Global modelling of soil organic matter under climate change: Assessment of the effects of closing yield gaps on cropland and grassland management

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Resumo

O carbono orgânico no solo (COS) é um indicador usado para análise da qualidade do solo e como este poderá intervir ao nível de mitigação e adaptação às alterações climáticas (AC). Esta tese foca-se na influência das AC no uso do solo e práticas de gestão.

Para agricultura, dois cenários climáticos foram testados usando 63 culturas em 17 203 regiões. Com o modelo RothC, analisou-se de que forma as AC poderão amplificar sumidouros, ou fontes, de gases com efeito de estufa (GEE) do solo. Os resultados mostram que entre 31 e 100% das regiões irão perder reservas de COS com AC. A perda acumulada encontra-se entre 18 e 500 tC.ano/ha, dependendo da cultura. Nestas regiões, a manutenção do COS foi testada aumentando a entrada de C por intensificação da atividade agrícola, aumentando a produtividade usando fertilização. Em algumas regiões o aumento da produtividade compensa o aumento da mineralização, mas a emissão de GEE devido à produção e aplicação de fertilizantes reverteria os ganhos na maioria das regiões.

Para pastagens, utilizaram-se medições locais de SOC em 4 explorações portuguesas e, usando aprendizagem computacional e o modelo RothC, foi possível obter os seguintes resultados: rácio raiz-folha aproximadamente 3,2 e 2,3 para pastagens seminaturais e fertilizadas respetivamente, fração de tempo despendida por animal de 0,49 e 0,51, fração consumida pelo gado de 0,6 tC/animal. O erro da estimativa de COS com estes parâmetros foi de 1 tC/ha, sendo que este passo é essencial para a análise dos efeitos das AC em pastagens.

Palavras-chave: Alterações Climáticas, Agricultura, Carbono Orgânico no Solo, Produtividade, Pastagens, Explorações Agrícolas

Abstract

Soil organic carbon (SOC) is a broad sustainability indicator for assessing soil quality and contribution for mitigation and adaptation to climate change (CC). This dissertation focuses on understanding how CC, land use and management practices affect SOC.

Croplands were analyzed using two CC scenarios for 63 crop types in 17,203 unique homogenous territorial units globally. Using the RothC model, trends were analyzed to understand how CC can amplify the effects of soils as sink or source of greenhouse gases. Results show that between 31 and 100% of Earth’s regions will lose SOC due to CC. The accumulated loss of SOC is between 18 and 500 t C/ha depending on crop type. For these regions, an assessment was performed of the feasibility of overcoming the loss through increased C inputs to soil due to increasing yields. In some regions increased C inputs can potentially compensate for increased mineralization, but intensification could require increasing fertilizer use and generate new greenhouse gas emissions.

For grasslands, measured SOC stocks were used to overcome gaps of information on 4 farms in Portugal. Using a machine learning method and RothC, results show a root-to-shoot ratio of 3.2 and 2.3

for unfertilized and fertilized pastures respectively, a fraction of time spent per livestock unit (LstU) equal to 0.49 and 0.51 livestock intake of 0.6 tC/LstU. The error of the posterior SOC estimation was approximately 1 tC/ha. This was a necessary step towards analyzing the effects of CC on grasslands.

Keywords: Climate Change, Agriculture, Soil Organic Carbon, Yields, Croplands, Pastures

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List of Acronyms

Bio – Microbial Biomass

C – Carbon

CC – Climate Change

DPM - Easily Decomposable Plant Material

DPM/RPM - Ratio between Easily Decomposable and Resistant Plant Material

GHG – Greenhouse Gases

HUM – Humified Organic Matter

IOM – Inert Organic Matter

IPCC – Intergovernmental Panel on Climate Change

LD – Livestock Dung

LI – Livestock Intake

LstU – Livestock Unit

LU – Land Use

LUC – Land Use Change

NCC – No Climate Change

N – Nitrogen

NPP – Net Primary Production

PET – Potential Evapotranspiration

RCP – Representative Concentration Pathways

RothC – Rothamsted Carbon Model

RPM – Resistant Plant Material

RS – Root to Shoot Ratio

SOC – Soil Organic Carbon

SOM – Soil Organic Matter

t – Time Fraction Spent per Livestock Unit on each Pasture Type

UHTU – Unique Homogeneous Territory Units

1. Introduction

1.1. CC and SOM Interaction

Human-induced climate change (CC) is now accepted throughout several scientific fields. Evidences connecting human activity as one of the main causes for the alteration of basic element cycles are overwhelming, including the Earth's climate system (IPCC, 2014). Soils contain the largest pool of terrestrial carbon (Davidson & Janssens, 2006) and, due to its large size and residence time, soil organic carbon (SOC) can act as a large sink of atmospheric C (Gottschalk et al., 2012; Le Quéré et al., 2009; Paustian et al., 2016) or as a support to several ecosystem services. These services can range from increased nutrient cycling and water retention to purification (Millennium Ecosystem Assessment, 2005).

The storage capacity presented by the soils is a key function of this terrestrial biome, influencing climate regulation and other soil functions (Wiesmeier et al., 2019). For the past five decades terrestrial ecosystems have been absorbing 25–30% of anthropogenic CO_2 emissions (Le Quéré et al., 2009).The majority of this uptake occurs via C accumulation in forest biomass and soils (Pan et al., 2011). There is also evidence that soils contributed with 37% of the global emissions from agricultural production, emitting mainly non-CO_2 gases (CH_4 and N_2O) (Tubiello et al., 2015). Yet, when the analysis is conducted at a global scale, the global growth rate of atmospheric CO_2 indicates that land and oceans have been maintaining their contributions at approximately the same rate as in the past (Ballantyne et al., 2012). This suggests that negative impacts of climate extremes on the global terrestrial C sink have neither been increasing nor decreasing disproportionately (Ernst Detlef et al., 2000).

Soil has a dual role as it simultaneously affects and is also affected by climate change. Soil organic matter (SOM) can be accumulated, or depleted, in soils depending on the balance between organic inputs into soil (from soil and plants) and organic matter mineralization through degradation of organic matter mediated by microorganisms. As approximately 58% of the organic matter in soils is C from biological sources, its accumulation produces C sequestration from the atmosphere, while its depletion produces C emissions (Pribyl, 2010). CC can affect soils mainly through the increase of temperature and increase of moisture. These will accelerate decomposition processes of SOC and its posterior loss. A positive land carbon–climate feedback emerges with this phenomenon due to its potential to accelerate CC even more (Crowther et al., 2016) with the increase of CO_2 release. However, this process can be slowed down by increased plant net yield. Photosynthetic favoring may occur due to climate shifts (J. Smith et al., 2005), leading to more C incorporation into the soil.

Crop growth and yield have been notably affected by CC since the 1980s (Tao et al., 2012). A balance of SOC can be used to assess whether a given soil system is a sink or a source of C. SOC balances are calculated as the difference between carbon inputs from plants, animal sources or other organic amendments, and the losses occurring due to the mineralization/decomposition of organic matter (Carvalhais et al., 2014; Smith, 2008). In future terms it can be expected that, due to the increase of temperature in cooler regions, the net primary production (NPP) will increase in those areas. At the same time, the SOC's decomposition will accelerate also due to the increase of temperature. The increase or decrease SOC stocks will depend on which process has a larger significance: increase in plant inputs to the soil or organic matter decomposition (Gottschalk et al., 2012). The uncertainty arises of the maintenance of this soil's C sink and its persistence over time despite the effects of CC. SOC's response to CC is also prone to be different depending on specific crop types. The uncertainty of the magnitude of these phenomena is recognized nowadays, and the shortage of detailed reliable SOC stocks data in permanent crops contributes significantly to the lack of knowledge for the total C budget (Marras et al., 2015). The estimation of those effects is critical to support both landscape policy and planning a sustainable development path, such as those related to an agricultural sustainable intensification perspectives (Caddeo et al., 2019).

1.2. <u>Land Use Systems</u>

The increased challenge in crop production associated with the deterioration of soil's health highlights the necessity for quantifying the potential of grassland and cropland soils to sequester C, store nutrients, and support growth of diverse microbial community to develop a sustainable agricultural system (Ghimire et al., 2019). An increasing soil fauna activity (Hu et al., 2016) results in a positive feedback regarding SOC's accumulation (Kallenbach et al., 2016) and, thus, a negative feedback on CC. Some soil physicochemical properties that reflect soil fertility and structure are soil texture, soil porosity, soil aggregate stability, and SOC which is widely used to indicate soil quality (Guo et al., 2018; Raiesi & Kabiri, 2016). Increasing SOC storage, and its associated improvements in soil health of agricultural fields, is important for maintaining agronomic production and environmental benefits emerge, such as soil C sequestration and greenhouse gas (GHG) mitigation (Ghimire et al., 2019).

Perennial grasses typically have deeper and denser root systems than annual agronomic crops such as wheat or sorghum (Bhandari et al., 2018). This means that grasslands with their abundant roots and litter significantly affect soil porosity, SOC, and other soil properties (Wu et al., 2010, 2016) such as soil texture and soil fertility regulation (Wu et al., 2016). Fine roots decompose significantly faster than coarse roots (Zhang et al., 2016) leading to the increase in SOM. Roots also favor the formation of soil pores, which influences soil properties due to change in burrowing activity and biomass of earthworms (Fischer et al., 2014) resulting in more abundant SOC.

Ghimire et al. (2019) compared grasslands and croplands in the semiarid Southern Great Plains and showed that grassland soils accumulated 18% more SOC than cropland soils in the 0–80 cm profile, whilst at 0–20 cm depth grasslands SOC stocks were 37% greater than in croplands. At lower soil depths, SOC content was not significantly different between both systems. The microbial community size on the topsoil layer, from 0–20 cm depth, was 90% greater, and enzyme activities were 131–155% greater in the grasslands than in the croplands. Within grasslands, cattle grazing increased microbial community size by approximately 42%. This study suggests that light grazing has the potential to improve soil health and resilience through an increase in SOC and microbial community responses related to nutrient cycling.

Artificial or managed grasslands are widely used throughout the world owing to their good ecological effects and feeding value of forage grasses (Li et al., 2007). This type of grasslands improves soil habitats and controls soil loss via fine root network development and litter accumulation (Wu et al., 2010). With abundant grass yield and lower water consumption, higher ecological benefits are associated to this kind of ecosystems than to traditional crops management (Cui et al., 2019). Grasslands can be considered as a suitable candidate for crop rotation to increase land productivity and promote sustainable agricultural management (Cui et al., 2019).

1.2.1. Croplands

To face CC, high expectations have been set for exploiting agricultural soils as sinks for atmospheric CO_2 (Rattan Lal et al., 2015; Minasny et al., 2017). Soils are able to store significant quantities of C over time via photosynthesis (Houghton & Nassikas, 2017; Scurlock & Hall, 1998). When lands are perturbed through the introduction of new crops, this C can re-enter the atmosphere via combustion or decay (Houghton et al., 1983). Natural C stocks are thus highly sensitive to the policy and economic conditions that drive land use and land management decisions (Lambin et al., 2001). Emissions vary according to the crop type under exploration, reflect the geography of crop-specific expansion and the characteristics of the land (Spawn et al., 2019). Strategies are then needed to reduce the need for expansion and to significantly reduce land use change (LUC) emissions (Spawn et al., 2019). Both, current and projected world demand, could be met through production on existing cropland by closing global 'yield gaps', reducing waste, modifying diets, and revising biofuel policy (Erb et al., 2016; Mauser et al., 2015; P. Smith et al., 2013).

LUC is a leading cause of anthropogenic C emissions and it is associated to impacts on CC (Foley et al., 2005; Houghton et al., 1983; Le Quéré et al., 2018). LUC has been pointed as the agent of nearly one-third of cumulative net emissions globally (Houghton & Nassikas, 2017) and currently accounts for roughly 10% of all annual emissions (Le Quéré et al., 2018). Many of these emissions result from tropical deforestation, which displaces large quantities of C stored primarily in plant biomass (Houghton & Nassikas, 2017; Le Quéré et al., 2018). Emissions from LUC are difficult to estimate and represent one of the most uncertain components of the global C budget (Ramankutty et al., 2007).

Regardless of the magnitude of soil's contribution to CC mitigation, increasing SOC content is also desirable to enhance the quality and functioning of arable soils. SOC is an important indicator of soil quality, contributing to land productivity and ecosystem health. The distribution of SOC can be influenced by the crop type under exploration, irrigation and fertilization, litter and root biomass (Jobbágy & Jackson, 2000; Meurer et al., 2019). Management practices might also impact the vertical distribution of C in the soil profile. Management practices such as organic inputs, sustainable fertilization, crop rotation, cover crops, change from annual to perennial crops and reduced tillage or no-till, have been identified to potentially accumulate SOC (Freibauer et al., 2004; R Lal, 2004; Paustian et al., 2016). For a farmer, however, the formulation of an environmentally-oriented mindset can be costly due to required investments as well as a possible decrease in yield (Kragt et al., 2012).

To increase SOC stocks in croplands, investing in perennial crops can constitute an advantage. The cultivation of perennial crops tends to enrich the C close to the soil surface in comparison to dominantly annual crops, which exhibited a less steep C gradient with depth (Heikkinen et al., 2020). The concentration of SOC in the upper soil layer is subject to the influence of vegetation (plant allocation of

C above and below ground) and possible agricultural soil alterations, whereas SOC in deeper soil layers is less easily affected (Börjesson et al., 2018; Jobbágy & Jackson, 2000; Menichetti et al., 2015). In the topsoil layer, for example, tillage affects the SOC's profile strongly (Angers & Eriksen-Hamel, 2008; Poirier et al., 2009). Under a no-tillage approach SOC accumulates closer to the soil surface, whereas ploughing mixes the SOC and distributes it more homogeneously throughout the ploughed layer (Angers & Eriksen-Hamel, 2008; Poirier et al., 2009).

1.2.2. Grasslands

Grasslands are, today, one of the most endangered ecosystems mainly due to LUC, agricultural intensification, and abandonment (Pärtel et al., 2015). As this ecosystem plays a central role in global food security (Schaub et al., 2020) the need for its monitoring (Fauvel et al., 2020) is emergent. The exponential growth of population worldwide, the continuous changes in demand and climatic challenges increase pressure on grassland-based production. This ecosystem covers a major share of the world's agricultural area. In Europe natural and unfertilized grasslands cover 22% of agricultural land surface (Bengtsson et al., 2019).

Grasslands, which are frequently referred to interchangeably as pastures, can be divided into categories. Throughout the development of this thesis, two specific types were studied: fertilized and unfertilized pastures. In general, fertilized grasslands tend to have fewer herbaceous species than those that are unfertilized (Socher et al., 2013). The most important factors affecting the yield of grassland communities are water and nutrient availability, which influences the biodiversity of the community. High values of phosphorus, nitrogen and potassium decrease the biodiversity of grasslands (Merunková & Chytrý, 2012). Limiting nutrients can then influence the richness pattern (Palpurina et al., 2019) forcing the present species to demonstrate their capability for adaptation to compose this type of ecosystem, with distinct species adapted to nitrogen and phosphorus limitation at different levels (Roeling et al., 2018). The plant species diversity in grasslands are known to increase and stabilize biomass yields (Schaub et al., 2020). The functional groups found in this habitat are usually categorized as graminoids, nitrogen-fixing legumes and other herbaceous species (Socher et al., 2013). The complementarity of these functional groups leads to a greater efficiency in acquisition of available resources. Different species have different needs or/and sources of resources. For example, a positive feedback can be found for the nitrogen (N) fixing ability of legumes from which other species in the community also benefit (Lüscher et al., 2014), particularly in grass-legume mixtures (Schaub et al., 2020). Biomass yields, and their quality, are highly affected by site-specific characteristics and farmers' management decisions (Milberg et al., 2020). These are essential to retain the characteristic diversity of flora and fauna found in these habitats (Milberg et al., 2020).

As plant species diversity plays an important role in grasslands (Schaub et al., 2020), and the ratio of particular functional group biomass depends largely on grassland type and local abiotic conditions, it leads to differences between countries or even subregions (Tóth et al., 2018). Factors such as site yield, site history and other local conditions may play a crucial role to define the ecosystem (Herrero-Jáuregui & Oesterheld, 2017) meaning that the results are rarely transferable, as they need to be replicated over many sites. To assess the conditions of grasslands, ecological surveys are required. This implies that the results are highly constrained in spatial extent and in temporal frequency, limiting grassland monitoring to a local scale and usually over a short period of time (Fauvel et al., 2020). Although field surveys provide valuable and high-quality data at a point scale, they cannot easily be upscaled while considering the landscape heterogeneity. Field surveys alone cannot address the need to monitor grassland biodiversity over large spatial extents and other techniques relating to field surveys should be considered (Fauvel et al., 2020).

The conversion of grasslands into arable land decreases soil C due to the reduced C input from litter and the loss of this component by tillage (Jones & Donnelly, 2004). Other factors controlled by mankind, including overgrazing, intensive agricultural production, deforestation, urbanization (Costanza et al., 2014; Newbold et al., 2016; O'Mara, 2012), drainage, intercropping, the use of pesticides, mineral and organic fertilizers (Török et al., 2019) can have devastating effects on flora and fauna, leading to a loss of biodiversity and its related ecosystem services (Hao & Yu, 2018). To maintain favorable conditions for grassland species, knowledge regarding how they occur in relation to grazing intensity and soil nutrient availability is key (Milberg et al., 2020).

The majority of the biomass produced in grasslands is used for animal husbandry, through either direct grazing or haymaking for winter forage (Heinsoo et al., 2020). Grazing by large herbivores is a major driver of the ecosystem processes in open landscapes worldwide. The effect of grazing on vegetation, and its suitability as a conservation tool, largely depends on the livestock type and its grazing intensity (Tóth et al., 2018). Due to the large body size of cattle, grazing intensity should be carefully chosen to prevent soil erosion (Salvati & Carlucci, 2015). Grazing can maintain a higher diversity in grasslands due to supporting the co-existence of several plant species by reducing intra and interspecific competition (Tóth et al., 2018). For example, cattle and horses eat the taller grasses while sheep prefer forbs and short grasses (Tóth et al., 2018). Grazing animals shapes species composition, not only through the consumption of biomass, but also by redistributing nutrients via deposition of dung and urine (Ma et al., 2016), soil compaction and erosion via trampling (Eichberg & Donath, 2018), and dispersal of seeds on their fur, hooves or dung (Freund et al., 2015). By doing so, grazers alter habitat conditions and create micro-habitats for plant species (Balázs et al., 2014; Smit & Putman, 2011). Extensive cattle grazing is effective in suppressing noxious species and creates a mosaic of short and tall species in the short run, which enables the maintenance of high species richness in the landscape (Török et al., 2016). It was also stated that high grazing intensity leads to land degradation, due to intensive trampling, nutrient input and excessive defoliation (Gaitán et al., 2018).

1.3. State of the Art

Multiple authors have tried to assess the effect of LU on the SOC balance. Smith et al. (2005) assessed future changes in cropland and grassland SOC stocks using Rothamsted Carbon Model (RothC) on a European grid with climate data from four global climate models developed by the Intergovernmental Panel on Climate Change (IPCC). It was shown that certain cropland and grassland soils would suffer a small increase in soil carbon per area under future climate. Results also show that total European cropland stocks decline in all scenarios, and grassland stocks decline in all but one scenario due to the decreasing area of cropland and grassland. According to this study, different trends are seen in different regions. Falloon and Smith (2006) followed then the same principles but only for European forests, an ecosystem which is not under the scope of this thesis.

Licker et al. (2010) presented spatial datasets of both potential yields and yield gap patterns for 18 crops around the year 2000. Using spatial datasets, yield patterns were compared to the most dominant crops within regions of similar climate. This analysis has allowed to conclude that even though climate is a key driver of global crop yields, there are still considerable factors in yields' behavior attributable to other factors. Factors like land management practices can majorly influence yields. This study also states that with conventional practices, it would be probably necessary to use more chemicals, nutrients and water inputs to bring crop yields up to their potential. This human intervention can adversely affect ecosystem goods and services, and in turn human welfare, which led to a reflection that society needs to develop more sustainable high-yielding cropping practices.

Gottschalk et al. (2012) found that there is no single possible answer regarding SOC's stocks evolution under the effect of CC. The model chosen was RothC (Coleman & Jenkinson, 1996) and it was used to examine possible soil responses to future climate. Land use (divided into 3 categories: arable, grass and forest land) and interactions with projected future LUC were considered. Even though the effects of LUC were examined, the effects of yield and how it will evolve due to CC were not. SOC's simulation was done using different climate scenarios, marking an evolution for the scientific community.

Stergiadi et al. (2016) assessed the effects of climate change and land management on SOC accumulation and SOC distribution across different pools to simulate past (1906–2012), present, and future (2013–2100). SOC levels were assessed in sandy and loamy soils under three aggregated land use types (forest, grassland, and arable land). Four future climate scenarios of the Royal Dutch Meteorological Institute were used. These scenarios, however, only cover the Netherlands and surrounding countries. Only one land management scenario was considered, which accounted for the implementation of the European Union guidelines concerning the maximum levels of nutrients added to the soil.

Morais et al. (2018) also used the process-based model RothC to establish the likely dynamic SOC evolution after LUC in the region of Alentejo in Portugal. The application of the climate scenarios was carried out with constant increments in temperature (ºC/month) and precipitation (mm/month) which would likely affect the role of LU in SOC accumulation, influencing the LUC choices today. The results show that attainable SOC stocks vary significantly depending on the LU class, particularly for croplands.

Wiesmeier et al. (2019) had the main objective to review and identify sets of indicators that enable a quantification of SOC storage at different spatial scales. Starting from micro-scales (particles to pedons) to a global one, the indicators for SOC storage identified were: clay mineralogy, specific surface area, metal oxides, calcium and magnesium cations, microorganisms, soil fauna, aggregation, texture, soil type, natural vegetation, land use and management, topography, parent material and climate. This identification did not allow to conclude if the yield depends on the behavior of SOC stocks. It allowed to set indicators for time and cost-efficient estimates of actual and potential SOC storage for a local, regional, and subcontinental scale. As a key element, the fine mineral fraction was identified to determine SOC stabilization in most soils. This can be refined by including climatic proxies, particularly elevation, as well as information on land use, soil management and vegetation characteristics.

All available studies showed one main limitation, which was the use of very aggregate LU classes. The only example available at the global scale that introduced subdivisions within classes is Morais et al. (2019). SOC dynamics was assessed in 28 LU classes related to agricultural (under different management practices), 16 forest classes and 1 grassland class using RothC globally. Even though the analysis was conducted for 17,000 regions of the world, the climate simulation did not take CC into account. For grasslands, the aggregation of LU occurred again, compiling all types of grasslands into one single LU class since there was no data available to differentiate and characterize grassland systems globally. The findings of this work showed that converting land to cropland can result in SOC increase in some regions, particularly when the soil remains covered with crop residues, or when using irrigation. It also provided a regional and detailed understanding of C sequestration.

1.4. *Dissertation Structure*

The goal of this thesis is to contribute to a better understating of the potential changes that land use, CC and management will produce on global SOC stocks. SOC is the most important component for the maintenance of soil quality (Vaneeckhaute et al., 2014). Its role on improving physical, chemical, and biological properties of the soil is determinant (Panakoulia et al., 2017). SOC affects the chemical and physical properties of the soil, such as water infiltration ability, moisture holding capacity, nutrient availability, and the biological activity of microorganisms (Gan et al., 2013). SOC is thus a strong determinant of soil fertility which in turn stimulates primary production (Panakoulia et al., 2017). Under CC, decomposition processes are expected to increase in magnitude in many regions of the World. As SOC loss is foreseeable, an urgent environmental problem arises. The magnitude of those problems is highly dependent on the ecosystem studied. By doing a LU characterization (croplands and pastures), it is possible to consider how their management can minimize possible effects arising from CC.

Regarding croplands, the objective is to understand how CC impacts SOC stocks and yield gaps at a global scale, and how C inputs can influence those variables. All the required calculations were made using the RothC model. RothC is a multi-pool SOC model that allows the assessment of SOC responses under different future climatic possibilities at global level. Its application will be similar to what was done by Morais et al. (2019) with the addition of future CC scenarios provided by IPCC for 17,203 regions and 63 crop types. Each crop will have its SOC content assessed and analyzed. After the results, a comparison between scenarios under CC and considering climate stabilization without CC (NCC) was made. This step was performed to understand the level of C inputs into soil required to maintain NCC SOC stocks for each crop for the 87 years of simulation. The yield computed was also compared with the available estimates of potential yields. If the required yield is lower than the potential, then maintaining SOM stocks is feasible through an increase in yield. If closing the gap is insufficient to maintain SOM, then climate change will necessarily generate additional emissions. For the regions where the computed yield to maintain SOC stocks is still lower than the potential, the increase of C inputs can be used to minimize those losses but would require fertilization. The production and application of the fertilizers needed to attain the computed yields under CC was evaluated to understand if the CO_{2eq} emissions of production and application of fertilizers is higher than the estimated loss of SOC in the CC scenarios when compared with the NCC scenario.

The conclusions of this analysis help understand if the path to satisfy an increasing population and demand for energy, food, fiber, and water (Steffen, 2003) can be accomplished by agricultural intensification (Licker et al., 2010). Intensification can bring other problems that were not assessed here, such as a greater vulnerability of yields to CC (Pugh et al., 2016) due to the presence of monoculture (Alexandratos & Bruinsma, 2012). The demand for agricultural products is expected to increase by 70–110% by 2050 (Alexandratos & Bruinsma, 2012) due to a projected world population of 9 billion people, leading to an increase in meat consumption and a growing use for bio-based materials and biofuel (Alexandratos & Bruinsma, 2012). Increasing agricultural production, without considering social and environmental externalities and changing climate conditions (Tilman et al., 2011), can cause trade-offs between different uses of land and ecosystem services (Zabel et al., 2014). Considering that climate is the main limiting factor for yields, CC cannot be excluded whilst SOC dynamics in croplands is studied.

The global heterogeneity and lack of detailed data for grasslands prevented the application of the same methodology described for croplands. In this case, the work carried out in this thesis involved one region, namely Alentejo, Portugal, and two specific pasture systems. RothC was also used, even though this model was developed originally for croplands and not pastures, as a tool for evaluating SOC in Portuguese pastures. The approach followed was similar to the work by Morais et al. (2018) for sown biodiverse pastures, using data published by Teixeira et al. (2011) this time distinguishing fertilized and natural pastures. Using only SOC measured from 4 farms in mainland Portugal from 2002, and knowing the estimated livestock excretion for beef cattle obtained by Morais et al. (2018), a reparameterization for those farms was performed. Missing data was estimated using a combination of machine learning with an inverse approach to RothC. Root to shoot (RS) ratio, livestock intake (LI), ratio between easily decomposable and resistant plant material (DPM/RPM) and the fraction of time that the animals spend at each pasture system were estimated. Those data were then used to calibrate the RothC model enabling the estimation of SOC stocks for each of the farms for 2003 and 2004. A comparison was then made with *in situ* measurements in those same farms and years.

The overall procedure for the thesis development previously explained is schematically represented at Figure 1 according to the respective land use system.

