamieson et al., 1998), an hourly canopy temperature module (Webber et al., 2016), a heat stress module (Gabaldón-Leal et al., 2016) and the soilCN module (Corbeels et al., 2005a). Lintul5 is a generic crop growth model which simulates crop growth under potential, water and nitrogen (N), phosphorous (P) and potassium (K) limitation. Plant growth is simulated in Lintul5 as a function of intercepted radiation and radiation use efficiency. Crop development stages (DVS) are simulated as function of daily temperature sums (thermal time) and crop specific thermal time requirements, TSUM1 and TSUM2, to develop from emergence to anthesis and from anthesis to maturity, respectively. Soil water balance and crop water uptake is simulated by SlimwaterModified and crop water demand is calculated with the FAO Penman-Monteith equation using the reference crop and dual crop coefficient method (Allen et al., 1998). The SlimwaterModified module estimates the daily change in soil water content in a variable number of soil layers based on the volumes of crop water uptake, soil evaporation, surface runoff and seepage below the root zone which no consideration of canopy interception nor lateral subsurface runoff.

The NPKDemandSlimNitrogen model calculates daily N, P and K demand, uptake and stress factors as well as nitrogen movement in the soil profile and leaching of soil mineral nitrogen (Nitrate-N and Ammonium-N). The turnover and leaching of nitrate and ammonium is closely related to the soil water dynamics where input data related to daily changes in soil water content and soil water fluxes are provided by SlimwaterModified. Daily total mineral N is an input to the module provided by the SoilCN module, described below. In this model setup, the simulated hourly canopy temperature is used as an input to the heat stress model (Gabaldón-Leal et al., 2016) when the hourly temperature is above a critical threshold temperature around the flowering period. Daily air temperature is used to drive all other processes.

The soilCN model simulates SOC and soil nitrogen dynamics assuming several litter pools and three different SOC pools and different soil layers. The three pools SOC are: (i) microbial biomass pool or active pool with a turnover time of few months, sub-divided into a labile (fast) and resistant fraction (slow), (ii) young soil organic matter pool or intermediate pool with 1–5 year turnover time and (iii) old soil organic matter pool or passive pool with more than 200 years turnover (Corbeels et al., 2005a). The initial values of the C/N ratios were set to the default for the three different SOC pools. The fluxes of carbon in the active and intermediate pools is a function of soil texture, soil temperature and water, while in the passive pool the fluxes of carbon is a function of only soil temperature and water. The decomposition rate of the active (K10act: decomposition rate for labile pool of active biomass and K11act: decomposition rates for resistant pool of active biomass) and intermediate (K12slo: decomposition rate of young SOC pool) are a function of soil texture and plant lignin content (Parton et al., 1987). The decomposition of each litter or SOC pool is primarily driven by carbon accessibility, while N mineralization-immobilization is driven by the growth of microbial biomass. In the model, there is no feedback between SOC and soil water holding characteristics in the SlimwaterModified module, which are treated as functions of soil texture only. For further description of the model components referred to https://wwwsimplace.net/index.php/documentation.

2.2. Input data

2.2.1. Nitrogen

Historical nitrogen data from 1982 to 2006 related to nitrogen inputs into European cropland were derived from data on nitrogen fertilizers, residues, atmospheric N deposition and manure (estimates based on animal numbers to derive manure input) from the CAPRI database for each NUTSII level (Webber et al., 2015). As data in CAPRI do not distinguish irrigated from rainfed production at the time of the study, a simple rule for nitrogen allocation was devised to estimate fertilizer N for simulations for both production system following the approach of Webber et al. (2015) and (Zhao et al., 2015). The rule is that the amount of nitrogen allocated to irrigated crops is set to 2 times the rate allocated to rainfed crops for any given location and the sum of nitrogen applied to irrigated and rainfed systems equals the value reported by CAPRI. However, this rule rarely had any implications, as with few exceptions most regions have predominantly rainfed or irrigated production for specific crops (Fig. S15). Data were detrended and years with missing data were filled with the mean value of the time series for each NUTSII. Future nitrogen scenarios were derived by adjusting the baseline nitrogen amount by the same percentage that water limited yields changed (Webber et al., 2015), based on the explicit assumption that the intensity of nitrogen use did not change in the scenarios.

The timing of nitrogen application was split according to the development stage of each crop (DVS) based on a general expert knowledge: three applications for winter wheat; one for silage and grain maize; and two applications for the remaining four crops. Applications varied for each location, crop, GCM (global climate model) and RCP (representative concentration pathway) combination, as well as for rainfed and irrigated conditions.

2.2.2. Climate data

Daily climate data at 25 km resolution were derived from the Joint Research Center's (JRC) Agri4Cast database (version 1.0) including daily minimum, and maximum air temperature, precipitation, global radiation, wind speed, actual vapor pressure, relative humidity at maximum air temperature and dew point temperature were used (http://open-research-data-zalf.ext.zalf.de/ResearchData/DK_59.html). Data were available for a baseline period (1980–2005) and the scenario period (2040–2065) for three RCPs: RCP2.6, RCP4.5 and RCP8.5 and five GCMs: GFDL-CM3, GISS-E2-R, HadGEM2-ES, MIROC5, and MPI-ESM-MR. Only two GCMs (HadGEM2-ES and MPI-ESM-MR) were available for RCP2.6 at the time of the study. Baseline data were driven from interpolated observed data at station and the scenarios were calculated using an enhanced delta change method that applies changes in aspects of temperature and precipitation variability in addition to changes in mean climate (Ruane et al., 2015). More details about the climate data processing are available at (Webber et al., 2018).

2.2.3. Soil data

Soil data was derived from two datasets: the European Soil database from the JRC European Soil Data Portal (http://eusoils.jrc.ec.europa.eu/) and the Land Use/Cover Area frame Survey) (LUCAS, Orgiazzi et al., 2018). The original JRC available data, at 1 km resolution, was resampled to the 250 m resolution of the Corine Land Cover 2000 raster to enable selecting only soil values associated with agricultural land (non-irrigated arable land; permanently irrigated land; rice fields; annual crops associated with permanent crops; complex cultivation patterns; and land principally occupied by agriculture with significant areas of natural vegetation). Data were then aggregated to the 25 km grid of the climate data by selecting the median soil depths available for the root growth, total available water, bulk density, total soil organic carbon and texture (clay, silt and sand). The selection was based on the soil class having the largest area in each 25-km unit.

The LUCAS database (https://esdac.jrc.ec.europa.eu/content/lucas-2009-topsoil-data) was used to derive the top soil organic carbon (20 cm) of the reference year 2009. We first joined the LUCAS top soil organic carbon geo-referenced samples (a total of 19967) to the corresponding LUCAS land cover database and selected a subset of 8829 samples that were classified as crop land. These samples were then joined to the JRC 25 km grids defined by the climate data. Within each grid, the mean value of top soil organic carbon was determined by averaging over all LUCAS samples. For missing grid cells, we used an extrapolation approach to select the value of the neighboring grid cell as an approximation of the soil organic carbon.

