EXTENDED ABSTRACT OF THE THESIS TO OBTAIN THE MASTER OF SCIENCE DEGREE IN ENVIRONMENTAL ENGINEERING

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

PROPONENT: Daniela Raquel Garrido Escada

SUPERVISOR: Professor Doctor Ricardo Filipe de Melo Teixeira
CO-SUPERVISOR: Engineer Tiago Gomes Morais

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 evaluated 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 tC.year/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 semi-natural 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

1. Introduction

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. 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).
Soil has a dual role as it simultaneously affects and is also affected by climate change (CC). 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 mineralization 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. 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 then depend on which process has a larger significance: increase in plant inputs to the soil or organic matter decomposition (Gottschalk et

al., 2012). There is already evidence that crop growth and yield have been notably affected by CC since the 1980s (Tao et al., 2012). SOC's response to CC is also prone to be different depending on specific crop types.

1.1. Land Use Systems

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. 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).

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).

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. 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. Grasslands can be considered as a suitable candidate for crop rotation to increase land productivity and promote sustainable agricultural management (Cui et al., 2019).

1.1.1. Croplands

To face CC, high expectations have been set for exploiting agricultural soils as sinks for atmospheric CO_2 (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).

However, natural C stocks are highly sensitive to the policy and economic conditions that drive land use (LU) and land management decisions (Lambin et al., 2001). 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.

The emissions vary also according to the crop type under exploration, reflect the geography of crop-specific expansion and the characteristics of the land (Spawn et al., 2019). For example, 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)

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).

1.1.2. Grasslands

Grasslands are, today, one of the most endangered ecosystems mainly due to land use change (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. This ecosystem covers a major share of the world's agricultural area. In Europe natural and semi-natural grasslands cover 22% of agricultural land surface (Bengtsson et al., 2019).

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. 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). This means 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.

1.2. Objectives

The goal here is to contribute to a better understanding of the potential changes that land use, CC and management will produce on global SOC stocks.

SOC is a strong determinant of soil fertility which in turn stimulates primary production (Panakoulia et al., 2017). 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. Each crop will have its SOC content assessed and analyzed. After the results' comparison between scenarios under CC and considering climate stabilization with no climate change (NCC), yields required to avoid loss of SOC were calculated. 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. 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 its production and application is higher than the estimated loss of SOC in the CC scenarios compared with the NCC scenario.

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 involved one region, namely Alentejo, in Portugal, and two specific pasture systems (fertilized and unfertilized pastures). 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). 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.

2. Materials and Methods

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

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 1, 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.

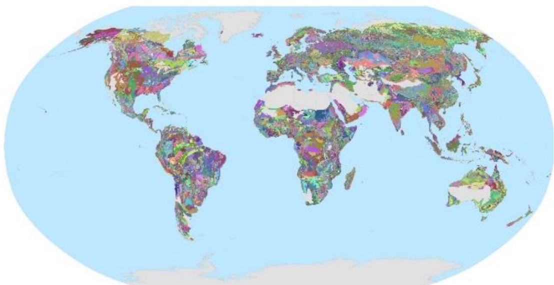

Figure 1 – Division of the simulated areas into unique homogeneous territory units (UHTUs).

2.1.2. Croplands Under Analysis

The analysis considered 63 crop types. 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 cultures which are barley, maize, rapeseed, sorghum, and wheat. For all other crops, the removal of residues is implicit.

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 International Panel for Climate Change (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 potential future possibilities (Ballantyne et al., 2012). Evaporation was calculated assuming that it is equal to two thirds of potential evapotranspiration (PET). PET was calculated using the Thornthwaite formula.

PET enables the calculation of the water needs for each crop. 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 water needs = PET * kc, 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). 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.

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).

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).

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, the function *fmincon* was used, provided by MATLAB. 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 approach 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

$$\int_{2013}^{2100} SOC_{NCC} \approx \int_{2013}^{2100} SOC_{CC}, \qquad (1)$$

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.

2.1.4. Comparison Between Yields

The potential yield for the crop types analyzed (IISA/FAO, 2012) was converted into dry matter (DM). To compare the required yield to avoid SOC loss due to CC with the potential yield, an adjustment was necessary.

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.

2.1.5. Increasing Yields Through Fertilization

For the crop types 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. 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 were gathered from Lassaletta et al. (2014).