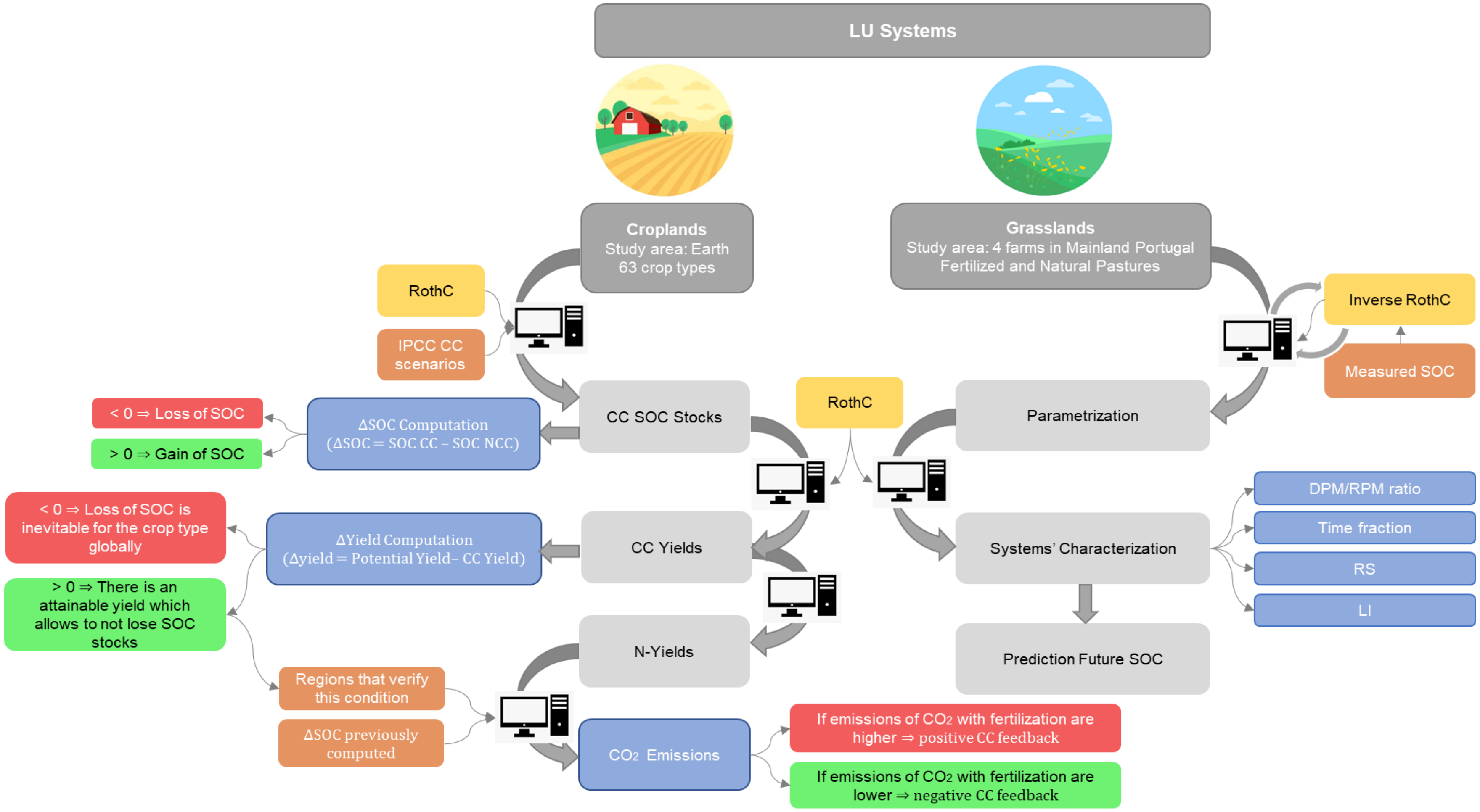

Figure 1 – Scheme to represent the procedure used for the thesis development.
Land use (LU) systems studied are colored in dark grey, the main steps are colored in light grey (CC – climate change, SOC – soil organic carbon, N – nitrogen), the models used are in yellow (RothC- Rothamsted Carbon Model), the main inputs required are in brown (IPCC – International Panel for Climate Change), the main results are in blue (ΔSOC – shows the losses or gains of SOC when comparing the SOC results with CC and without, Δyield – states if it is possible or impossible to maintain SOC stocks from the NCC reality under the CC scenarios implemented assessing if the required yield for this to occur is lower than the potential, DPM/RPM ratio - easily decomposable and the resistant plant matter, the fraction of time spent per livestock unit on natural pastures, RS - the root to shoot ratio, LI - the livestock intake), the main conclusions are colored in red (in case of a negative effect) and green (in case of a positive effect).

The structure followed throughout this thesis is based on 4 chapters: introduction, materials and methods, results and discussion, and concluding remarks. The first chapter, the introduction, reveals the importance of the study performed as well as the scientific knowledge gathered on the topic. This contributes to understanding what the state of the art is, and the importance of the topic under study. An extensive explanation of the main concepts is given before a deeper analysis, contributing for a better understanding on the topic and the results obtained.

Materials and methods, the following section, explains in detail the approach and methods followed to obtain the intended results. As this thesis focuses on two main LU systems, croplands and pastures, this section was also split into two different sub-sections. For croplands, the approach follows the logic sequence of explaining how the data was treated and collected, the explanation of the RothC model implementation, the different approaches used to calculate yields, the correlation analysis between the climate variables and the effects on crops according to each CC scenario. It is also explained how the fertilization scenarios were applied and evaluated, in the cases where the potential yield is higher than the computed one. Regarding Portuguese pastures, as the approach does not take into account different CC scenarios and the scale reduces from global to regional, the materials and methods section explains why the Alentejo region is relevant for this kind of study, as well as the optimization procedure used.

The next chapter, results and discussion, is also divided into two sub-sections. The results found for the global modelling of SOC for croplands show what are the global climate trends first, distinguishing the main trends identified for both CC scenarios simulated. The results for SOC stocks are then presented for all the 63 crop types as well as the yields necessary to maintain the computed NCC stocks under the influence of CC scenarios. Results are then presented for Spearman correlations between yield gaps and residues, and climate, where it is possible to assess which of the climate variables, precipitation or temperature, can explain the evolution found for each crop type. The results found for fertilization are the last ones to be presented and they state if the increase in yields through this method reflects, or not, a positive feedback to CC due to the associated CO_2 emissions. All these results are then assessed and compared with the literature to understand if they are corroborated by prior research. The results for grasslands are evaluated differently due to the different approach followed. The parameters that characterize the farms under analysis were found in the first place. This data set is then used to compute the SOC results for each of the farms. These results were then compared with the actual measured SOC stocks. The discussion is then based on explaining the feasibility of this method, namely if the difference between measured and computed is acceptable. Literature was also evaluated to validate the results obtained.

To complete the dissertation, concluding remarks can be found. The objective of this chapter is to answer all the main questions presented in the beginning of the study so that all main findings are highlighted. In addition, a bibliographic section is presented, which characterizes the importance and relevance of the subjects here addressed as well as the scientific robustness presented by this work.

2. Materials & Methods

2.1. SOC Global Modelling in Croplands Under CC

2.1.1. Study Area

The area covered by the analysis was the entire world, divided into 17,203 regions. These regions were defined as unique homogeneous territorial units (UHTU), presented in the following Figure 2, which can be seen as the result of the intersection of three geographical layers: present LU class, soil type and soil texture (Morais et al., 2019). Some areas were excluded similarly to what was done by Morais et al. (2019), namely arctic and desert regions. This happens due to the lack of information for the parameters defined and the lack of agricultural potential.

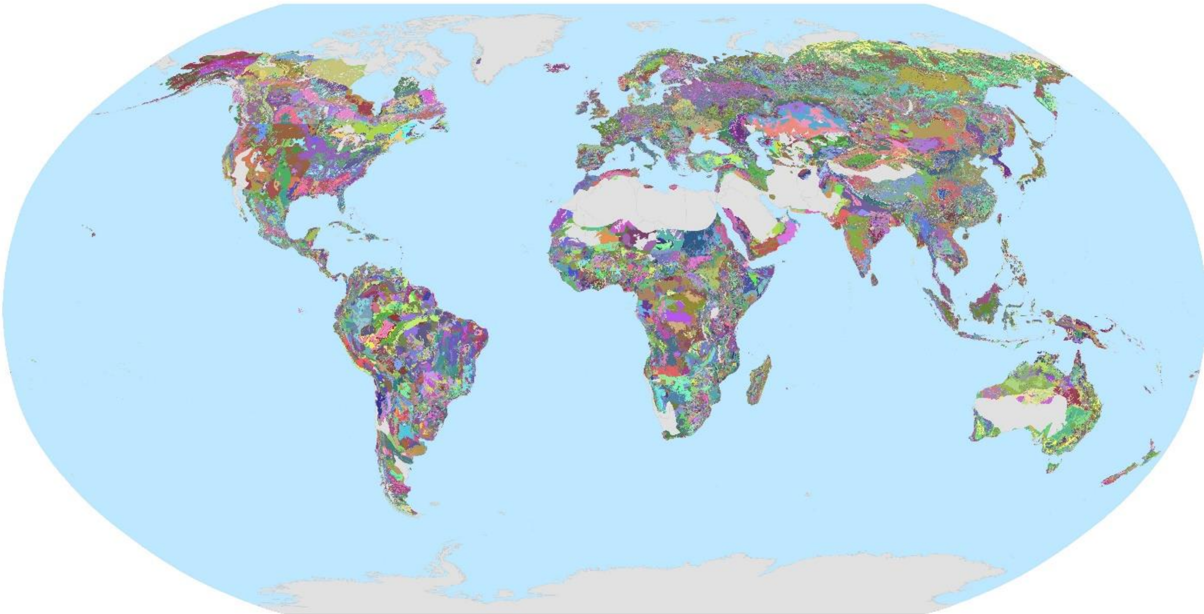

Figure 2 – Division of the simulated areas into unique homogeneous territory units (UHTUs).

2.1.2. Croplands Under Analysis

The analysis considered 63 crop types, as shown in Table 1. These crop types were chosen because they were considered the most produced and traded between 2004 and 2014 in the World (FAO, n.d.). When applicable, two variants of each crop were introduced for irrigation system (rainfed or irrigated) and from management decisions (to remove or not the residues after the harvesting period). This removal is only accounted for cereal crops which are barley, maize, rapeseed, sorghum, and wheat. For all other crops, the removal of residues is implicit.

Table 1 – Crop types used for the simulation of soil organic carbon (SOC) global modelling in croplands under climate change (CC) scenarios

Crop Types		Crop Types	
1	Irrigated bananas	***33***	Rainfed rice
2	Rainfed bananas	***34***	Irrigated sorghum with residues left on the field
3	Irrigated barley with residues left on the field	***35***	Rainfed sorghum with residues left on the field
4	Rainfed barley with residues left on the field	***36***	Irrigated sorghum with residues removed from the field
5	Irrigated barley with residues removed from the field	***37***	Rainfed sorghum with residues removed from the field
6	Rainfed barley with residues removed from the field	***38***	Irrigated soybeans
7	Irrigated cabbages	***39***	Rainfed soybeans
8	Irrigated carrots	***40***	Irrigated sugar beet
9	Irrigated oranges	***41***	Rainfed sugar beet
10	Rainfed oranges	***42***	Irrigated sugarcane
11	Irrigated coconuts	***43***	Rainfed sugarcane
12	Rainfed coconuts	***44***	Irrigated sunflower
13	Irrigated coffee	***45***	Rainfed sunflower
14	Rainfed coffee	***46***	Irrigated sweet potatoes
15	Irrigated cotton	***47***	Rainfed sweet potatoes
16	Rainfed cotton	***48***	Irrigated tobacco
17	Irrigated groundnuts	***49***	Rainfed tobacco
18	Rainfed groundnuts	***50***	Irrigated tomatoes
19	Irrigated maize with residues left on the field	***51***	Rainfed tomatoes
20	Rainfed maize with residues left on the field	***52***	Irrigated wheat with residues left on the field
21	Irrigated maize with residues removed from the field	***53***	Rainfed wheat with residues left on the field
22	Rainfed maize with residues removed from the field	***54***	Irrigated wheat with residues removed from the field
23	Irrigated palm oil	***55***	Rainfed wheat with residues removed from the field
24	Rainfed palm oil	***56***	Irrigated cocoa
25	Irrigated onions	***57***	Rainfed cocoa
26	Irrigated potatoes	***58***	Irrigated grapes

Crop Types		Crop Types	
27	Rainfed potatoes	***59***	Rainfed grapes
28	Irrigated rapeseed with residues left on the field	***60***	Irrigated olives
29	Rainfed rapeseed with residues left on the field	***61***	Rainfed olives
30	Irrigated rapeseed with residues removed from the field	***62***	Irrigated apples
31	Rainfed rapeseed with residues removed from the field	***63***	Rainfed apples
32	Irrigated rice		

2.1.3. RothC Application

The model chosen to run all simulations was RothC due to its history of prior applications for estimating recent and future trends in SOC in cropland soils at the local (Liu et al., 2011; Morais et al., 2018), regional (Coleman et al., 1997; Smith et al., 2005; Lark et al., 2019), and global scales (Gottschalk et al., 2012; Morais et al., 2019). This model also enables decision making and land users to assess the impact of management practices on SOC (Dechow et al., 2019) by iteratively adjusting C inputs from plants and animals to soil (Falloon & Smith, 2006). This model requires a relatively manageable set of inputs regarding land, soil, and climate data. The implementation of RothC was made using MATLAB vR2017a . Due to the code's extension it will not be presented here explicitly, however it will be available by request to the thesis' proponent.

For the global modelling of SOC for croplands, climate data are required. The climate variables used were precipitation (mm), mean air temperature (ºC) and open pan evaporation (mm). As RothC has a monthly step, all these variables were adjusted in accordance with the model's necessities. Temperature and precipitation were obtained from the IPCC (Bruun et al., 2015). The data sets start at 2005 and reach the year 2100, offering a time series of 95 years. The aim of working with scenarios is not to predict the future, but to better understand uncertainties in order to reach decisions that are robust under a wide range of possible future possibilities (Ballantyne et al., 2012).

These scenarios are needed because they allow to describe plausible trajectories of climate conditions, and other aspects, of the future that are uncertain. The implications of CC for the environment and society will depend not only on the response of the Earth system to changes in radiative forcing, but also on how humankind responds through changes in technology, economy, lifestyle and policy, leading to extensive uncertainties (Moss et al., 2010). When applied in CC research, scenarios help to evaluate the uncertainty related to human contributions, possible Earth system responses to human activities, the impacts of a range of future climates, and the implications of different approaches to mitigation (measures to reduce net emissions) and adaptation (actions that facilitate response to new climate conditions) (Moss et al., 2010). Scientific community identified a specific emission scenario from peerreviewed literature as a plausible pathway towards reaching each target radiative forcing trajectory. These were given the label representative concentration pathways (RCPs) (Moss et al., 2010). Moss et al. (2010) explains that the word 'representative' means that each RCP provides one out of many possible scenarios that leads to a specific radiative forcing characteristic. The term 'pathway' emphasizes that the trajectory taken over time to reach concentration levels are of interest, not only the concentrations *per se*. From the four RCPs, each of which corresponding to a specific radiative forcing pathway, two were chosen for the development of this work: RCP 4.5 and RCP 8.5.

Hurtt et al. (2011) explained the main differences between the two climate scenarios chosen. RCP 4.5 assumes that global GHG emissions prices are used to limit emissions, meaning that a penalty price is used to limit radiative forcing. C removals from LUC were assumed to be a mitigation strategy. Agricultural land was assumed to decline slightly due to afforestation. Food demand was met through crop yield improvements, dietary shifts, production efficiency and international trade. Radiative forcing stabilizes at 4.5 Wm^{-2} (approx.650 ppm CO_{2eq}) before 2100 without ever exceeding that value. For RCP 8.5, energy and industry's CO_2 emissions represent 90% of the reference emissions range. The emissions pathway is assumed to reach a radiative forcing of 8.5 W/m^{-2} and rising in 2100. An important feature of the RCP 8.5 was the assumption of increasing cultivated land by about 185 million ha from 2000 to 2050 and another 120 million ha from 2050 to 2100. While aggregate arable land use in developed countries was predicted to decrease, all the net increases are assumed to occur in developing countries. Yield improvements and intensification were assumed to account for most of the needed production increases: while global agricultural output in the scenario increased by 135% by 2080, cultivated land expanded by only 16% above 2005 levels. As agricultural land expands, forest cover is expected to decline over the century by 300 million ha from 2000 to 2050 and another 150 million ha from 2050 to 2100.

Regarding the implementation, it was simultaneously done for a baseline scenario, that considers climate stabilization at current average levels (NCC), as well as for the two chosen CC scenarios. In the NCC case, temperature and precipitation were kept constant throughout the 87 years of simulation. This value was obtained doing the average of the first 96 months of the available data sets by IPCC for each CC scenario yearly (from 2005 to 2013). That means that for each UHTU there is a monthly value for precipitation and temperature that results from averaging past data for eight years kept constant for the remaining 87 years of simulation. It is then expectable that both temperature and precipitation have different values according to the scenario under implementation. The starting point for the CC simulation is the same but at the 8th year the results start to diverge according to the different CC scenarios.

To understand the main differences between climate scenarios over the entire period of analysis, an average from the first 10 years was made, as well and the last 10. These two averages were then subtracted leading to the results presented further below in Figure 4. This procedure was repeated for precipitation and temperature.

Adding to the precipitation and temperature provided by the two RCPs used, evaporation also needs to be considered. This variable was calculated assuming that it is equal to two thirds of potential evapotranspiration (PET). PET was calculated using the Thornthwaite formula (Equation (1)). This formula requires the mean daily air temperature (T_d, which, if negative, should be set to zero), number of sunlight hours per day (L), a parameter (α) dependent on the heat index (I, that is dependent on 12 monthly mean temperatures, T_{mi}) computed using Equation (2), and number of days per month (N). This variable is then used in the following steps to calculate the water needs for each crop for a specific region. PET is therefore calculated as

$$\text{PET} = 16\left(\frac{L}{12}\right)\left(\frac{N}{30}\right)\left(\frac{10*T_d}{I}\right)^{\alpha}, \tag{1}$$

where

$$\alpha=(6.75*10^{-7})I^3-(7.71*10^{-5})I^2+(1.792*10^{-2})I+0.49239, \tag{2}$$

and

$$I=\sum_{i=1}^{12}\left(\frac{T_{mi}}{5}\right)^{1.514}. \tag{3}$$

PET enables the calculation of the water needs for each crop (Equation (4)). For this variable it was considered the single crop coefficient (kc), known for each of the crop types (Chapagain & Hoekstra, 2004), which was then multiplied by the previously calculated PET.

Knowing that

$$\text{water needs} = \text{PET} * \text{kc}, \tag{4}$$

it is possible to know what the required irrigation for a given region under a certain crop type is because:

$$\begin{cases} \text{If water needs} > \text{precipitation} \Rightarrow \text{irrigation} \\ \text{If water needs} < \text{precipitation} \Rightarrow \text{irrigation} = 0 \end{cases}.$$

That is, if the water needs presented by a certain crop type in each region of the world are higher than what nature can provide locally through precipitation, then irrigation is necessary. Irrigation was then equalized to the gap found between water needs and precipitation. If precipitation is sufficient to fulfill a given crop's needs, then there is no necessity of providing irrigation.

The soil characteristics also had to be defined. The soil depth considered was 30 cm. The percentage of clay and initial distribution of SOC between the 5 existing pools were obtained from Morais et al. (2019). In RothC, these pools are the inert organic matter (IOM), easily decomposable plant material (DPM), resistant plant material (RPM), microbial biomass (BIO) and humified organic matter (HUM) (Morais et al., 2018). The IOM pool is resistant to decomposition and does not change over time (Coleman & Jenkinson, 1996).

It is important to highlight that this initial distribution of SOC was established regardless of the crop type implemented locally for each region. The modelling starts with a simple case of LUC due to the lack of sensibility regarding the already existent crop type. Emissions from LUC are notoriously difficult to estimate and represent one of the most uncertain components of the global C budget (Ramankutty et al., 2007). Adding this uncertainty to the lack of future predictions for LUC considering the influence of CC for croplands, LUC was not considered throughout the 87 years of simulation. The only way where it was necessary to implicitly assume the existence of LUC in the simulation was through the allocation of the SOC stock present locally to the potential crop existent, and that SOC stock may be representative of a different cropland system.

Information about the land it is also important namely the definition of land cover and plant residues. Land coverage of each UHTU in each month and crop type is used as binary variable (1 – crop is present; 0 – crop is absent). This variable can affect the capture of carbon due to C inputs into the soil and also mineralization and it was only calculated when the previous parameter was different than zero. For each crop, a crop calendar was used to obtain the soil coverage period (Chapagain & Hoekstra, 2004) .

As the objective is to estimate the gap between yields with CC and NCC, it was necessary to determine the production yields with the crop's characteristics and residues. Residues calculation was made following the method presented by Morais et al. (2019) where the IPCC methods (IPCC, 1997; IPCC, 2003; IPCC, 2006) were applied.

For croplands, C residues are determined for an entire year and then distributed monthly. This distribution considered the monthly NPP and the life stages of plants. This method was proposed by Jebari et al. (2018) and Morais et al. (2018) where crops are divided into two categories. In the case of cereal crops, 50% out of the total residues occur in the harvesting month and the remaining is equally distributed for the three months before harvesting. Permanent crops see 70% of their residues allocated to the pruning months and the remaining distributed to the four months before. The months for harvesting and pruning were obtained from Chapagain et al. (2004).

With the residues, yields could be calculated knowing that they are related through a linear function for most croplands according to

$$\text{residues} = (\text{AG} + \text{RB}) * 0.5 \,, \tag{5}$$

where AG stands for aboveground productivity, and RB stands for reserve bases. The value of 0.5 is repeated throughout all the expressions because it is assumed that 50% of the plants' biomass is carbon (IPCC, 2006). These two variables can be calculated as

$$\text{AG} = \text{yield} * \text{slope} + \text{intersect}, \tag{6}$$

and

$$\text{RB} = \text{yield} * \text{RS}. \tag{7}$$

The final expression to compute yields is

$$\text{yield} = \frac{\left[\frac{\text{residues}}{0.5} - \text{intersect}\right]}{\text{slope} + \text{RS}}. \tag{8}$$

The values for slope and intersect for each crop were obtained from IPCC (2006).

There are exceptions, as for example crops with a null slope. The particularity of this crop type is not contemplated on the procedure presented by IPCC (2006) and therefore the expression used comes from IPCC (1997). To calculate the yield for these crops it is then required to use

$$\text{residues} = \text{yield} * \text{RS} * 0.5 \Leftrightarrow \tag{9}$$

$$\Leftrightarrow \text{yield} = \frac{\text{residues}}{\text{RS} * 0.5}. \tag{9.1}$$

Another exception comes when the straw, after the harvesting period, is only partially removed from the site. Another expression for yield's calculation must then be used. For these, it was assumed that 50% of the residues are removed from the field (IPCC, 1997). This expression is identical to the first one with only one particularity, AG productivity is also multiplied by 0.5 and it can be stated as

$$\text{residues} = (0.5 * \text{AG} + \text{RB}) * 0.5 \Leftrightarrow \tag{10}$$

$$\Leftrightarrow \text{yield} = \frac{\left[\frac{\text{residues}}{0.5} - 0.5 * \text{intersect}\right]}{0.5 * \text{slope} + \text{RS}}. \tag{10.1}$$

After the formulation for yields' calculation, the model still needed an initial SOC content to distribute between the 5 different pools. The data here used was gathered from Weihermüller et al. (2013).

As previously mentioned, NCC and CC results were calculated simultaneously. The intention was to know what yield would be necessary to maintain the NCC SOC stocks for a given crop type in a specific region of the world under CC. This required the addition of another step in the simulation. To do these calculations, 3 methods were tested. All the approaches tested used the function *fmincon*, provided by MATLAB considering different stop conditions. This function finds the minimum of constrained nonlinear multivariable function using an 'interior-point' algorithm. The establishment of a stop condition is then necessary, and it was set to 10^{-6}.

The first approach tested checked what would be the yield required under CC to maintain the total accumulated SOC in the case of climate stabilization for each crop type and UHTU throughout the 87 years of simulation. This approach required that

$$\int_{2013}^{2100} \text{SOC}_{\text{NCC}} \approx \int_{2013}^{2100} \text{SOC}_{\text{CC}}, \tag{11}$$

which in practice performed a search for the yield that, under the new climate conditions, would make the area under the curve of SOC, i.e. the integral, equal in NCC and CC scenarios.

In terms of the code, the implementation of the *fmincon* function was made to minimize the difference between the area below the curve of NCC and CC SOC stocks. After the calculation of the CC SOC with the respective climate variables, the *fmincon* would solve the condition

$$\text{Solve} = |A_{\text{NCC}} - A_{\text{CC}}|, \tag{12}$$

where A_{NCC} represents the area below the curve of the computed SOC stocks under NCC, that is, the accumulated SOC throughout the 87 years of simulation; and A_{CC} is the same but under CC.

Another approach tested was to find the yield that made SOC stocks in the year 2100 equal under NCC and CC, which means that

$$SOC_{NCC}^{2100} \approx SOC_{CC}^{2100}. \quad (13)$$

The calculations were made iteratively to find a yield that in 2100 approximated Equation (13).

The coding implementation was similar the previous one. The adjustment made allowed the *fmincon* function to minimize the difference between the SOC stocks found for the year 2100 under CC and NCC. The formulation used was

$$\text{Solve} = \left|SOC_{NCC}^{2100} - SOC_{CC}^{2100}\right|. \quad (14)$$

The last approach tried to find a single yield that equalized SOC stocks yearly for every year of the simulation. This means that

$$SOC_{NCC}^{\text{year i}} \approx SOC_{CC}^{\text{year i}}, \quad (15)$$

where i is the year between 2013 and 2100.

The difference of SOC stocks between NCC and CC scenarios was implemented onto the code using a yearly regression. The minimization criteria that the function *fmincon* had to follow was the sum of all calculated differences for the 87 years of simulation. The formulation for the resolution of this problem was

$$\text{Solve} = \text{sum}\left|SOC_{NCC}^{i} - SOC_{CC}^{i}\right|. \quad (16)$$

From these 3 approaches, the one that obtained the SOC under CC closer to the NCC scenario was the first one. No viable results were obtained for the other two approaches. Consequently, all results presented further below for yields, and further estimates that require this parameter, were based on the first approach only.

2.1.4. Comparison Between Yields

The potential yield for the crop types analyzed (IISA/FAO, 2012) consider the difference between irrigation or rainfed provision of water and include fertilization by C. These yields are supplied in dry matter (DM) and so, to compare the required yield to avoid SOC loss due to CC with the potential yield, an adjustment was necessary. This adjustment was the division of the results already obtained for yield by DM content. For this reason, DM is omitted from the previous equations.

Comparing yields allows to determine in which UHTUs is possible to compensate the effect of CC, and the UHTUs where this is not possible. Yield gaps are henceforth designated as ∆yield and were calculated by subtracting the potential and the calculated yields. This means that every time that ∆yield is negative the crop yield needs to increase above the potential to generate sufficient C inputs and maintain total SOC stocks over the period analyzed, in which cases it is impossible to avoid losing SOC.

When ∆yield is positive, there is a feasible (lower than potential) increased yield for that crop that ensures sufficient C inputs into soil to maintain the SOC stocks under CC.

Another approach was followed to compare the yields' results. A comparison between NCC and CC yields was conducted by dividing the NCC results by the required yields to maintain SOC stocks, from the respective scenario. The same was repeated using potential yield and those computed yields with CC. This allowed to understand how many times the yield under NCC, or the potential yield, would have to increase to reach the yield computed under CC.

2.1.5. Spearman Correlation

After the results for SOC stocks and yields were obtained, under CC and NCC, it was necessary to explain them using the main input variables, namely precipitation and temperature. With this it was possible to conclude for each crop type which of the variables influences more the results for ∆yield.

The method chosen to do this correlation was the Spearman correlation coefficient. This approach allows the assessment through a statistical variable (ρ) where the dependence of two variables is tested using a monotonic function. It is tested if a monotonic function can explain the behavior of one of the variables in function of the other. The perfect Spearman correlation occurs when ρ is equal to +1 or -1. A score close to these values means that the variables have a monotonic function that fits into the trends shown by both variables. If the resulting coefficient is found to be positive it shows that the monotonic function explaining the variables' behavior is crescent (when one of the variables increase, the second follows this trend). When the data sets are completely opposite, the correlation factor should be closer to -1 (when the reduction of one variable occurs, the other one is increasing) and follow a descendent monotonic function.

Besides the ρ variable, the p-value was also calculated. This parameter is important because it measures how probable it is for the correlation to occur by chance. The p-value is confined in the interval between 0 and 1. A p-value closer to the unit suggests no statistically significant correlation, whilst a p-value closer to zero suggests that there is a very high probability that there is real a correlation between the data sets evaluated.

2.1.6. Increasing Yields Through Fertilization

For the crop types, and regions, that have a potential yield higher than the required yield to preserve SOC stocks, the impact of the production and application of additional fertilizers needed was considered (assuming fertilizers were of mineral origin). These emissions were then compared with the ones avoided due to the stabilization of SOC. With this approach it is possible to understand if the increase in yields to keep SOC stocks stable does not backfire through increased emissions from intensification and fertilization. This required the conversion of the calculated CC and potential yields, per region and crop type, into N-yields. The parameters used for this conversion (Lassaletta et al., 2014) are listed in the Annex I per crop type.

