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Modelling soil organic carbon stocks in global change scenarios: a CarboSOIL application

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Abstract

Global climate change, as a consequence of the increasing levels of atmospheric CO_2 concentration, may significantly affect both soil organic C storage and soil capacity for C sequestration. In this research we develop a methodology to predict soil organic C (SOC) contents and changes under global change scenarios. CarboSOIL model is a new component of the land evaluation decision support system MicroLEIS, which was designed to assist decision makers to face specific agro-ecological problems. CarboSOIL, developed as a GIS tool to predict SOC contents at different depths, was previously trained and tested in two Mediterranean areas: Andalusia (SW Spain) and Valencia (E Spain). The model was applied under different IPPC scenarios (A1B, A2 and B1) according to different global climate models (BCCR-BCM2, CNRMCM3 and ECHAM5) and output data were linked to spatial datasets (soil and land use) to quantify SOC stocks. CarboSOIL model has proved its ability to predict the short-, medium- and long-term trends (2040s, 2070s and 2100s) of SOC dynamics and sequestration under projected future scenarios of climate change. Results showed an overall trend towards decreasing of SOC stocks in the upper soil sections (0–25 cm and 25–50 cm) for most soil types and land uses, but predicted SOC stocks tend to increase in the deeper soil section (50–75 cm). Soil types as Arenosols, Planosols and Solonchaks and land uses as “permanent crops” and “open spaces with little or no vegetation” would be severely affected by climate change with large decreases of SOC stocks, in particular under the medium-high emission scenario A2 by 2100. The information developed in this study might support decision-making in land management and climate adaptation strategies in Mediterranean regions and the methodology could be applied to other Mediterranean areas with available soil, land use and climate data.

1 Introduction

Global climate is changing as a consequence of the increasing levels of atmospheric CO_2 concentration and global mean temperatures (IPCC 2007). Soil organic carbon (SOC) is strongly influenced by climate conditions and SOC stocks are determined by the balance between the total amount of C released to the atmosphere in the form of CO_2, and the total amount withdrawn from the atmosphere as net C inputs to the soil (Janssens et al., 2005). Carbon stored in soils is the largest C pool in most terrestrial ecosystems holding approximately 1500 Pg C in the top metre (Batjes, 1996), roughly twice the amount of C in the atmosphere and three times the amount in vegetation (Lal, 2004). Thus, small changes in the SOC pool could have a vast impact on atmospheric CO_2 concentrations. Only a difference of 10 % in SOC would equal the total anthropogenic CO_2 emissions of the last 30 yr (Kirschbaum, 2000).

Global climate change may significantly affect both SOC storage and soil capacity for C sequestration. Increases in soil temperature and atmospheric CO_2 have been related to higher decomposition rates and changes in net primary productivity (NPP). Increased temperatures might enhance the release of CO_2 to the atmosphere from SOC, leading to higher CO_2 levels and accelerated global warming (Davidson and Janssens, 2006). On the other hand, soil carbon sequestration, considered as the net removal of CO_2 from the atmosphere, could help to alleviate the problem of global warming and climate change. Carbon sequestration in terrestrial ecosystems is one of the most important ecosystem services due to its role in climate regulation (IPCC, 2007). At the same time, it provides important benefits for soils, crops and environment quality associated with increasing levels of SOC carbon such as improved soil structure, soil fertility, water holding capacity, infiltration capacity, water use efficiency and soil biological health (which results in higher nutrient cycling and availability). Additionally, soil organic C prevents from soil erosion and desertification and enhances bio-diversity. Soil carbon accumulation capacity should be considered regarding to adaptation strategies to climate change, in view of the high resilience of soils with an adequate level of organic C to a warming, drying climate (Christensen et al., 2011). The potential effects of climate change on SOC dynamics are still largely uncertain (Álvaro-Fuentes and Paustian, 2011; Powlson, 2005; Zaehle et al., 2007). In order to formulate adaptation policies in response to climate change impacts, it is crucial to assess soil carbon stocks and evaluate their dynamics in future climate scenarios (Chiesi et al., 2010).

Different approaches have been used to assess the impact of global warming and climate change on SOC stocks. Several studies have estimated regional and global soil organic C stocks based on extrapolations from measured data to future climate scenarios (Eswaran et al., 1993; Smith et al., 2000a; Smith et al., 2000b). The major drawback of these methods is the assumption of a constant rate of SOC change over the time period. Models are effective tools to assess C stocks and C dynamics (Falloon and Smith., 2003; Falloon et al., 2002; Jones et al., 2005; Paustian et al., 1997), what makes them appropriate for C reporting and assessment studies. They are particularly useful as decision support tools (DSSs) on climate change issues (Smith et al., 2005). DSSs combine data and knowledge from different sources to help in the organization and analysis of information, making thereby possible the evaluation of underlying hypotheses (Janssen et al., 2005; Sauter, 1997; Wang et al., 2010).

Modelling allows us to predict the short-, medium- and long-term trends of SOC dynamics and SOC sequestration under projected future scenarios of climate change (Lucht et al., 2006; Smith et al., 2005; Wan et al., 2011) which is crucial in order to take measures for an adequate management in agroforest ecosystems. By linking simulation models to spatial datasets (soils, land use), it is possible to determine current and future estimates of regional SOC stocks and SOC sequestration (Batjes, 2006; Falloon et al., 1998; Hashimoto et al., 2012). Moreover, patterns in SOC dynamics related to soil and land use features can be analyzed.