With the N content for the CC and potential yields it was possible to apply the following fertilization response curve. 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 production used was 6.2 kg CO_{2e}/kg N (FAO, 2017). The application factor depends on the country where the fertilizer is being applied (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).

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. <u>*RothC Calibration for Portuguese Semi-Natural Pastures*</u>

2.2.1. Study Area

Figure 2 shows the location of the 4 farms considered in this work. Most of the farms under analysis, regarding semi-natural pastures, are in Alentejo's region (3 out of the 4 farms) and other one is located near Covilhã.

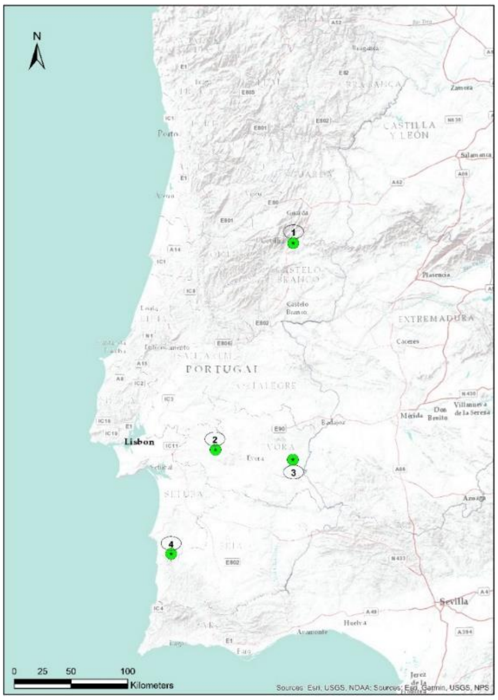

Figure 2 – Spatial localization on Mainland Portugal for the 4 farms under analysis.

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.

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

$$I_{plant}(t\,C/ha) = [(1 - LI) + RS] * AGP * CF, \tag{2}$$
and

$$I_{animal}(t\,C/ha) = LD * SR * \text{fraction of time}. \tag{3}$$

The variables in Equations (2) and (3) 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.

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 that 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 value for the parameter was selected randomly 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

$$\text{minimize} \sum_{i=1}^{n} \left(\frac{SOC_{measured,i} - SOC_{estimated,i}}{SOC_{measured,i}}\right)^2 + \sum_{i=1}^{n} \left(\frac{SOC_{measured,i} - SOC_{estimated,i}}{SOC_{measured,i}}\right), \tag{4}$$

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.
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 and Discussion

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

3.1.1. Data Analysis

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 per year.

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 climate 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 will often reduce evapotranspiration and reduce the cooling effect (Peng et al., 2014).

3.1.2. SOC Global Tendencies

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.

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% of 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 number of regions that suffer from SOC loss. 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.

It is important to highlight that the variable ∆SOC here presented is a global average for all regions with potential for the presence of each crop type. No matter what 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 ∆SOC 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 8.5, the intervals of accumulated SOC's loss are from 18 to 469 t C.year/ha, and from 48 to 515 t C.year/ha. These results can be explained by the differences in terms of annual global temperature and precipitation between the two CC scenarios. The difference in 2100 reaches almost 4 ºC and around 26 mm, for temperature and precipitation, respectively.

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) occurs, leading to the small difference between scenarios.

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; J. Smith et al., 2005).

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, per crop type and throughout the 87 years of simulation.

The regions where the loss of SOC is avoidable with an increase in yield, because the necessary yield is still lower than the potential one, are labeled as "positive regions". The number of "positive regions" was then divided by the number of regions where the crop can potentially be produced. The difference between the potential and the required yield to maintain SOC stocks is also analyzed (∆yield).

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 will not be enough to compensate for the SOC losses.
For this cropland yield analysis, a global 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. 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 (8% and 5%) and maximum (89% and 88%) values correspond to irrigated sugar beet and rainfed sorghum with residues removal, respectively. The difference between crops can be explained through the regions where the crop types are preferably settled.
The difference of yields (between required and present NCC 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 maximum difference found for the cultures where it is infeasible to maintain SOC was found for irrigated tomatoes (-51 t/ha). 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). 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 rainfed sorghum with no straw, also with approximately 1 t/year, while the minimum difference is from rainfed palm oil (0.01 t/year).
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. This shows that most crop types will not be able to maintain their SOC stocks. The number of crop types that present this characteristic decreases to 10 when RCP 8.5 is used.