With the N content for the CC and potential yields it was possible to apply the following fertilization response curve

$$Y_{CC}(F) = Y_{potential} \frac{F}{F + Y_{potential}}, \tag{17}$$

where Y_{CC} (t/ha) represents the N-yield calculated using each of the CC scenarios per region and crop type, $Y_{potential}$ (t/ha) is the potential yield that a certain region of the world has for a given crop type and F (t/ha) is the total amount of N inputs for the fertilization. The equation was then inverted to obtain F as

$$F = \frac{Y_{CC}}{1 - \frac{Y_{CC}}{Y_{potential}}}. \tag{18}$$

The emissions were calculated using this amount of N required knowing the amount of emissions generated for its application, as well as the emissions made for its production. The emissions' factor for fertilizer application used was 6.2 kg CO_{2eq}/kg N (FAO, 2017). The production factor depends on the country where the fertilizer is being fabricated (FAO, 2017). Some adaptations for the utilization of these factors were required due to a discrepancy of the division of world regions from FAO and Morais et al. (2019). For Morais et al. (2019) the American continent is divided into North and Latin America, whilst FAO has a Central and South America as one region. The factor assigned for North and Latin America was then the same and equal to the value presented for Central and South America by FAO. In the table presented by FAO, Australia and New Zealand are divided, whilst for Morais et al. (2019) they are classified only as Oceania. The value assigned was correspondent to the Australian factor due to the major significance in terms of area for the continent. FAO's table did not contemplate the African continent, thus the factor assigned was the global average. These adaptations are listed below on Table 2.

Table 2 – Factor to convert the production of fertilizers to CO_{2eq} emissions per region of the world.
A conversion was required due to a discrepancy of the FAO's division of the world and the approach used on the unique homogeneous territory units (UHTU). For this reason, New Zealand saw its factor increase from 3.06 up to 6.92 due to the higher significance of Australia in the Oceania continent, and Africa was not originally in the FAO's table, leading to use global average.

Regions FAO	UHTUs Regions	Factor (kg CO_{2e}/kg of product)
West Europe	Western Europe	5.62
East Europe including Russian Federation	Eastern Europe	6.87
Central and South America	North America	3.53
	Latin America	3.53
Asia	Asia	4.00
Australia	Oceania	6.92
New Zealand		
Global Average	Africa	5.66

Finally, the total emissions were calculated using

$$CO_2 emissions = F * (Production\ factor + Application\ Factor) * 87, \tag{19}$$

where the 87 is the number of simulated years.

If the increase in yield required to maintain SOC stocks was lower than the potential yield, the difference between the integral of SOC under NCC and CC was considered. The loss, or gain, of SOC was also converted into CO_{2eq} emissions, using a mass balance and the molar mass (i.e. using the factor 44/12). These results were compared with the emissions originated from the production and application of the fertilizers. If emissions are higher with fertilization than without, then the yield increase would mean a positive feedback to CC (i.e. a backfiring rebound), because the emissions' balance is higher with the fertilizers than with SOC loss. If the emissions are lower than what was previously computed with the SOC loss, then increasing yields with fertilizers is a feasible strategy to mitigate CC.

2.2. *RothC Calibration for Portuguese Unfertilized Pastures*

2.2.1. *Study Area*

Due to the extensive areas dominated by shallow and rocky soils, mainly degraded through erosion and loss of nutrients, the use of fields as pasture is particularly important in southern Portugal where extensive animal husbandry is the predominant activity (Serrano et al., 2011). Alentejo, an area where pastures are mainly present, is a region located at the central-southern area of Portugal and it is typically characterized as having a Mediterranean climate. The summers of this type of climate are hot and dry followed by a winter with excess of precipitation and low temperatures. Under these Mediterranean conditions, grasslands' productivity is typically low (Smit et al., 2008; Valada et al., 2012) showing the extreme importance to know how these soil–pasture systems work due the urgency of taking action towards a more sustainable management of these Mediterranean agroecosystems (Serrano et al., 2013).

Figure 3 shows the location of the 4 farms considered in this work. Most of the farms under analysis, regarding unfertilized pastures, are in Alentejo's region (3 out of the 4 farms) and other one is located near Covilhã.

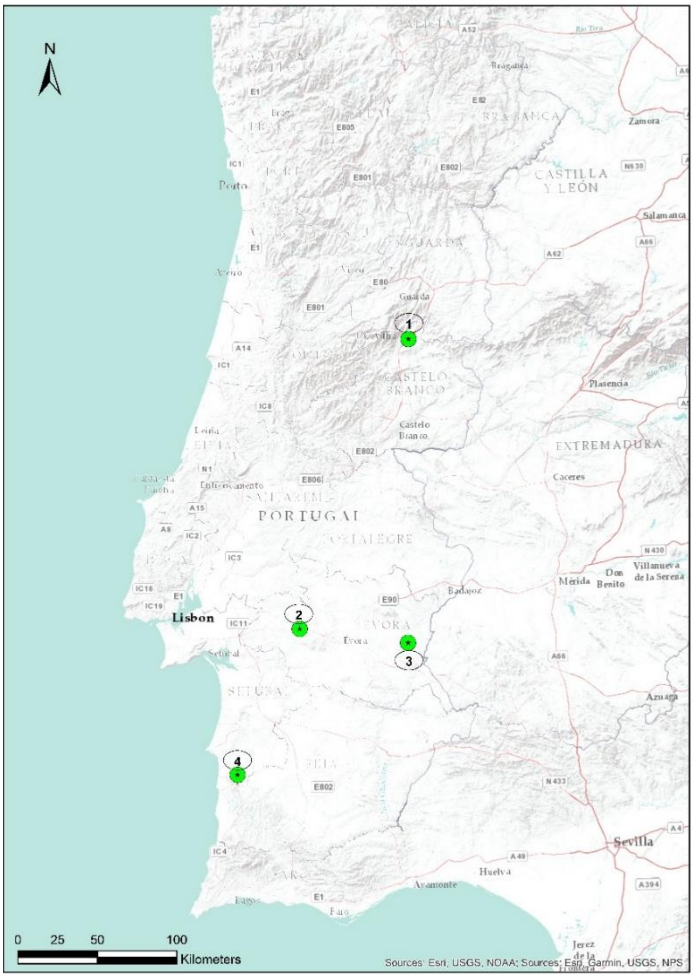

Figure 3 – Spatial localization on Mainland Portugal for the 4 farms under analysis.

The data used to run the model was acquired from four different farms for the years 2002, 2003 and 2004. The farms were divided into two main pasture types: fertilized and unfertilized. For both pasture types, the data acquired included SOM content (%), which was then converted into SOC content by multiplying by the average C fraction in organic matter (0.58, Pribyl, 2010), soil density (g/m^3) and soil depth (0.1 m). Soil density and soil depth adopted were obtained from the LUCAS-topsoil database (Tóth et al., 2013)).

SOM was determined using soil field sampling, at 10 cm depth, in several parcels for each farm. To get a sample representative from each farm, one composite sample was obtained by mixing of a variable number of sub-samples collected throughout each parcel. Samples were dried overnight at 35–37ºC and crumbled mechanically, passing then through a 2 mm stainless steel sieve before the measurement of the organic matter content (Teixeira et al., 2011).

The soil covered period is also a required variable and was considered binary. Between the months September and June, the value attributed was 1, and, for the rest of the simulation year 0 was assigned. This is the typical agronomic practice: to fully graze the pasture before summer, meaning that the soil is not covered. Regarding monthly irrigation, the fields were rainfed, not needing the provision of external irrigation. Monthly input of plant residues and manure farmyard (t C/ha) are also required. Manure was not applied in these experimental farms. Carbon inputs were introduced from two sources, from plants and animals using

$$I_{plant}(t\,C/ha) = [(1 - LI) + RS] * AGP * CF, \tag{20}$$

and

$$I_{animal}(t\,C/ha) = LD * SR * \text{fraction of time}. \tag{21}$$

The variables in Equations (20) and (21) for the calculation of carbon inputs are root to shoot ratio (RS), proportional livestock intake (LI) (which is presented as kg of dry matter (DM) eaten dividing per kg of DM pasture yield), livestock dung excreted (LD) (presented as tons of C per livestock unit (LstU)), aboveground productivity (AGP) (presented has kg of dry matter per hectare), stocking rate (SR) (presented has LstU per hectare), carbon fraction of legumes and grasses (CF) (which was equal to 0.4 t C/t DM (IPCC, 2006)) and the fraction of time that a LstU spends at the pasture. The time that LstU spends at fertilized pastures is represented by the subtraction of 1 and the time spent on the unfertilized pastures.

More variables were needed for the initialization of the simulation, in this case the monthly air temperature and precipitation. These came from the “Global Precipitation Climatology Project (GPCP)” (Pendergrass et al., 2020) and the Land Processes Distributed Active Archive Center (LP DAAC) project (Wan et al., 2015). As for the croplands approach, the monthly open pan evaporation was assumed to be two thirds of the potential evaporation which was calculated using the Thornthwaite model, presented at equation (1).

2.2.2. Optimization Procedure

The optimization procedure used allowed the computation of the data that was not collected on site through field measurements but would be required to run simulations using RothC. As explained by Morais et al. (2018), to obtain this information indirect ways were used. The parameters required this type of calculation were the RS (which is necessary for estimating belowground productivity (BGP) as a function of AGP), the time that each of the LstU spent at the respective pasture, LI (kg DM/ kg DM) and the DPM/RPM ratio. To calibrate the model, the parameters were determined once (using data collected for the year 2002) and applied for all farms and production years.

The first step was to establish a plausible domain of variation for each of the parameters. Afterwards a a value for the parameter was selected at random within that domain to initialize the optimization procedure. The initial SOC considered for each farm was collected on the year 2002, whereas the remaining SOC information was used for comparison. RothC was used to run and to calculate the SOC associated to each of those sets of numbers. 100 iterations were made and the difference between the computed SOC ($SOC_{estimated}$) and the real one ($SOC_{measured}$) was determined. This difference was subjected to the stop condition

$$\text{minimize}\sum_{i=1}^{n}\left(\frac{SOC_{measured,i} - SOC_{estimated,i}}{SOC_{measured,i}}\right)^2 + \sum_{i=1}^{n}\left(\frac{SOC_{measured,i} - SOC_{estimated,i}}{SOC_{measured,i}}\right), \quad (22)$$

where n represents the total number of data points simulated, that is, the number of production years, farms, and grassland types. This equation indicates that the algorithm is searching for the minimization of the difference between both variables in relative terms. If that condition was not reached, then the cycle would restart.

The plausible intervals for the parameters subject to optimization are presented in Table 3, with respective references.

Table 3 – Intervals of variation for each parameter subjected to randomized initialization.
These variables are the root-to-shoot (RS), livestock intake (LI), the ratio between easily decomposable and resistant plant matter (DPM/RPM) and the time fraction, as well as the literature that supports these intervals where AGP stands for aboveground productivity.

Parameter	Maximum	Minimum	Explanation/Literature
RS	8.0	0.5	IPCC, 2006; MOKANY et al., 2006
DPM/RPM	1.44	0.60	Coleman et al., 2014
LI	1	0	0 – indicates no grazing 1 – 100% AGP grazed by animals
Time fraction	1	0	0 – indicates no time spent on the pastures 1 – indicates 100% of time spent on the pastures

For this non-linear problem the same function used on croplands, “*fmincon*”, was used.

When the stop condition was met, it was possible to confirm that the “best” set of values was found. With that information, SOC was estimated for the years 2003 and 2004 for the exact same farms. This was made using RothC again to allow the comparison between the data collected on the field for both pastures with the calculated SOC amount predicted by the model.

3. Results & Discussion

3.1. <u>SOC Global Modelling in Croplands Under CC</u>

3.1.1. Data Analysis

Temperature and precipitation are the main variables responsible for SOC's behavior in scenarios under CC due to their impact on C inputs into the soil and SOC decomposition (Wiesmeier et al., 2019). To understand what impacts CC has on croplands, two CC scenarios were tested. The difference between scenarios is due to the assumptions made in the construction of the RCPs, as previously explained, and some of those differences are related with CO_2 emissions and their radiative force (Hurtt et al., 2011).

Figure 4 shows the difference of average temperature and precipitation in each UHTU between the start and end of the simulations in each scenario. The maps result from the subtraction of the average from 2013 to 2023, and the average from 2090 and 2100.

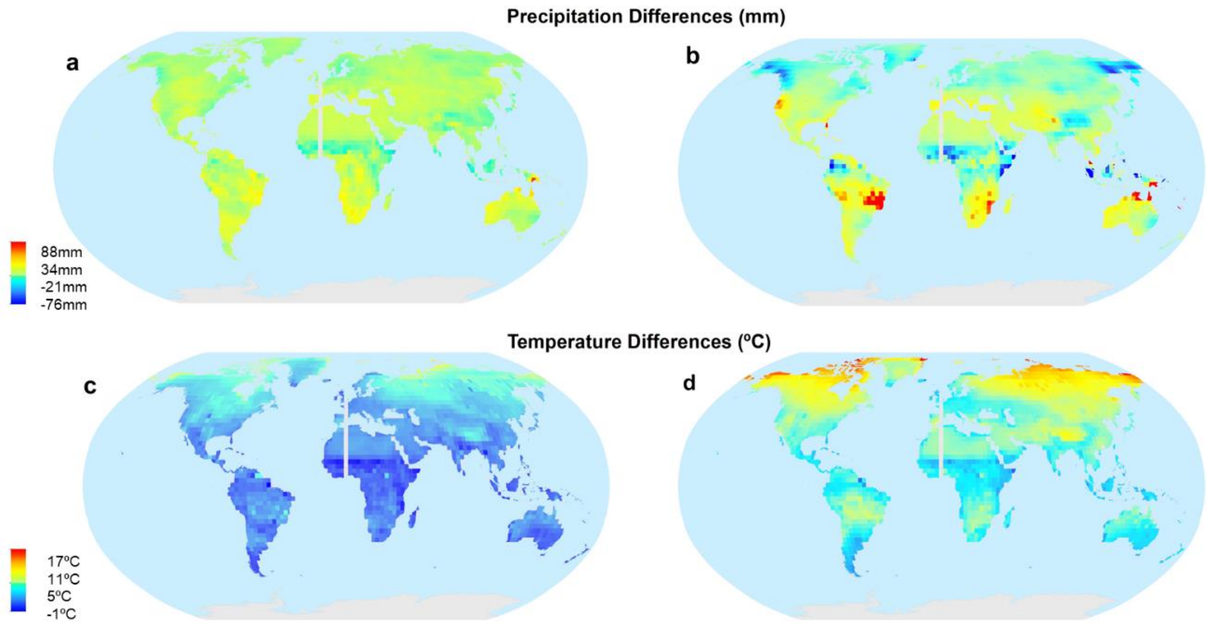

Figure 4 – Maps resulting from the subtraction of the average precipitation (a, b) and temperature (c, d) between the first 10 years of simulation and the average for the final 10 years.
The first row shows the maps developed when differences for precipitation were calculated using (a) RCP 4.5 and (b) RCP 8.5. The second row shows the maps obtained for temperature using (c) RCP 4.5 and (d) RCP 8.5.

For the RCP 4.5 CC scenario, if a global average is calculated using all simulation years, average yearly temperature increases from 17 ºC up to 19 ºC. The average maximum annual temperature is 33 ºC and the minimum -12 ºC under RCP 4.5. In the IPCC RCP 8.5 climate scenario the increase of temperature is higher. For this scenario, global average annual temperature increases from 17 ºC to 21 ºC. The average maximum is 35 ºC and the minimum -9 ºC. If a constant increment is calculated over the simulation period, the increase is 0.03 ºC per year under RCP 4.5 and, under RCP 8.5, the yearly temperature increment is 0.04 ºC.

The same kind of analysis was done for accumulated annual precipitation. To enable comparisons global averages were also computed. Using this approach, under RCP 4.5, the average maximum accumulated annual precipitation is 4,336 mm and the minimum is 0 mm. Using RCP 4.5, the average annual accumulated precipitation is expected to increase from 1,007 mm in 2013 to 1,098 mm in 2100. For RCP 8.5, the expected increase of mean global accumulated precipitation is from 1,016 mm in 2013 to 1,075 mm in 2100. Here the peak is at 4,565 mm and the annual minimum precipitation is also null. This means that RCP 4.5 expects an increase of 1 mm per year of global annual precipitation and, for RCP 8.5, precipitation increases by 0.7 mm/year.

Annual averages for the climate variables previously shown are different for the year 2013. This happens because some effects of CC are already visible from 2005 to 2013 in the data set, which was used for calibration and computing the stable values for temperature and precipitation for the NCC scenario. It is also important to highlight that these values are global averages and, therefore, the maximum and/or minimum values in each region of the globe are higher, or lower, accordingly.

RCP 4.5 predicts a higher increase in annual precipitation on average than RCP 8.5, which was expected due to the prediction of an increase of areas suffering from drought for RCP 8.5 (Reichstein et al., 2013; Schwalm et al., 2012). These regions are the ones with the highest potential of being affected by CC in C cycling, showing a higher probability to cause a shift from a carbon sink towards a carbon source (Frank et al., 2015; Reichstein et al., 2013). Potential climate feedbacks (like what was predicted for extreme drought in Europe by Schwalm et al. (2012) are expected. These extreme events are not only responsible for immediate responses from the ecosystems, but they can also be responsible for time-lagged ones, such as mortality, fires or insect infestations (Frank et al., 2015; Reichstein et al., 2013). Their effects on C fluxes and stocks are thus nonlinear. A variation in the frequency or severity of climate extremes can then impact carbon sinks and may result in local positive feedbacks to climate warming (Reichstein et al., 2013). These concerns are relevant due to, in many biological systems, the presence of a higher resilience when it comes to gradual CC whilst showing a higher sensibility to climate extremes, since generally they require a greater strength in response and shorter response times (Hanson et al., 2006).

New climate models predict an intensification of heavy precipitation events globally as well as the occurrence of heat extremes, and, therefore, regions with stronger or longer-lasting droughts (E. M. Fischer & Knutti, 2014). These climactic extremes, droughts, storms and extreme heat waves, cannot be seen as independent phenomena as in many regions they are intrinsically connected (Mueller & Seneviratne, 2012). Combining high temperatures with droughts can initiate a positive regional feedback mechanism (E. M. Fischer et al., 2007; Hirschi et al., 2011) as extreme drought often reduces evapotranspiration and reduce the cooling effect (Peng et al., 2014). The extreme values analysis is crucial as a future step to understand what is happening on Earth’s ecosystems.

3.1.2. SOC Global Tendencies

SOC results were analyzed through an accumulated difference between the values of SOC in the baseline scenario (NCC) and the results under CC with the chosen RCPs. To assess these differences the global average ∆SOC per crop type is presented. This variable shows the difference between the integral of both curves, namely for SOC's evolution under CC and NCC scenarios throughout the 87 years of simulation. The detailed results for the accumulated SOC per crop type throughout the 87 years of simulation in each CC scenario are on the appendix, as Annex II. In this table, the loss of SOC stocks can also be observed per number of regions where it occurs as a percentage of the potential ones. That is, regions with decreasing SOC stocks are divided by the regions with potential for the existence of each respective crop type. Figure 5 displays the regional results considering the RCP 4.5 scenario for each LU class on a box-and-whisker plot.

By applying IPCC's scenario RCP 4.5, global trends show that, on average, there is a loss of SOC on 31% up to 100% regions of the world depending on the crop type. The crop that is less affected, meaning that there are less regions with potential for its cultivation that lose SOC, is rainfed olives (SOC decreases in only 31% of regions). The opposite cases, the cases where there is a loss of SOC in 100% of the UHTUs, are irrigated coffee, sugarcane, cocoa, olives, and apples. In the climate scenario where conditions are more hostile (RCP 8.5), global trends show that the intervals are the same (between 31% and 100%) regarding the decrease in SOC stocks regionally. The crop that feels minimally the implementation of a new CC scenario is still rainfed olives, whereas the crops more affected, where 100% of regions where they can be cultivated lose SOC, are irrigated potatoes, sugarcane, cocoa, olives, and apples.

The other way to analyze the results is to check directly what is happening for each crop type on ΔSOC. It is important to highlight that the variable ΔSOC here presented is a global average for all regions with potential for the presence of each crop type. Whatever the conclusion is for each crop type, it does not mean that it is a true statement for all regions with potential for implementation of that cropland. As the universe of UHTUs under analysis is large, and some crop types have different number of regions with growth potential, by doing global averages in terms of cropland types, some minority results can get diluted.

The global average for SOC loss is different between scenarios: 60 out of the 63 crop types under analysis have a ΔSOC lower when the simulation is done with RCP 8.5 than with the RCP 4.5 CC scenario even though the difference between scenarios is small. Respectively to RCP 4.5 and to 8.5, the intervals of accumulated SOC's loss are from 18 to 469 t C/ha, and from 48 to 515 t C/ha. These results can be explained by the differences in terms of annual global temperature and precipitation between the two CC scenarios, as highlighted in section 3.1.1. The difference in 2100 reaches almost 2 ºC and around 26 mm, for temperature and precipitation respectively. The difference between the precipitation events is small when compared to the increase in temperature. As the world is getting hotter without an equivalent increase in moisture, a slight acceleration of the decomposition processes for SOC (Building & Pasteur, 2005; Crowther et al., 2016) explaining the small decrease in global stocks under different scenarios.

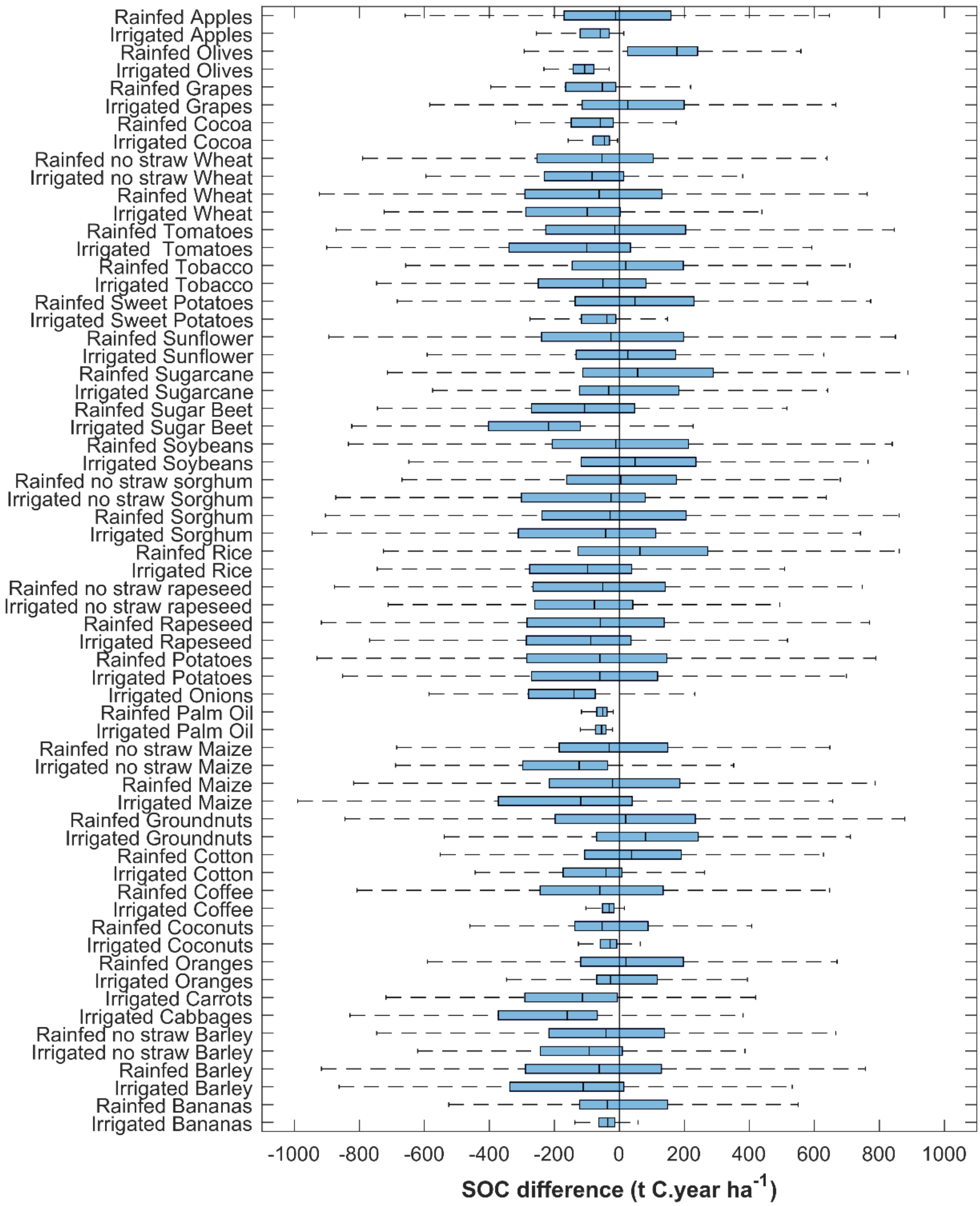

Figure 5 – The effect of climate change on the difference between SOC curve with and without climate change for all the 63 unique land use systems, considering RCP 4.5

The box-and-whisker plots represent the accumulated SOC stock difference between SOC curve without climate change and the SOC curve with climate scenario applied.

Croplands present in tropical and temperate regions are the ones with higher loss in terms of number of regions. However, these regions are not the ones with the largest decreases in ∆SOC, apart from irrigated sugarcane. This crop is the one that suffers the most SOC loss independently of the climate scenario under simulation. The strongest SOC losses are then found for irrigated sugarcane in both climate scenarios, where the loss is equal to -1,148 t C/ha for and -1,147 t C/ha for RCP 4.5 and RCP 8.5, respectively. The maximum ∆SOC is also independent of the CC scenario. Whether RCP 4.5 or RCP 8.5 are applied, rainfed olives, present around the Mediterranean area, show a positive ∆SOC, as represented on Figure 6. What differs is the capability for C sequestration, changing from 96 t C/ha to 78 t C/ha respectively. This positive result can be due to the flexibility presented by this crop to CC. On the Mediterranean area summers are hot and dry, followed by a winter with excess of precipitation and low temperatures. Also, under the influence of both RCPs analyzed the differences in temperature and precipitation for these regions are minimal, justifying the adaptability presented by this crop.

The crops where this positive ∆SOC exist, meaning that they are increasing their SOC stocks, can act as a sink of C. This phenomenon can minimize the impacts of CC around the globe. This result can also show an increase for NPP for these crops, meaning that they are leaving more residues in the soil. This increase in SOC stocks can occur due to an approximation to their climate optimal. For these crops, the effect of increase in NPP is surpassing SOC's decomposition process (Building & Pasteur, 2005; Crowther et al., 2016) in most of the regions analyzed.

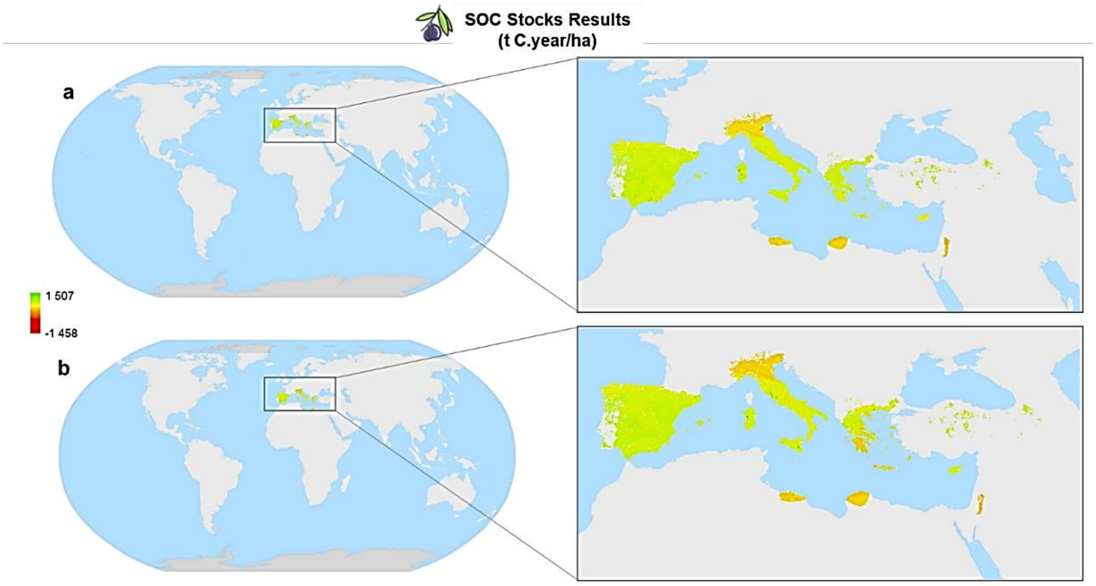

Figure 6 – Representation of the accumulated soil organic carbon (SOC) stocks results for the rainfed olives. (a) – using RCP 4.5; (b) – using RCP 8.5.