Scenario-driven impact assessments require detailed spatial and temporal data on the projected future climate. Several Global Climate Models (GCMs) have been developed, providing adequate simulations of atmospheric general circulation at the continental scale and projecting precipitation, temperature, and other climate variables

(Mitchel et al., 2004). GCMs require information on future GHG emissions generated by socio-economic scenarios and models. The IPCC SRES (Special Report on Emissions Scenarios – SRES) make available estimates of future anthropogenic CO2 emission. These scenarios contain various driving forces of climate change and are widely used to assess potential climate changes (Christensen et al., 2011).

Some of the current available SOC models simulate SOC dynamics only in the topsoil (upper 20–30 cm) (Parton et al., 1987) whereas others are specific for certain agricultural management conditions (Coleman and Jenkinson, 1999). There is evidence that in deeper soil layers a considerable amount of carbon can be stored and this form of C has proven to be more stable (Jobbágy and Jackson, 2000). Therefore, models should consider vertical SOC distribution in order to improve SOC stocks predictions.

Climate change will affect SOC stocks differently under diverse land uses and soil types. Each soil type and land use show different properties (Albadalejo et al., 2013; Muñoz-Rojas et al., 2012a) and consequently different vulnerability to climate conditions and C sequestration capacity. Consequently there is a need to predict the potential SOC stocks in different soil types and under different land uses (Christensen et al., 2011).

In this study, CarboSOIL model together with climate outputs from different GCMs (BCCR-BCM2, CNRMCM3, and ECHAM5) driven by SRES scenarios (A2, A1B and B2) were used to study the effects of climate change on SOC dynamics in a Mediterranean region (Andalusia, S Spain). The main objectives are: (a) to test and validate CarboSOIL model in climate change scenarios, (b) to determine CarboSOIL model sensitivity to climate variables, (c) to estimate SOC contents in future climate projections for different soil and land use types, (d) to obtain the spatial distribution and SOC stocks for different climate projections.

2 Materials and methods

2.1 CarboSOIL model description and application

CarboSOIL is a land evaluation tool for soil carbon accounting under global change scenarios (Anaya-Romero et al., 2012; Muñoz-Rojas, 2012). This model is part of a global project for developing a land evaluation tool for assessment of soil C sequestration capacity, as a new component of the MicroLEIS Decision Support System (Anaya-Romero et al., 2011; De la Rosa et al., 2004). MicroLEIS DSS was developed to assist decision-makers with specific agro-ecological problems and it was designed as a knowledge-based approach incorporating a set of information tools, linked to each other.

CarboSOIL was developed to simulate soil C dynamics of natural or cultivated systems under different scenarios of climate or land use change. The model is divided in 4 modules or sub models which predict SOC contents at different depths: (a) CarboSOIL25 (0–25 cm), (b) CarboSOIL50 (25–50 cm), (c) CarboSOIL75 (50–75 cm) and (d) CarboSOILTOTAL (0–75 cm). The input variables to run the model are divided in (I) climate variables (mean winter/summer temperature and annual precipitation), (II) site variables (elevation, slope, erosion, type-of-drainage), (III) soil (pH, N, cation exchange capacity, sand/clay content, bulk density and field capacity), and (IV) land use, with a total of 15 independent variables and a predictor variable (soil organic carbon) (Table 1). CarboSOIL was trained and tested in two Mediterranean areas, Andalusia (Southern Spain) and Valencia (Eastern Spain) (Fig. 1). To build the model, 1504 soil profiles were selected from Andalusia (training dataset) and 45 soil profiles from Valencia (test dataset), and a number of statistical techniques were applied, such as multiple linear regression (MLR), support vector machines (SVM) and artificial neural networks (ANN).

The final model was built with Multiple Linear Regression in the total soil section (0–75 cm) and Multiple Linear Regression with Box-Cox Transformation Techniques in the soil subsections (0–25, 25–50 and 50–75 cm) (Muñoz-Rojas, 2012). These techniques offered a higher predictive ability and comprise multiple advantages such as ease in application and simplicity of interpretation (Hastie et al., 2001; Oliveira et al., 2012). The list of variables with statistical parameters is shown in Table 2.

CarboSOIL has been developed as a computer application in a Geographical Information System (GIS) environment by using the Model Builder and Visual Basic applications of ArcGIS v.10 (ESRI, 2011), allowing users to perform spatial analysis and to obtain output maps of SOC content under different scenarios. CarboSOIL submodels run independently as script tools in the ArcToolbox environment within the ArcGIS 10 software (Fig. 2).

To assess SOC and SOC changes in future climate scenarios, CarboSOIL model has been applied to 1356 plots covering a range of soil types, land uses, site and climate conditions throughout the study area (Andalusia, Southern Spain). Although CarboSOIL is applied at plot-scale, output data can be linked to spatial datasets to perform spatial analysis and quantify SOC stocks.