3.1.4. Increasing Yields Through Fertilization

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 region 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 the 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 t $CO_{2\ eq}$.year/ha and 21,000 t $CO_{2\ eq}$.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 t $CO_{2\ eq}$.year/ha and 1,525 t $CO_{2\ eq}$.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 in 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.

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 (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.

3.2. <u>*RothC Calibration for Portuguese Semi-Natural Pastures*</u>

3.2.1. Parameter Analysis

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. 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, it will be unable to exit this cycle and this set will be considered as 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

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. 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. 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. This can lead also to the discrepancy felt on RS ration between fertilized and unfertilized pastures.

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

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 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.

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.

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.

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, 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, the tools for depicting the effects of CC in farmland, and vice-versa, are available and should be increasingly deployed.

5. References

Angers, D., & Eriksen-Hamel, N. (2008). Full-Inversion Tillage and Organic Carbon Distribution in Soil Profiles: A Meta-Analysis. *Soil Science Society of America Journal - SSSAJ*, *72*. https://doi.org/10.2136/sssaj2007.0342

Ballantyne, A. P., Alden, C. B., Miller, J. B., Tans, P. P., & White, J. W. C. (2012). Increase in observed net carbon dioxide uptake by land and oceans during the past 50 years. *Nature*, *488*(7409), 70–72. https://doi.org/10.1038/nature11299

Bengtsson, J., Bullock, J. M., Egoh, B., Everson, C., Everson, T., O'Connor, T., O'Farrell, P. J., Smith, H. G., & Lindborg, R. (2019). Grasslands—more important for ecosystem services than you might think. *Ecosphere*, *10*(2), e02582. https://doi.org/doi:10.1002/ecs2.2582

Bruun, T. B., Elberling, B., de Neergaard, A., & Magid, J. (2015). Organic Carbon Dynamics in Different Soil Types After Conversion of Forest to Agriculture. *Land Degradation & Development*, *26*(3), 272–283. https://doi.org/doi:10.1002/ldr.2205

Building, C., & Pasteur, P. (2005). *J.1365-2486.2005.001075.Pdf*. *44*(January), 2141–2152. https://doi.org/10.1111/j.1365-2486.2005.01075.x

Chapagain, a K., & Hoekstra, a Y. (2004). Water footprint of nations. Volume 1 : Main report. *Value of Water Research Report Series*, *1*(16), 1–80. http://waterfootprint.org/media/downloads/Report16Vol1.pdf

Coleman, K. and D. . J. (2014). *RothC - A model for the turnover of carbon in soil*. *June*, 1–44. papers3://publication/uuid/29E0B023-7CFB-4782-8C2C-71191AA24E43

Coleman, K., Jenkinson, D. S., Crocker, G. J., Grace, P. R., Klír, J., Körschens, M., Poulton, P. R., & Richter, D. D. (1997). Simulating trends in soil organic carbon in long-term experiments using RothC-26.3. *Geoderma*, *81*(1), 29–44. https://doi.org/https://doi.org/10.1016/S0016-7061(97)00079-7

Crowther, T. W., Todd-Brown, K. E. O., Rowe, C. W., Wieder, W. R., Carey, J. C., MacHmuller, M. B., Snoek, B. L., Fang, S., Zhou, G., Allison, S. D., Blair, J. M., Bridgham, S. D., Burton, A. J., Carrillo, Y., Reich, P. B., Clark, J. S., Classen, A. T., Dijkstra, F. A., Elberling, B., … Bradford, M. A. (2016). Quantifying global soil carbon losses in response to warming. *Nature*, *540*(7631), 104–108. https://doi.org/10.1038/nature20150

Cui, Z., Liu, Y., Huang, Z., He, H., & Wu, G. L. (2019). Potential of artificial grasslands in crop rotation for improving farmland soil quality. *Land Degradation and Development*, *30*(18), 2187–2196. https://doi.org/10.1002/ldr.3415

Davidson, E. A., & Janssens, I. A. (2006). Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. *Nature*, *440*(7081), 165–173. https://doi.org/10.1038/nature04514