2.3. Crop rotations

Crop rotations were selected using historical statistical data (1984–2013) from the CAPRI database at NUTSII level. Data were first aggregated over years for each NUTSII region and crop, and then again aggregated to environmental zones (ENZ). The share of each crop production activity per utilized agricultural area was calculated and ordered for the crops simulated by SIMPLACE in this study. Up to six crops were selected for each ENZ based on the highest area shares. Then for each ENZ, the selected crops were combined into plausible rotations based on good agronomic practices and phytosanitary impacts of the preceding crop. The agronomic rules used to generate the rotations followed the approach of (Reckling et al., 2016a, 2016b):

(i) combine selected crops to produce all possible two-crop combinations by applying sequence restrictions defined with expert knowledge on plausible crop rotations considering timing, nutrient demand and pest and disease management to validate the rotations generated with the method of (Reckling et al., 2016b)

(ii) combine the crop sequences into 3–6 years rotation. For a given generated rotation, a filter is applied based on minimum sequential break of a crop, maximum frequency of crop, maximum frequency of crop type.

The result was a series of 3–6 year rotations (cover crops were neglected). One rotation was selected for each ENZ, except for two ENZs (4 and 6) where several rotations were simulated with more data available (Fig. 1) to test the sensitivity of results to the selected rotation. The resulting rotations for each ENZ were then resampled to the simulation units. For each grid, RCP-GCM combination, simulations were repeated by the number of crops in the rotation, each time starting the simulations with a new crop ordering to avoid year by crop order effects (Teixeira et al., 2015). Finally, average yields for the target crop were calculated as the average over all possible sequences.

2.4. Model parameterization and testing

The SIMPLACE model has been widely applied at European scale for assessing the climate change impacts (Webber et al., 2015, 2018; Zhao et al., 2015) and for modeling crop rotations (Kollas et al., 2015; Yin et al., 2017).

For phenology, observations of crop sowing, anthesis, maturity and harvest from the JRC Mars database (https://ec.europa.eu/eurostat/web/main) were used to calibrate the crop model thermal time parameters. First phenology observations were aggregated to the level of environmental zone across Europe (Metzger et al., 2005). Then the phenology observations were assigned to each simulation unit (grid cell), and thermal time requirement TSUM1 (from emergence to anthesis) and TSUM2 (from anthesis to maturity) were calibrated for each simulation unit based on the approach used in Zhao et al. (2015) adopted from (Therond et al., 2011; Balkovič et al., 2013). Therefore, in each environmental zone there are different crop varieties as related to a specific temperature within a grid cell. When phenology observations were missing, sowing dates were generated from similar crops in the same environmental zone (Metzger et al., 2005) by preserving the relationship between the average differences for these crops.

All others crop growth parameters, for grain maize and winter wheat cultivars were derived from Webber et al. (2018). Silage maize values were based on those of grain maize. Cultivar parameters for winter barley, winter rapeseed and sugar beet used calibrated values reported by Kuhn et al. (2020). Finally, crop growth parameters for potato used default values reported by Boons-Prins et al. (1993). There was no effect of elevated [CO_2] on radiation use efficiency (RUE) for C4 crops: grain maize and silage maize (Kimball, 2016; Durand et al., 2018). For C3 crops, RUE increased of 8%, 13% and 20% when [CO2] increased from 442 ppm for RCP2.6, 499 ppm for RCP4.5 and 571 for RCP 8.5, respectively, relative to the baseline of 360 ppm (Wolf, 2012). The effect of elevated [CO_2] on crop transpiration and RUE were parametrized based on Kimball (2016).

SOC model was parametrized and tested in North Rhine-Westphalia (NRW), Germany with most of the parameters were derived from (Corbeels et al., 2005b) and from our sensitivity analysis (for details see Section 2.5).

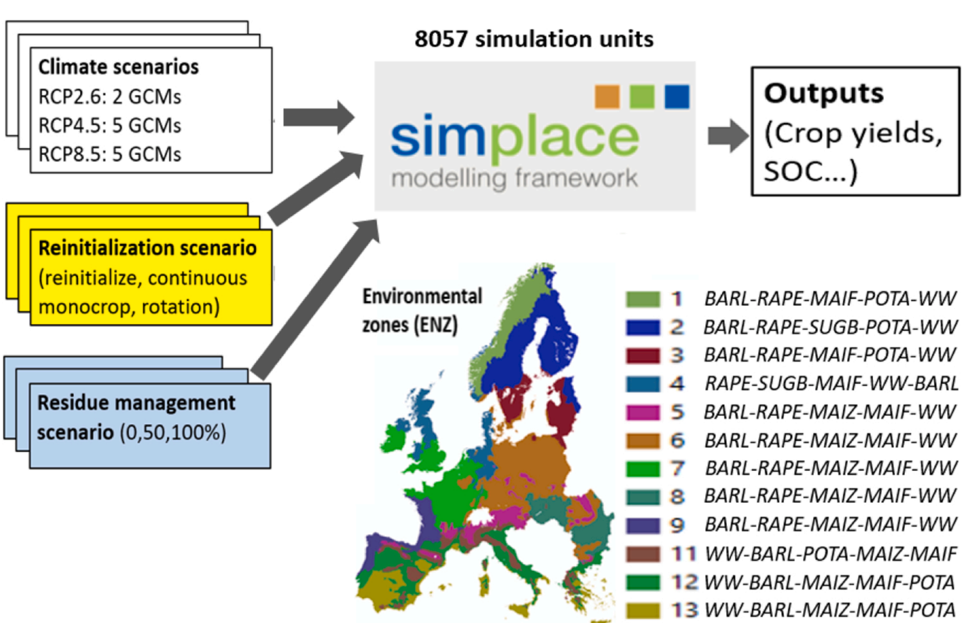

Fig. 1. Schematic overview of the simulation experiment. BARL: winter barley; MAIF: silage maize, MAIZ: grain maize, POTA: potato, RAPE: winter rapeseed, SUGB: sugar beet and WW: winter wheat. The environmental zone are: Alpine North (1), Boreal (2), Nemoral (3), Atlantic North (4), Alpine South (5), Continental (6), Atlantic Central (7), Pannonian (8), Lusitanian (9), Mediterranean Mountains (11), Mediterranean North (12) and Mediterranean South (13). RAPE-WW-WW-WW-BARL and WW-BARL-RAPE-WW-BARL-POTA rotation are additionally simulated in ENZ4 and WW-BARL-MAIF, RAPE-BARL-MAIF-WW-BARL and RAPE-WW-BARL in ENZ6.