2.2 Study area

Andalusia (Southern Spain) covers an area of approximately 87 000 km^2 (Fig. 1). Climate is mostly Mediterranean type, characterized by the particular distribution of temperatures and precipitations. Annual rainfall decreases from western Atlantic areas to the eastern region, which has a dry Mediterranean climate and values ranging between 170 mm yr^{-1} and > 2000 mm yr^{-1}. Western Atlantic areas are more rainy and humid, while the eastern portion has a dry Mediterranean climate, almost desertic. Average annual temperatures vary between < 10 and 18 °C, although milder temperatures are observed at the coast. There is a large altitudinal range in Andalusia and elevation varies between 0 and 3479 m a.s.l. with the highest peak Mulhacén. The main soils in the area are Cambisols (33 %), Regosols (20 %), Luvisols (13 %) and Leptosols (11 %) (CSIC-IARA, 1989).

Most of the natural vegetation is Mediterranean forest, mainly oaks, pines and firs with dense riparian forests and Mediterranean shrubs. At present, approximately

44.1 % of the region is occupied by agricultural areas and 49.8 % by natural areas. Both urban and water spaces cover 3 % of the area respectively (Bermejo et al., 2011). Agriculture has traditionally been based on wheat crops, olive trees and vineyards, but in recent decades they have been substituted with intensive and extensive crops (e.g., rice, sugar beet, cotton and sunflower). Likewise, intensive greenhouse crops under plastic have spread through some areas. In the coastal area, the decline of traditional crops has been imposed mainly by massive urbanization and the development of tourist infrastructures (Bermejo et al., 2011).

2.3 Climate data and scenarios

CarboSOIL model requires the following climate parameters to run: annual precipitation (mm), mean winter temperature (average of December, January and February monthly temperature, °C) and mean summer temperature (average of June, July and August monthly temperature, °C).

Climate data for baseline and future climate change scenarios were obtained from the time series of the CLIMA subsystem of the Environmental Information Network of Andalusia (REDIAM), which integrates several databases from a set of over 2200 observatories since 1971. These data include climate spatial datasets in raster format for different SRES scenarios, obtained by statistical downscaling of different GCMs. The downscaling techniques are based on inverse distance interpolation and regression modelling of regional/local physiographic features.

Three GCMs were selected for the application of CarboSOIL, (a) BCCR-BCM2 (Bjerknes Centre for Climate Research, Norway), (b) CNRMCM3 (Centre National de Recherches Meteorologiques, Meteo France, France) and (c) ECHAM5 (Max Planck Institute for Meteorology, Germany). These three GCMs represent a spread of model characteristics and thus their scenario climates (Mitchell et al., 2004).

For each GCM, we obtained monthly temperature and annual precipitation under three different CO_2 emissions scenarios (B1, AIB, A2) as defined in the IPPC Report, 4th Assessment in Emissions scenarios (Nakicenovic et al., 2000; IPPC, 2007). We selected climate series for four periods: 1961–2000 (baseline climate period), 2011–2040 (the "near-future" period), 2041–2070 (the "mid-future" period) and 2071–2100 (the "far-future" period). Data was extracted by using ArcGIS Spatial Analyst extension tool (ESRI, 2011) and analyses were performed with SPSS software (SPSS, 2009).

2.4 Site and soil data

Elevation and slope data were extracted from the digital elevation model (DEM) of Andalusia with resolution of 100 m (ICA, 1999), which is derived from the topographic map of Andalusia (S 1 : 10 000).

Type of fluvial network (drainage) and active soil erosion processes (sheet erosion, rill erosion and gully erosion) were obtained from 1356 soil profiles reported and described by Jordán and Zavala (2009) and the SEISnet soil databases (http://www.evenor-tech.com/banco/seisnet/seisnet.htm). Selection of soil profiles was carried out considering homogeneous sampling and analysis methods. These geo-databases consist of descriptive and analytical data, including site attributes, horizon description, chemical and physical analysis.

Likewise, soil data were obtained from the 1356 soil profiles, and soil variables used in this study were soil depth (cm), nitrogen (g/100 g), pH, cation exchange capacity (meq/100 g), sand (%), clay (%), bulk density (g/cc), field capacity (g/100 g) and organic carbon content (%).

In order to homogenize information from soil profiles, soil variables were re-coded and imported to the geo-referenced SDBm Plus Multilingual Soil Profile Database, which contains a large amount of descriptive and analytical data fields (De la Rosa et al., 2002). Soil profiles showed a range of depths, therefore soil data (Table 1) were homogenized and re-sampled to standard soil depths for computing (0–75, 0–25, 25–50 and 50–75 cm). The SDBM Plus database incorporates a "control section" function, which allows determining the thickness of the layer to be analyzed within the soil profile. This function calculates the weighted average value for each variable in standard control sections.

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2.5 Land use and land cover data

Land use for the model application was obtained from the Land Use and Land Cover Map of Andalusia (LULCMA) for 2007 at scale 1 : 25 000 and minimum map unit 0.5 ha (Moreira, 2007). This digital spatial dataset, obtained after the analysis of satellite images (Landsat TM, IRS/PAN and SPOT-5) and digital aerial photographs, is a result of the Coordination of Information on the Environment (CORINE) programme, promoted by the European Commission in 1985 for the assessment of environmental quality in Europe. Within the CORINE programme, CORINE Land Cover (CLC) project provides consistent information on land cover and land cover changes across Europe. The LULCMA for 2007 provides an updated version of the original maps at scale 1 : 100 000 and constitutes a more detailed and accurate database, both thematically and geometrically.