Dechow, R., Franko, U., Kätterer, T., & Kolbe, H. (2019). Evaluation of the RothC model as a prognostic tool for the prediction of SOC trends in response to management practices on arable land. *Geoderma*, *337*(March 2018), 463–478. https://doi.org/10.1016/j.geoderma.2018.10.001

Erb, K.-H., Lauk, C., Kastner, T., Mayer, A., Theurl, M. C., & Haberl, H. (2016). Exploring the biophysical option space for feeding the world without deforestation. *Nature Communications*, *7*(1), 11382. https://doi.org/10.1038/ncomms11382

Falloon, P., & Smith, P. (2006). Simulating SOC changes in long-term experiments with RothC and CENTURY: model evaluation for a regional scale application. *Soil Use and Management*, *18*(2), 101–111. https://doi.org/10.1111/j.1475-2743.2002.tb00227.x

FAO. (2017). *Global database of GHG emissions related to feed crops: A life cycle inventory. Version 1. Livestock Environmental Assessment and Performance Partnership*.

Fauvel, M., Lopes, M., Dubo, T., Rivers-Moore, J., Frison, P. L., Gross, N., & Ouin, A. (2020). Prediction of plant diversity in grasslands using Sentinel-1 and -2 satellite image time series. *Remote Sensing of Environment*, *237*(July 2019). https://doi.org/10.1016/j.rse.2019.111536

Fischer, C., Roscher, C., Jensen, B., Eisenhauer, N., Baade, J., Attinger, S., Scheu, S., Weisser, W. W., Schumacher, J., & Hildebrandt, A. (2014). How Do Earthworms, Soil Texture and Plant Composition Affect Infiltration along an Experimental Plant Diversity Gradient in Grassland? *PLOS ONE*, *9*(6), e98987. https://doi.org/10.1371/journal.pone.0098987

Fischer, E. M., & Knutti, R. (2014). Detection of spatially aggregated changes in temperature and precipitation extremes. *Geophysical Research Letters*, *41*(2), 547–554. https://doi.org/doi:10.1002/2013GL058499

Fischer, E. M., Seneviratne, S. I., Lüthi, D., & Schär, C. (2007). Contribution of land-atmosphere coupling to recent European summer heat waves. *Geophysical Research Letters*, *34*(6). https://doi.org/doi:10.1029/2006GL029068

Ghimire, R., Thapa, V. R., Cano, A., & Acosta-Martinez, V. (2019). Soil organic matter and microbial community responses to semiarid croplands and grasslands management. *Applied Soil Ecology*, *141*(April), 30–37. https://doi.org/10.1016/j.apsoil.2019.05.002

Gottschalk, P., Smith, J. U., Wattenbach, M., Bellarby, J., Stehfest, E., Arnell, N., Osborn, T. J., Jones, C., & Smith, P. (2012). How will organic carbon stocks in mineral soils evolve under future climate? Global projections using RothC for a range of climate change scenarios. *Biogeosciences*, *9*(8), 3151–3171. https://doi.org/10.5194/bg-9-3151-2012

Heikkinen, J., Keskinen, R., Regina, K., Honkanen, H., & Nuutinen, V. (2020). Estimation of carbon stocks in boreal cropland soils - methodological considerations. *European Journal of Soil Science*, *July*, 1–12. https://doi.org/10.1111/ejss.13033

Hirschi, M., Seneviratne, S. I., Alexandrov, V., Boberg, F., Boroneant, C., Christensen, O. B., Formayer, H., Orlowsky, B., & Stepanek, P. (2011). Observational evidence for soil-moisture impact on hot extremes in southeastern Europe. *Nature Geoscience*, *4*(1), 17–21. https://doi.org/10.1038/ngeo1032

Houghton, R. A., & Nassikas, A. A. (2017). Global and regional fluxes of carbon from land use and land cover change 1850–2015. *Global Biogeochemical Cycles*, *31*(3), 456–472. https://doi.org/10.1002/2016GB005546

IISA/FAO. (2012). *Global Agro-ecological Zones*.

IPCC. (2006). 2006 IPCC Guidelines for National Greenhouse Inventories – A primer, Prepared by the National Greenhouse Gas Inventories Programme, Eggleston H.S., Miwa K., Srivastava N. and Tanabe K. *Iges*, 20.