2.5. Simulation exercise setup

This study is conducted at EU-27 level at 25 km resolution based on climate data for seven crops (winter wheat, winter barley, winter rapeseed, potato, sugar beet, silage maize and grain maize). Simulations were conducted for baseline (1980–2005) and scenario (2040–2065) periods. We assumed no adaptation in varieties between baseline or climate change scenarios.

The simulation experiment was performed based on three sets of scenarios (climate, re-initialization, and crop residue retention rate, see Fig. 1) using a factorial design, combining all levels of each scenario (where feasible, explained below). The first set of scenarios explored focused on climate: RCP2.6 (2 GCMs), RCP4.5 (5 GCMs) and RCP8.5 (5 GCMs). In the second set of scenarios, the implication of the re-initialization procedure were explored for three cases: (i) monocrop with re-initialization of initial soil water, nitrogen and carbon each year, (ii) continuous monocrop allowing soil water, nitrogen and carbon balance calculations to continue over the entire simulation period; and (iii) plausible crop rotation allowing soil water, nitrogen and carbon balance calculations to continue over the entire simulation period. Finally, in the third set of scenarios, three residue retention rates in the field after harvest were considered (0, 50 or 100% above ground residues retained, where residues refer to leaves and stems above the cutting height for the grain crops). The total amount of green and dry leaves and stems was calculate after harvest and multiply by a factor of 0 or 0.5 or 1 for the three respective cases above for the amount of residue retained in the field. Note, for silage maize this set of scenarios could not be assessed as leaves and stems constitute part of the main harvest product. Again, all levels of each scenario were combined in factorial combination, except that for re initialization scenario, because there was no impact of residue retention as initial soil values are reset. As the model does not simulate tillage systems, residues were not incorporated into the soil, but rather simulated as remaining on the soil surface. Therefore, our consideration of no tillage systems here was due to the fact that our current model does not yet simulate soil tillage processes.

A 50 years spin-up period was used to initialize simulations for both the continuous monocrop and rotation cases, for both baseline and scenario simulations to allow the soilCN module to reach an equilibrium to initialize the carbon pools. The 50 years spin-up was chosen based on an evaluation of the SOC evolution over a 400 years period in three different ENZ which showed that 50 years period with the original parameterization was satisfactory to nearly reach equilibrium (Fig. S3). This initialization minimizes any implications of how the initial value of SOC is specified to influence the mineralization and immobilization of nitrate and ammonium. A sensitivity analysis was performed to determine the most sensitive parameters in the soilCN module using a simulation period for 400 years though repeating the same 30 years of weather data (1981–2010). The parameters used in the sensitivity analysis were identified based on literature concerning this and other SOC models (Table S1). The fast99 method of Saltelli et al. (1999) was implemented in R with the sensitivity package. The results of the main effects and the interactions for each parameters are represented for the case of no fertilizer application with 100% residue retention in Fig. S4. The soilCN was parametrized using specific crop characteristics as well as soil variables such as soil sand and clay content, soil depth of each horizon, surface litter amount, litter composition, depth of mineralization, where parameter values used were taken from literature.

Final results are presented for simulations that considered water - nitrogen limited yields. To derive plausible nitrogen rates to be used in the climate scenarios, we made the assumption that production intensity, as indicated by nitrogen fertilization to achieve a particular yield gap, would remain approximately the same (Webber et al., 2015). To estimate this, all simulations were first conducted with only water limitation and relative yield changes calculated. Finally, we assumed no adaptation of new crop varieties in simulated future periods (growing season duration).

2.6. Simulation results aggregation and relative yield change

Fully irrigated and fully rainfed simulations were conducted for each of 8057 simulation units across the EU-27 at 25 km x 25 km resolution Simulated grain yields were aggregated over each simulation period and crop rotation using the MIRCA2000[2] (Monthly Irrigated and Rainfed Crop Areas around the year 2000) dataset to allowing weighting of rainfed and irrigated simulations at the simulation unit level (Eq. (2)). The MIRCA2000 dataset was also used as an area weighting based on current production areas for aggregation to EZ or European level. Final yield was determined by production divided by harvest area for a given level after combining the shared rainfed and irrigated production. In each simulation unit production was determined as the yield simulated by production area, while at European level production was determined as the sum over all pixels with:

$$Y_{EU} = \frac{P}{A} \tag{1}$$

where Y_{EU} yield at EU level either for rainfed or irrigated using MIRCA production area, P is the total production (rainfed or irrigated) and A is the harvest area (rainfed or irrigated).

$$Y_{aggregated} = \frac{\left((100 - IR) * Y_{rainfed} + IR * Y_{irrigated}\right)}{100} \tag{2}$$

where $Y_{aggregated}$ is the final yield either at pixel level or EU level, $Y_{rainfed}$ is the rainfed yield, $Y_{irrigated}$is the irrigated yield and IR is the irrigation ratio in % calculated in Eq. (3).

$$IR = \frac{\text{Irrigated area}}{\text{Irrigated area} + \text{Rainfed area}} * 100 \quad [\%] \tag{3}$$

The relative change in grain yield was calculated as:

$$\Delta Y = \frac{Y_{scenario} - Yi_{baseline}}{Y_{baseline}} * 100 \quad [\%] \tag{4}$$

where ΔY is the relative yield change, $Y_{scenario}$ is the simulated yield for the scenarios period and $Y_{baseline}$is the simulated yield for the baseline.

To aid in understanding what was driving differences in projected yield changes between the different initialization and residue retention cases, we also quantified the relative change in SOC as:

$$\Delta SOC = \frac{SOC_s - SOC_b}{SOC_b} * 100 \quad [\%] \tag{5}$$

where ΔSOC is the relative SOC change, SOC_s is the simulated SOC average value over the future scenario 2040–2065 and SOC_b is the simulated SOC average value over the baseline 1980–2005, always for the same respective initialization and residue retention cases.