Regarding the changes in SOC for the world, results show that between 31 and 100% of Earth's regions, depending on the crop type under analysis, are prone to lose SOC stocks without land transformation. It is important to highlight that there are some crop types where all regions can suffer SOC loss. Even though the crop types where this happens may vary with climate scenario, overall, the crops where this phenomenon occurs are predominantly in lower latitude regions, mainly regions with a tropical or temperate moist climate. As the loss of SOC is associated with decomposition processes, which can be accelerated by having a combination of increasing temperatures and soil moisture, regions with lower latitudes see these conditions favored by CC (Gottschalk et al., 2012; Smith et al., 2005). An increase in temperature is also felt at higher latitudes, but it is not supported by an expressive increase in soil moisture. This means that the decomposition processes do not become faster due to the soil's dryness (Gottschalk et al., 2012).

These results are more pessimistic than the ones presented by Stergiadi et al. (2016). Here SOC losses in agricultural systems reached only around 8%, but those results were only relative to Northwestern Europe. Also, another model was used to perform the simulation, in this case Century model. The results presented by Smith et al. (2005) show a difference when the analysis is conducted per unit area and at continental scale for Europe. This demonstrates the importance of the scales for this type of analysis. Per unit area, it was possible to achieve a small increase in SOC stocks, whilst, for the European continent, SOC stocks decrease for all scenarios in the order of 39-54% by 2080 for croplands. This report used only Europe for the simulation and other CC scenarios were applied: HadCM3, CSIRO2, PCM, and CGCM2, which are four global climate models from IPCC. The results obtained in this thesis contradict the ones found by Gottschalk et al. (2012). Even though the model chosen was the same, RothC, the results predicted that SOC stocks would continuously increase from 1971 up to 2100 with varying intensity in all scenarios except one. However, two sets of climate data from seven AOGCMs and four SRES scenarios were used in this study, which can influence SOC's behavior.

3.1.2.1. SOC Dynamics for Selected Crop Types

To analyze data with more detail four crop types from different categories were selected: one cereal, one legume, one grass and one fruit. The crop chosen that fits into the cereal category was maize due to its massive production around the world, being considered as the most cultivated cereal (Mejía, 2003). The legume and the grass selected were, respectively, soybeans and sugarcane due to their environmental importance related to deforestation in tropical areas. Regarding the fruit category, the chosen example was grapes because it is categorized as a permanent crop. It is important to highlight that all four crops are rainfed and the residues are maintained on the field for maize.

Table 4 summarizes the SOC results found previously for each chosen crop types under both climate scenarios and, on Figure 7 and Figure 8, it is then possible to spatially depict those results. This table shows that, independently of the crop's category and CC scenario, the loss of SOC is inevitable when yields are the same as in the NCC scenario.

The results shown in Table 4 were calculated as the difference between the accumulated SOC for the CC scenario and the NCC one (∆SOC). When the accumulated SOC throughout the 87 years of simulation from the CC scenario is lower than the one accumulated on the NCC scenario, a loss of SOC stocks for a particular region under a certain crop type can be found. In that case, the value presented is negative.

Table 4 – Soil organic carbon (SOC) results for selected crops under the influence of both climate scenarios under analysis (RCP 4.5 and RCP 8.5).
Here results (∆SOC) are shown for the difference between the total accumulated SOC for the 87 years of simulation under climate change (CC) and a stable climate (NCC). ∆SOC was defined as the difference between the accumulated SOC under CC and the NCC stating a positive value when SOC stocks increase, and a negative value where SOC is lost. The percentage of regions that lose SOC is calculated by dividing the number of regions that lose SOC by the total regions with the potential for the existence of the crop under analysis.

	CC Scenario RCP 4.5		CC Scenario RCP 8.5	
Crop Type	Regions with SOC loss (%)	Average ∆SOC (t C/ha)	Regions with SOC loss (%)	Average ∆SOC (t C/ha)
Rainfed maize with residues left on the field	75	-498	77	-540
Rainfed soybeans	85	-708	81	-754
Rainfed sugarcane	98	-1,148	98	-1,147
Rainfed grapes	83	-336	83	-365

For the representation of the ∆SOC variable a “heatwave” type of map (Figure 7 for RCP 4.5 and Figure 8 for RCP 8.5) was chosen where the more negative values are represented through a red vibrant color which evolve for the positive results represented by a vibrant green color.

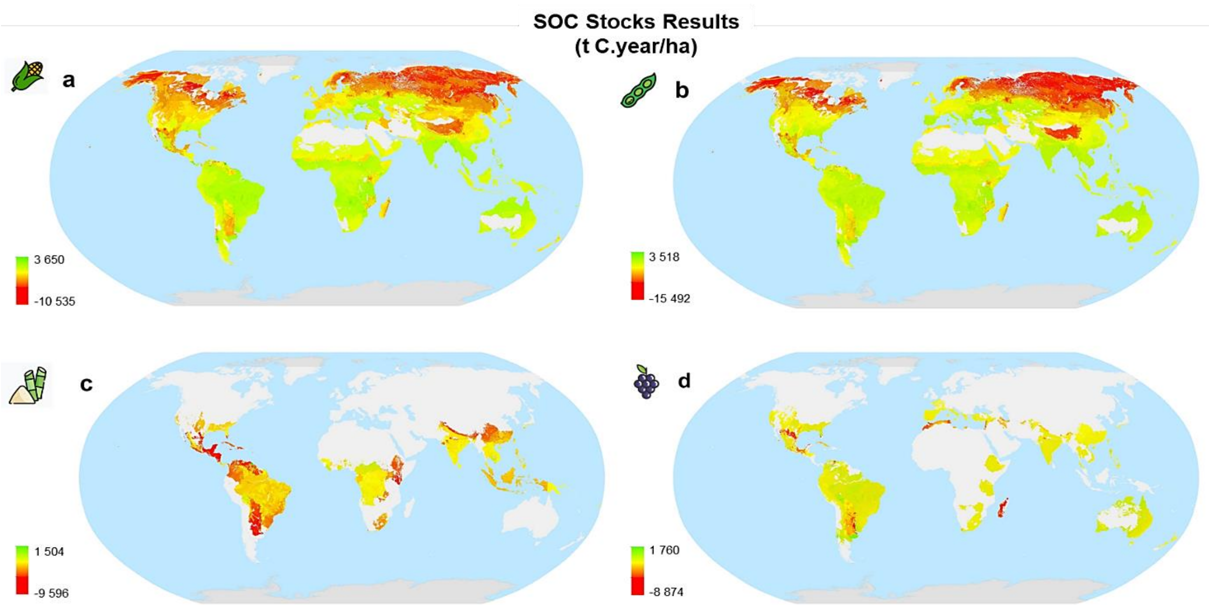

Figure 7 – Difference between the accumulated soil organic carbon (SOC) from the scenario under climate change (CC), using RCP 4.5, and the baseline scenario where climate is stable at current levels (NCC).
When the accumulated SOC throughout the 87 years of simulation in the CC scenario is lower than SOC accumulated in the NCC scenario, the value is negative, stating a SOC loss. This approach was used for the representation of (a) rainfed maize with residues left on the field, (b) rainfed soybeans, (c) rainfed sugarcane and (d) rainfed grapes.

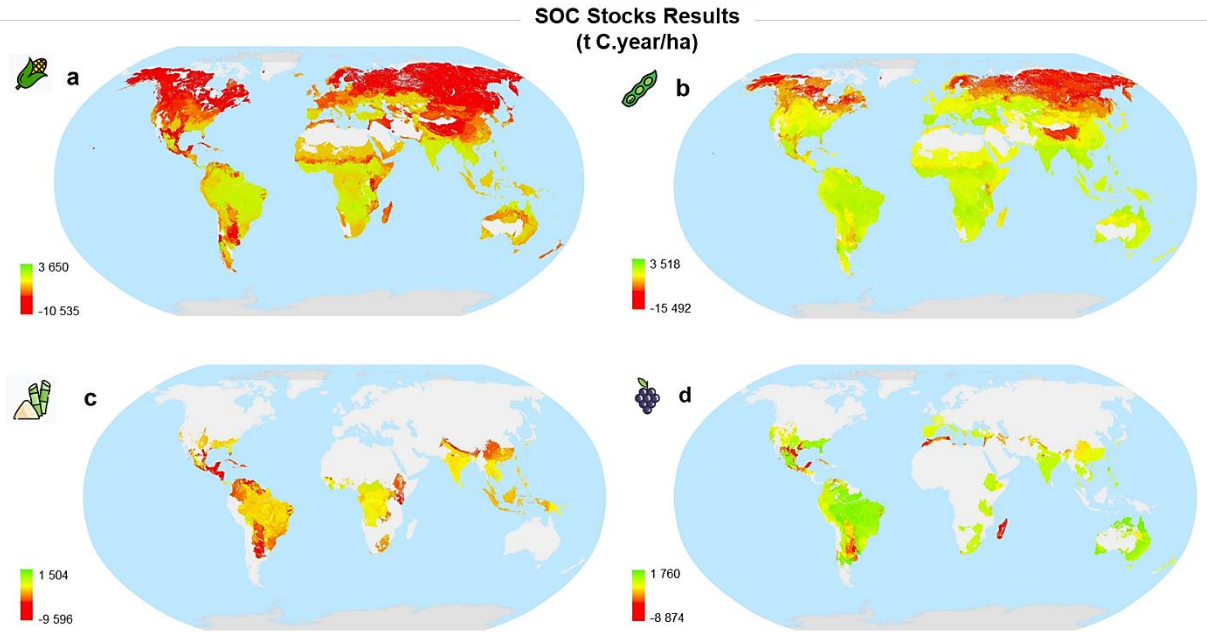

Figure 8 – Difference between the accumulated soil organic carbon (SOC) from the scenario under climate change (CC), using RCP 8.5, and the baseline scenario where climate is stable at current levels (NCC).
When the accumulated SOC throughout the 87 years of simulation in the CC scenario is lower than SOC accumulated in the NCC scenario, the value is negative, stating a SOC loss. This approach was used for the representation of (a) rainfed maize with residues left on the field, (b) rainfed soybeans, (c) rainfed sugarcane and (d) rainfed grapes.

For maize, SOC stocks decrease globally in RCP 4.5 and RCP 8.5 in the order of 498 t C/ha and 540 t C/ha, respectively. For soybeans, results for the same climate scenarios are -708 t C/ha and -754 t C/ha. Maize and soybeans have a widespread potential for production across the globe and in the global Northern areas the loss of SOC is higher. This can be due to the fact that, using Figure 4 as a reference, the increase of temperature is expected to be more intense in those areas. As previously mentioned, the increase of temperature, without an increase in moisture, leads to a slight acceleration of SOC's decomposition, depleting the soil of this important asset.

Grapes is the crop type with the least negative results regarding SOC loss, loosing globally an average of 336 t C/ha for RCP 4.5 and 365 t C/ha for RCP 8.5 throughout the 87 years of simulation. The regions where this crop has potential for growth are placed in UHTUs that do not feel drastic CC impacts. Both temperature and precipitation are expected to remain approximately constant.

With a completely different behavior there is sugarcane. This crop is the one with the most significant SOC loss. The global average ΔSOC is equal to -1,148 t C/ha for RCP 4.5 and -1,147 t C/ha for RCP 8.5. One of the reasons to explain this SOC loss arises from the necessity that this crop has to spend long times with water availability and within a specific temperature range (Silva et al., 2020). This is something that, with the increase of climate extremes, may be compromised. Another reason can be its necessity for fertilization (Václavík et al., 2013), although this effect was not explicitly addressed in this part of the work. Currently, in the inner tropics, adequate temperature and moisture is present throughout the year, but soil quality often restricts cultivation due to low organic content (Ramankutty et al., 2002).

These results show a very negative future for agriculture globally. To understand if the maintenance of SOC stocks calculated for the NCC reality was feasible, the increase in carbon inputs through increasing yields was tested. The following section will assess this for the same crop types, using the same CC scenarios and 87 years of simulation.

3.1.3. Comparison of Potential and Required Yields for SOC Stabilization

The analysis for the crops yields was conducted using the annual value. A comparison was made using the values from the baseline scenario and the potential yields with the results under CC using RCPs. The difference between NCC yields and the yield required under CC, and the difference between the potential and the CC yield, were computed for each UHTU and per crop type throughout the 87 years of simulation. The results for this approach per crop type are presented as an appendix in Annex III. In this table, the regions where the loss of SOC is avoidable with an increase in yield, are shown as the “positive regions” (because the difference between required and potential yield is a positive number). The number of “positive regions” was then divided by the number of regions where the crop can potentially be produced, leading to the percentage shown. The difference between the potential and the required yield to maintain SOC stocks is also analyzed in this table (∆yield). This variable was calculated by subtracting the required yield for SOC’s maintenance for the different CC scenarios from the potential one. If this difference is found to be negative, then it shows that the potential yield is lower than the required yield to maintain SOC stocks. This means that the maintenance of those stocks is impossible because the required yield cannot be reached. If this difference is found to be positive, then it is feasible to compensate the SOC losses with an increase in yield (and consequent increase of C inputs into soil).

It is possible to conclude that there are no large differences between the application of both climate scenarios, in percentual terms and in terms of number of regions. The difference represents, on average for the whole globe between the RCP 4.5 and 8.5 scenarios, a 4% difference in regions where the increase in yield is not enough to compensate for the SOC losses.

For this cropland yield analysis, an average for all crop types was made to enable comparisons between CC scenarios. It is possible to see that in 8 to 89% of regions the NCC SOC stocks, depending on the crop type analyzed, can be maintained with the RCP 4.5 CC scenario because the necessary yield is still lower than the potential one. The values vary from 8% (found for irrigated sugar beet), meaning that only about 8% of the regions with the potential to produce this crop are able to increase the yield in order to compensate for increased SOC mineralization due to CC, up to 89% for the production of rainfed sorghum with residues removal. In the RCP 8.5 scenario, and doing the same type of assessment, it is observed an interval of 5% to 88% of regions with capability to maintain SOC stocks due to the possibility of attaining the necessary yields to compensate the SOC loss depending on the crop type analyzed. The minimum (5%) and maximum (88%) values correspond to irrigated sugar beet and rainfed sorghum with residues removal again.

The difference between crops can be explained through the regions where the crop types are preferably settled. Sugar beet can be mainly found in temperate regions of the northern hemisphere (Figure 9) whereas sorghum has a nearly global potential for its settlement (Figure 10). Temperate regions are some of the areas where climate fluctuations are expected to be stronger due to CC. It is also important to highlight that different crop types have different requirements from the environment where they are settled. For example, sugar beet has greater soil and climate requirements, requiring a substantial rainfall level as well as heavy fertilization due to the high biomass production potential (Intermag, n.d.). Sorghum can grow on low potential and shallow soils with high clay, can better tolerate short periods of waterlogging and is characterized as being a warm-weather crop, which requires high temperatures for good germination (du Plessis, 2008). Sorghum can even be produced in South Africa under fluctuating rainfall conditions showing its ability to tolerate drought better than most other grain crops (du Plessis, 2008).

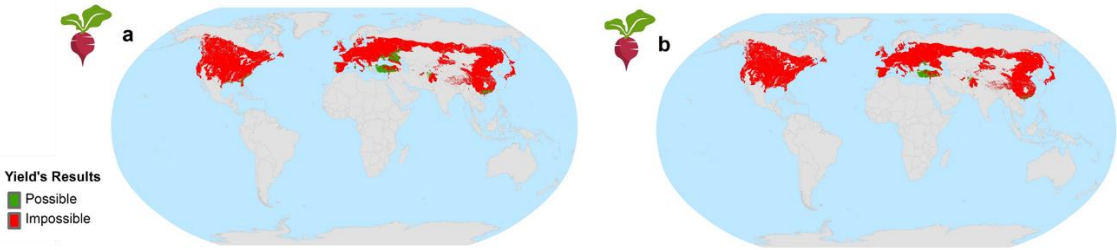

Figure 9 – Representation of the ∆yield (difference between the potential yield and the yield calculated for the respective climate change (CC) scenario) for irrigated sugar beet.
Here (a) corresponds to the RCP 4.5 CC scenario, whilst (b) are results for the RCP 8.5 scenario. In the cases where this variable is found to be negative, the red color is attributed due to the impossibility to increase yields to guarantee the maintenance of SOC stocks. When the ∆yield is found to be positive, then the green color shows the areas where the loss of SOC is avoidable by increasing yields.

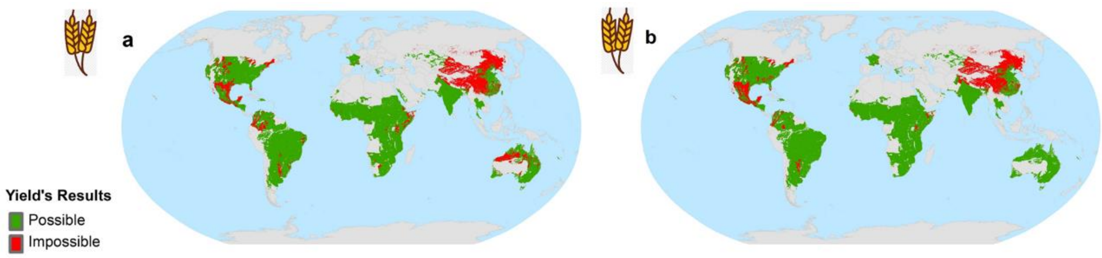

Figure 10 – Representation of the ∆yield (difference between the potential yield and the yield calculated for the respective climate change (CC) scenario) for rainfed sorghum.
Here (a) corresponds to the RCP 4.5 CC scenario, whilst (b) are results for the RCP 8.5 scenario. In the cases where this variable is found to be negative, the red color is attributed due to the impossibility to increase yields to guarantee the maintenance of SOC stocks. When the ∆yield is found to be positive, then the green color shows the areas where the loss of SOC is avoidable by increasing yields.

A quantitative analysis can also be conducted. For this type of analysis, the variable ∆yield allows to see, doing a global average, the results for yields when both climate scenarios are applied so that SOC stocks are maintained from the NCC scenario. The difference of yields (between required and potential yields) increased when the simulation passed from RCP 4.5 to 8.5. The minimum differences are -51 t/ha and -54 t/ha, and the maximum differences are around 1 t/ha, for each respective CC scenario. This is corroborated by the fact that for 49 out of 63 crop types the required difference of yields is larger for RCP 8.5, the more hostile CC scenario. This evolution can happen due to the increase in number of regions where the necessary production yield to maintain SOC stocks is higher than the soil's potential.

The main qualitative results for most of the crop types are similar in both climate scenarios. If the difference between required yields and NCC yields is found to be negative under RCP 4.5, it is also negative when RCP 8.5 is used. The same is true for cases where this difference is positive, except for 3 crop systems (irrigated barley where residues are removed from the soil, rainfed oranges and irrigated palm oil). For these 3, it is impossible to maintain SOC stocks globally in RCP 8.5. These crops denote the degradation of conditions for SOC stocks' maintenance even with a boost in yields due to worse climate conditions. There are also crops where minimizing the difference between the potential and the required yield is possible even under RCP 8.5. These crops are: rainfed barley with straw, rainfed oranges, irrigated coconuts, rainfed cotton, irrigated and rainfed maize without residues removal, rainfed maize with no straw, rainfed palm oil, irrigated and rainfed sorghum with no straw, irrigated sweet potatoes, irrigated wheat without residues removal, rainfed wheat with residues removal, irrigated grapes and rainfed olives.

If the difference between required yields and potential yields is closer to zero, it means that the potential yield of a certain crop is closer to the one needed for the maintenance of SOC stocks using the respective RCP. When the difference starts increasing it can go in two different directions: negative (which means that the crop needs to increase the yield above its respective potential and requires more than what the field can potentially give, implying that it is impossible to maintain SOC stocks at the same level as in the NCC scenario) and positive (meaning that it is still, theoretically, possible to increase the crops' output in that region to maintain the SOC stocks of the baseline scenario). For RCP 4.5 the regional differences are displayed on Figure 11 through a box-and-whisker plot. Here, the maximum difference found for the crops where it is unfeasible to maintain SOC was found for irrigated tomatoes (-51 t/ha). The spatial distribution of tomato results can be seen in Figure 12. The causes for this result are not geographical because it is found potentially throughout all potential UHTUs globally. For cases where it is feasible to maintain SOC, the one with largest difference between required and present yields is rainfed sorghum with no straw (1 t/ha), whose spatial distribution of results is shown in Figure 10. Finally, the minimum difference can be found for irrigated palm oil (0.005 t/ha). For RCP 8.5 results are similar, with the wider negative difference found for irrigated tomatoes, but with a higher absolute value (54 t/year), and the wider positive difference can be found for the rainfed sorghum with no straw, but now with approximately 1 t/year, while the minimum difference is from rainfed palm oil (0.01 t/year).

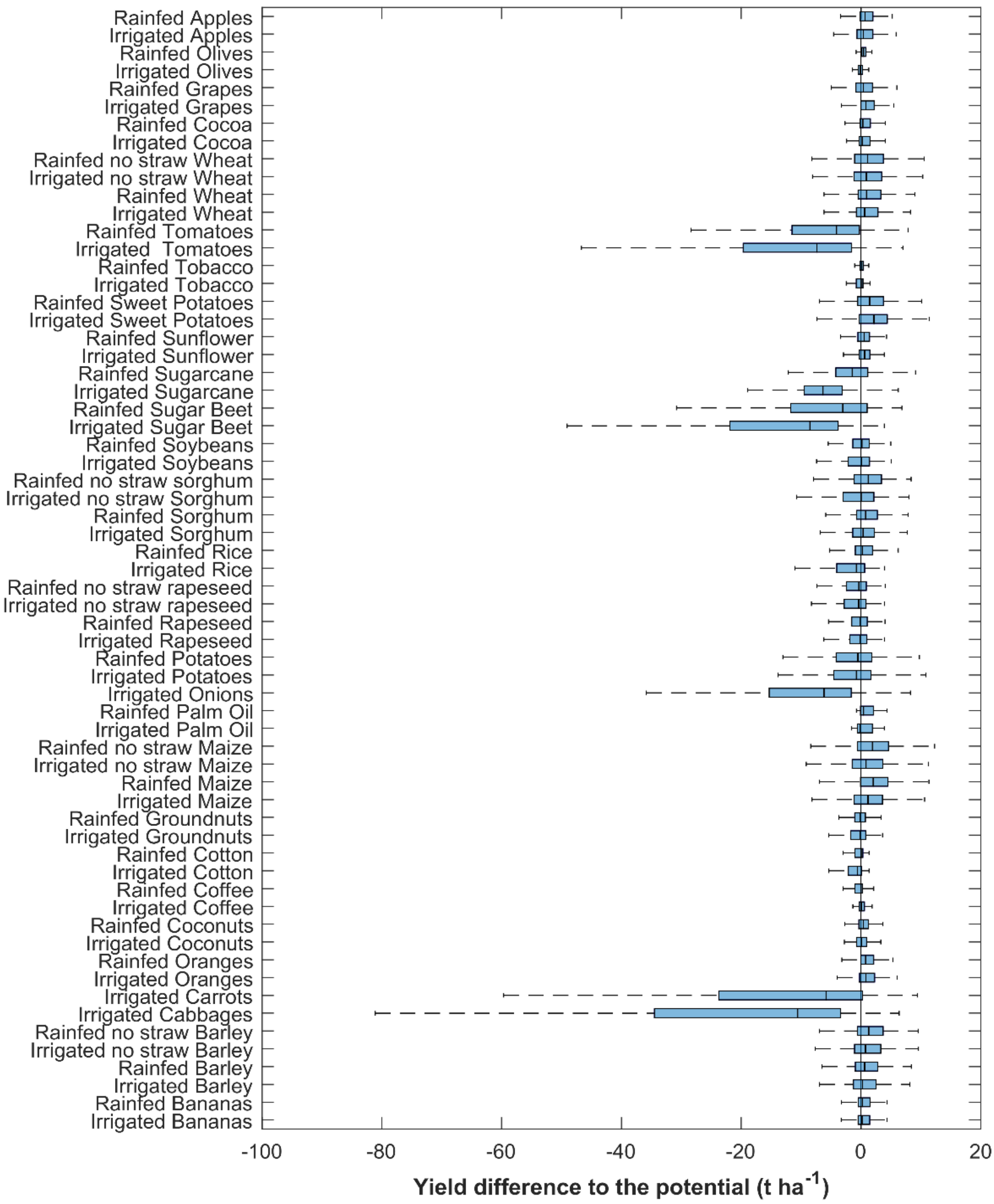

Figure 11 – Comparison between the potential yield and the required yield to compensate the effect of climate change on SOC for all the 63 unique land use systems, considering RCP 4.5.

The box-and-whisker plots represents the required yield to maintain NCC stocks and the potential, i.e. a positive value means that potential yield is higher than the required yield, and negative means that required yield is higher that potential yield.

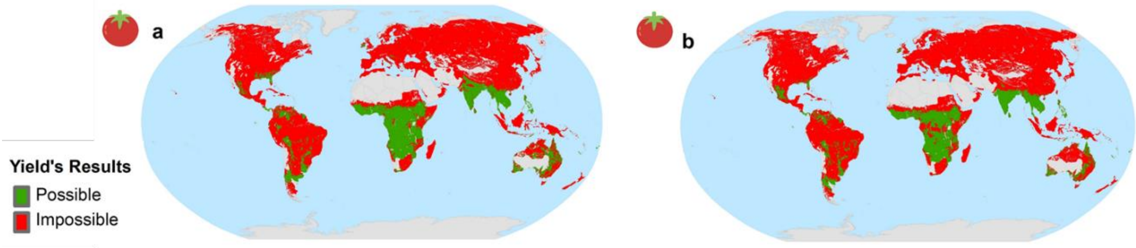

Figure 12 – Representation of the ∆yield (difference between the potential yield and the yield calculated for the respective climate change (CC) scenario) for irrigated tomatoes.
Here (a) corresponds to the RCP 4.5 CC scenario, whilst (b) are results for the RCP 8.5 scenario. In the cases where this variable is found to be negative, the red color is attributed due to the impossibility to increase yields to guarantee the maintenance of SOC stocks. When the ∆yield is found to be positive, then the green color shows the areas where the loss of SOC is avoidable by increasing yields.

Passing now to the analysis of the extreme values it is possible to see that the negative values become more negative and the positive values decrease when using RCP 8.5 rather than RCP 4.5. In the first case, in regions where it was already impossible to maintain the SOC stocks, if CC effects become more extreme, the imbalance between required and present yields is even larger. The same happens with decreasing ∆yields on positive values. That shows the approximation to the plant optimal conditions in specific regions due to CC.

Globally, the necessity to increase yields to preserve SOC stocks has not yet been studied extensively. However, Müller & Robertson (2014) showed that CC led to strong decreases in agricultural productivity in most of the agricultural areas without additional measures. On a global scale, crop yields were estimated to decrease by 10% to 38% by 2050 for the five crops simulated (wheat, maize, rice, soybean, groundnut) for both CC scenarios (RCP 4.5 and RCP 8.5). This shows that, if nothing is done regarding the SOC stocks on croplands, soil conditions can deteriorate faster. Due to lower productivity, less C inputs is introduced into the soils. This leads to the necessity of increasing more the yield to compensate the SOC losses. The decrease in yields found by Müller & Robertson (2014) has high spatial variability. This variability could be explained by local-scale variables including the current SOC stock, soil clay content, mean annual temperature and precipitation (Wang et al., 2016), as well as crop type.