Jebari, A., del Prado, A., Pardo, G., Rodríguez Martín, J. A., & Álvaro-Fuentes, J. (2018). Modeling Regional Effects of Climate Change on Soil Organic Carbon in Spain. *Journal of Environmental Quality*, *47*(4), 644–653. https://doi.org/doi:10.2134/jeq2017.07.0294

Jiang, Z., Zhong, Y., Yang, J., Wu, Y., Li, H., & Zheng, L. (2019). Effect of nitrogen fertilizer rates on carbon footprint and ecosystem service of carbon sequestration in rice production. *Science of the Total Environment*, *670*, 210–217. https://doi.org/10.1016/j.scitotenv.2019.03.188

Lal, R., Negassa, W., & Lorenz, K. (2015). Carbon sequestration in soil. *Current Opinion in Environmental Sustainability*, *15*, 79–86. https://doi.org/https://doi.org/10.1016/j.cosust.2015.09.002

Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., Coomes, O. T., Dirzo, R., Fischer, G., Folke, C., George, P. S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E. F., Mortimore, M., Ramakrishnan, P. S., Richards, J. F., … Xu, J. (2001). The causes of land-use and land-cover change: moving beyond the myths. *Global Environmental Change*, *11*(4), 261–269. https://doi.org/https://doi.org/10.1016/S0959-3780(01)00007-3

Lark, R. M., Ander, E. L., & Broadley, M. R. (2019). Combining two national-scale datasets to map soil properties, the case of available magnesium in England and Wales. *European Journal of Soil Science*, *70*(2), 361–377. https://doi.org/doi:10.1111/ejss.12743

Lassaletta, L., Billen, G., Grizzetti, B., Juliette, A., & Garnier, J. (2014). 50 year trends in nitrogen use efficiency of world cropping systems: The relationship between yield and nitrogen input to cropland. *Environmental Research Letters*, *105011*, 105011. https://doi.org/10.1088/1748-9326/9/10/105011

Le Quéré, C., Raupach, M. R., Canadell, J. G., Marland, G., Bopp, L., Ciais, P., Conway, T. J., Doney, S. C., Feely, R. A., Foster, P., Friedlingstein, P., Gurney, K., Houghton, R. A., House, J. I., Huntingford, C., Levy, P. E., Lomas, M. R., Majkut, J., Metzl, N., … Woodward, F. I. (2009). Trends in the sources and sinks of carbon dioxide. *Nature Geoscience*, *2*(12), 831–836. https://doi.org/10.1038/ngeo689

Li, C., Li, C., Han, J., Zhang, J., Wang, Y., Yang, F., Wen, X., & Liao, Y. (2019). Greenhouse gas mitigation potential of balanced fertilization cropland under double-cropping systems: a case study in Shaanxi province, China. *Environmental Monitoring and Assessment*, *191*(2), 55–60. https://doi.org/10.1007/s10661-019-7203-z

Liu, D. L., Chan, K. Y., Conyers, M. K., Li, G., & Poile, G. J. (2011). Simulation of soil organic carbon dynamics under different pasture managements using the RothC carbon model. *Geoderma*, *165*(1), 69–77. https://doi.org/https://doi.org/10.1016/j.geoderma.2011.07.005

Mauser, W., Klepper, G., Zabel, F., Delzeit, R., Hank, T., Putzenlechner, B., & Calzadilla, A. (2015). Global biomass production potentials exceed expected future demand without the need for cropland expansion. *Nature Communications*, *6*(1), 8946. https://doi.org/10.1038/ncomms9946

Minasny, B., Malone, B. P., McBratney, A. B., Angers, D. A., Arrouays, D., Chambers, A., Chaplot, V., Chen, Z.-S., Cheng, K., Das, B. S., Field, D. J., Gimona, A., Hedley, C. B., Hong, S. Y., Mandal, B., Marchant, B. P., Martin, M., McConkey, B. G., Mulder, V. L., … Winowiecki, L. (2017). Soil carbon 4 per mille. *Geoderma*, *292*, 59–86. https://doi.org/https://doi.org/10.1016/j.geoderma.2017.01.002

MOKANY, K., RAISON, R. J., & PROKUSHKIN, A. S. (2006). Critical analysis of root : shoot ratios in terrestrial biomes. *Global Change Biology*, *12*(1), 84–96. https://doi.org/10.1111/j.1365-2486.2005.001043.x