The standard CLC nomenclature includes 44 land cover classes, grouped in a three-level hierarchy. Land cover classes of LULCMA were reclassified into CLC nomenclature at level 3 (the most detailed level) according to the method described in Muñoz-Rojas et al. (2011), in order to apply CARBOSOIL model. Agricultural areas, natural and semi-natural areas and wetlands were selected composing a total of 14 land cover classes (Non irrigated arable land, permanently irrigated land, vineyards, fruit trees and berry plantations, olive groves, complex cultivations patterns, agro-forestry areas, broad-leaved forests, coniferous forests, mixed forests, natural grasslands, sclerophyllous vegetation, transitional woodland-scrub and salt marshes).

2.6 Calculation of soil organic C stocks and simulation process/Prediction of soil organic carbon stocks

To determine soil organic carbon contents (SOCC) in current scenarios, the following equation was applied for each soil layer of the 1356 soil profiles:

$$\mathrm{SOCC} = \mathrm{SOCP} \times \mathrm{BD} \times D \times (1 - G) \quad (1)$$

where SOCC is soil organic carbon content ($\mathrm{Mg\,ha^{-1}}$), SOCP is soil organic carbon percentage ($\mathrm{g\,100^{-1}\,g^{-1}}$), BD is bulk density ($\mathrm{g\,cm^{-3}}$), D is the thickness of the studied layer (cm) and G is the proportion in volume of coarse fragments. Similar approaches at different scales were used by Rodríguez-Murillo (2001) in peninsular Spain and by Boix-Fayos et al. (2009) in Murcia (SE Spain). Soil profiles were classified according to original soil profile descriptions, into 10 soil reference groups (IUSS Working Group WRB, 2006): Arenosols, Calcisols, Cambisols, Fluvisols, Leptosols, Luvisols, Planosols, Regosols, Solonchaks and Vertisols, and 7 land use types (following CLC nomenclature at level 2: "Arable land", "Permanent crops", "Heterogeneous agricultural areas", "Forest", "Scrub and/or vegetation associations", "Open spaces with little or no vegetation", and "Maritime wetlands"). Subsequently, soil profiles were grouped into association of soil and land use units (landscape units). These landscape units are defined by one soil reference group and one aggregated land cover type at level 2 of CLC nomenclature. To predict SOCC in climate change scenarios at different soil depth, CarboSOIL model (CarboSOIL 25, CarboSOIL50, CarboSOIL75 and CarboSOILTOTAL) was run under the different climate change scenarios for each soil profile. Data analyses were performed using ArcGIS v.10 software (ESRI, 2011) and SPSS (SPSS, 2009).

To determine SOC stocks and to obtain soil carbon maps in present and future scenarios, the study area was divided into landscape units using a topological intersection of the LULCMA for 2007 and the Soil Map of Andalusia (CSIC-IARA, 1989) at scale 1 : 400 000. The overlay of both maps resulted in a new spatial dataset composed by 85 492 new polygons. Mean values of SOC contents ($\mathrm{Mg\,ha^{-1}}$) of the different landscape units, which were previously determined for each climate change scenario, were assigned to all the new polygons. SOC stocks were determined by multiplying SOC content mean values by the area occupied by the landscape unit in the overlay map.

2.7 CarboSOIL model validation and sensitivity analysis

Correlation between modelled baseline scenarios (current scenario) and measured SOC pools from soil databases were determined. The Kolmogorov–Smirnov test was used to test whether differences between observed and predicted SOC contents were significant. Analyses were performed with SPSS software for each submodel (CarboSOIL 25, CarboSOIL50, CarboSOIL75 and CarboSOILTOTAL).

A sensitivity analysis of SOC dynamics was carried out with CarboSOIL model to assess the causal relationship between climate and land use variables, and SOC dynamics on the other hand. Sensitivity of the model for annual precipitation, mean summer temperature and mean winter temperature was tested for each land use type. The model was applied modifying these climate variables (using minimum and maximum values, Table 3), whereas the rest of variables were set with their average values.

3 Results

3.1 Model performance and validation

Measured SOC contents were well correlated with predicted values in baseline scenarios for each submodel of CarboSOIL, with R Spearman values ranging between 0.8840 and 0.9912 (Table 4). Model performance proved to be more accurate at the submodel level (CarboSOIL25, CarboSOIL50 and CarboSOIL75) yet CarboSOILTOTAL showed a satisfactory ability to predict SOC contents.

The results of the sensitivity analysis showed that CarboSOIL model was sensitive to climate parameters in all land uses (Fig. 3). In particular, modelling under different temperature regimes showed that SOC increases with winter temperature in all sections of the soil profile and decreases with summer temperature in the total profile and the upper layers (up to 50 cm). However, in the deeper layer (50–75 cm) the opposite process took place, and SOC enlarged with summer temperatures.

3.2 Prediction of SOC stocks and projected changes in response to climate change

3.2.1 SOC stocks under SRES scenarios and GCM models at different soil depth

Total SOC stocks predicted by application of CarboSOIL for the periods 2040, 2070 and 2100 under SRES scenarios and GCMs, are shown in Fig. 4. In the upper 25 cm, SOC stocks ranged between 228.5 and 234.5 Tg in 2040, 229.1 and 235.1 Tg in 2070, and 226.5 and 234.2 Tg in 2100. In the soil section between 25 cm and 50 cm, the SOC pool varied from 151.5 to 154.9 Tg in 2040, 149.9 to 153.5 Tg in 2070, and 146.7 to 153.3 Tg in 2100. SOC stocks in the deeper soil section (50–75 cm) ranged between 129.0 and 130.0 Tg in 2040, 129.3 and 131.7 Tg in 2070, and 130.9 and 134.7 Tg in 2100. Finally, the projected SOC stocks in the total soil profile (0–75) varied from 378.7 to 401.7 Tg in 2040, from 371.6 to 395.5 in 2070 Tg, and 350.2 to 392.3 Tg in 2100.