Wang et al. (2016) used RothC in the wheat-growing regions of the world to simulate SOC change in the top 30 cm of soil under various types of management. Globally, the average amount of C input required to maintain SOC stocks was estimated to be 2.0Mg C ha^{-1} yr^{-1} (Wang et al., 2016). This critical amount of C necessary to keep the SOC stocks stable to compare with the results previously attained, would require the translation into yields. Through the methods developed in this thesis, the C inputs required to attain the CC yields to maintain SOC stocks are listed in the Table 5 below accordingly to the management practices considered. On this table is possible to assess the global required residues results necessary to attain the yield that would minimize SOC losses. It is thus possible to conclude that there is a notorious difference between Wang et al., (2016) results (2.0t C ha^{-1} yr^{-1}) and the ones found here (averagely between 0.002t C ha^{-1} yr^{-1} and 0.005t C ha^{-1} yr^{-1}, according to the crop type). That difference can be explained by the regions used, because Wang et al., (2016) used only regions where wheat was effectivelly present whilst, in this dissertation, all regions with potential for its cropping were used.

Table 5 - Residues required to attain the computed climate change (CC) yields for wheat accordingly to the management practices and CC scenarios.
Per crop type it is possible to analyze the necessary amount of residues to attain the computed CC yields previously shown. It is also possible to assess the average results for ∆yield globally, which translates into the difference between the potential yield of a certain region and the required yield to maintain SOC stocks.

Crop Type	**CC Scenario RCP 8.5**			
	RCP 4.5		RCP 8.5	
	Residues (t ha^{-1} $year^{-1}$)	∆yield (t/ha)	Residues (t ha^{-1} $year^{-1}$)	∆yield (t/ha)
Irrigated wheat with residues left on the field	0.004	-1.0	0.005	-1.0
Rainfed wheat with residues left on the field	0.002	0.5	0.002	0.8
Irrigated wheat with residues removed from the field	0.003	0.2	0.004	-0.3
Rainfed wheat with residues removed from the field	0.003	0.7	0.004	0.4

3.1.3.1. Comparison of Required Yields for SOC stabilization with current NCC Yields

Table 6 shows how far the yield required under CC is from the potential. Here it is possible to see the number of times that the respective yield (potential and/or NCC) had to be multiplied to achieve the yield required under CC to maintain SOC stocks. For that analysis, the yield obtained *per* CC scenario was divided by the potential and the NCC yields. The analysis comparing the CC with the NCC scenario was conducted because most of the yields increased when considering CC.

Between climate scenarios it is necessary to increase NCC yields more for RCP 8.5 (for 55 out of the 63 crop types under simulation). On average it would be necessary to increase around 27 times the yields to reach the ones found required when CC is simulated using RCP 4.5, whilst with RCP 8.5 this average increases up to around 32 times (ignoring for the moment the yield gaps). When the analysis passes to the comparison of how far required yields for SOC stabilization are from the potential, either above or below, the overall results are the same and for the same crop types. That is, when the previous ratio was higher for RCP 8.5 than for RCP4.5, the same happens for the ratio considering the potential yield. Hence, the same 55 crops present a bigger difference between the potential and the required yield when comparing both RCPs. On average, it is necessary to increase 3 times the potential yield for RCP 4.5, and 4 times when RCP 8.5 is used.

It is also possible to analyze that when the RCP 4.5 scenario is used, only 13 crop types present a global yield below the potential one (presented in Table 6 with a ratio lower than 1). This shows that most crop types are not able to maintain their SOC stocks. The number of crop types that present this characteristic decreases to 10 when RCP 8.5 is used.

Table 6 – Comparison between the different yields: required for SOC stabilization with climate change (CC) under RCP 4.5 and RCP 8.5, baseline without CC (NCC) and the potential yield through closure of yield gaps.
For this analysis a division of the CC yield by the NCC yield was made, as well as a division of the CC yield by the potential yield allowing to understand how many times would the NCC yield and the potential yield have to increase to attain the required yield under both scenarios of CC.

	Yield CC / Yield NCC		Yield CC / Yield Potential	
	Climate Scenario		Climate Scenario	
Crop Type	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Irrigated bananas	11	14	2.7	3.3
Rainfed bananas	7	8	1.7	1.9
Irrigated barley with residues left on the field	19	25	1.1	1.5
Rainfed barley with residues left on the field	21	23	0.9	1.0
Irrigated barley with residues removed from the field	10	10	1.2	1.3
Rainfed barley with residues removed from the field	7	7	0.7	0.7
Irrigated cabbages	74	89	13.2	15.8
Irrigated carrots	67	76	8.1	9.2
Irrigated oranges	12	13	2.2	2.5
Rainfed oranges	7	8	0.9	1.1
Irrigated coconuts	29	29	6.9	6.8
Rainfed coconuts	12	13	1.4	1.5
Irrigated coffee	12	19	2.4	3.8
Rainfed coffee	0	0	2.2	2.6
Irrigated cotton	19	28	18.8	27.5
Rainfed cotton	12	10	8.9	7.6
Irrigated groundnuts	144	150	5.4	5.6
Rainfed groundnuts	134	157	3.7	4.4
Irrigated maize with residues left on the field	24	24	1.5	1.5
Rainfed maize with residues left on the field	18	20	0.8	0.9
Irrigated maize with residues removed from the field	7	9	1.3	1.6
Rainfed maize with residues removed from the field	5	5	0.6	0.6

Crop Type	Yield CC / Yield NCC		Yield CC / Yield Potential	
	Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Irrigated palm oil	1	18	1.0	18.0
Rainfed palm oil	0	0	0.0	1.0
Irrigated onions	87	104	5.5	6.6
Irrigated potatoes	21	24	4.7	5.5
Rainfed potatoes	23	27	4.0	4.7
Irrigated rapeseed with residues left on the field	37	39	2.8	2.9
Rainfed rapeseed with residues left on the field	30	36	1.6	1.9
Irrigated rapeseed with residues removed from the field	62	74	4.7	5.7
Rainfed rapeseed with residues removed from the field	55	71	2.9	3.8
Irrigated rice	45	49	4.5	4.8
Rainfed rice	27	36	2.0	2.7
Irrigated sorghum with residues left on the field	69	88	2.5	3.2
Rainfed sorghum with residues left on the field	54	63	1.4	1.6
Irrigated sorghum with residues removed from the field	9	10	0.7	0.8
Rainfed sorghum with residues removed from the field	4	4	0.2	0.3
Irrigated soybeans	84	98	4.9	5.8
Rainfed soybeans	96	99	3.9	4.0
Irrigated sugar beet	18	27	12.2	18.0
Rainfed sugar beet	19	21	7.1	7.7
Irrigated sugarcane	1	1	2.9	3.1
Rainfed sugarcane	1	1	1.4	1.8
Irrigated sunflower	13	13	2.3	2.3
Rainfed sunflower	18	24	1.6	2.0
Irrigated sweet potatoes	70	67	5.0	4.8
Rainfed sweet potatoes	39	47	1.8	2.2
Irrigated tobacco	31	35	3.0	3.4
Rainfed tobacco	25	28	1.6	1.8

Crop Type	Yield CC / Yield NCC		Yield CC / Yield Potential	
	Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Irrigated tomatoes	31	32	22.7	23.8
Rainfed tomatoes	23	28	9.7	11.7
Irrigated wheat with residues left on the field	10	10	1.3	1.4
Rainfed wheat with residues left on the field	10	9	0.8	0.7
Irrigated wheat with residues removed from the field	6	7	0.9	1.1
Rainfed wheat with residues removed from the field	7	9	0.7	0.8
Irrigated cocoa	0	0	1.8	2.3
Rainfed cocoa	0	0	0.5	0.3
Irrigated grapes	9	8	1.2	1.0
Rainfed grapes	16	19	1.5	1.8
Irrigated olives	9	10	1.8	2.0
Rainfed olives	0	0	0.4	0.4
Irrigated apples	13	17	2.8	3.8
Rainfed apples	7	9	1.1	1.3

3.1.3.2. Correlation analysis

The results obtained above were then correlated with temperature and precipitation. The correlation of these variables was analyzed using Spearman correlation. It is important to highlight that this correlation only states that, in case of a ρ value closer to the unit, in absolute terms, there is a function that is able to explain the behavior of both variables under study. This correlation does not state what is the relationship between them, for example, if it is a direct connection between the variables. A positive correlation coefficient shows that the function found has an increasing monotonic trend meaning that an increase in yield differences is associated with a monotonic function dependent of the increase in the respective climate variable. When the coefficient has a negative value, it is then associated to a monotonic function that explains the behavior of the differences in yield versus climate variable where while one of them is increasing, the other is decreasing.

The relationship between cropland residues and the climate variables was also assessed using the same method. The best way to address this topic is through residues as they are directly connected to the calculation of yields. As different parameters and different ways to compute yields vary according to crop type, the results obtained for yields are not directly comparable. In the case of residues, the results can be compared between crop types because residues are the main C input into the soil that changes with CC independently of which crop type is under simulation. The results for the correlation between residues and the climate variables for both climate scenarios are presented below as Table 7.

Table 7 – ρ results from Spearman correlation between crop residues and the climactic variables (temperature and precipitation) for both climate change (CC) scenarios (RCP 4.5 and RCP 8.5).
ρ is the correlation coefficient and it varies between -1 (high negative correlation) and 1 (high positive correlation), where 0 is no evidence for correlation. The p-values were also assessed. A p-value closer to zero suggests a statistically significant correlation between the data sets evaluated. ** - p-values lower than 0.01; * - p-values between 0.05 and 0.01.

	Correlation residues-temperature		Correlation residues-precipitation	
Crop Type	**Scenario RCP 4.5**	**Scenario RCP 8.5**	**Scenario RCP 4.5**	**Scenario RCP 8.5**
Irrigated bananas	0.08	-0.05	-0.27	0.07
Rainfed bananas	-0.16	-0.29	0.48	0.19**
Irrigated barley with residues left on the field	0.19**	0.19**	0.19**	0.21
Rainfed barley with residues left on the field	0.23**	0.18**	0.34	0.30**
Irrigated barley with residues removed from the field	0.32	0.25	0.15**	0.30
Rainfed barley with residues removed from the field	0.26	0.11**	0.29	0.37
Irrigated cabbages	0.34	0.19	0.03	0.20
Irrigated carrots	0.34	0.38	0.07	0.14**
Irrigated oranges	0.13**	-0.03**	-0.12**	0.09**
Rainfed oranges	-0.01	-0.28	0.31	0.19
Irrigated coconuts	-0.07	0.13	-0.28	-0.06
Rainfed coconuts	-0.21	-0.13	0.42	-0.13**
Irrigated coffee	0.06	0.45	-0.24	-0.36
Rainfed coffee	-0.18	-0.45	0.42	0.35**
Irrigated cotton	0.09**	-0.02	0.07	0.24
Rainfed cotton	0.00	-0.05	0.30	0.23**
Irrigated groundnuts	0.26**	0.38	0.18**	0.21
Rainfed groundnuts	0.27**	0.19**	0.37	0.33**
Irrigated maize with residues left on the field	0.35	0.25**	0.21**	0.21
Rainfed maize with residues left on the field	0.24**	0.19**	0.33	0.28
Irrigated maize with residues removed from the field	0.41	0.25	0.14	0.26

	Correlation residues-temperature		Correlation residues-precipitation	
Crop Type	**Scenario RCP 4.5**	**Scenario RCP 8.5**	**Scenario RCP 4.5**	**Scenario RCP 8.5**
Rainfed maize with residues removed from the field	0.24	0.11**	0.32	0.33
Irrigated palm oil	-0.31	0.34	0.36	-0.10
Rainfed palm oil	-0.23*	-0.33	0.62	-0.41
Irrigated onions	0.30	0.17**	0.03	0.12**
Irrigated potatoes	0.29	0.33	0.24**	0.26
Rainfed potatoes	0.28**	0.19**	0.37	0.31
Irrigated rapeseed with residues left on the field	0.25**	0.35	0.16	0.23*
Rainfed rapeseed with residues left on the field	0.26**	0.16**	0.36	0.32
Irrigated rapeseed with residues removed from the field	0.27**	0.36	0.17**	0.23
Rainfed rapeseed with residues removed from the field	0.27**	0.19**	0.36	0.32**
Irrigated rice	0.24**	0.22**	0.13	0.21
Rainfed rice	0.25	0.20	0.37	0.33**
Irrigated sorghum with residues left on the field	0.19**	0.14**	0.22**	0.25
Rainfed sorghum with residues left on the field	0.24**	0.17**	0.37	0.32
Irrigated sorghum with residues removed from the field	-0.14	-0.21	0.17**	0.19
Rainfed sorghum with residues removed from the field	-0.09	-0.19	0.31	0.21**
Irrigated soybeans	0.30	0.37	0.24**	0.27**
Rainfed soybeans	0.27**	0.20**	0.36	0.33
Irrigated sugar beet	0.57	0.38	0.09	0.38
Rainfed sugar beet	0.43	0.36	0.11	0.15**
Irrigated sugarcane	0.14**	0.13**	-0.35	-0.08
Rainfed sugarcane	-0.09	-0.18	0.24	0.08**
Irrigated sunflower	0.21	0.16**	0.10	0.39
Rainfed sunflower	0.20**	0.03	0.29	0.43**
Irrigated sweet potatoes	0.24**	0.40	0.11**	0.27
Rainfed sweet potatoes	0.26**	0.19**	0.36	0.32**
Irrigated tobacco	0.11**	-0.02	0.18	0.13

	Correlation residues-temperature		Correlation residues-precipitation	
Crop Type	**Scenario RCP 4.5**	**Scenario RCP 8.5**	**Scenario RCP 4.5**	**Scenario RCP 8.5**
Rainfed tobacco	0.05	-0.10	0.33	0.17
Irrigated tomatoes	0.36	0.24**	0.22**	0.24
Rainfed tomatoes	0.26**	0.18**	0.36	0.32
Irrigated wheat with residues left on the field	0.16**	0.15**	0.14**	0.26
Rainfed wheat with residues left on the field	0.25**	0.17**	0.35	0.31
Irrigated wheat with residues removed from the field	0.35	0.31	0.06**	0.33**
Rainfed wheat with residues removed from the field	0.34	0.20	0.23	0.36
Irrigated cocoa	-0.06	0.06	-0.17	-0.09
Rainfed cocoa	-0.02	-0.04	0.55	-0.18**
Irrigated grapes	0.02	-0.24	0.25	0.21
Rainfed grapes	0.11**	-0.07**	0.23	0.11
Irrigated olives	0.42	0.10	-0.15	-0.02
Rainfed olives	0.49	-0.32**	0.19	0.30
Irrigated apples	0.31	0.19**	-0.15**	0.08**
Rainfed apples	0.04	-0.27**	0.35	0.31

An overall weak, but significant, correlation can be found due to the ρ absolute values. For the RCP 4.5 and 8.5 CC scenarios, the average ρ are, respectively, for temperature, 0.17 and 0.11, and for precipitation 0.20 and 0.19. In this case, a weak correlation means that the variation of the climate variables can explain only part of the variance in the distribution of residues between regions. Other external factors can be influencing the results. However, as the results obtained for p-value indicate in general a statistically significant correlation, temperature and precipitation are in fact important factors to explain the amount of residues generated.

It is possible to analyze which of the climate variables are more correlated with residue production. In the case of RCP 4.5, 60% of LU categories (meaning 38 from all 63), have higher ρ for precipitation. For 5 crop types ρ is negative (production of residues is negatively influenced by precipitation). Under RCP 8.5, the production of residues is also slightly more correlated with precipitation, as 59% of land uses (37 out of the total 63) have a higher ρ for precipitation. Most crop types (59 out of 63) are positively correlated with precipitation. This high correlation of precipitation with residues and SOC was also studied at a regional level (Hobley et al., 2015), at a global scales (Jobbágy & Jackson, 2000), as well as the correlation between SOC residence time and precipitation (Carvalhais et al., 2014). Other studies have reported stronger relationships between SOC with temperature than with precipitation (Allen et al., 2013).

The explanation for the higher correlation with precipitation in this study may be the influence that this climate variable has on NPP in many ecosystems. Several terrestrial environments are water limited. Water limits plant growth and consequentially the input of C into the soil. Humid conditions also favor the formation of SOC, stabilizing mineral surfaces through intensified weathering of the parent material (Doetterl et al., 2015) and often cause soil acidification leading to reduced decomposition of soil organic matter (Meier & Leuschner, 2010). This does not mean that temperature is irrelevant for SOC dynamics. Temperature largely affects the microbial decomposition of SOC as its complex molecular attributes have a high intrinsic temperature sensitivity (Conant et al., 2011). As shown before, temperature is critical for results obtained for overall SOC changes under CC. Although this relationship is governed by multiple constraints, numerous studies have indicated a decrease of SOC with increasing temperatures (Koven et al., 2017; Smith et al., 2005) generally associated to negative correlations mainly due to decomposition of SOC as a response to this trend (Davidson & Janssens, 2006). These results, taken in combination, suggest that precipitation is primarily an important driver of C input into soil, while temperature is primarily an important driver of C mineralization and loss to the atmosphere.

3.1.3.3. Yield Evolution for Selected Crop Types

To analyze the yield data acquired with more detail, the same four crop types from section 3.1.2.1 were analyzed. Figure 13 and Figure 14 show the spatial distribution of results for RCP 4.5 and RCP 8.5 respectively. The figures were elaborated considering the difference between the potential yield predicted for a certain region under a determined crop type and the yield required for stabilizing SOC when applying different climate scenarios. As previously mentioned, when this ∆yield is negative, it means that the necessary yield to maintain SOC stocks from the NCC baseline is higher than what the land can potentially give. This case was represented in red and labeled as “Impossible”, because SOC loss is unavoidable through increased C inputs into soil. On the other hand, ∆yield can be positive, meaning that it is possible to increase the yield, and consequently C inputs, so that its SOC is not lost. Those cases are represented in green, having the label “Possible”.

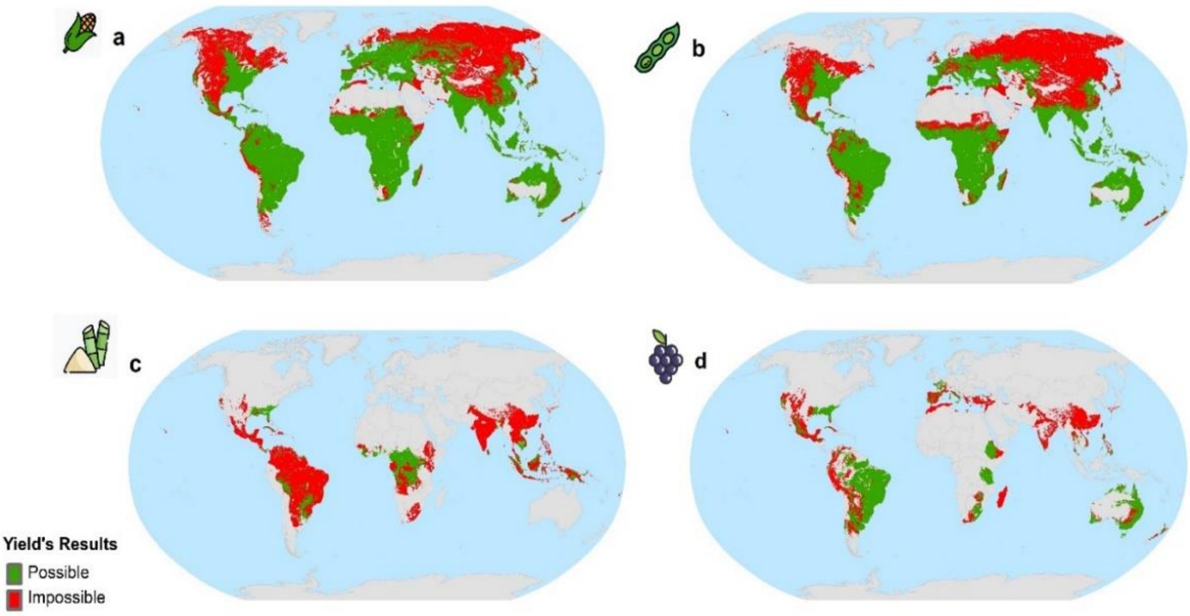

Figure 13 – Representation of the ∆yield (difference between the potential yield and the yield required for the stabilization of soil carbon under climate change (CC)).
Here (a) represents rainfed maize with residues removed from the field, (b) rainfed soybeans, (c) rainfed sugarcane and (d) rainfed grapes under the CC scenario RCP 4.5. Cases where this variable is negative are shown in red due to the impossibility to increase yields to guarantee the maintenance of SOC stocks. Cases when the ∆yield is found to be positive are depicted in green and are areas where the loss of SOC is avoidable by increasing yields.

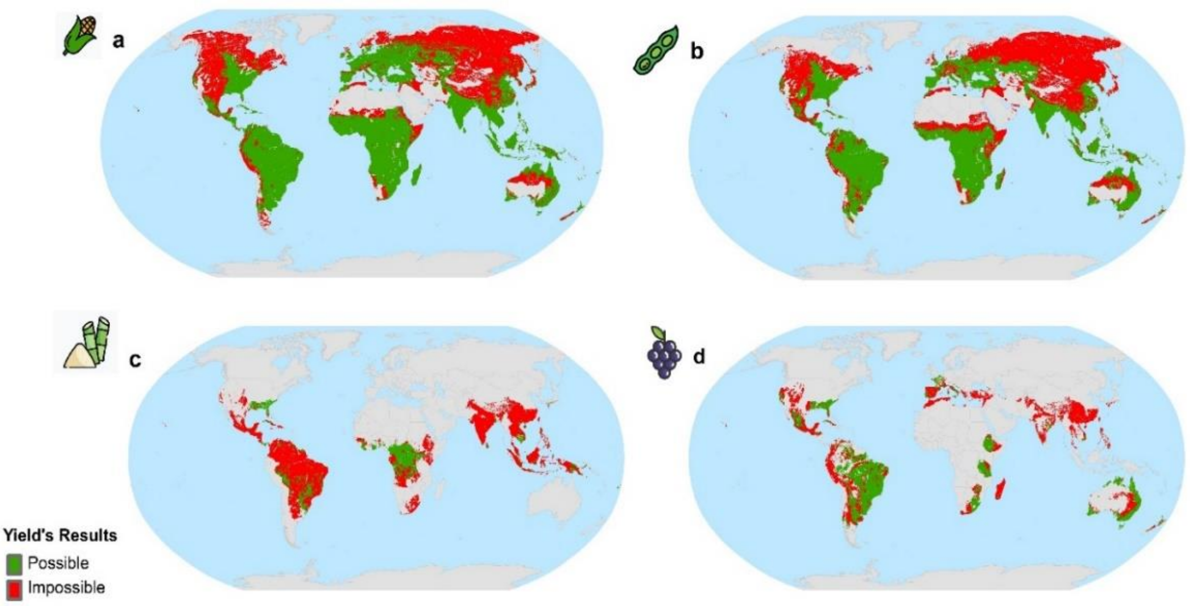

Figure 14 – Representation of the ∆yield (difference between the potential yield and the yield required for the stabilization of soil carbon under climate change (CC)).
Here (a) represents rainfed maize with residues removed from the field, (b) rainfed soybeans, (c) rainfed sugarcane and (d) rainfed grapes under the CC scenario RCP 8.5. Cases where this variable is negative are shown in red due to the impossibility to increase yields to guarantee the maintenance of SOC stocks. Cases when the ∆yield is found to be positive are depicted in green and are areas where the loss of SOC is avoidable by increasing yields.

Table 8 –summarizes the difference in yield between the potential and the required yield to maintain NCC SOC stocks results for the selected cropland systems for both climate scenarios, adding also the results per region by showing the percentage of regions where it is possible to increase yields in order

to maintain the SOC stocks (“Positive Regions”) out of the total potential regions where a certain crop type could be harvested.

Table 8 – Yield results for selected crops under both climate scenarios analyzed (RCP 4.5 and RCP 8.5). The analysis involves the difference between the yield necessary for the maintenance of soil organic carbon (SOC) where climate change (CC) acts, and the potential one (∆yield). ∆yield is the difference between the potential yield (closing yield gaps) and the NCC yield. A positive value denotes cases where it is possible to overcome the loss in SOC stocks by increasing yields, and a negative value states the opposite. The percentage of regions with a positive ∆yield was calculated by dividing the number of regions with a positive ∆yield by the total regions with potential for the existence of the crop type under analysis

	CC Scenario RCP 4.5		CC Scenario RCP 8.5	
Crop Type	Positive Regions (%)	Average ∆yield (t/ha)	Positive Regions (%)	Average ∆yield (t/ha)
Rainfed maize with residues left on the field	83	0.9	82	0.6
Rainfed soybeans	73	-5.0	72	-5.2
Rainfed sugarcane	43	-0.9	36	-1.5
Rainfed grapes	59	-0.6	56	-0.9

The most positive result among the selected cropland types was maize. In RCP 4.5 its yield can increase in 83% of the potential regions to prevent losing SOC. The difference between the potential yield and the scenario with CC is, on average, around 1 t/ha. This number conveys the capacity of this crop to maintain its SOC stocks on potential arable lands. In the areas where this cropland cannot avoid the loss of SOC, due to the new conditions imposed by CC, the average ∆yield is approximately -14 t/ha. In the green areas shown in Figure 13 (a), the average ∆yield can be as high as almost 4 t/ha. With RCP 8.5, maize is still the strongest crop when compared to the other three. In this case 82% of regions are capable of increasing yields to avoid losing SOC. However, the average difference of yields decreases to around 0.6 t/ha. This can be explained by the trend shown for extreme negative values: they decrease to almost -15 t/ha, meaning that the necessary yield to maintain SOC stocks is increasing more when compared to the potential yield of the UHTU. Adding to this is the analysis of the correlation between cropland residues and the climate variables. Maize residues are more strongly correlated with precipitation in both climate scenarios. The p-value, that translates the not randomness of the data collected, is minimum. These findings corroborate the conclusion that the results for maize are mainly due to the precipitation evolution in RCP 4.5, and in RCP 8.5, with an increasing trend.

In the case of soybeans, the result is similar, but with a slight decrease of the percentage of positive regions around the globe. This crop is capable to keep SOC stocks by increasing yields in 73% of all land where there is potential for its cultivation for RCP 4.5 and 72% for RCP 8.5. The decrease can be seen in the existing ∆yield between potential and calculated requirement. In the RCP 4.5 case the ∆yield is, on average, approximately -5 t/ha, whilst in the RCP 8.5 scenario this value decreases to around -5 t/ha. This slight decrease is not visible through the number of regions, neither from changes in extreme values. For this crop type the results previously identified are not observed in the extreme values, where the minimum increases slightly and, in the areas where there is potential for increasing yields, this capacity is similar for both RCPs. Regarding Spearman's correlation, it is possible to see higher and statistically significant precipitation correlations with both RCPs. It is possible to conclude that the cropland's residues evolution is also dependent on changes in precipitation for both CC simulated scenarios.

As previously seen for SOC and yield results, the case of sugarcane is worrisome. Here only 43% of potential regions are able to increase yield to keep SOC stocks with the RCP 4.5 CC scenario. This represents an average Δyield of -1 t/ha, showing that in areas where it is impossible to avoid losing SOC, the difference in yields is only slightly negative even though the extreme negative value can reach -4 t/ha. In the UHTUs where the necessary yield to keep SOC stocks is still below the potential one, Δyield can be only 3 t/ha. This explains why, even though it is not present in many regions, it does not have a more negative global Δyield . With the RCP 8.5 scenario, the value around the world decreases in number of regions, down to 36%. Its average Δyield also decreases to -2 t/ha, which can be explained by the abrupt decrease in the extreme negative value that reaches -6 t/ha. The positive values remain in the same order of magnitude of the previous scenario with a slight increase. Regarding the Spearman's correlation of residues with the climate variables it is possible to see that in RCP 4.5 the precipitation is the one with higher absolute ρ, whilst in RCP 8.5 the residues' evolution is more dependent on temperature. The first case shows a positive correlation. For the second CC scenario applied the correlation is negative. Adding to this fact, the values calculated to p-value show that the correlations are statistically significant.

For the grapes' case, it is possible to see that 59% of the regions enable the increase of yield to maintain SOC stocks. Like all other previous cases, RCP 8.5 does not favor this culture that sees its positive regions down to 56%. The global average for the Δyield follows the already addressed decreasing trend according to the CC scenario. This is not only due to the reduction of regions where the loss of SOC is preventable, but also from the increase gap between the potential and the required yield under CC. The negative extreme values are -5 t/ha and -6 t/ha in RCP 4.5 and RCP 8.5, respectively. Regarding the positive interval, the value is approximately the same for both scenarios. Through the Spearman's correlation results it is possible to conclude that grape residues, under RCP 4.5 scenario and RCP 8.5, are positively correlated with precipitation.