3. Results

Comparing across all crops and various climate, re-initialization and residue retention scenarios, European aggregate relative yield changes ranged between + 36% yield gains for C3 crops (winter wheat) to as much as 21% yield losses for grain maize, a C4 crop (Table S4) for individual simulation units and years. Irrespective of the RCP, re-initialization or residue retention scenario, across crops it was evident that climate change impacts were generally positive for the C3 crops (winter barley, winter rapeseed, winter wheat and sugar beet) except for potato where there was relatively limited yield change projected. On the other hand, for grain maize relative yield changes were negative, while for silage maize relative yield changes depicted a slight positive impacts (Fig. 2). For the winter sown C3 crops, relative yield changes were

[2] https://www.uni-frankfurt.de/45218031/data_download

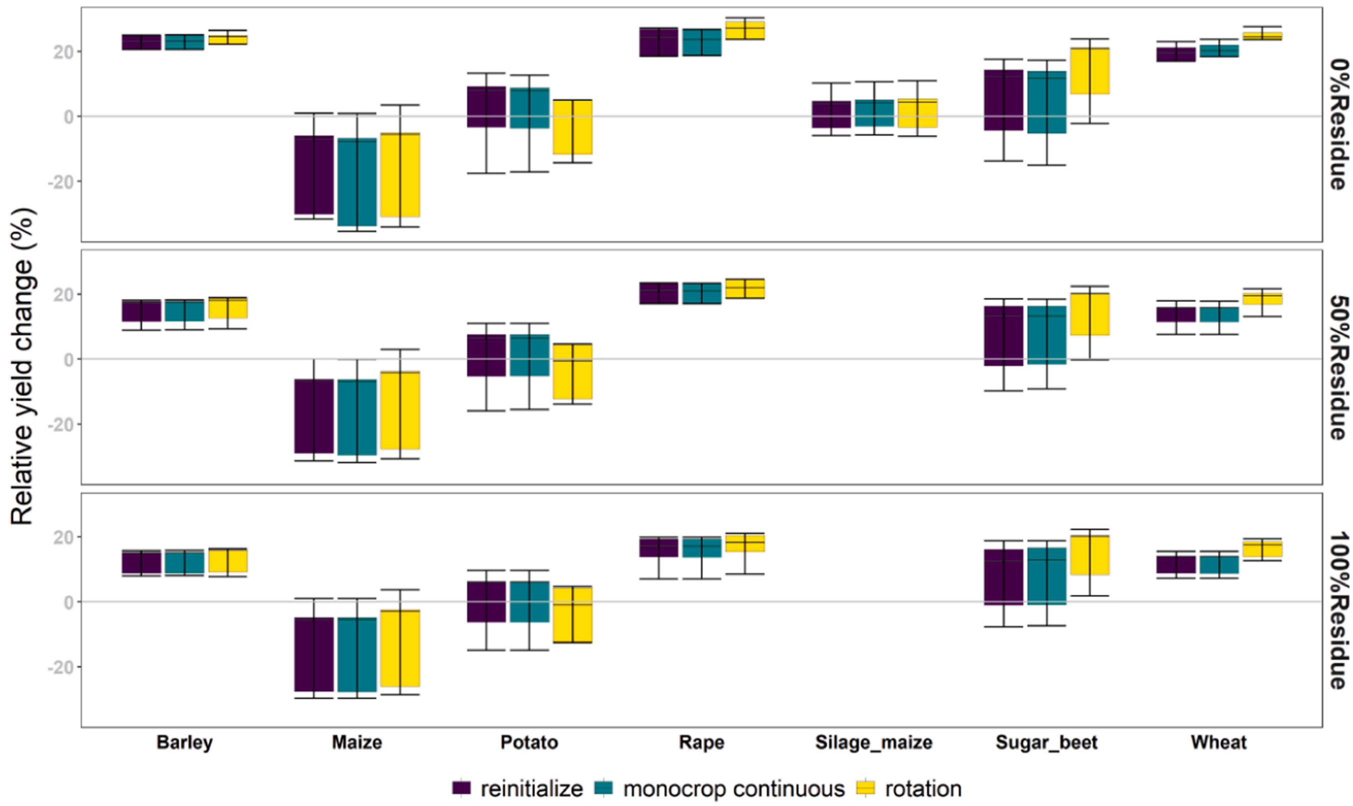

Fig. 2. Relative yield change for RCP4.5 on winter barley, maize grain, potato, winter rape, silage maize, sugar beet and winter wheat. The yields at pixel level were aggregated over years and EU level for the estimated period 2040–2065 relative to the baseline 1980–2005 using MIRCA2000 landuse data. Box-and-whisker plots depict distribution across GCMs for the 25th and 75th percentile the median is shown as a horizontal bar in each box and whiskers extend to the maximum/minimum value within 1.5 times the interquartile range (outliers are not shown). Purple, dark cyan and yellow bars depict annual re-initialization, continuous monocrop and plausible rotations, respectively. Three residues retention rates were considered: 0% residue (top row), 50% residue (medium row) and 100% residue (bottom row).

highest for RCP8.5 and lowest for RCP2.6. Comparing across crop types, there was less uncertainty across GCMs (as indicated by the spread of boxplots in Fig. 2) for the winter sown crops compared to grain maize, potato and sugar beet, where there was much greater uncertainty across GCMs in the simulated yield impacts, particularly with warmer scenarios (RCP4.5 and RCP8.5). When considering the impact of the re-initialization strategy, simulations conducted considering plausible rotations generally had more positive relative yield changes for winter rapeseed, winter wheat and winter barley and sugar beet. The influence of residue retention strategy is less pronounced, but removal of all residues tended to increase the projected positive impacts on the C3 crops compared to the 50% or 100% residue retention cases (Table S4). Indeed for all crops, the uncertainty across GCMs was generally much greater than any signal from residue management or re-initialization scenario, especially for grain maize (Fig. 2). Across all crops, the key observation was that the largest differences were across C3 crops vs C4 crops and between climate scenarios (Fig. S5). For the C3 crops, the climate signal varied most with RCP whereas for the C4 crops, the greatest source of uncertainties was rather across GCMs. The effects of re-initialization and residues retention scenario were less pronounced and were crops dependent.

These aggregate results hide much information about the spatial variation of simulated yield changes, shown in Fig. 3 for winter wheat and RCP4.5. Regardless of the re-initialization or residue retention scenario, simulated yield changes were generally more positive in the northern areas. For the case of 0% residue retention, relative yield changes were highest in the north and north east with wheat yield change projected as high as 60% in Norway and Finland when rotations were considered (Fig. 3). On the other hand, we see in large parts of Southern Europe and France that wheat yields were essentially unchanged and even had negative trends in some areas of Spain. Across crops, the spatial patterns for 50% and 100% residue retention were largely the same and less pronounced as for the case of 0% residue retention (Fig. 3). However, there was no marked difference between simulations with re-initialization, continuous monocropping or rotations. Spatial variability of the relative yield changes across GCMs increased with RCP8.5 irrespective of the crops (Fig. S10). Considering the difference between GCMs, simulations with the GFDL-CM3 model had greater spatial variability across Europe than the others (Fig. S9).

To facilitate understanding the results, for the rest of the results section we will focus on contrasting results for maize and winter wheat. Consideration of residues retention scenario did not have a substantial effect on the simulated yield impacts for either maize or wheat (Fig. 4). Leaving all residues on the field after harvest (100% residue retention) had a marginal tendency to reduce yield losses in maize, whereas it limited the positive yield change for winter wheat by − 10% points for the RCP8.5.