Morais, T. G., Silva, C., Jebari, A., Álvaro-Fuentes, J., Domingos, T., & Teixeira, R. F. M. (2018). A proposal for using process-based soil models for land use Life cycle impact assessment: Application to Alentejo, Portugal. *Journal of Cleaner Production*, *192*, 864–876. https://doi.org/10.1016/j.jclepro.2018.05.061

Morais, T. G., Teixeira, R. F. M., & Domingos, T. (2019). Detailed global modelling of soil organic carbon in cropland, grassland and forest soils. *PLoS ONE*, *14*(9), 1–27. https://doi.org/10.1371/journal.pone.0222604

Morais, T. G., Teixeira, R. F. M., Rodrigues, N. R., & Domingos, T. (2018). Characterizing livestock production in Portuguese sown rainfed grasslands: Applying the inverse approach to a process-based model. *Sustainability (Switzerland)*, *10*(12). https://doi.org/10.3390/su10124437

Mueller, B., & Seneviratne, S. I. (2012). Hot days induced by precipitation deficits at the global scale. *Proceedings of the National Academy of Sciences*, *109*(31), 12398 LP – 12403. https://doi.org/10.1073/pnas.1204330109

Panakoulia, S. K., Nikolaidis, N. P., Paranychianakis, N. V, Menon, M., Schiefer, J., Lair, G. J., Krám, P., & Banwart, S. A. (2017). Chapter Nine - Factors Controlling Soil Structure Dynamics and Carbon Sequestration Across Different Climatic and Lithological Conditions. In S. A. Banwart & D. L. B. T.-A. in A. Sparks (Eds.), *Quantifying and Managing Soil Functions in Earth's Critical Zone* (Vol. 142, pp. 241–276). Academic Press. https://doi.org/https://doi.org/10.1016/bs.agron.2016.10.008

Pärtel, M., Bruun, H., & Sammul, M. (2015). *Biodiversity in temperate European grasslands: origin and conservation*.

Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G. P., & Smith, P. (2016). Climate-smart soils. *Nature*, *532*(7597), 49–57. https://doi.org/10.1038/nature17174

Pendergrass, A., Wang, J.-J., & National Center for Atmospheric Research Staff (Eds). (2020). *The Climate Data Guide: GPCP (Monthly): Global Precipitation Climatology Project.* https://climatedataguide.ucar.edu/climate-data/gpcp-monthly-global-precipitation-climatology-project

Peng, S.-S., Piao, S., Zeng, Z., Ciais, P., Zhou, L., Li, L. Z. X., Myneni, R. B., Yin, Y., & Zeng, H. (2014). Afforestation in China cools local land surface temperature. *Proceedings of the National Academy of Sciences*, *111*(8), 2915 LP – 2919. https://doi.org/10.1073/pnas.1315126111

Poirier, V., Angers, D., Rochette, P., Chantigny, M., Ziadi, N., Tremblay, G., & Fortin, J. (2009). Interactive Effects of Tillage and Mineral Fertilization on Soil Carbon Profiles. *Soil Science Society of America Journal*, *73*, 255–261. https://doi.org/10.2136/sssaj2008.0006

Pribyl, D. W. (2010). A critical review of the conventional SOC to SOM conversion factor. *Geoderma*, *156*(3), 75–83. https://doi.org/https://doi.org/10.1016/j.geoderma.2010.02.003

Schaub, S., Buchmann, N., Lüscher, A., & Finger, R. (2020). Economic benefits from plant species diversity in intensively managed grasslands. *Ecological Economics*, *168*(July 2018). https://doi.org/10.1016/j.ecolecon.2019.106488

Scurlock, J. M. O., & Hall, D. O. (1998). The global carbon sink: a grassland perspective. *Global Change Biology*, *4*(2), 229–233. https://doi.org/10.1046/j.1365-2486.1998.00151.x

Smith, J., Smith, P., Wattenbach, M., Zaehle, S., Hiederer, R., Jones, R. J. A., Montanarella, L., Rounsevell,

M. D. A., Reginster, I., & Ewert, F. (2005). Projected changes in mineral soil carbon of European croplands and grasslands, 1990-2080. *Global Change Biology*, *11*(12), 2141–2152. https://doi.org/10.1111/j.1365-2486.2005.001075.x