Table 5 shows the simulated future change of SOC stocks in the long-term scenario (year 2100) compared to the values in the baseline scenarios for each SRES scenario and GCM. SOC changes ranged from −3.4 % to −13.0 % in the 0–75 soil section. The CNRMCM3 GCM forced by A2 SRES scenario predicted larger decreases of SOC stocks in the upper 25 cm, the 25–50 cm layer and the total soil profile (0–75). In the soil section from 50–75 cm, all scenario combinations showed increases of SOC stocks and ECHAM5 GCM forced by A1B SRES scenario projected the largest increment. Figure 5 displays the spatial distribution of changes in SOC contents for the different climate change scenarios and the different periods (2040, 2070 and 2100) considered in this research. In general, the northwestern and the eastern areas of Andalusia would be the most affected by climate change, with SOC losses above 4 $\mathrm{Mg\,ha^{-1}}$ in 2040 and up to 8 $\mathrm{Mg\,ha^{-1}}$ in 2070 and 2100.

3.2.2 Changes in SOC stocks for each soil type and land use at different soil depth

Future changes of SOC stocks predicted by CarboSOIL for different soil types and soil depths are shown in Fig. 6. Although there is an overall trend in all soil types towards decreasing of SOC stocks in the upper soil sections (0–25 and 25–50), predicted SOC stocks tend to increase in the deeper soil section (50–75) in future climate scenarios.

In the upper 25 cm, the predictions showed that SOC stocks decrease in most of the soil types under A1B, A2 and B1 scenarios, in particular in Arenosols, Planosols and Solonchaks. In Arenosols, SOC contents would decrease by 2.3–2.7 % in 2040, 2.3–3 % in 2070 and up to 3.6 % in 2100. In Solonchaks, rates of change in SOC stocks in the upper 25 cm are similar than those predicted for Arenosols. However, larger decreases were projected in Planosols, in which SOC would decrease by 4.3–4.6 % in 2040, 4.4–5.4 % in 2070 and 4.7–6.3 % in 2100.

In the soil section ranging from 25 to 50 cm, larger decreases of SOC stocks were predicted in the same soil types (Arenosols, Planosols and Solonchaks) in addition to Cambisols, with SOC declines up to 5.4 % in 2100 for the A2 scenario.

In general, SOC stocks would increase in the deeper layer (50–75 cm) of most soil types, and these rates would be particularly large in Cambisols, with predictions of SOC accumulation rates between 5.7 % and 5.9 % in A1B and A2 scenarios respectively. Opposite, SOC stocks decline in the deeper soil section of Planosols and Solonchaks.

A similar pattern was found in SOC stocks under projected scenarios for the different land uses, with SOC declining in the upper layers and increasing in the deeper section of the soil profile.

Among agricultural uses, “permanent crops” would be the most affected by climate change with SOC decreases between 3.1 and 3.8 %, in 2040, 3.2 and 4.4 % in 2070, and up to 5.7 % in 2100 in the upper layer (0–25 cm). In the soil section from 50 to 75, SOC would decline up to 6.2 % (A2 scenario), but projections in the deeper layer (50–75) indicated an increase 5–12 % in the SOC contents of this agricultural type.

In natural areas CarboSOIL predicted important losses of SOC contents in the upper layers of the soil profile of “open spaces with little or no vegetation”. In this land use type, 9.3 % of the SOC would be lost under the A2 scenario by 2100 in the 0–25 soil section and 28.6 % in the 25–50 soil section. However, positive rates of change were predicted in the 50–75 cm, with SOC increases ranging from 10.2 to 16.3 % in 2100. Minor decreases of SOC were observed in “shrubs” in the upper layers, with average values of 2.4 % by 2040 and 2070 and 2.8 % by 2100 in the 0–25 cm section, and 0.4 % by 2014, 1.2 % by 2070 and 2.3 % in the 25–50 section. Nonetheless, it is remarkable that the model predicted large increments of SOC contents in the 50–75 cm section of the soil profile, in particular by 2100 with positive changes of SOC stocks ranging from 11.7 to 13.1 %.

4 Discussion

4.1 Soil C modelling in climate change scenarios

A number of studies have investigated SOC changes in future climate scenarios applying Climate Models forced by IPPC SRES scenarios (Berthelot et al., 2005; Lucht et al., 2006; Wan et al., 2011). Among soil carbon models, one the most widely used is Century SOC model (Parton et al., 1987, 1992), which has been applied at site and regional scales (Álvaro-Fuentes at al., 2012; Shrestha et al., 2009; Tornquist et al., 2009). Likewise, the Rothamsted carbon model (RothC; Coleman and Jenkinson, 1999), has been widely used to estimate the SOC change in response to climate change or land use management alterations (Guo et al., 2007; Smith et al., 2005; Xu et al., 2011).