3.1.4. Overall Assessment

An overall assessment can be made for all the highlighted crops. For example, rainfed olives were highlighted due to being benefitted by expected conditions under CC. This crop also presents a positive difference between required yield for SOC stabilization and the potential, showing that an increase in productivity is possible. Analyzing the correlation of the climate variables with the residues, it is possible to conclude that even though the correlations are higher for temperature for rainfed olives, they are still far from a strong correlation. This shows that temperature and precipitation do not influence much the behavior of this crop in terms of the level of C inputs into soil. Through the figures presented for the differences of temperature and precipitation, it is possible to see that the areas where this crop has potential to grow, the differences are also not particularly significant, showing that the trend presented by rainfed olives to potentially capture C from the atmosphere, and its ability to still be able to increase its yields, cannot be correlated to the climate variables here studied.

On the opposite side, irrigated tomatoes show SOC loss if the CC scenarios are used, as well as a negative difference between required and potential yields for SOC stabilization. This shows that SOC is always lost because the necessary yield to keep it is higher than the potential that the UHTUs can provide in most regions. This crop, even though it is spread globally, also shows weak correlations for temperature and precipitation with residues. It is possible to conclude that the conditions for the settlement of this crop is willing to deteriorate unless some external factor enters in action such as fertilization.

Another case is rainfed sorghum with residues removed from the field. It is possible to see that even though the CC scenarios show decreasing SOC stocks, it is possible to stabilize those stocks by increasing yields. This happens because the necessary yield is still lower than the potential in most regions. Even though the correlations between the climate variables and the residues are weak, this crop shows a significant correlation with precipitation in both CC scenarios. By analyzing the precipitation figures, a substantial increase is expected in most of the regions where this crop can be settled.

For maize it would be necessary a significant change in yield with CC in the high latitudes in both rainfed and irrigated areas (Müller & Robertson, 2014). Maize is expected to lose more than half of its current suitable area in Andean-Amazon foothills (Beltrán-Tolosa et al., 2020). Scenarios for the future also project a loss of climate suitability areas for maize in Sub-Saharan Africa, but an expansion in Europe (Ramirez-Cabral et al., 2017). The projected increase in temperatures could have a critical negative impact on this crop's production because higher temperatures lead to reductions in the crop life cycle, light interception, growing season, grain-filling period, and fertility (Tripathi et al., 2016). This crop is then presented as having a high risk of exposure to CC, where exposure is defined by the IPCC as "the presence of people's livelihoods, environmental services, infrastructure, socioeconomic or cultural assets in places that could be adversely affected by physical events" (Field et al., 2012), making both temperature and precipitation limiting factors for growing maize in areas of low suitability (Beltrán-Tolosa et al., 2020).

3.1.5. Regional Analysis

The changes in climate are what controls the results presented here. It is then possible to see that the main results were dependent on the main climate areas that form the planet Earth. After the selection of representative crop types, maps were drawn and patterns identified, for example in Figure 13 and Figure 14.

The climate areas can be characterized as being tropical, temperate, boreal, and polar. In general, the temperate and tropical areas known for a moist climate can maintain their yields under CC without major losses of SOC, whilst the dry areas cannot. It is important to consider that the majority of Earth's desert areas were excluded from the analysis, as were the polar zones and part of the tropical dry areas (for example the Sahara Desert in Africa and the Great Sandy Desert in Australia).

Starting from the North of the globe, the first climate area present is boreal. In terms of yield, it is possible to conclude that where there is not potential for the maintenance of SOC stocks by increasing yields, like rainfed maize and soybeans. This mainly happens in parts of Russia, China, and Canada. In boreal regions, nowadays, the growing season over all stages of phenology is usually too short for cultivation (Ramankutty et al., 2002). The future for these areas, however, shows different possible outcomes. On the one hand, with the warming, induced soil C losses through mineralization are expected, which has the potential to lead to a stronger insulation of the soil in the winter and to increase soil temperatures, favoring the melting of permafrost (Gouttevin et al., 2012). Under the climate projections, it is then expected wetter areas in the boreal zone will increase (Bond-Lamberty & Thomson, 2010). This affects, consequentially, the respiration rates in high latitude ecosystems, considered to be the largest global relative change, consistent with the large C stocks in these areas (Bond-Lamberty & Thomson, 2010). All of this is likely to occur in Arctic and subarctic regions, where the potential to offset these vegetation responses is high (Crowther et al., 2016). On the other hand, there are predictions that show increases in SOC at high latitudes, presumably due to the increases in plant productivity (Koven et al., 2017), as well as the growing season productivity (Monson et al., 2006). The results here obtained show that the yield necessary to cultivate the four representative crop types is higher than the potential for those regions, which is the reason why they are in red in Figure 13 and Figure 14. An important result is that boreal areas can become an important C input for the atmosphere, representing a positive feedback for CC.

Regarding temperate regions it is possible to see optimistic results especially for rainfed maize and soybeans in Europe with some differences when the Asian continent is reached. For the Asian continent the maintenance of SOC stocks with yield increment starts to be impossible. In North America, it is possible to see that the areas under a moist temperate climate, from Michigan State to Alabama and from North Carolina to Missouri, have the a positive ∆yield while the Western areas, considered to have a dry temperate climate, have a negative ∆yield.

Tropical wet and moist regions present positive ∆yield throughout the globe for the crops under analysis apart from rainfed sugarcane. This crop, as previously mentioned, is one of the most impacted crops out of the 63 studied. North America near the states of Florida and Louisiana, and in Central Africa near Democratic Republic of the Congo, are exceptions. The variable ∆yield is positive showing a contrast between these regions and the tropical dry region. On the tropical dry regions, the conclusions are completely different since the necessary yield to maintain the SOC stocks increases so much that it surpasses the potential yield that the land can provide. Currently, in the inner tropics, the adequate temperature and moisture is present throughout the year, but soil quality often restricts cultivation due to low organic content (Ramankutty et al., 2002). One possible reason to explain this behavior is the need that this culture has to go long times with water availability and a specific temperature range (Silva et al., 2020). With the increase of climate extremes this may be compromised. Another reason may be its necessity for supplements, such as fertilizers (Václavík et al., 2013), which is not being simulated here.

The difference between temperate and tropical regions comes from the fact that temperate zones have seasonally adequate temperatures and enough precipitation and often sufficient soil, while in subtropical regions the annual distribution of precipitation strongly determines crop growth (Ramankutty et al., 2002). Mediterranean areas and subtropical ecosystems are already shaped by strong seasonality of water availability (Zabel et al., 2014). Changes in precipitation patterns with longer dry periods and more intense precipitation events are very likely (Seneviratne et al., 2012) to affect croplands and its production capacity as seen on the Figure 13 and Figure 14. In the tropics, susceptibility of the carbon cycle to climate extremes will strongly depend on the interaction with human drivers (Frank et al., 2015) such as fertilizers and irrigation. The most sensitive regions with decreasing suitability are found in the Global South, mainly in tropical regions, where also the suitability for multiple cropping decreases (Zabel et al., 2014).

The particular case of Africa is that about 20% of the agricultural suitable area is currently not used for agriculture or is statistically not recorded in the data of currently used as agricultural land (Ellis & Ramankutty, 2008). The data used here shows that there is extraordinary potential for Sub Saharan Africa for future expansion of agricultural land, especially in central areas (Zabel et al., 2014). This shows the extraordinary potential of Africa for future expansion on agricultural land (Zabel et al., 2014). The expansion of croplands would, however, always take place with ecological costs like the conversion of grassland and savannah (Zabel et al., 2014) to agricultural fields.

3.1.6. Increasing Yields Through Fertilization

The regions where it is still possible to ensure the maintenance of SOC stocks by increasing its yields and C inputs into soil were the subject of a deeper analysis. For these regions it was evaluated what impact would arise by increasing yields using fertilization. The impact of fertilization was quantified using the CO_{2eq} emissions due to their production and application on the field. The required increases in yields previously calculated necessary to maintain the SOC stocks from the NCC baseline in cases under CC were converted to their N content. It was assumed that the increase in N in biomass must be provided by fertilization and studied the case of mineral fertilizers only. With this conversion it was possible to compare the emissions of increasing the yield on the crop types per region, which are the emissions from fertilizer production and application, with the SOC that would have been depleted throughout the 87 years of simulation in case of no yield increase. The results of this analysis are in Annex IV.

The regions where the increase of CO_{2eq} emissions due to the additional required fertilizer use is lower than the loss of CO_2 due to SOC's depletion under CC, were labeled has "positive regions" and the analysis was conducted per region and per crop type. The accumulated balance per region type was made subtracting ΔSOC and the sum of all the emissions from the N-fertilizers' application at the regional level for the 87 years. For the emissions per crop type, a sum of the emissions per regions was made. Afterwards, per crop type a regional average was made where the sum of the emissions per crop type was divided by the number of regions where it was still possible to increase yields (because it is still lower than the potential).

The results show that only 17 for RCP 4.5, and 13 for RCP 8.5, out of the 63 crop types under analysis have a positive emissions' balance, i.e. it is preferable to intensify cropland production to the extra production of residues despite emissions from increased fertilizer production and application. This means that strategies proposing the closure of yield gaps, despite potentially being positive for SOC conservation, may backfire due to the emissions from fertilizers used to increase yields. It is also shown that increasing yields would mean to increase CO_{2eq} emissions between 37 and 21,000 t CO_{2eq}.year/ha for both RCP's when the average per region was made, for the entire 87 years analyzed according to the crop type. This analysis is dependent on crop types and it is important to highlight that there are crop types that have a positive balance. These crop types show that between 32 and 1,525 t CO_{2eq}.year/ha can be avoided through intensification. It is interesting to highlight that even though RCP 4.5 has more crop types where the balance between emissions with fertilizers, and without, contributes more towards a negative feedback to CC, it is for RCP 8.5 that average emissions are lower. This happens because under RCP 8.5 there are more regions and crop types where the loss of SOC stocks is unavoidable. This means that they do not enter this simulation. As the difference in yields is not highly significant, by having less regions count towards the average, under RCP 8.5 the emissions using fertilizers are less impactful.

The crop type that has the worst performance regarding the introduction of fertilizers under the influence of RCP 4.5 is irrigated maize with no removal of residues (where the average emissions per region of CO_{2eq} is around 21,000 t CO_{2eq}.year/ha) and, for RCP 8.5, it is irrigated soybeans (where the average emissions per region of CO_{2eq} was around 17,000 t CO_{2eq}.year/ha). These two crop types, in the yield analysis, showed that most of the regions (71 and 72%) were able to avoid losing SOC stocks by increasing yield. These results now show that the use of mineral fertilizers cannot be the solution due to the emissions' increase when compared to the loss of SOC stocks. Rainfed sweet potatoes, for both RCPs, is the crop type with the most positive result. Using fertilization to increase yields avoids the emission of 1,500 t CO_{2eq}.year/ha under RCP 4.5 and 1,300 t CO_{2eq}.year/ha for RCP 8.5 when the average per region is made. Previously, on the analysis of SOC stocks, the loss was around 25% of its global SOC stocks. This crop type also showed that most of the regions (76 and 73%) could increase their yields to guarantee the maintenance of baseline SOC stocks.

Optimizing the N-inputs in agroecosystems may be an effective strategy for reducing GHG emissions and improving C sequestration (Jiang et al., 2019), but only in some regions and for some crop types. For example comparing the results from the cropping of rice in two different provinces of China, in one of them the use of N-fertilizers increased the C-footprint (Jiang et al., 2019) whilst the other was a C-sink (C. Li et al., 2019). These results strongly suggest that the use of intensification strategies towards the closure of yield gaps should weigh possible rebounds such as the fact that more C may be emitted simply from producing fertilizers than accepting the loss of SOC, besides other negative effects of excessive N input on GHG emissions. Management strategies should be reexamined in relation to crop production and GHG mitigation.

3.1.6.1. The Effects of Intensification for Selected Crop Types

To compare previous results for the 4 selected crops, Table 9 was elaborated. The evolution of ΔSOC (which is the difference between the accumulated SOC from the CC scenario and the NCC one throughout the 87 years of simulation), Δyield (the difference between the potential yield predicted for a certain region under a determined crop type and the yield calculated when applying different climate scenarios) and finally the results obtained for the fertilizer's' application are here summarized. The calculation of the average regional balance between fertilizer use and potential SOC depletion was calculated only for regions with positive Δyield even when the global average Δyield is negative for that crop.

Table 9 – Accumulated emissions of N-fertilizers' production and application for certain crop types under the influence of both climate change (CC) scenarios (RCP 4.5 and RCP 8.5) for the 87 years of simulation.
The variable ΔSOC is the difference between the accumulated SOC under CC and NCC, showing a positive value when an increase in SOC stocks occurs, and a negative value where SOC is lost. The variable Δyield states the difference between the potential and the required CC yield, showing a positive value when it is possible to overcome the loss of SOC by increasing yields, and a negative value affirms the opposite. A balance of CO_{2eq} emissions using N-fertilizers per crop type was made to assess the overall balance per crop type (adding all the avoided emissions from SOC stabilization previously calculated and subtracting the sum of the emissions from the use of fertilizers for all regions) and per region (dividing the previous sum by the total number of regions where the CC yield was lower than the potential yield). When a positive value is found the increase in yields avoids more emissions than the additional emissions due to N-fertilizers.

	CC Scenario RCP 4.5			CC Scenario RCP 8.5		
Crop Type	ΔSOC (t C/ha)	Δyield (t/ha)	Average Regional Balance (tCO_{2eq}.year/ha)	ΔSOC (t C/ha)	Δyield (t/ha)	Average Regional Balance (t CO_{2eq}.year/ha)
Rainfed maize with residues left on the field	-498	0.9	-3,481	-540	0.6	-5,217
Rainfed soybeans	-708	-5.0	-2,622	-754	-5.2	-14,888
Rainfed sugarcane	-1,148	-0.9	1,287	-1147	-1.5	-1,947
Rainfed grapes	-336	-0.6	-1,630	-365	-0.9	-599

Maize is the only crop on the previous table that has a positive global average Δyield for both CC scenarios. This demonstrates the possibility to use the increment of yields to avoid the SOC loss. However, the application of N-fertilizers, and therefore an intensification of this crop, is globally on average worse. As Table 9 shows, the application of fertilizers is prone to contribute to a rebound for this crop type as the CO_{2eq} emissions would increase by using them in comparison to allowing SOC to be depleted.

Sugarcane was previously identified as one of the crops that would suffer the most from SOC loss globally. This statement is due to the negative ∆yield presented, which shows that the required yield to not lose the SOC stocks is already higher than the potential one. However, in the UHTUs where ∆yield is positive, the application of fertilizers would result in less CO_{2eq} emissions than emissions from SOC mineralization due to CC without intensification.

Soybeans and grapes have similar results. These crops are subject to the loss of SOC, as well as a global negative ∆yields. This negative ∆yield shows that, in general, the required yield to avoid losing SOC is already higher than the potential. Even in regions where ∆yield is positive, the use of fertilizers to increase yields would never be worthwhile as it generates an increase of CO_{2eq} emissions when compared to the potential loss of SOC.

3.1.7. Main Limitations

Some limitations were found for the work here developed. It is important to highlight how unpredictable the evolution of CC may be. All variables accounted for the RCP's formulation can take different paths according to not only agreements done between countries (like the Kyoto Protocol or Paris Agreement), but also the feedbacks that nature can give locally. Nature is then one of the biggest uncertainties identified and, consequently, the patterns of precipitation and temperature can be completely different from the ones used here. As a result, conclusions taken from SOC and yield trends can only be considered a possible path if the climate trend is like the one considered here.

Regarding the simulation *per se*, there are multiple improvements that could be done to achieve results closer to reality. For example, the effect of soil type on yield and mineralization should be introduced into the model. It is known that different soil types retain differently water, organic matter, important minerals and gases for plants development (Bruun et al., 2015) which can have a significant impact on SOC stocks and, consequently, on yields. This would require using models that simulate more processes than RothC or expanding the current version of this model.

In terms of crop types, only croplands were considered and not forests and grasslands. Forests are important both in terms of aboveground carbon stocks and carbon uptake (Frank et al., 2015). The future path that they will take in terms of SOC is, then again, uncertain. They can either have the largest net effects on the terrestrial carbon balance compared to other ecosystems (Frank et al., 2015) because they have large SOC stocks, or forested areas can be less impacted by CC in terms of SOC stock when compared to agricultural lands (Caddeo et al., 2019) due to mainly multicultural systems (Jarecki & Lal, 2003). The doubt is the same as with agricultural lands, but, as previously seen, it depends on the site under study, the climate zone and the meteorological activity, as well as the fertilization (Prietzel et al., 2016). Despite the increased pressure for resources represented in all future scenarios, future increases in agricultural land and decreases in forest area may be avoidable because is now known that additional agricultural land use can reduce carbon storage and reduce forest habitat for biodiversity can have other negative impacts on ecosystem services (Sala et al., 2000). Potential reductions in agricultural land and gains in forest could do the opposite (Pereira et al., 2010).

As croplands are the only land use under simulation here, two other limitations arise: the missing fertilization scenarios and management techniques. In croplands, many climate extreme impacts can theoretically be mitigated through management. Even within the same year, for example increased irrigation may enhance root biomass production, microbial activity and erosion rates, leading to increased or decreased SOC stocks (Reichstein et al., 2013) depending on which process has more significance. It can also be done through longer term adaptation, using, for example, drought- and/or heat-resistant cultivars (Frank et al., 2015), or regular harvesting and soil treatment makes long-term biological legacy effects of climate extremes more unlikely than in forests or grasslands (Reichstein et al., 2013). The extent of human interventions present another great uncertainty in assessing the impact of climate on the carbon balance of croplands (Porter & Semenov, 2005).

As humanity and its needs are increasing at a high rate (Alexandratos & Bruinsma, 2012; Pugh et al., 2016), LUC is happening constantly and, therefore, it can have an impact on the results here presented. However, future LUC scenarios under CC for the evolution of individual crops were unavailable at the time that this thesis was written, which is the reason why it is not contemplated in this study. But, has previously mentioned, it can have a serious impact on the overall C budget for the planet Earth.

After the understanding that the climate variables trigger drastic changes in SOC dynamics, there was the necessity to understand what stabilization of SOC could mean. As previously mentioned, three different ways were tested but only one, the test done using the approach that computed SOC using the integral (i.e. equalization of average SOC across the 87 years), produced results. This happened because the algorithm developed here was unable to find a solution due to the regressive yearly adjustment where the objective was to see how the curve from SOC would adjust if the SOC in the year 2100 was equal to the NCC scenario. In the case of the yearly adjustment this was unrealistic due to the existence of a wide difference between SOC in the NCC scenario and the calculated SOC under CC. The approach considered more accurate, due to the minimal differences between the baseline scenario and the predicted one, was the first mentioned. This is a limitation because a comparison between methods would enrich the analysis.

The understanding of the influence of climate variables on the results faces also a limitation. The method chosen to assess the relationship between the climate variables and the evolution of yield gaps, and residues, was the Spearman correlation. The limitation arises because crop-specific parameters and calculation methods were used, meaning that the results obtained for yields are not directly comparable. In the case of residues, the results can be compared between crop types because these represent the C that enters directly into the soil, independently of which crop type is under simulation. Therefore, a direct conclusion about the influence of climate in yield gap was not attainable.

Another aspect is the fact that results cannot be fully analyzed by region due to the extensive research area and division in approximately 17,000 UHTUs. Certain regions with micro-climates can see their results diluted in the trend presented by the majority.

Discussing now more technical issues, the validation of RothC for 2100 can be questioned considering that it was calibrated for the early 2000's. The same happens for water needs calculation where the coefficient kc is constant from 2005 to 2100, even though some crops may be modified and change this parameter throughout the years to readjust their necessities. The choice to keep it constant was made so that all scenarios could be comparable (NCC, RCP 4.5 and RCP 8.5), changing only precipitation and temperature. As the uncertainty about CC is a parameter that cannot be dissociated from the analysis throughout this work, it is important to highlight that some regions may keep their climate conditions when subjected to all three simulations. As a conservative measure, the approach of maintaining the calibration and the coefficient equal from early years until the end of the simulation was considered the most suited for the case under study.

3.1.8. Future Work

For future approaches to the same topic, the limitations identified should be introduced into the model chosen to perform the simulation which will probably require more detailed and advanced modelling. Regarding CC, a clear definition of the extreme conditions should be set (e.g. by a return interval), a consistent classification of resulting extreme impacts, in particular, indirect effects need to receive increased atention given the complexity of the mechanisms involved and the lack of current studies (Frank et al., 2015). The research should also be encouraged to characterize a broad range of possible future climate conditions giving more attention to evaluating adaptation needs and strategies, exploring mitigation options, and improving understanding of potentially large feedbacks (that is, impacts of CC such as melting of permafrost or dieback of forests that cause further changes in climate) (Moss et al., 2010).

The expansion of agricultural land into forested or protected areas must be viewed critically, in order to conserve valuable ecosystem services like for regulating climate or conserving biodiversity (Tilman et al., 2011). LUC should be taken into consideration not only because of the dynamics of afforestation and deforestation, but also because there may be transformations of cropland between crop types. As shown here, different crops can have drastically different patterns of SOC dynamics, which means that “agriculture” should not be considered a homogeneous class in any future modelling studies.

Here it was shown that, when SOC is considered, there will be a greatly reduced capacity to intensify crop production beyond current levels through efforts to close the yield gap on existing croplands. Intensification of production on current croplands appears highly unlikely to be able to meet growing global demand over the next decades without further emissions. Highly developed countries, where yield gaps are already very small, may face difficulties in sustaining current production without new technological interventions to increase attainable yield, for example, breeding novel crop cultivars (Licker et al., 2010; Pugh et al., 2016).

Providing strategies and incentives for the adoption of the recommended management practices to increase crop yield could enhance food security and contribute to climate equity while increasing croplands SOC and mitigating climate change (Lal, 2004), which has been shown to have positive results in China (Deng et al., 2017; Fulu Tao et al., 2019; Zhao et al., 2018). For this purpose, the overall sustainability assessments concerning management practices aiming for SOC accumulation in croplands are needed (Fulu Tao et al., 2019). Practices for SOC accumulation should be implemented to improve the inherent soil yield, while nutrients input or fertilization management should be adjusted in accordance with the temporal and spatial changes of SOC in recent decades to optimize fertilizer application (Fulu Tao et al., 2019). Application of fertilization should be optimized to increase crop yield while minimizing environmental cost (Zhang et al., 2016) because, even though fertilizers are needed to increase food production, a growing concern is arising from the impact of industrial N-fertilizer production. It has become difficult to ignore the impact associated to global warming that this industry has. Almost all N-fertilizers are fixed on a large scale using the Haber-Bosch (H-B) ammonia synthesis process via reaction of N with hydrogen in the presence of a catalyst (Riesbaum et al., 2012). This process consumes approximately 1–2% of the world's total energy, and emits 830 megatons of CO_2 annually (IEA, 2019), hence a decarbonization of this process should be assessed. If the production of fertilizers was fully decarbonized, then results presented here would change as the additional emissions from fertilization would be zero, and therefore avoiding emissions from SOC depletion would always be a climate-positive measure.

3.2. <u>RothC Calibration for Portuguese Unfertilized Pastures</u>

3.2.1. *Parameter Analysis*

From Figure 15 it is possible to see all parameters (RS ratio, time fraction, LI and DPM/RPM ratio) found from all 100 iterations made by the model for unfertilized pastures and, in Figure 16, the results for the same parameters for fertilized pastures. The "best" value of each parameter, namely the one with the lowest score, is highlighted in orange. That set is the one that minimizes the imposed stopping conditions. For RS, the results are approximately 3.2 and 2.3, 0.49 and 0.51 for time fraction spent per LstU, 0.6 for LI and 1 for DPM/RPM ratio, respectively for unfertilized and fertilized pastures. This set of parameters obtained the lowest score, close to 0.2.

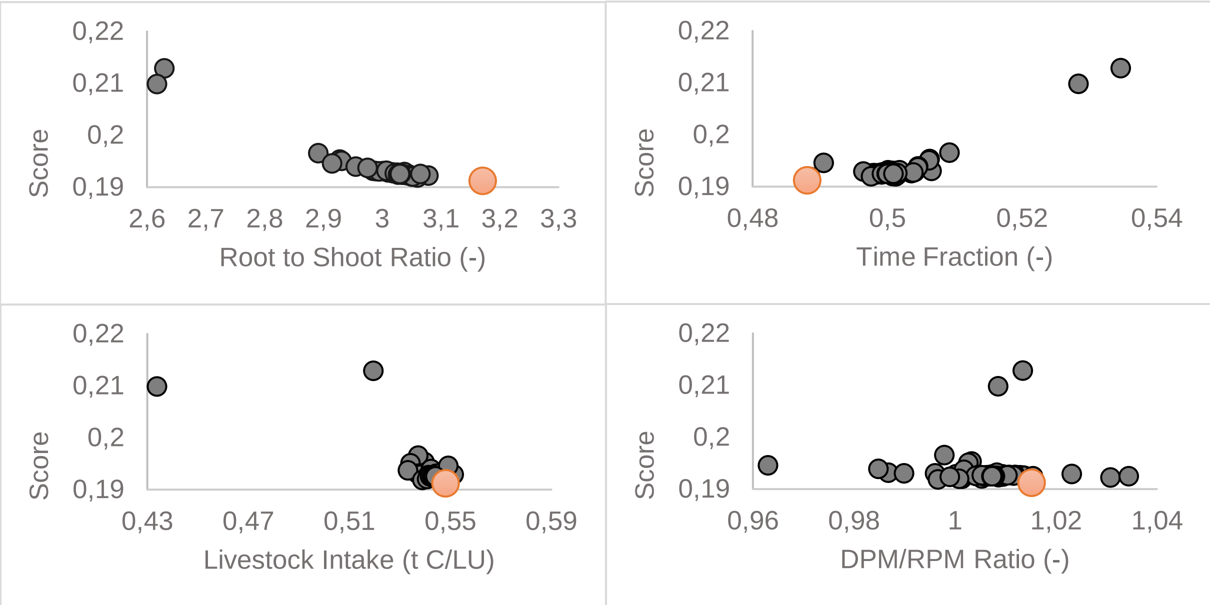

Figure 15 – Results obtained iteratively for the variables root to shoot (RS), time fraction spent by the livestock (t), livestock intake (LI) and the ratio between easily decomposable and resistant plant matter (DPM/RPM ratio) as a function of the score.
This score depicts how far the error function was from the minimization criteria, for the unfertilized pastures. The set of parameters marked with an orange circle was named "best set" because it was the one that presented the lower score.

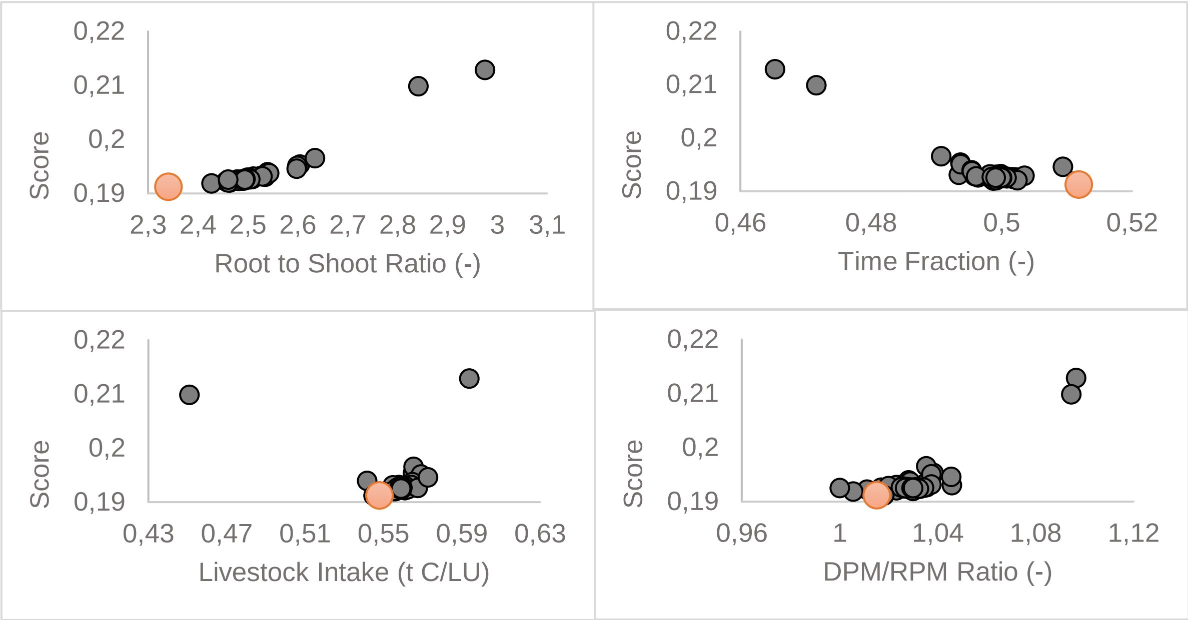

Figure 16 – Results obtained iteratively for the variables root to shoot (RS), time fraction spent by the livestock (t), livestock intake (LI) and the ration between easily decomposable and resistant plant matter (DPM/RPM ratio) as a function of the score.
This score depicts how far the error function was from the minimization criteria, for the fertilized pastures. The set of parameters marked with an orange circle was named "best set" because it was the one that presented the lower score.