Considering results for the re-initialization strategy, relative yield changes for winter wheat were more positive when rotations were simulated compared to the annual re-initialization case or continuous monocrop simulations. For grain maize, relative yield changes were largely insensitive to the re-initialization strategy, though yield changes tended to be slightly less negative when rotations were simulated. There was less uncertainty in simulated impacts across GCMs for winter wheat when rotations were simulated compared to annual re-initialization or continuous monocrop, though this effect was not present for maize (Fig. 4).

For understand what was driving these different yield responses in our model between initialization and residue retention cases, we also considered the relative climate change impacts on SOC for each assumed

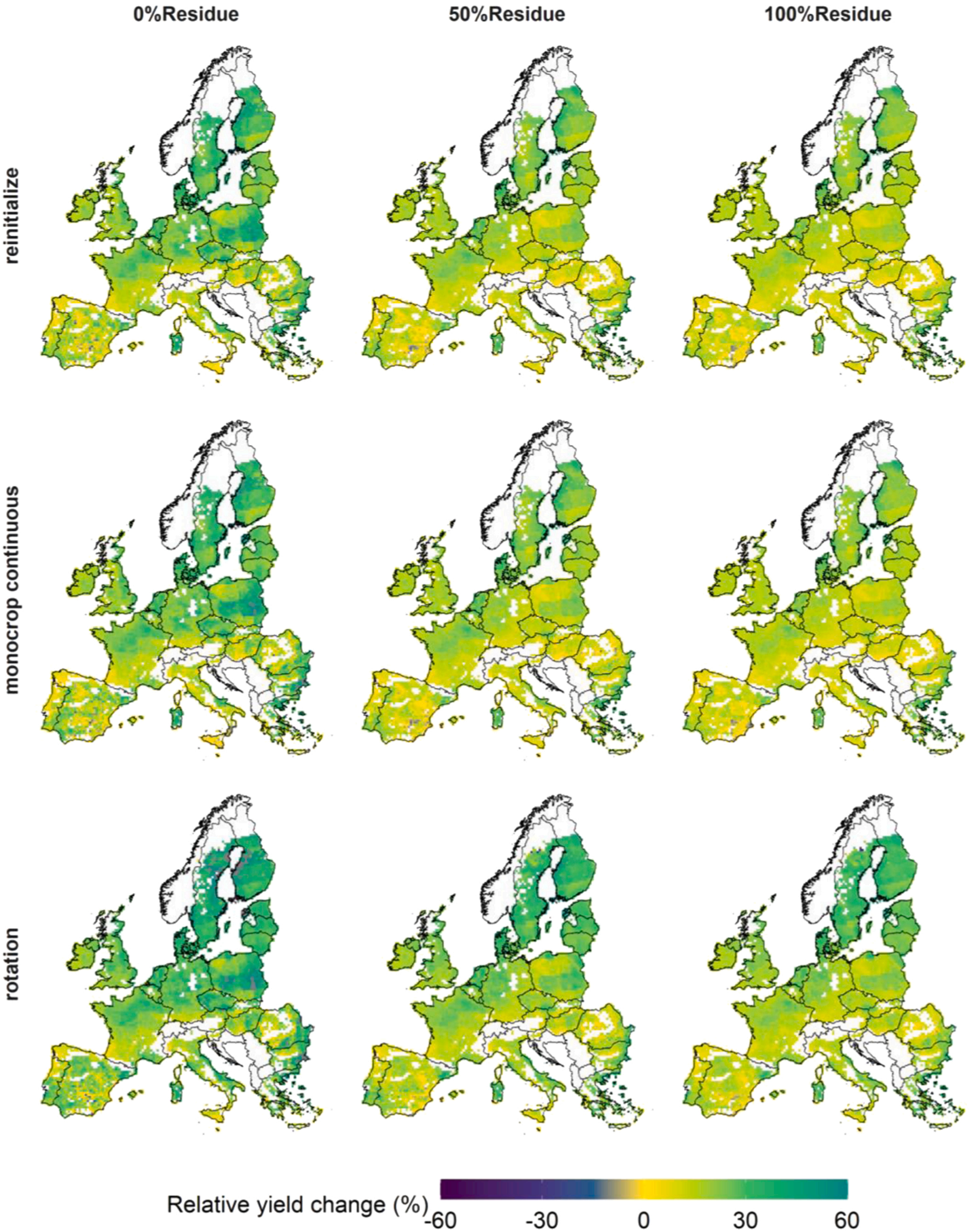

Fig. 3. Spatial patterns of relative yield change for winter wheat and RCP4.5 for each residue retention rate (0%, 50% and 100% residues retention rates in the columns). The top row shows simulations with re-initialization, the middle row the continuous monocrop simulations and the bottom row the simulations with rotations. Results are shown here for the MPI-ESM-MR GCM.