In the past years, these models have been implemented in the Mediterranean region to determine SOC changes in future climate scenarios. In Italy, Mondini et al. (2012), applied Roth-C model to evaluate SOC stocks between 2001 and 2100. They used 3 different GCMs, namely HadCM, PCM and GCM2 (Mitchell et al., 2004) forced by 4 SRES scenarios (A1F1, A2, B1, A2) described in Nakicenovic et al. (2000). In the same region, Lugato and Berti (2008) projected future climate simulations from 2008 to 2080 using Century SOC model and four GCMs forced by four IPPC SRES.

A recent study in northeast Spain (Alvaro-Fuentes et al., 2012) reported SOC changes between 2007 and 2087. In their work, they used the Century SOC model in the 0–30 cm soil depth over an agricultural area of 40 498 km^2. Climate scenarios considered in their work were ECHAM4 and CGCM2 forced by A2 and B2 SRES emissions. Likewise, Álvaro-Fuentes and Paustian (2011) applied Century SOC model in different semiarid areas of Spain, at field and regional scale level, under the same climate change scenarios.

A comprehensive pan-European assessment of changes in SOC stocks was carried out by Smith et al. (2005). They applied the Roth-C model in European croplands and grasslands to project changes in SOC stocks between 1990 and 2080. Four GCMs were used for the projections (HadCM3, CSIRO2, PCM and CGM2; Mitchell et al., 2004) in four SRES scenarios (A1F1, A2, B1 and B2).

Nonetheless, few studies considering the different sections along the soil profile in the assessment of future SOC stocks have been undertaken in Mediterranean areas. Generally, most of the research on modelling SOC dynamics has focused on the upper layer without specification of the vertical distribution, such as the Century SOC model (Parton et al., 1987) or EPIC (Izaurralde et al., 2006). Although a number of studies have developed models for soil depth up to 1 metre such as Roth-C model (Coleman and Jenkinson, 1999) or Yasso (Liski et al., 2005), these tools are specifically designed for either agricultural areas or forests, but not for both natural and transformed land use type.

Several researches have proved that deeper layers in the soil profile are able to store a substantial amount of organic C (Batjes, 1996; Jobbágy and Jackson, 2000; Muñoz-Rojas et al., 2012a; Tarnocai et al., 2009). Therefore, new methods and tools are necessary to explore the potential impacts of future climate changes in SOC contents at different soil depths and land use types.

This study applies four sub models of a SOC model (CarboSOIL) in order to quantify SOC at different soil depths. The model is driven by BCCR-BCM2, CNRMCM3 and ECHAM5 climate predictions, with three IPCC forcing scenarios (A1B, A2 and B2) to predict the effects of climate change on SOC contents and sequestration. CarboSOIL model has proved its ability to predict SOC stocks at different soil depths (0–25, 25–50 and 50–75 cm) in global change scenarios. Designed as a GIS tool, the model has shown a high capacity to quantify and understand soil carbon distribution for different land use and soil types. The methodology is easily applicable to other Mediterranean areas with available data on climate, site, soil and land use. Additionally, coupling detailed spatial databases with CarboSOIL model allows measuring regional SOC stocks and sequestration potential.

4.2 Predicted future SOC stocks under climate change scenarios

Our research provides with the first estimates of SOC stocks in Southern Spain in future scenarios and allows analysing C sequestration trends associated to climate change. Overall, our results suggest that climate change will have a negative impact on SOC contents in the upper layers of the soil section.

According to our findings, annual precipitation has an important effect on SOC contents. In the top soil layers, SOC stocks decrease when diminishing rainfall, opposite to the increases in deeper layers. Additionally, although climate change scenarios predict a decrease in annual precipitation, more intensive rainfall events are expected. These events are likely to change soil structure and soil quality, particularly in upper layers, which together with SOC depletion makes the soil more susceptible to erosion processes (Christensen et al., 2011; Muñoz-Rojas et al., 2012b).

Increasing summer temperatures will affect the SOC pools up to 50 cm, with a consequent depletion of this pool, mainly in sensitive land areas such as “salt marshes” and “fruit trees and berries plantations”. On the other hand, the sensitivity analysis suggests that winter temperatures are desirable for increasing SOC contents. It has been reported that increasing temperatures will accelerate C decomposition due to the rise of temperatures (Zhang et al., 2005). Consequently, direct climate impacts on croplands and grasslands soils will tend to decrease SOC stocks all over Europe (Smith et al., 2005). However, temperature sensitivity of soil carbon decomposition depends on the soil type or the land use class. Although temperature clearly affects decomposition of a labile SOC fraction, a significant portion of SOC is influenced by other environmental factors (Davidson and Janssens, 2006). The effects of climate change on SOC stocks will be particularly severe in Arenosols, Planosols and Solonchaks with large decreases of SOC stocks in the upper layers. However, these soil groups, commonly found in semi-arid areas of Andalusia, only represent 0.5, 4.7 and 6.0 % respectively, of the study area (Muñoz-Rojas et al., 2012a). Among the agricultural areas, the upper layers of "permanent crops" will be largely affected. This land use type include olive groves, vineyards and sensitive crops such as fruit trees and berry plantations, which occupy more than 15 % of the total area of Andalusia (Muñoz-Rojas et al., 2011). Therefore management practices should be considered to avoid SOC losses in these areas. In the natural areas, CarboSOIL model predicted minor losses of SOC stocks in "forests" but areas as "open spaces" will undertake important declines of SOC stocks in the 0–25 and the 25–50 sections of the soil profile. "Open spaces" are particularly vulnerable since are usually burnt areas or areas under erosive processes (Muñoz-Rojas et al., 2011). In the deeper layers of "scrubs" the model projected considerable increments in SOC stocks, which might be explained by the growth in depth of the vegetation roots of new species adapted to arid conditions of a future climate. Similar predictions have been outlined by Albadalejo et al. (2013) in semi-arid areas in Spain, who explained it as a consequence of accelerated soil erosion in arid and semi-arid areas.