The 100 iterations show a wide range of results, as well as a wide range of scores. For the case of the RS ratio, the values for this parameter are comprised within the interval of 2.6 up to 3.2 for unfertilized pastures and around 2.3 and 3 for fertilized pastures. Regarding the time that the animals spend on each plot, the values range around 0.5 for unfertilized pastures and fertilized pastures. LI, for unfertilized and fertilized pastures respectively, is within the following intervals: from around 0.4 to 0.6, and from around 0.5 to 0.6. DPM/RPM ratio varies around 1 and 1.03 in the unfertilized pastures and fertilized pastures. Scores varied around 0.2, being the best score equal to 0.19.

The estimated parameters for each pasture type show a small dispersion when it comes to score, which is a good indicator of the method's accuracy. The existence of outliers can have several reasons. One of reasons is the fact that the data set for the estimation of parameters is relatively small. This can lead the model to make mistakes when minimizing the stop condition. If a local minimum is found, as the value is lower than the neighbors, the model is unable to exit this cycle and this set is considered to be one of the final possibilities, even though its conditions are far from the absolute minimum. Another possible explanation can come from the attribution of random numbers to initialize the iterations' loop. This may lead to sets of data that are not precise. In terms of the parameters' value *per se*, it is possible to evaluate that the changes that occur between iterations have a small dispersion also. This dispersion occurred for both pasture types and it is in the order of the decimals. The type of dispersion is different from parameter to parameter. For example, for the parameter LI the "best score" is in the middle of the variation range of the parameter, something that does not happen for DPM/RPM ratio. This means that the initialization provided by the function was farthest from the place where the stop condition was minimized for the DPM/RPM ratio's case.

When comparing both pastures under analysis, it is possible to infer that the RS ratio is more than one third higher for unfertilized pastures than in the fertilized ones. The result of approximately 3 for unfertilized pastures and 2 for fertilized pastures places these pastures between the category of "temperate grasslands" (4.224) and the "tropical/sub-tropical grassland" (1.887) according Mokany et al. (2006). Plants with a higher proportion of roots can compete more effectively for soil nutrients, while those with a higher proportion of shoots can collect more light energy. A correct utilization of fertilizer can increase pasture production, improve pasture quality, increase seasonal pasture availability, improve tolerance of pastures to grazing and drought, reduce weed levels due to pasture competition, improve pasture water use efficiency and potentially increase stocking rate help to reduce runoff and erosion, amongst many other advantages (Havilah et al., 2005). This happens because, for optimum pasture growth, all essential nutrients must be present in the sufficient amounts. If any nutrient is deficient, pasture growth is limited by this deficiency, even if all other nutrients are in abundance (Havilah et al., 2005). The fact that fertilized pastures had a lower RS can mean that, because N was provided, the plant did not need to develop their root systems as much to access N from the soil.

LI was the same for both pasture systems, around 0.6. For this simulation, the same animals were grazing in both plots it is then normal that the intake is the same. The difference could come from the time they choose, or are obliged, to spend in each type of pasture.

The fraction of time that each LstU spent in the fertilized fields is slightly higher (0.51) than in the unfertilized ones (0.49). This can occur because, as mentioned previously, fertilized pastures can have reduced levels of weeds and more grass production. The animals may then prefer to spend most of their time at a field where their needs are suppressed more easily due to the higher availability of grass per unit area.

For the DPM/RPM ratio, the value is approximately the same for both type of pastures (around 1 for both). The explanation for this can come from the presence of the same species on both pasture types even though the management choices applied to the fields are different. The ratio between easily decomposable and resistant plant material can be kept approximately the same consequently. The results are close to the default for croplands and improved grasslands, which is equal to 1.44 (Coleman et al., 2014).

The results obtained by Morais, et al. (2018), using the same methodology, for a specific type of improved grassland, namely sown biodiverse pastures rich in legumes, reached values that corresponded to a "temperature arid shrubland" (an RS ratio and DPM/RPM ratio approximately equal to 1, and the LI equal to 0.6). Some important differences between that study and this thesis are important to point out. Morais, et al. (2018) used 8 farms to parametrize the variables which are more spread across the Mainland Portugal than the four here presented (where only one can be considered as a spatial outlier). The original data was available for 5 years, whilst here, for the parametrization, data was collected from only 3 years, and only 1 year was used for the model's calibration and two for validation. Besides these reasons, the animals involved in both studies were different for both studies. If all of this is weighted and considering that the pasture systems were different, the discrepancies in values are acceptable and justifiable.

3.2.2. SOC Results

When using the highlighted set of parameters, SOC was calculated for all farms and pasture types in order to get a sense for the estimation errors. The results can be found in Figure 17. Here it is possible to see that there is a slight underestimation of SOC contents.

Figure 17 – Comparison of the predicted soil organic carbon (SOC) stocks obtained (marked with a black star) using the best set of parameters identified previously with the measurements made in situ (marked with an orange circle), for both pasture systems in 2003 and 2004.

The results show, considering farm 4 as an exception, that all SOC stocks increased from 2003 to 2004. Farm 4 was the exception because, even though the estimated SOC values are increasing, that trend is not followed by the measurements done in situ. This decreasing trend can occur due to the higher temperatures registered in the south of Portugal. This increase in temperature can be responsible for the acceleration of the SOC's decomposition processes. This was not foreseen by the model because all other farms see its stocks increasing.

Comparing both pasture types, it is possible to see that the SOC results are higher for unfertilized pastures than for fertilized ones. Some reasons can be pointed such as the fact that the RS ratio is higher on natural pastures. Abundant roots and litter significantly affect soil porosity, SOC, and other soil properties (Wu et al., 2010, 2016). Fine roots decompose significantly faster than coarse roots (Zhang et al., 2016) leading to the increase in SOM. Roots also favor the formation of soil pores, which influences soil properties due to change in burrowing activity and biomass of earthworms (Fischer et al., 2014) resulting in more abundant SOC. Also, the type of fertilizer used, the amounts and if it was provided in the right period to guarantee that it was not completely washed out or to avoid its percolation into the soil. These results are opposite to what was observed in China (Du et al., 2020; Lu, 2020) when comparing natural and fertilized pastures. As grasslands have so many variables to consider, this divergency can be explained because of climate, fertilizer used, management options, climate, and grazing. The extrapolations and comparisons between different case sites are, thus, hard to make.

The following Table 10 shows the results from the calculated and measured *in situ* SOC stocks for the respective farm in each year. The difference was analyzed through the variation column that states the difference between the estimated and the measured SOC, dividing by the measured one. With this approach it is possible to assess if the SOC calculated is an underestimation or an overestimation, as well as the percentage of this discrepancy.

Table 10 – Comparision between the estimated soil organic carbon (SOC) and the measured SOC for the 4 farms under analysis.
A percentual variation was also assessed as the difference between the estimated and the measured SOC, dividing then by the measured one.

		2003			2004		
		Estimated SOC (t C/ha)	**Measured SOC** (t C/ha)	**Variation (%)**	**Estimated SOC** (t C/ha)	**Measured SOC** (t C/ha)	**Variation (%)**
Unfertilized	Farm 1	27	24	10 (3 t C/ha)	30	36	-18 (-6 t C/ha)
	Farm 2	41	37	12 (4 t C/ha)	44	42	4 (2 t C/ha)
	Farm 3	8	9	-8 (-1 t C/ha)	9	10	-2 (-1 t C/ha)
	Farm 4	23	25	-7 (-2 t C/ha)	26	23	9 (3 t C/ha)
	Average			2% (1 t C/ha)	Average		-2% (-1 t C/ha)
Fertilized	Farm 1	23	22	6 (1 t C/ha)	26	32	-20 (-6 t C/ha)
	Farm 2	38	37	4 (1 t C/ha)	41	44	-7 (-3 t C/ha)
	Farm 3	6	6	9 (1 t C/ha)	6	6	3 (0.21 t C/ha)
	Farm 4	23	27	-13 (-4 t C/ha)	25	21	18 (4 t C/ha)
	Average			2% (-0.3 t C/ha)	Average		-2% (-1 t C/ha)

The score per farm, using Equation (22), was also calculated and the results are displayed in Table 11 . The estimated SOC was added for both years and pasture types under simulation, as well as the measured one.

Table 11 – Score obtained for the 4 farms under study, using the approach presented on Equation (22), where the soil organic carbon (SOC) stocks calculated as well as the measured ones were added for both years and pasture types.

Farms	Score
Farm 1	0.09
Farm 2	0.03
Farm 3	0.01
Farm 4	0.01

These values are once more corroborating the small differences obtained and re-enforcing the idea of the robustness of the method applied.

Regarding SOC's estimation, it is possible observe an average underestimation in the order of 1t C/ha between the overall estimated and measured values. The highest underestimation found was -7 t C/ha for Farm 1 in 2004, and the highest overestimation was 5 t C/ha, corresponding to Farm 2 in 2003.

- Farm 1: in this farm similar results were found for unfertilized and fertilized pastures. For 2003 the model overestimates de SOC content in 10% for unfertilized and 6% for fertilized pastures.

The opposite happens for the year 2004, where an underestimation of 18% is seen for unfertilized pastures and 20% for fertilized pastures. This farm presents an overall underestimation in the order of 8%, which in absolute terms corresponds to 10 t C/ha.

- Farm 2: here an overestimation occurs for the year 2003 in the unfertilized pasture, and the gap decreases when the year of simulation is 2004, from 12% to 4%. For fertilized pastures there is an overestimation in 2003, in the order of 4%, and an underestimation occurs for 2004, 7%. On average, for Farm 2, the trend shows an overestimation of 3%, meaning that there are 5 t C/ha in excess.
- Farm 3: the analysis of this farm's results for SOC stocks show that for unfertilized pastures an underestimation occurs, evolving from 8% to 2% in the years of 2003 and 2004, respectively. For the fertilized pastures, there is an overestimation in the order of 9% and 3% for 2003 and 2004, respectively. This farm then shows an overall overestimation of 1%, which corresponds to 0.2 t C/ha.
- Farm 4: the case of this farm is the exact opposite of what occurs for Farm 1. For the unfertilized pastures case an underestimation occurs, in the order of 7%, for the year 2003, whilst, for the year 2004, an overestimation of 9% is seen. Regarding fertilized pastures this trend is kept but with a different order of magnitude: -13% and 18% respectively for the years 2003 and 2004. On average, this farm presents a 1% overestimation, meaning that there are 0.7 t C/ha in excess in the estimated SOC values.

The differences between SOC stocks at different farms can be explained by their geographical position and their meteorological conditions. The management options done by different landowners can also influence the results. It is then possible to understand why it is so difficult to comprehend and explain the grasslands' behavior. As there are a lot of variables to consider, it is still not possible to extrapolate results from one farm to the other, or even from one year to another in an exact way. The results obtained by simulation, on average, correspond to a 1% difference between the measured and estimated values, which in absolute terms correspond to -1 t C/ha on average for all farms. The discrepancy increases when each farm is analyzed yearly.

3.2.3. Main Limitations

Due to the carbon storage potential, grasslands are getting more and more attention from the scientific community. That is the reason why the majority of work developed, and measurements, are done primarily with SOM. This variable helps to understand and quantify the amount of carbon sequestration potential that a given land has, but it is not enough to explain why this occurs for this specific ecosystem.

This work helps to fill the gaps in knowledge present in pasture's modelling studies even though the RothC model was developed originally for croplands. RothC can be considered as a relatively simple model due to the reduced number of inputs and processes simulated. The processes of SOC accumulation can require more complex and detailed models, something that another model, like Century (Parton et al., 1987), could compute with higher efficiency due to the higher number of variables and processes that are taken into account. More studies and tests should be made in order to validate the results and the approach followed. Using optimization techniques and process-based modelling it was demonstrated that it is possible to estimate the necessary parameters with only the SOM data collected *in situ*.

It is, however, impossible to extrapolate and apply the same methods for different locations and years as previously mentioned, because the conditions can vary. Some complementary techniques, like remote sensing, should receive an increasing attention (Buck et al., 2015; Turner, 2014) for application to grasslands surveys and management, as they have been rarely studied for these LU systems when compared to other land covers like crops or forest (Newton et al., 2009). The downside comes from the typical coverage that the areas where pastures are present, at least in Portugal. They are characterized by *Montado* forests, meaning that the tree cover can difficult remote data for these ecosystem types. A combination of approaches is the most preferable methodology possible.

The introduction of more production sites and years should be considered to calibrate better the model. It would then be possible to attain better results for both pasture-specific parameters and SOC. The calibration, in this case, was made using one year and 4 farms, with the objective to predict SOC for the same 4 farms and for the next 2 years. However, the collection of this type of data requires field work and the treatment of soil samples for the acquisition of SOC values.

Another important aspect to consider is the gathering of information from the same source. For SOM measurements *in situ* were made, whilst temperature and precipitation were not measured locally but rather obtained from other more general data products. This constitutes a limitation because data used in the products could have lagged in time, as well as in spatial terms, when compared to the SOM measurements.

3.2.4. Future Work

In terms of future work, it is possible to highlight that this study enables the calculation of site-specific and pasture system-specific parameters, that were not collected with the SOC measurements on site. These parameters enable a distinction of SOC dynamics for unfertilized and fertilized pastures. This is a necessary first step towards the replication of the work carried out for cropland (section 3.1) but now for grasslands, as these specific parameters do not exist in the literature for pasture systems. The approach used here to use those parameters for calculating SOC stocks of a farm also showed to be feasible considering that it had a very small deviation from what could be possibly measured *in situ*. But there is much more to be done in what pastures are concerned.

The calibration of the model should take into account more recent and more extensive data sets. More sites and longer periods should be included in order to enable the extrapolation for other study sites. Even though the gathering of SOC's data sets throughout time is hard and costly, the optimal solution can pass from combining the approach here followed with remote sensing, such as, for example, aerial visible and near-infrared photographs and/or satellite data (Morais et al., 2018).

Grasslands, as they are mainly manipulated by man, can be an important asset to consider in terms of sinking carbon (Post & Kwon, 2000). A similar study to what was conducted for croplands should be done focusing on this type of ecosystem. With a more accurate parametrization, a global analysis could be done also using CC scenarios. Besides the climate data, it would be necessary to gather information regarding grassland management (Erb et al., 2007), as well as the data for the LtsU present (Gilbert et al., 2018). All of these for the present and for the future. SOC data, for the present and future, would be required, which, besides statistical data from FAO (2017) it still does not exist.

4. Concluding Remarks

CC is bound to produce major changes in Earth's ecological cycles and reshape ecosystems. Many of the effects of CC have been estimated, and important feedbacks considered such as the loss of methane due to permafrost melting. However, the effects of CC on SOM have so far only been coarsely estimated. SOM is the largest terrestrial pool of stable C and therefore even minimal quantities of SOC stock depletion can contribute with CO_2 emissions that are likely to accelerate CC. These problems are global because CC does not have barriers.

The challenge of accurately estimating these feedbacks is different for each type of land use. For cropland, sufficient data is available to assess the effects of CC on SOC in cases without land transformation. The accumulated average loss estimated situates between 18 up to 469 t C/ha under RCP 4.5 and 48 up to 515 t C/ha for RCP 8.5. There are, however, crop types where increasing SOC is possible. Under RCP 4.5 this occurs in rainfed olives, with an accumulation of 96 t C/ha. Under RCP 8.5 rainfed cocoa and olives are responsible for an accumulation of 19 and 78 t C/ha, respectively. In 5 up to 89% of regions with arable land (interval dependent on crop type), partial or complete closure of yield gaps would ensure stability of SOC stocks and reverse the loss due to CC due to increased C inputs into soils. Climate scenarios slightly change results but play no significant role in terms of overall conclusions.

Intensification of farming for the closure of yield gaps comes with added environmental burdens. Assuming mineral fertilizers to be the source of N supporting the increased yields and considering the emissions of its production and its application, a positive feedback to CC can be found for 50 and 46 out of the 63 crop types. The emissions from using fertilizers are larger than the emissions of CO_2 from SOC depletion in the same regions in case no intensification takes place.

Grasslands have new sets of challenges to overcome. Grassland systems are extremely variable as the environmental pressures they are exposed to depend on the region, and their performance depends on multiple other factors – such as plant composition, grazing/harvesting intensity, etc. There is a general lack of data available to perform, for this type of ecosystems, the same analysis performed for cropland. This means that new approaches and methods are required before considering a study on the effects of CC for each type of grassland system. As illustrated here, approaches from machine learning can be combined with process-based modelling to overcome data limitations. This thesis showed that applying this method for Portuguese unfertilized pastures results in a deviation around of 1 t C/ha from *in situ* measurements, ranging from an underestimation of around -6.5 t C/ha to an overestimation of 4.6 t C/ha for individual farms. These discrepancies probably arise from lack of data points for statistical representability of the model, but local heterogeneity of pastures, even at regional scale, cannot be discarded. The extrapolation for other pasture systems, farms and even years is dependent of the gathering of more data and the introduction of more management parameters into the simulation.

All in all, whether the systems studied here are C sinks or sources is highly dependent on land occupation and how that land is managed, but the contribution of each factor is certain to change with CC. The complex two-way effects between CC and land management choices must be more thoroughly considered in a rapidly changing world. These management choices from tillage to fertilization, from LUC to crop choice, should have in mind the environmental factors that will be affected because the global food security is at stake. For cropland, it is no longer acceptable to consider all agricultural use types as the same, as different crops will behave differently (and SOC will respond differently) to CC, and for some it may be impossible to prevent any climate feedback even with increased C inputs to soil due to the blowback effect from fertilizer use. For grassland, there are too many unknowns as the systems vary with location and management. However, as demonstrated in this thesis, the tools for depicting the effects of CC in farmland and vice-versa are available and should be increasingly deployed.

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Appendix

Annex I – Parameters used to convert the calculated yields to N-yields for each respective crop type

Crop Type		% N content	Crop Type		% N content
1	Irrigated bananas	0.112	***33***	Rainfed rice	1.600
2	Rainfed bananas	0.112	***34***	Irrigated sorghum with residues left on the field	1.616
3	Irrigated barley with residues left on the field	1.760	***35***	Rainfed sorghum with residues left on the field	1.616
4	Rainfed barley with residues left on the field	1.760	***36***	Irrigated sorghum with residues removed from the field	1.616
5	Irrigated barley with residues removed from the field	1.760	***37***	Rainfed sorghum with residues removed from the field	1.616
6	Rainfed barley with residues removed from the field	1.760	***38***	Irrigated soybeans	6.080
7	Irrigated cabbages	0.357	***39***	Rainfed soybeans	6.080
8	Irrigated carrots	0.144	***40***	Irrigated sugar beet	0.208
9	Irrigated oranges	0.180	***41***	Rainfed sugar beet	0.208
10	Rainfed oranges	0.180	***42***	Irrigated sugarcane	0.032
11	Irrigated coconuts	0.272	***43***	Rainfed sugarcane	0.032
12	Rainfed coconuts	0.272	***44***	Irrigated sunflower	1.968
13	Irrigated coffee	1.072	***45***	Rainfed sunflower	1.968
14	Rainfed coffee	1.072	***46***	Irrigated sweet potatoes	0.112
15	Irrigated cotton	0.088	***47***	Rainfed sweet potatoes	0.112
16	Rainfed cotton	0.088	***48***	Irrigated tobacco	4.000
17	Irrigated groundnuts	2.992	***49***	Rainfed tobacco	4.000
18	Rainfed groundnuts	2.992	***50***	Irrigated tomatoes	0.140
19	Irrigated maize with residues left on the field	1.520	***51***	Rainfed tomatoes	0.140
20	Rainfed maize with residues left on the field	1.520	***52***	Irrigated wheat with residues left on the field	1.952
21	Irrigated maize with residues removed from the field	1.520	***53***	Rainfed wheat with residues left on the field	1.952
22	Rainfed maize with residues removed from the field	1.520	***54***	Irrigated wheat with residues removed from the field	1.952

	Crop Type	% N content		Crop Type	% N content
23	Irrigated palm oil	0.000	***55***	Rainfed wheat with residues removed from the field	1.952
24	Rainfed palm oil	0.000	***56***	Irrigated cocoa	0.640
25	Irrigated onions	0.272	***57***	Rainfed cocoa	0.640
26	Irrigated potatoes	0.256	***58***	Irrigated grapes	0.300
27	Rainfed potatoes	0.256	***59***	Rainfed grapes	0.300
28	Irrigated rapeseed with residues left on the field	3.136	***60***	Irrigated olives	0.380
29	Rainfed rapeseed with residues left on the field	3.136	***61***	Rainfed olives	0.380
30	Irrigated rapeseed with residues removed from the field	3.136	***62***	Irrigated apples	0.050
31	Rainfed rapeseed with residues removed from the field	3.136	***63***	Rainfed apples	0.050
32	Irrigated rice	1.600			

Annex II – Soil organic carbon (SOC) results for both climate scenarios under analysis (RCP 4.5 and RCP 8.5), showing the total accumulated SOC for the 87 years of simulation under climate change (CC), in the baseline (NCC) and the difference between both results (∆SOC).
∆SOC is the difference between the accumulated SOC under CC and the NCC scenarios. It is positive in case of increase of SOC stocks, and negative where SOC is lost. The regions where this loss occurs are denominated as "negative regions" where a percentage is made of the division of these "negative regions" by the total regions with potential for the existence of the crop type under analysis (denominated "potential regions").

Crop Type	Percentage of regions with SOC's loss (negative regions/potential ones)		Accumulated SOC NCC (t C/ha)		Accumulated SOC CC (t C/ha)		Global average ∆SOC (t C/ha) (∆SOC=SOC CC–SOC NCC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Irrigated bananas	67 (1,191/1,769)	68 (1,198/1,769)	1,576	1,580	1,520	1,502	-56	-78
Rainfed bananas	64 (1,132/1,769)	64 (1,132/1,769)	2,105	2,108	1,966	1,968	-139	-140
Irrigated barley with residues left on the field	86 (14,737/17,152)	87 (15,005/17,152)	3,829	3,841	3,167	3,126	-662	-715
Rainfed barley with residues left on the field	73 (12,566/17,152)	75 (12,830/17,152)	3,819	3,831	3,344	3,315	-475	-516
Irrigated barley with residues removed from the field	79 (3,770/4,771)	83 (3,952/4,771)	2,608	2,626	2,230	2,193	-378	-433
Rainfed barley with residues removed from the field	62 (2,960/4,771)	65 (3,100/4,771)	2,600	2,617	2,374	2,347	-226	-270
Irrigated cabbages	87 (6,522/7,505)	89 (6,712/7,505)	2,804	2,816	2,278	2,236	-526	-580
Irrigated carrots	76 (5,493/7,181)	78 (5,580/7,181)	2,662	2,670	2,312	2,273	-350	-397

Crop Type	Percentage of regions with SOC's loss (negative regions/potential ones)		Accumulated SOC NCC (t C/ha)		Accumulated SOC CC (t C/ha)		Global average ∆SOC (t C/ha) (∆SOC=SOC CC–SOC NCC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Irrigated oranges	66 (4,395/6,611)	67 (4,460/6,611)	1,915	1,919	1,795	1,775	-119	-143
Rainfed oranges	54 (3,557/6,611)	55 (3,660/6,611)	2,241	2,269	2,142	2,149	-99	-120
Irrigated coconuts	71 (654/923)	73 (672/923)	2,067	2,077	1,811	1,789	-256	-288
Rainfed coconuts	64 (594/923)	64 (587/923)	2,634	2,617	2,521	2,521	-114	-97
Irrigated coffee	100 (536/536)	100 (536/536)	1,859	1,854	1,656	1,635	-203	-219
Rainfed coffee	71 (380/536)	69 (372/536)	2,608	2,656	2,473	2,483	-135	-173
Irrigated cotton	85 (2532/2,963)	88 (2612/2,963)	1,669	1,683	1,375	1,358	-294	-325
Rainfed cotton	54 (1586/2,963)	55 (1622/2,963)	1,658	1,674	1,588	1,585	-71	-89
Irrigated groundnuts	85 (14,664/17,152)	86 (14,826/17,152)	3,555	3,567	2,837	2,795	-718	-772
Rainfed groundnuts	89	91	3,781	3,798	2,995	2,965	-787	-833

Crop Type	Percentage of regions with SOC's loss (negative regions/potential ones)		Accumulated SOC NCC (t C/ha)		Accumulated SOC CC (t C/ha)		Global average ∆SOC (t C/ha) (∆SOC=SOC CC–SOC NCC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5 (15,245/17,152)	RCP 8.5 (15,538/17,152)	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Irrigated maize with residues left on the field	88 (15,057/17,152)	89 (15,304/17,152)	3,865	3,878	3,080	3,031	-785	-847
Rainfed maize with residues left on the field	75 (12,866/17,152)	77 (13,132/17,152)	3,842	3,854	3,344	3,314	-498	-540
Irrigated maize with residues removed from the field	87 (4,602/5,320)	89 (4,728/5,320)	2,571	2,587	2,114	2,081	-457	-506
Rainfed maize with residues removed from the field	62 (3,306/5,320)	65 (3,446/5,320)	2,560	2,575	2,357	2,332	-203	-243
Irrigated palm oil	82 (60/73)	82 (60/73)	1,753	1,756	1,735	1,708	-18	-48
Rainfed palm oil	78 (57/73)	78 (57/73)	1,958	1,965	1,819	1,792	-139	-173
Irrigated onions	92 (2,811/3,042)	92 (2,796/3,042)	2,357	2,345	2,062	2,028	-295	-317
Irrigated potatoes	81 (13,878/17,152)	82 (14,053/17,152)	3,509	3,520	2,861	2,819	-649	-701
Rainfed potatoes	83 (14,235/17,152)	85 (14,561/17,152)	3,687	3,702	2,995	2,965	-692	-737

Crop Type	Percentage of regions with SOC's loss (negative regions/potential ones)		Accumulated SOC NCC (t C/ha)		Accumulated SOC CC (t C/ha)		Global average ∆SOC (t C/ha) (∆SOC=SOC CC–SOC NCC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Irrigated rapeseed with residues left on the field	80 (13,770/17,152)	81 (13,950/17,152)	3,708	3,716	3,137	3,092	-571	-623
Rainfed rapeseed with residues left on the field	78 (13,396/17,152)	80 (13,686/17,152)	3,896	3,908	3,344	3,314	-552	-594
Irrigated rapeseed with residues removed from the field	80 (13,706/17,152)	81 (13,880/17,152)	3,402	3,412	2,786	2,741	-617	-671
Rainfed rapeseed with residues removed from the field	77 (13,272/17,152)	79 (13,527/17,152)	3,592	3,606	2,994	2,964	-597	-642
Irrigated rice	98 (16,864/17,152)	99 (16909/17,152)	4,008	4,027	2,792	2,748	-1,216	-1,279
Rainfed rice	95 (16,291/17,152)	96 (16,397/17,152)	4,002	4,021	2,995	2,965	-1,007	-1,056
Irrigated sorghum with residues left on the field	92 (15,729/17,152)	94 (16,072/17,152)	4,027	4,041	3,218	3,181	-809	-860
Rainfed sorghum with residues left on the field	85 (14,579/17,152)	87 (14,923/17,152)	4,020	4,034	3,344	3,315	-676	-719
Irrigated sorghum with residues removed from the field	63 (3,703/5,878)	66 (3,889/5,878)	1,963	1,992	1,686	1,681	-277	-311
Rainfed sorghum	52	54	1,959	1,988	1,877	1,882	-83	-106