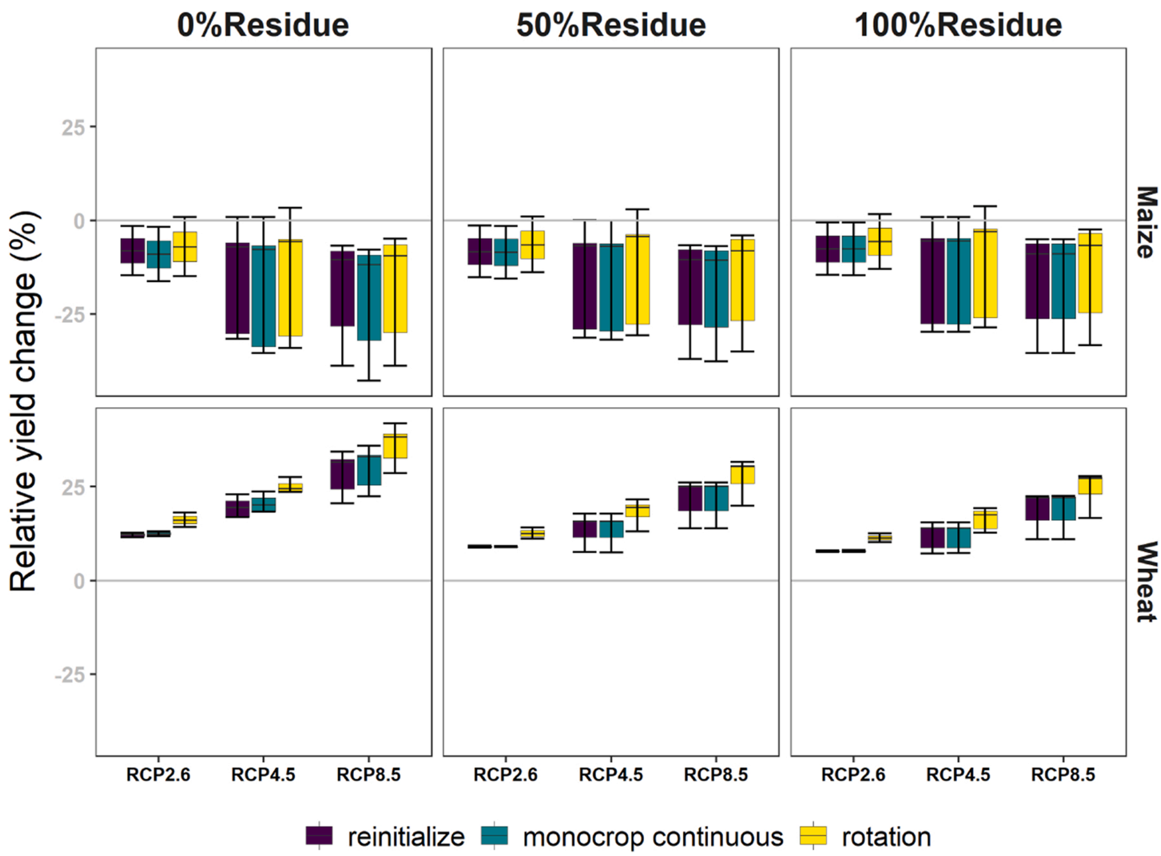

Fig. 4. Effect of residues retention on yield change under elevated scenario on grain maize (top row) and winter wheat (bottom) RCP2.6, RCP4.5 and RCP8.5. Data were aggregated over years and to the EU level considering current production shares for the scenario period 2040–2065 relative to the baseline 1980–2005. Box-and-whisker plots depict distribution across GCMs for the 25th and 75th percentile, with median and whiskers extend to the maximum/minimum value within 1.5 times the interquartile range (outliers are not shown). Purple, dark cyan and yellow bars depict re-initialization, continuous monocrop and rotation respectively. Column depict 0% residue (left), 50% residue (middle) and 100% residue (right) retention rates.

case. Our model projections showed that the relative change in SOC was negative for continuous monocrop and rotation simulations, irrespective of the residue retention with higher uncertainty for the warming scenarios (Fig. 5). The relative change in SOC ranged between − 1% to − 2% for 0% and 100% of residue retention rates respectively (Table S5). Recall that this is a comparison of climate impact on the different residue management strategies (i.e., same management was assumed in baseline and scenario) and does not imply that SOC would be lower when all residues were left on the field than when they were removed. However, comparing the continuous monocrop and rotation simulates revealed no substantial interactions with residue retention or RCP scenarios. There was greater uncertainty across GCMs when rotations were simulated as compared to continuous monocrop simulations in particular with RCP 4.5 and 8.5. Across RCPs, both sets of simulations had higher SOC losses with RCP8.5 than with RCP4.5 or RCP2.6. The spatial patterns of changes in SOC across Europe revealed regions in the South and East of Europe (Spain and Italy) would have losses of approx. − 5%, considerably larger than in Northern regions. The spatial variability in SOC changes were higher under the RCP8.5 than RCP4.5 or RCP2.6 (Fig. 5).

4. Discussion

4.1. Impact of climate change on crop yield in Europe

Our study coupled a process-based SOC model assuming first order kinetics governing SOC mineralization with a process-based crop model to evaluate the sensitivity of climate change impacts on crop yield across Europe with respect to different model settings regarding model re-initialization and residue management. The projected increase in yield of C3 crops for large parts of Europe in our study was largely explained by CO_2 fertilization, which provides much less benefit for C4 crops except in cases of low to moderate drought stress (Fig. S11). The positive response of C3 crop is attributed by the fact that the higher temperature effect on growth and phenology is compensated by the effect of CO2 fertilization, which reduces stomatal conductance and transpiration and improves water use efficiency. Also, winter crops can also profit from avoiding summer drought conditions by accelerated phenology from warming in large parts of Europe. These findings were consistent with previous work of Webber et al. (2018) and Jägermeyr et al. (2021) who reported yield gains for winter wheat and yield losses for grain maize. Similarly, a global study on wheat found an increase in wheat yields in Europe for the 1.5 and 2.0 °C scenarios compared to the baseline 1980–2010 (Liu et al., 2019). There was a slight increase in potato yield for RCP4.5 and RCP8.5 while Raymundo et al. (2018) projected yield reductions in Eastern Europe and a yield increase for Western Europe by 2055 for RCP8.5. These results were largely consistent with other climate impact studies that have used process-based crop models for these crops in Europe (Zhao et al., 2015; Zimmermann et al., 2017; Webber et al., 2018) though studies using statistical models have projected yield declines for winter wheat and winter barley in France (Gammans et al., 2017) which could be explained by the water availability and heat stress for the scenario RCP8.5.