Smith, P., Haberl, H., Popp, A., Erb, K., Lauk, C., Harper, R., Tubiello, F. N., de Siqueira Pinto, A., Jafari, M., Sohi, S., Masera, O., Böttcher, H., Berndes, G., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E. A., Mbow, C., … Rose, S. (2013). How much land-based greenhouse gas mitigation can be achieved without compromising food security and environmental goals? *Global Change Biology*, *19*(8), 2285–2302. https://doi.org/10.1111/gcb.12160

Socher, S. A., Prati, D., Boch, S., Müller, J., Baumbach, H., Gockel, S., Hemp, A., Schöning, I., Wells, K., Buscot, F., Kalko, E. K. V, Linsenmair, K. E., Schulze, E.-D., Weisser, W. W., & Fischer, M. (2013). Interacting effects of fertilization, mowing and grazing on plant species diversity of 1500 grasslands in Germany differ between regions. *Basic and Applied Ecology*, *14*(2), 126–136. https://doi.org/https://doi.org/10.1016/j.baae.2012.12.003

Spawn, S. A., Lark, T. J., & Gibbs, H. K. (2019). Carbon emissions from cropland expansion in the United States. *Environmental Research Letters*, *14*(4). https://doi.org/10.1088/1748-9326/ab0399

Tao, F., Zhang, Z., Zhang, S., Zhu, Z., & Shi, W. (2012). Response of crop yields to climate trends since 1980 in China . *Climate Research*, *54*(3), 233–247. http://www.int-res.com/abstracts/cr/v54/n3/p233-247/

Teixeira, R. F. M., Domingos, T., Costa, A. P. S. V., Oliveira, R., Farropas, L., Calouro, F., Barradas, A. M., & Carneiro, J. P. B. G. (2011). Soil organic matter dynamics in Portuguese natural and sown rainfed grasslands. *Ecological Modelling*, *222*(4), 993–1001. https://doi.org/https://doi.org/10.1016/j.ecolmodel.2010.11.013

Tóth, E., Deák, B., Valkó, O., Kelemen, A., Miglécz, T., Tóthmérész, B., & Török, P. (2018). Livestock Type is More Crucial Than Grazing Intensity: Traditional Cattle and Sheep Grazing in Short-Grass Steppes. *Land Degradation & Development*, *29*(2), 231–239. https://doi.org/doi:10.1002/ldr.2514

Wan, Z., Hook, S., & Hulley, G. (2015). *Land Processes Distributed Active Archive Center (LP DAAC)*. MOD11C3 MODIS/Terra Land Surface Temperature/Emissivity Monthly L3 Global 0.05Deg CMG V006 [Data Set]. NASA EOSDIS Land Processes DAAC. https://doi.org/https://doi.org/10.5067/MODIS/MOD11C3.006

Wiesmeier, M., Urbanski, L., Hobley, E., Lang, B., von Lützow, M., Marin-Spiotta, E., van Wesemael, B., Rabot, E., Ließ, M., Garcia-Franco, N., Wollschläger, U., Vogel, H. J., & Kögel-Knabner, I. (2019). Soil organic carbon storage as a key function of soils - A review of drivers and indicators at various scales. *Geoderma*, *333*(November 2017), 149–162. https://doi.org/10.1016/j.geoderma.2018.07.026

Wu, G.-L., Liu, Z.-H., Zhang, L., Hu, T.-M., & Chen, J.-M. (2010). Effects of artificial grassland establishment on soil nutrients and carbon properties in a black-soil-type degraded grassland. *Plant and Soil*, *333*(1), 469–479. https://doi.org/10.1007/s11104-010-0363-9

Wu, G.-L., Yang, Z., Cui, Z., Liu, Y., Fang, N.-F., & Shi, Z.-H. (2016). Mixed artificial grasslands with more roots improved mine soil infiltration capacity. *Journal of Hydrology*, *535*, 54–60. https://doi.org/https://doi.org/10.1016/j.jhydrol.2016.01.059

Zhang, X., Xu, M., Sun, N., Xiong, W., Huang, S., & Wu, L. (2016). Modelling and predicting crop yield, soil carbon and nitrogen stocks under climate change scenarios with fertiliser management in the North China Plain. *Geoderma*, *265*, 176–186. https://doi.org/https://doi.org/10.1016/j.geoderma.2015.11.027