Despite the diversity of SOC contents associated to different climate change scenarios, our results show an evident decrease of SOC in Southern Spain. In the total soil profile (first 75 cm), SOC changes between 2000 and 2100 vary from −3.4 % in CNRMCM3-B1 to −13.0 % in CNRMCM3-A2. Our results are generally in agreement with the works of Mondini et al. (2012), Smith et al. (2005) and Wan et al. (2011) and which applied Roth-C model and projected a decrease of SOC during the 21st century. Absolute values cannot be directly compared due to the differences in the soil sections, but percentage change can be contrasted.

Smith et al. (2005) predicted SOC changes between −10 % and −14 % of the 1990 mean SOC stock of European croplands, and between −6 and −10 % of the 1990 mean SOC stock of European grasslands. Wan et al. (2011) reported a percentage decrease of 5.5 %, 12 % and 15 % in SOC by the years 2020, 2050 and 2080 respectively, in northern China. In their study, Mondani et al. (2012) projected SOC losses in Italy between 2001 and 2100 with values ranging from −4.4 % in the PCM-B1 scenario to −11.5 % in the CGM2-A1F1 scenario, in consistence with our results.

Álvaro-Fuentes and Paustian (2011) and Álvaro-Fuentes et al. (2012) predicted increases in SOC contents of Spanish agroecosystems under future climate change scenarios, which differ from our simulations. However, in both studies they applied Century model, which account SOC stocks only in the upper 30 cm.

4.3 Uncertainties and limitations

Changes in land use are expected in the future decades at global, regional and local scales. However, in our projections land use remains invariable between the 2000–2100 periods. The purpose of this study is to apply and test CarboSOIL in climate change scenarios and to assess SOC changes in response to climate change, therefore, land uses are considered constant over the simulation period.

Results obtained from application of simulation models in climate change scenarios are related to different sources of uncertainty, associated mainly with the model imprecision and the climate scenarios. CarboSOIL is an empirical model based on regression/correlation techniques. Although these statistical procedures are not able to explain complex mechanisms within the soil system, this type of models are useful tools to identify different drivers of SOC dynamics and perform projections of SOC stocks (Viaud et al., 2010). According to the results obtained in the validation process, CarboSOIL model has proved to be consistent, and measured values were well cor-

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related with the modeled values. Sensitivity analysis evidence the ability of the model to identify cause–effect relationships. Moreover, the advantages of CarboSOIL model include easiness in application and simplicity of interpretation.

A range of model projections is considered in this study. We obtain different results of SOC contents associated to different climate predictions, which highlights the uncertainty in future climate scenarios. In climate projections, uncertainties can be related to emissions, climatic drivers (e.g., carbon cycle), climate sensitivity and adaptive capacity, among others (Van Vuuren et al., 2011).

In areas of complex topography, like the Mediterranean region, application of GCMs might result in considerable biases in the prediction of precipitation and temperature (Giorgi and Lionello, 2008). In particular precipitation involves local processes of larger complexity than temperature, and projections are usually less robust than those for temperature. Regionalized climate data used here contribute to a better adjustment of climate change scenarios to the physiographic environment of the study area. The climate system suffers variations on different timescales. In this work we consider time periods of 30 yr, given that this time-slice has been traditionally considered (Christensen et al., 2011; IPPC, 2007) to assess climate factors with some confidence.

5 Conclusions

In our study, we applied CarboSOIL in climate change scenarios to determine SOC changes in 2040, 2070 and 2100 in a Mediterranean region (Southern Spain). The model has proved to be consistent, and measured values were well correlated with the modelled values. Linking CarboSOIL model to detailed spatial databases allows measuring regional SOC stocks and sequestration potential. This research provides with SOC contents and stocks estimates in Southern Spain in future climate scenarios, assessing C sequestration trends associated to climate change. Our results showed that climate change will have a negative impact on SOC contents in the upper layers of the soil section (0–25 and 25–50 cm), in particular in soils as Arenosols, Planosols and

Solonchaks. The model predicted declines of SOC stocks in the 0–25 and 25–50 soil sections of "permanent crops" among agricultural areas and "scrubs" among natural areas.

The methodology can be easily applied to other Mediterranean areas with available data on soil, site, land use and climate factors. This study might support decision-making in land management and climate adaptation strategies in Mediterranean regions.

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Table 1. CarboSOIL model input variables, units and sources.