4.2. Sensitivity of simulated impacts to re-initialization and residue management

Our study suggests that simulated climate change impacts were not

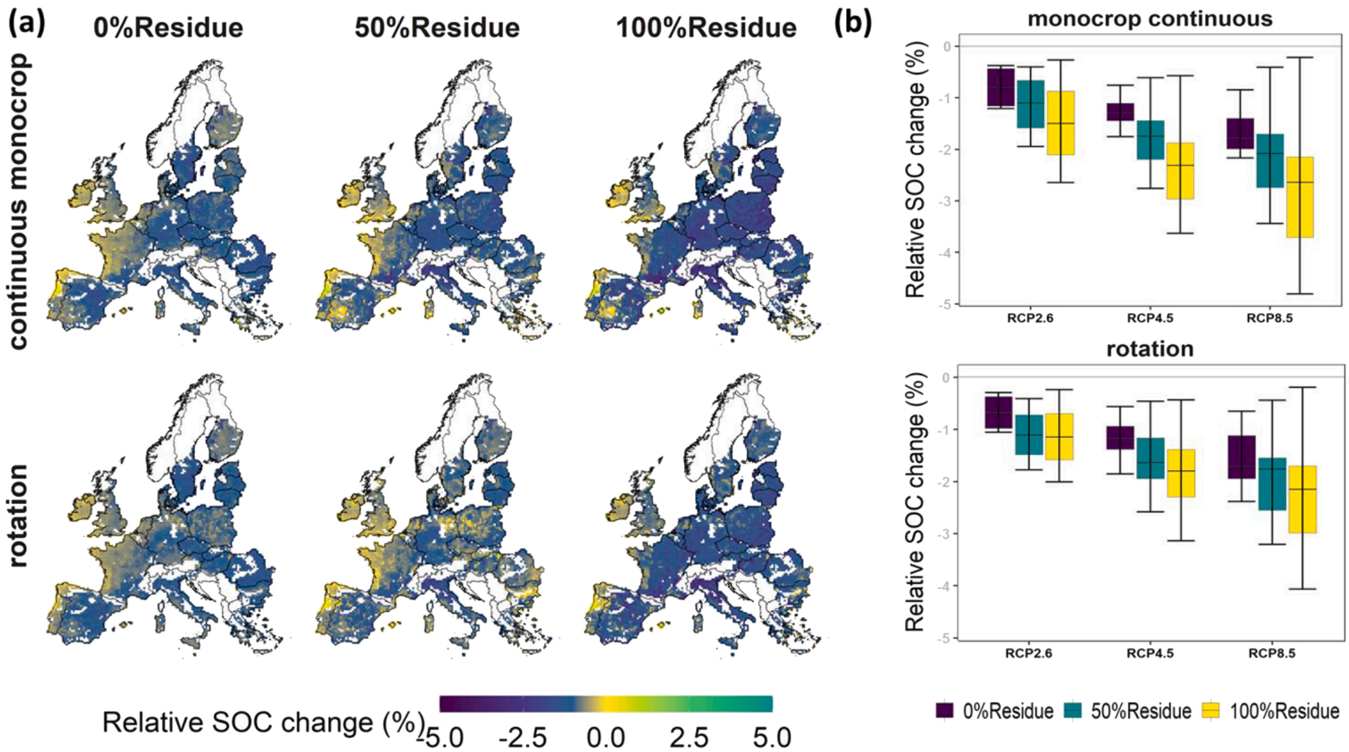

Fig. 5. (a) Spatial patterns of relative change in SOC for RCP4.5 for each residue retention rate (0%, 50% and 100% residues retention rates in the columns). The top row shows simulations with continuous monocrop simulations and the bottom row the simulations with rotations. (b) Relative change in SOC for continuous monocrop (top row) and rotation (bottom row) for RCP2.6, RCP4.5 and RCP8.5. Data are aggregated over years and EU level for the estimated period 2040–2065 relative to the baseline 1980–2005. Box-and-whisker plots depict distribution across GCMs for the 25th and 75th percentile, with median and whiskers extend to the maximum/minimum value within 1.5 times the interquartile range (outliers are not shown). Purple, dark cyan and yellow bars depict 0% residue, 50% residue and 100% residue retention respectively.

as sensitive to assumptions about the re-initialization or residue retention strategies as compared to the effects of the RCPs or even the uncertainty across GCMs. However, our results show that the amount of residue retained had an effect on the magnitude of the simulated climate change impacts for winter cereals. This was related to the direct role that residues play in reducing soil water evaporation from the soil surface in the model through a parameter in the FAO-56 dual coefficient procedure for partitioning evapotranspiration to transpiration and soil evaporation. This parameter “Fraction of soil surface available for evaporation” controlling the effects of residue retained on the soil water evaporation was adjusted between 0.7, 0.15 and 0.05 for the 0, 50 or 100% of residues retention respectively (Allen et al., 1998). The relative yield change due to climate change was more positive when all residues were removed from the field. However this largely reflects that with residues retained on fields, absolute yields were higher (for both 50% and 100% retention rates) by 22–42% yield gain respectively compared to 0% residue retention for winter wheat (Fig. S12). One explanation of the greater yield increases due to climate change with no residue retention was that, simulated yields were lower in both baseline and future scenario with no residue retention. This lower yield under the 0% residue retention case in the baseline leads to larger relative yield changes, though the absolute future yield changes are still small. In the 50 or 100% of residue retention cases, higher yields in the baseline simulations lead to relatively lower relative yield increases simulated for the scenarios.

To aid understanding simulated sensitivity to residues and re-initialization strategy, we looked at how our model was projecting SOC to change with climate change for each assumed case. Note, for a number of reasons discussed in the next section, we do not consider these results as robust projections of how SOC will evolve under climate change. We saw that SOC generally decreased under climate change for both simulations assuming a continuous monocrop and the plausible rotation, irrespective of the residue retention scenario. The relative decrease in SOC was highest under RCP8.5 likely due to higher temperature which increase the mineralization rate in the active and intermediate pool (Poeplau et al., 2011). These results were consistent with Qi et al. (2016) who reported that temperature changes regulate soil enzyme activities by changing the soil labile organic carbon fractions and driving higher rates of SOC mineralization. In addition to temperature, soil enzyme activities and soil labile organic carbon fractions could be affected by management factors, such as fertilization, tillage, irrigation (Mandal et al., 2007; Lefevre et al., 2014). Other factor such as a good supply of organic matter could influenced the labile organic carbon fractions. When soil moisture was not limiting, in our model soil organic carbon mineralization increases with increasing temperature, which acts to a decrease of SOC. Similarly, Xu et al. (2011) found SOC losses due to increase SOC mineralization driven by the future increase in temperature. These findings are supported by Crowther et al. (2016) who report that increased temperature would increase soil carbon losses to the atmosphere.

Relative SOC losses decreased with increasing residue retention rates for both continuous monocrop and rotation, with the difference between residue retention rates being higher under continuous monocrop. These results were comparable with findings from Stella et al. (2019) who found that returning all crop residues to the soil can reduce SOC losses in North Rhine-Westphalia (Germany). However, the decrease of SOC with all residues retention scenarios was mainly an artifact of how we were calculating the relative change in SOC, as we assume the same residues retention strategy in both the baseline and scenario period. This assertion was supported by Liu et al. (2006) who found that the choice of crop rotations can maintain or increase SOC quantity and quality, whereas residue management alone could not maintain SOC levels.

4.3. Uncertainties and limitation of the study

Given the already very complex nature of our simulation experiment, we had to make a number of assumptions and simplification which may have implications for generalizing our results. Our study did not consider adaptations of sowing dates and growing season length. Adaptation strategies were expected to reduce yield losses in Europe depending on the crop and region (Zimmermann et al., 2017). Challinor et al. (2014) reported that adaptation strategies will be more effective for wheat than maize, an assertion supported by the study Webber et al. (2018). However, Moore and Lobell (2014) suggested a larger adaptation potential for maize and sugar beet than for wheat, though it was unclear the extent to which their study differentiated irrigated from rainfed production, which would moderate high temperature responses (Siebert et al., 2017).

Another limitation of our study was that we used only one crop model despite the large uncertainty embedded in the choice of the crop model, which was demonstrated in many studies (Bassu et al., 2014; Martre et al., 2015; Müller et al., 2017), and even model setup procedures (Confalonieri et al., 2016; Folberth et al., 2019). Another limitation was that we considered only seven crops in generating crop rotations and generally only one crop rotation was used for each ENZ except in ENZ 4 and ENZ 6. This was clearly not representative of actual crop management, as farmers can use many rotations in a given area for different reasons. However, in our evaluation for ENZ 4 and 6, simulated yield impacts demonstrated that the choice of rotation did not have an effect on the climate change signal (Fig. S13). However, the rotations generated also did not consider legume crops, grass leys or fallows as rotation components that are well known to diversify cropping systems (Hufnagel et al., 2020), affect yields and environmental impacts (Costa et al., 2021). The assumptions about residues retained would not be representative of the actual farmers' practices as the residues management will depend on crop rotations and soil tillage. Additionally, in this study we did not include the effect of cover crops which increase SOC as investigated by Poeplau and Don (2015) and Kaye and Quemada (2017) who demonstrated a substantial benefit of cover crops for SOC maintenance. Finally, we did not address the effect of crop rotations and crop residues on the soil microbial activity which, may improve the nutrient availability to roots (Reinhold-Hurek et al., 2015).