Crop Type	Percentage of regions with SOC's loss (negative regions/potential ones)		Accumulated SOC NCC (t C/ha)		Accumulated SOC CC (t C/ha)		Global average ∆SOC (t C/ha) (∆SOC=SOC CC–SOC NCC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
with residues removed from the field	(3,056/5,878)	(3,195/5,878)						
Irrigated soybeans	80 (13,768/17,152)	81 (13,952/17,152)	3,462	3,473	2,809	2,764	-653	-710
Rainfed soybeans	85 (14,660/17,152)	87 (14,965/17,152)	3,703	3,719	2,995	2,965	-708	-754
Irrigated sugar beet	96 (2,931/3,058)	98 (2,996/3,058)	4,198	4,200	3,356	3,275	-842	-925
Rainfed sugar beet	78 (2,381/3,058)	79 (2,428/3,058)	4,160	4,161	3,615	3,556	-545	-605
Irrigated sugarcane	100 (4,000/4,018)	100 (4,000/4,018)	3,504	3,505	1,745	1,724	-1,760	-1,782
Rainfed sugarcane	98 (3,944/4,018)	98 (3,920/4,018)	3,300	3,312	2,152	2,164	-1,148	-1,147
Irrigated sunflower	56 (2,645/4,754)	57 (2,720/4,754)	2,440	2,440	2,205	2,167	-235	-273
Rainfed sunflower	59 (2,797/4,754)	62 (2,953/4,754)	2,625	2,660	2,340	2,318	-285	-342
Irrigated sweet potatoes	93 (15,957/17,152)	93 (15,966/17,152)	3,430	3,440	2,639	2,584	-791	-856

Crop Type	Percentage of regions with SOC's loss (negative regions/potential ones)		Accumulated SOC NCC (t C/ha)		Accumulated SOC CC (t C/ha)		Global average ∆SOC (t C/ha) (∆SOC=SOC CC–SOC NCC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Rainfed sweet potatoes	82 (14,071/17,152)	84 (14,380/17,152)	3,647	3,662	2,995	2,965	-652	-697
Irrigated tobacco	70 (7,427/10,641)	72 (7,663/10,641)	2,159	2,175	1,878	1,864	-281	-311
Rainfed tobacco	52 (5,492/10,641)	54 (5,766/10,641)	2,163	2,179	2,083	2,076	-80	-103
Irrigated tomatoes	94 (16,189/17,152)	96 (16,426/17,152)	3,706	3,722	2,703	2,652	-1,003	-1,069
Rainfed tomatoes	82 (14,005/17,152)	83 (14,284/17,152)	3,670	3,685	2,995	2,965	-675	-720
Irrigated wheat with residues left on the field	91 (15,619/17,152)	92 (15,712/17,152)	3,861	3,869	3,124	3,082	-738	-788
Rainfed wheat with residues left on the field	74 (12,654/17,152)	75 (12,909/17,152)	3,841	3,853	3,344	3,314	-498	-538
Irrigated wheat with residues removed from the field	80 (6,329/7,892)	82 (6,466/7,892)	3,429	3,442	2,890	2,844	-539	-598
Rainfed wheat with residues removed from the field	67 (5,272/7,892)	69 (5,445/7,892)	3,458	3,475	3,025	2,992	-433	-483
Irrigated cocoa	100	100	2,358	2,344	2,005	1,977	-353	-368

Crop Type	Percentage of regions with SOC's loss (negative regions/potential ones)		Accumulated SOC NCC (t C/ha)		Accumulated SOC CC (t C/ha)		Global average ∆SOC (t C/ha) (∆SOC=SOC CC–SOC NCC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5 (286/286)	RCP 8.5 (286/286)	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Rainfed cocoa	78 (223/286)	71 (202/286)	2,984	2,929	2,940	2,948	-44	19
Irrigated grapes	55 (2,693/4,874)	57 (2,774/4,874)	2,192	2,220	2,084	2,095	-108	-125
Rainfed grapes	83 (4,049/4,874)	83 (4,056/4,874)	2,176	2,203	1,840	1,839	-336	-365
Irrigated olives	100 (236/236)	100 (236/236)	1,487	1,489	1,334	1,309	-153	-180
Rainfed olives	31 (74/236)	31 (73/236)	1,643	1,639	1,739	1,718	96	78
Irrigated apples	100 (4,388/4,394)	100 (4,394/4,394)	1,948	1,954	1,646	1,617	-301	-337
Rainfed apples	62 (2,724/4,394)	63 (2,776/4,394)	2,300	2,325	2,132	2,145	-168	-180

Annex III – Yield results where it is possible to see the percentage of the regions where the potential yield is higher than the calculated required yield for soil carbon stabilization under climate change (CC) scenarios (RCP 4.5 and RCP 8.5).
The difference between these two yields was assessed individuality via ∆yield (difference between the potential yield and the yield required for the respective CC scenario), as well as the difference between yields from a scenario with no climate change (NCC) and the required yield for the respective CC scenario. If ∆yield is negative, then the loss of SOC stocks is inevitable because the yield required is higher than what the land can offer, which corresponds to the potential yield.

	Percentage of Positive Regions (positive regions / existent ones)		Average NCC Yield (t/ha)		Average CC Yield (t/ha)		Yield NCC – Yield CC (t/ha)		Average Potential Yield (t/ha)		Average ∆Yield (t/ha) (∆yield=yield potential–yield CC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
Crop Type	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Irrigated bananas	59 (530/905)	56 (510/905)	0,07	0,07	0,79	0,96	-0,72	-0,89	0,29	0,29	-0,50	-0,68
Rainfed bananas	65 (589/905)	66 (593/905)	0,07	0,07	0,49	0,54	-0,42	-0,47	0,29	0,29	-0,20	-0,25
Irrigated barley with residues left on the field	63 (6781/10,706)	60 (6380/10,706)	0,15	0,15	2,85	3,76	-2,70	-3,61	2,57	2,57	-0,28	-1,19
Rainfed barley with residues left on the field	72 (7656/10,706)	69 (7401/10,706)	0,11	0,11	2,26	2,48	-2,15	-2,37	2,57	2,57	0,31	0,09
Irrigated barley with residues removed from the field	70 (2911/4,151)	66 (2749/4,151)	0,15	0,15	1,44	1,50	-1,29	-1,35	1,20	1,20	-0,24	-0,30

Crop Type	Percentage of Positive Regions (positive regions / existent ones)		Average NCC Yield (t/ha)		Average CC Yield (t/ha)		Yield NCC – Yield CC (t/ha)		Average Potential Yield (t/ha)		Average ∆Yield (t/ha) (∆yield=yield potential–yield CC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Rainfed barley with residues removed from the field	80 (3312/4,151)	78 (3229/4,151)	0,11	0,11	0,81	0,79	-0,70	-0,69	1,20	1,20	0,39	0,41
Irrigated cabbages	12 (644/5,496)	9 (522/5,496)	0,23	0,23	17,12	20,58	-16,89	-20,35	1,30	1,30	-15,81	-19,27
Irrigated carrots	28 (1835/6,525)	25 (1617/6,525)	0,17	0,17	11,33	12,90	-11,16	-12,73	1,40	1,40	-9,93	-11,50
Irrigated oranges	71 (3362/4,739)	68 (3207/4,739)	0,27	0,27	3,12	3,54	-2,85	-3,27	1,44	1,44	-1,68	-2,10
Rainfed oranges	75 (3537/4,739)	72 (3433/4,739)	0,19	0,19	1,28	1,53	-1,09	-1,34	1,44	1,44	0,15	-0,09
Irrigated coconuts	56 (233/415)	49 (203/415)	0,04	0,04	1,17	1,15	-1,12	-1,10	0,17	0,17	-0,99	-0,97
Rainfed coconuts	68 (284/415)	67 (280/415)	0,02	0,02	0,23	0,25	-0,21	-0,23	0,17	0,17	-0,06	-0,07
Irrigated coffee	53 (208/392)	45 (177/392)	0,01	0,01	0,12	0,19	-0,11	-0,18	0,05	0,05	-0,06	-0,14
Rainfed coffee	51	42	0,00	0,00	0,11	0,13	-0,11	-0,13	0,05	0,05	-0,06	-0,08

Crop Type	Percentage of Positive Regions (positive regions / existent ones)		Average NCC Yield (t/ha)		Average CC Yield (t/ha)		Yield NCC – Yield CC (t/ha)		Average Potential Yield (t/ha)		Average ΔYield (t/ha) (Δyield=yield potential–yield CC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5 (199/392)	RCP 8.5 (165/392)	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Irrigated cotton	28 (782/2,816)	22 (616/2816)	0,08	0,08	1,50	2,20	-1,42	-2,12	0,08	0,08	-1,42	-2,12
Rainfed cotton	52 (1461/2,816)	51 (1439/2,816)	0,06	0,06	0,71	0,61	-0,65	-0,55	0,08	0,08	-0,63	-0,53
Irrigated groundnuts	76 (9068/11,891)	73 (8719/11,891)	0,04	0,04	5,75	6,01	-5,71	-5,97	1,07	1,07	-4,68	-4,94
Rainfed groundnuts	72 (8515/11,891)	70 (8283/11,891)	0,03	0,03	4,01	4,72	-3,98	-4,69	1,07	1,07	-2,93	-3,65
Irrigated maize with residues left on the field	71 (10465/14,803)	68 (10126/14,803)	0,25	0,25	6,08	5,95	-5,83	-5,70	3,95	3,95	-2,13	-2,00
Rainfed maize with residues left on the field	83 (12323/14,803)	82 (12101/14,803)	0,17	0,17	3,01	3,36	-2,84	-3,20	3,95	3,95	0,94	0,59
Irrigated maize with residues removed from the field	67 (3397/5,045)	63 (3179/5,045)	0,25	0,25	1,87	2,20	-1,62	-1,95	1,40	1,40	-0,47	-0,80

Crop Type	Percentage of Positive Regions (positive regions / existent ones)		Average NCC Yield (t/ha)		Average CC Yield (t/ha)		Yield NCC – Yield CC (t/ha)		Average Potential Yield (t/ha)		Average ΔYield (t/ha) (Δyield=yield potential–yield CC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Rainfed maize with residues removed from the field	83 (4182/5,045)	81 (4085/5,045)	0,17	0,17	0,88	0,89	-0,71	-0,72	1,40	1,40	0,52	0,51
Irrigated palm oil	47 (15/32)	44 (14/32)	0,01	0,01	0,01	0,18	0,00	-0,18	0,01	0,01	0,00	-0,17
Rainfed palm oil	69 (22/32)	53 (17/32)	0,00	0,00	0,00	0,01	0,00	-0,01	0,01	0,01	0,01	0,01
Irrigated onions	15 (397/2,736)	12 (339/2,736)	0,04	0,04	3,49	4,15	-3,45	-4,11	0,63	0,63	-2,86	-3,52
Irrigated potatoes	55 (5693/10,420)	52 (5419/10,420)	0,61	0,61	12,65	14,87	-12,05	-14,26	2,68	2,68	-9,98	-12,19
Rainfed potatoes	58 (6032/10,420)	56 (5795/10,420)	0,47	0,47	10,79	12,47	-10,33	-12,01	2,68	2,68	-8,11	-9,79
Irrigated rapeseed with residues left on the field	57 (6151/10,831)	53 (5752/10,831)	0,10	0,10	3,66	3,86	-3,56	-3,76	1,31	1,31	-2,35	-2,55
Rainfed	63	61	0,07	0,07	2,10	2,51	-2,03	-2,44	1,31	1,31	-0,78	-1,19

Crop Type	Percentage of Positive Regions (positive regions / existent ones)		Average NCC Yield (t/ha)		Average CC Yield (t/ha)		Yield NCC – Yield CC (t/ha)		Average Potential Yield (t/ha)		Average ΔYield (t/ha) (Δyield=yield potential–yield CC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
rapeseed with residues left on the field	(6,802/10,832)	(6,567/10,831)										
Irrigated rapeseed with residues removed from the field	54 (5,877/10,831)	51 (5,504/10,831)	0,10	0,10	6,15	7,41	-6,04	-7,31	1,31	1,31	-4,83	-6,10
Rainfed rapeseed with residues removed from the field	60 (6,529/10,831)	58 (6,297/10,831)	0,07	0,07	3,82	4,96	-3,76	-4,90	1,31	1,31	-2,51	-3,65
Irrigated rice	48 (5,219/10,831)	44 (4,749/10,831)	0,13	0,13	5,87	6,31	-5,74	-6,18	1,31	1,31	-4,56	-5,00
Rainfed rice	77 (6,158/7,991)	76 (6,085/7,991)	0,16	0,16	4,29	5,82	-4,13	-5,66	2,15	2,15	-2,14	-3,67
Irrigated sorghum	70 (10,342/14,742)	67 (9,926/14,742)	0,10	0,10	6,92	8,83	-6,81	-8,72	2,72	2,72	-4,19	-6,10

Crop Type with residues left on the field	Percentage of Positive Regions (positive regions / existent ones)		Average NCC Yield (t/ha)		Average CC Yield (t/ha)		Yield NCC – Yield CC (t/ha)		Average Potential Yield (t/ha)		Average ΔYield (t/ha) (Δyield=yield potential–yield CC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Rainfed sorghum with residues left on the field	78 (11,453/14,742)	76 (11,200/14,742)	0,07	0,07	3,77	4,38	-3,70	-4,31	2,72	2,72	-1,05	-1,66
Irrigated sorghum with residues removed from the field	79 (4,523/5,757)	76 (4,352/5,757)	0,10	0,10	0,85	1,00	-0,75	-0,89	1,22	1,22	0,37	0,23
Rainfed sorghum with residues removed from the field	89 (5,128/5,757)	88 (5,063/5,757)	0,07	0,07	0,25	0,31	-0,17	-0,24	1,22	1,22	0,98	0,91
Irrigated soybeans	75 (10,289/13,663)	72 (9,897/13,663)	0,10	0,10	8,39	9,84	-8,29	-9,74	1,71	1,71	-6,68	-8,13
Rainfed	73	72	0,07	0,07	6,70	6,92	-6,63	-6,85	1,71	1,71	-4,99	-5,21

Crop Type	Percentage of Positive Regions (positive regions / existent ones)		Average NCC Yield (t/ha)		Average CC Yield (t/ha)		Yield NCC – Yield CC (t/ha)		Average Potential Yield (t/ha)		Average ∆Yield (t/ha) (∆yield=yield potential–yield CC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
soybeans	(9,999/13,663)	(9,800/13,663)										
Irrigated sugar beet	8 (233/3,043)	5 (140/3,043)	0,79	0,79	14,58	21,55	-13,80	-20,76	1,20	1,20	-13,39	-20,36
Rainfed sugar beet	35 (1,067/3,043)	32 (965/3,043)	0,45	0,45	8,47	9,29	-8,02	-8,84	1,20	1,20	-7,27	-8,09
Irrigated sugarcane	11 (422/3,937)	10 (413/3,937)	5,05	5,05	5,74	6,11	-0,68	-1,06	1,95	1,95	-3,79	-4,17
Rainfed sugarcane	36 (1,405/3,937)	36 (1,400/3,937)	2,70	2,70	2,80	3,45	-0,10	-0,75	1,95	1,95	-0,86	-1,50
Irrigated sunflower	71 (3,195/4,503)	69 (3,100/4,503)	0,10	0,10	1,31	1,34	-1,21	-1,24	0,58	0,58	-0,72	-0,76
Rainfed sunflower	68 (3,063/4,503)	66 (2,965/4,503)	0,05	0,05	0,90	1,18	-0,85	-1,12	0,58	0,58	-0,32	-0,59
Irrigated sweet potatoes	76 (7,837/10,272)	73 (7,539/10,272)	0,26	0,26	18,15	17,50	-17,90	-17,25	3,61	3,61	-14,54	-13,90
Rainfed sweet potatoes	83 (8,577/10,272)	82 (8,413/10,272)	0,17	0,17	6,61	8,07	-6,44	-7,91	3,61	3,61	-3,00	-4,47
Irrigated tobacco	52 (5,147/9,848)	47 (4,672/9,848)	0,03	0,03	0,92	1,05	-0,90	-1,03	0,31	0,31	-0,62	-0,75

Crop Type	Percentage of Positive Regions (positive regions / existent ones)		Average NCC Yield (t/ha)		Average CC Yield (t/ha)		Yield NCC – Yield CC (t/ha)		Average Potential Yield (t/ha)		Average ∆Yield (t/ha) (∆yield=yield potential–yield CC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Rainfed tobacco	68 (6,648/9,848)	65 (6,386/9,848)	0,02	0,02	0,50	0,55	-0,48	-0,53	0,31	0,31	-0,19	-0,24
Irrigated tomatoes	30 (4,393/14,549)	26 (3,798/14,549)	1,73	1,73	53,46	55,91	-51,73	-54,18	2,35	2,35	-51,11	-53,56
Rainfed tomatoes	52 (7,621/14,549)	50 (7,210/14,549)	0,98	0,98	22,85	27,58	-21,87	-26,59	2,35	2,35	-20,50	-25,23
Irrigated wheat with residues left on the field	66 (7,077/10,276)	62 (6,683/10,726)	0,36	0,36	3,67	3,74	-3,31	-3,38	2,72	2,72	-0,95	-1,02
Rainfed wheat with residues left on the field	75 (8,000/10,726)	73 (7,787/10,726)	0,21	0,21	2,18	1,97	-1,97	-1,76	2,72	2,72	0,54	0,76
Irrigated wheat with residues removed from the field	72 (5,177/7,194)	68 (4,891/7,194)	0,36	0,36	2,02	2,54	-1,66	-2,18	2,24	2,24	0,22	-0,30
Rainfed wheat with residues removed from	77 (5,560/7,194)	75 (5,408/7,194)	0,21	0,21	1,51	1,84	-1,30	-1,63	2,24	2,24	0,73	0,40

Crop Type	Percentage of Positive Regions (positive regions / existent ones)		Average NCC Yield (t/ha)		Average CC Yield (t/ha)		Yield NCC – Yield CC (t/ha)		Average Potential Yield (t/ha)		Average ∆Yield (t/ha) (∆yield=yield potential–yield CC)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
the field												
Irrigated cocoa	56 (114/202)	48 (97/202)	0,00	0,00	0,11	0,14	-0,11	-0,14	0,06	0,06	-0,05	-0,08
Rainfed cocoa	66 (134/202)	68 (138/202)	0,00	0,00	0,03	0,02	-0,03	-0,02	0,06	0,06	0,03	0,04
Irrigated grapes	75 (2,782/3,713)	73 (2,721/3,713)	0,15	0,15	1,36	1,16	-1,21	-1,01	1,14	1,14	-0,23	-0,02
Rainfed grapes	59 (2,189/3,713)	56 (2,063/3,713)	0,11	0,11	1,73	2,04	-1,62	-1,93	1,14	1,14	-0,59	-0,90
Irrigated olives	43 (85/199)	31 (61/199)	0,01	0,01	0,09	0,10	-0,08	-0,10	0,05	0,05	-0,04	-0,05
Rainfed olives	83 (165/199)	80 (160/199)	0,00	0,00	0,02	0,02	-0,01	-0,02	0,05	0,05	0,03	0,03
Irrigated apples	58 (1,971/3,391)	54 (1826/3,391)	0,23	0,23	2,89	4,02	-2,66	-3,79	1,05	1,05	-1,83	-2,97
Rainfed apples	72 (2,436/3,391)	70 (2366/3,391)	0,16	0,16	1,12	1,38	-0,96	-1,22	1,05	1,05	-0,07	-0,33

Annex IV – Results from the balance made between emissions from soil organic carbon (SOC) mineralization under climate change (CC) scenarios (RCP 4.5 and RCP 8.5) and the emissions due to the additional fertilizers needed to attain the required yield to avoid losing SOC for the 87 years of simulation.

When emissions from fertilizers production and application are higher than the avoided emissions from SOC mineralization, then that region is considered a "negative region" because the fertilizer use that supports the increase in yield would actually lead to an increase in CO_{2eq} emissions, and vice-versa. A balance per crop type was also made (adding all the emissions from the SOC previously calculated and subtracting the sum of the emissions from the fertilizers application for all regions) as well as an average per region. When a positive value is found for these two columns, it means that the increase in yields is environmentally positive because the CO_{2eq} emissions from fertilizer use are lower than the avoided emissions from the stabilization of SOC through intensification.

	Number of positive regions		Number of Negative Regions		Crop Type Balance (t CO_{2eq}.year/ha)		Average Region Balance (t CO_{2eq}.year/ha)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
Crop Type	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Irrigated bananas	357	314	173	196	17,394	116,372	33	228
Rainfed bananas	285	286	304	307	341,274	361,383	579	609
Irrigated barley with residues left on the field	2,231	1,750	4,550	4,630	-60,179,801	-52,189,308	-8,875	-8,180
Rainfed barley with residues left on the field	2,702	2,390	4,954	5,011	-60,549,778	-26,166,807	-7,909	-3,536
Irrigated barley with residues removed from the field	461	363	2,450	2,386	-42,121,879	-20,627,252	-14,470	-7,504
Rainfed barley with residues removed from the field	452	376	2,860	2,853	-19,938,094	-11,401,559	-6,020	-3,531
Irrigated cabbages	58	31	586	491	-1,674,580	-2,006,966	-2,600	-3,845
Irrigated carrots	72	78	1,763	1,539	-8,041,772	-1,920,578	-4,382	-1,188
Irrigated oranges	1,729	1,568	1,633	1,639	1,566,416	962,350	466	300
Rainfed oranges	1,382	1,321	2,155	2,112	566,842	-46,918	160	-14

Crop Type	Number of positive regions		Number of Negative Regions		Crop Type Balance (t CO_{2eq}.year/ha)		Average Region Balance (t CO_{2eq}.year/ha)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Irrigated coconuts	116	88	117	115	19,380	-170,363	83	-839
Rainfed coconuts	158	138	126	142	115,411	84,166	406	301
Irrigated coffee	34	16	174	161	-110,289	-178,230	-530	-1,007
Rainfed coffee	27	22	172	143	-229,698	92,176	-1,154	559
Irrigated cotton	352	253	430	363	25,081	-16,949	32	-28
Rainfed cotton	249	227	1,212	1,212	814,984	784,795	558	545
Irrigated groundnuts	5,803	5,165	3,265	3,554	-11,981,144	-27,679,971	-1,321	-3,175
Rainfed groundnuts	5,554	5,266	2,961	3,017	-39,382,032	-19,299,676	-4,625	-2,330
Irrigated maize with residues left on the field	2,670	2,208	7,795	7,918	-201,046,767	-141,881,424	-19,211	-14,012
Rainfed maize with residues left on the field	4,055	3,784	8,268	8,317	-42,891,817	-63,130,065	-3,481	-5,217
Irrigated maize with residues removed from the field	470	291	2,927	2,888	-44,159,523	-34,352,067	-13,000	-10,806
Rainfed maize with residues removed from the field	737	630	3,445	3,455	-87,505,831	-64,460,664	-20,924	-15,780
Irrigated palm oil	2	0	13	14	-111,153	-180,055	-7,410	-12,861
Rainfed palm oil	2	0	20	17	-14,187	-40,629	-645	-2,390
Irrigated onions	8	10	389	329	-5,458,280	-1,583,685	-13,749	-4,672
Irrigated potatoes	4,076	3,876	1,617	1,543	-4,275,964	-15,034,397	-751	-2,774

Crop Type	Number of positive regions		Number of Negative Regions		Crop Type Balance (t CO_{2eq}.year/ha)		Average Region Balance (t CO_{2eq}.year/ha)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Rainfed potatoes	4,311	4,239	1,721	1,556	-25,499,690	-2,585,112	-4,227	-446
Irrigated rapeseed with residues left on the field	2,211	1,834	3,940	3,918	-66,083,171	-77,402,434	-10,743	-13,457
Rainfed rapeseed with residues left on the field	2,416	2,180	4,386	4,387	-71,352,499	-85,009,181	-10,490	-12,945
Irrigated rapeseed with residues removed from the field	2,100	1,744	3,777	3,760	-61,902,708	-78,717,519	-10,533	-14,302
Rainfed rapeseed with residues removed from the field	2,211	1,962	4,318	4,335	-58,573,692	-45,048,407	-8,971	-7,154
Irrigated rice	3,961	3,405	1,258	1,344	-21,863,550	-23,126,643	-4,189	-4,870
Rainfed rice	4,948	4,886	1,210	1,199	-12,087,455	-11,499,604	-1,963	-1,890
Irrigated sorghum with residues left on the field	5,975	5,589	4,367	4,337	-80,581,684	-66,308,826	-7,792	-6,680
Rainfed sorghum with residues left on the field	6,515	6,275	4,938	4,925	-59,711,876	-48,443,822	-5,214	-4,325
Irrigated sorghum with residues removed from the field	1,266	1,252	3,257	3,100	-30,983,640	-43,179,412	-6,850	-9,922
Rainfed sorghum with residues removed from the field	1,453	1,490	3,675	3,573	-4,567,509	-3,525,646	-891	-696
Irrigated soybeans	4,114	3,909	6,175	5,988	-77,243,508	-165,310,714	-7,507	-16,703

Crop Type	Number of positive regions		Number of Negative Regions		Crop Type Balance (t CO_{2eq}.year/ha)		Average Region Balance (t CO_{2eq}.year/ha)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Rainfed soybeans	4,067	4,076	5,932	5,724	-196,222,433	-145,904,323	-19,624	-14,888
Irrigated sugar beet	22	19	211	121	-610 901	-1 054,459	-2,622	-7,532
Rainfed sugar beet	43	29	1,024	936	-3 020 916	-2 896,101	-2,831	-3,001
Irrigated sugarcane	369	363	53	50	643,511	544,728	1,525	1,319
Rainfed sugarcane	1,261	1,236	144	164	1,807,952	-2,726,113	1,287	-1,947
Irrigated sunflower	101	83	3,094	3,017	-30,790,250	-37,495,003	-9,637	-12,095
Rainfed sunflower	93	69	2,970	2,896	-22,879,401	-19,503,286	-7,470	-6,578
Irrigated sweet potatoes	6,545	6,249	1,292	1,290	4,482,709	3,321,144	572	441
Rainfed sweet potatoes	5,872	5,948	2,705	2,465	4,830,365	5,217,372	563	620
Irrigated tobacco	258	192	4,889	4,480	-34,829,384	-19,443,728	-6,767	-4,162
Rainfed tobacco	197	142	6,451	6,244	-15,756,638	-22,615,260	-2,370	-3,541
Irrigated tomatoes	2,936	2,674	1,457	1,124	-4,775,118	-3,093,198	-1,087	-814
Rainfed tomatoes	4,128	3,928	3,493	3,282	-282,819	-2,115,576	-37	-293
Irrigated wheat with residues left on the field	2,156	1,579	4,921	5,104	-115,791,686	-55,413,461	-16,362	-8,292
Rainfed wheat with residues left on the field	2,767	2,371	5,233	5,416	-63,475,924	-59,469,345	-7,934	-7,637
Irrigated wheat with residues removed from the field	887	572	4,290	4,319	-52,307,832	-65,916,820	-10,104	-13,477
Rainfed wheat	879	664	4,681	4,744	-112,523,872	-56,114,588	-20,238	-10,376

Crop Type	Number of positive regions		Number of Negative Regions		Crop Type Balance (t CO_{2eq}.year/ha)		Average Region Balance (t CO_{2eq}.year/ha)	
	Climate Scenario		Climate Scenario		Climate Scenario		Climate Scenario	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
with residues removed from the field								
Irrigated cocoa	13	5	101	92	-28,542	-79,838	-250	-823
Rainfed cocoa	44	39	90	99	57,539	45,669	429	331
Irrigated grapes	992	949	1,790	1,772	737,192	-786,447	265	-289
Rainfed grapes	1,259	1,078	930	985	-3,567,042	-1 236,744	-1,630	-599
Irrigated olives	20	6	65	55	-113,832	-108,172	-1,339	-1,773
Rainfed olives	13	9	152	151	114,413	102,151	693	638
Irrigated apples	1,892	1,758	79	68	588,403	677,603	299	371
Rainfed apples	1,244	1,202	1,192	1,164	1,363,372	159,980	560	68