Importantly, our SOC model relies on modeling concepts on soil organic matter (SOM) dynamics that are relatively outdated and not state of the art in the soil organic matter community. There, SOC is now conceived of and measured as particulate and mineral associated organic matter, differing in size and density, as well as turn over dynamics. Nevertheless, to the best of our knowledge, no cropping system models consider such pools and our SOC model is quite representative of others in crop models. Additionally, the study also suffers from the lack of a long term SOC dataset at European scale for model calibration and testing. Nevertheless, the model was tested with long term SOC dataset a field scale (Seidel, 2020). A second dataset were considered for model evaluation. This study reports SOC changes from a long term experiment with nine crops (winter wheat, sugar beet, silage maize, winter rye, linseed, potato, spring barley, field pea and pea) from Brandenburg, Germany, a continental agro-ecological region with very sandy soils (Fig. S1). Further, though our model considered the effect of crop residues on soil water evaporation rates by adjusting the parameter of the wetted soil fraction in the FAO-56 dual coefficient module (Allen et al., 1998), it did not consider effects of increased SOC on altering water holding capacity. Our SoilCN model does not directly link SOC to soil water holding characteristics of the soil, e.g. field capacity or wilting point which would be important to explore and evaluate these effects on SOC dynamics. This was because these are treated as static values in the SlimWaterModified module. There was no linear relationship between the relative change in yield and the relative change in SOC. This was because the impacts of weather variables on crop yields (temperature and precipitation) are most sensitive than the impacts of SOC (Fig. S14). Finally, our model did not consider the effect of crop residues to reduce the vulnerability to soil erosion by wind and water though continues soil coverage (Panagos et al., 2015). Soil erosion effects on yield decreases or even yield failure and on SOC loss with sediment transport maybe is more relevant with the climate change scenarios because of a higher frequency of extreme rainfall events (Auerswald and Menzel, 2021).

4.4. Implications and next steps

Our study has demonstrated that simulation of climate change impacts on crops was not particularly sensitive to how model re-initialization or residue management strategies were specified, for our SIMPLACE based crop model solution. This result provides some validation of previous climate change impact studies that have reinitialized their model each year (Asseng et al., 2013; Zimmermann et al., 2017; Webber et al., 2018). This allows greatly simplified simulation setups as compared to the current study. Inclusion of rotations involves many uncertainties related to the lack of data specifying rotations and associated fertilization and residue treatments, as well as the potential for error propagation in the year-to-year carryover effects in specifying rotations.

On the other hand, simulation of SOC dynamics under climate change seems to require consideration of both crop rotations as well as being sensitive to assumptions about residue retention rates. This clearly suggests that for mitigation studies, formulation of plausible rotation and their simulation was required, and this will be fraught with uncertainties about future land use, crop prices and other crop management technologies for pest, weed and disease control, among others. While the SoilCN model does account for feedbacks with SOC, mineralization and soil plant available N, this was not very relevant for the highly fertilized crops typical of large parts of Europe. However this mechanism is obviously more important for world regions were SOC mineralization constitutes a main source of nutrients for crops (Corbeels et al., 2019). It will become more important also in Europe where adaptation and socio-economic pathways related to climate change call for energy saving, resource efficient production (Mitter et al., 2020). Here, traditional agronomic measures employing agro-ecological principles including diversified crop rotations and residue management for pest and disease control and nutrient management may witness a renaissance. They may well be combined with modern digitalized management and sensing technologies (Basso and Antle, 2020). Modeling such systemic interactions is a challenging but necessary step to provide the evidence base for future agronomic management decision. Such a systemic approach would also need to address other, not immediately agronomic soil service such as water purification and belowground biodiversity (Vogel et al., 2018).

Parametrization of the process-based SOC model to simulate the soil carbon dynamics was challenging as very few countries and regions have published long-term carbon datasets which can be used to verify model accuracy. Ogle et al. (2010) demonstrated that uncertainty in simulating SOC accumulation was associated with model structure and that improvement will depend on model parameterization and the number of field measurements. Here, the availability of data from long term field experiments (LTE) for systematic reuse would be an important step forward, if their locations can represent spatial agro-climatic and soil quality variations (Grosse et al., 2020). The uncertainty in simulating SOC would be exacerbated in a very sandy soil. Additionally, the initialization of the carbon distribution between the different carbon pools was critical for the SOC model prediction which in general assumes that carbon stocks were near steady state. However, optimization of the initialization procedure was a necessary exercise that could improve the estimation of the SOC in the soil. With measured data at specific locations, Basso et al. (2011) developed a procedure to facilitate initialization of the SOC pools focusing on the intermediate carbon pool. In our study, we used sensitivity analysis testing the most sensitive parameters in the model (Corbeels et al., 2005b). A comparison of simulations from different models, such as performed by Ozturk et al. (2018) could further confirm these results and better inform about the relative importance of each source of uncertainty related to the assumptions investigated here.

5. Conclusions

This study assessed climate change impacts on crop yield for European cropping systems to the sensitivity of assumptions about re-initialization strategy and residue management for winter barley, grain maize, potato, winter rapeseed, silage maize, sugar beet and winter wheat for a scenario period 2040–2065 relative to the baseline 1980–2005. Our analysis showed yield gains for C3 crops and yield losses for C4 crops across climate, re-initialization and residue management scenarios. The effects of re-initialization and residues retention scenarios were less pronounced than climate scenarios and were crop dependent and were more important for SOC than for crop yields.

Further, investigation on SOC effect on water holding capacity is needed to be explored in order to better evaluate the overall picture of the C and N dynamics. Data from long-term field studies across Europe will be beneficial in this regard. A comparison of simulations from different models will also be helpful to inform about the uncertainty of the considered model components and assumptions.

CRediT authorship contribution statement

Babacar Faye: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft. **Heidi Webber:** Supervision, Conceptualization, Methodology, Writing – original draft. **Frank Ewert:** Project administration, Funding acquisition, Writing – review & editing. **Thomas Gaiser:** Conceptualization, Writing – review & editing. **Christoph Müller**: Writing – review & editing. **Yinan Zhang:** Writing – review & editing. **Tommaso Stella:** Writing – review & editing. **Catharina Latka:** Writing – review & editing. **Moritz Reckling:** Writing – review & editing. **Thomas Heckelei:** Writing – review & editing. **Katharina Helming:** 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.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.eja.2022.126670.

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