Variable type	Variable name	Code	Unit	Source and reference
Dependent variable	Soil Organic C	SOC	$Mg\,ha^{-1}$	Jordán y Zavala (2009) and Sdbm Plus database (2002)
Climate	Total precipitation	PRPT	mm	REDIAM-CLIMA http://www.juntadeandalucia.es/medioambiente/site/web/rediam; State Meteorological Agency www.aemet.es
	Winter Temperature	TDJF	°C	
	Summer Temperature	TJJA	°C	
Site	Elevation	ELEV	m	Digital Elevation Model of Andalusia, 100 m (ICA, 1999)
	Slope	SLOP	%	
	Drainage	DRAI		Jordán and Zavala (2009) and SDBm Plus database (2002)
	Soil Erosion	SERO		
Soil	Nitrogen	NITRO	g/100 g	
	pH	PHWA		
	Cation Exchange Capacity	CEXC	meq/100 g	
	Sand	SAND	g/100 g	
	Clay	CLAY	g/100 g	
	Bulk density	BULK	$g\,cc^{-1}$	
	Field capacity	FCAP	g/100 g	
Land use	Land use/ land cover	LULC		Land use and land cover Map of Andalusia (2007); SIOSE project www.siose.es

Table 2. Coefficients and confidence intervals (95 %) of model variable for each submodel of CarboSOIL. QT: quantitative, QL: qualitative.

		CarboSOIL 25			Carbosoil50			Carbosoil75			Carbosoil TOTAL		
Variable	Type	Coef	BCainf	BCasup	Coef	BCainf	BCasup	Coef	BCainf	BCasup	Coef	BCainf	BCasup
Intercept		774.69	745.17	802.13	1085.65	1059.45	1111.74	1150.92	1120.70	1172.05	546.54	482.75	608.97
Climate													
PRPT	QT	0.00	−0.01	0.00	0.00	−0.01	0.01	0.00	−0.01	0.00	0.02	0.00	0.03
TDJF	QT	1.43	0.38	2.56	0.62	−0.29	1.53	0.64	−0.11	1.40	3.52	1.36	5.73
TJJA	QT	−0.93	−1.74	−0.09	−0.69	−1.39	0.09	0.07	−0.49	0.77	−1.91	−3.59	−0.31
Site													
ELEV	QT	0.00	−0.01	0.01	0.00	−0.01	0.00	0.00	0.00	0.01	0.00	−0.02	0.01
SLOP	QT	0.00	−0.03	0.02	0.00	−0.01	0.01	0.00	−0.01	0.01	0.01	−0.03	0.04
DRAI	QL												
Adequate		–	–	–	–	–	–	–	–	–	–	–	–
Deficient		−2.08	−3.65	−0.34	−1.50	−2.90	−0.21	−0.21	−1.34	0.87	−4.60	−8.25	−1.13
Excessive		1.89	−1.05	4.04	−2.39	−6.00	−0.56	−4.08	−8.24	−2.34	−10.48	−15.36	−5.16
SERO	QL												
No-erosion		–	–	–	–	–	–	–	–	–	–	–	–
Sheet erosion		−1.00	−3.02	0.95	−0.88	−2.50	0.69	−0.40	−1.83	0.84	−0.44	−4.91	3.74
Rill erosion		−0.16	−2.22	2.01	0.45	−1.32	2.32	−0.47	−1.82	0.85	−2.05	−6.85	2.33
Gully erosion		−0.33	−2.85	2.25	1.22	−1.77	3.27	−0.88	−3.62	0.75	−8.45	−14.03	−3.07
Soil													
NITRO	QT	1.93	−9.64	10.39	26.31	15.04	34.54	6.06	−0.56	12.20	−4.57	−28.71	21.65
PHWA	QT	0.84	0.05	1.63	0.07	−0.48	0.72	1.04	0.55	1.61	2.30	0.74	3.99
CEXC	QT	−0.01	−0.05	0.02	0.00	−0.04	0.03	0.03	−0.02	0.07	0.06	−0.03	0.15
SAND	QT	0.80	0.76	0.85	1.06	1.02	1.10	1.16	1.13	1.20	0.49	0.39	0.58
CLAY	QT	−1.19	−1.26	−1.13	−1.60	−1.65	−1.54	−1.69	−1.73	−1.64	−0.54	−0.67	−0.41
BULK	QT	−493.9	−501.1	−486.0	−686.5	−693.8	−676.6	−746.99	−755.15	−734.38	−348.9	−368.9	−330.7
FCAP	QT	0.02	−0.11	0.15	−0.07	−0.16	0.04	0.00	−0.09	0.09	0.03	−0.24	0.30
Land use													
LULC	QL												
Other		–	–	–	–	–	–	–	–	–	–	–	–
Non irrigated areas		1.17	−2.19	8.46	−0.53	−3.42	5.59	−0.47	−2.65	4.75	1.41	−8.03	11.38
Irrigated areas		−1.48	−5.46	5.26	0.86	−2.27	7.28	−0.58	−2.98	4.42	8.48	−1.80	18.74
Vineyards		−0.21	−10.16	6.99	−3.23	−9.86	2.22	−1.82	−6.55	2.58	7.61	−8.40	24.86
Fruit trees and berries		−1.01	−8.66	5.87	−0.52	−6.96	4.55	1.07	−2.82	6.35	−5.73	−20.34	7.88
Olive groves		1.48	−2.08	8.41	−0.23	−3.45	5.99	−0.31	−2.58	4.67	3.56	−6.29	13.60
Complex cultivation patterns		−0.37	−5.09	6.50	−1.07	−5.61	4.26	−2.22	−5.39	2.65	0.68	−10.53	11.95
Agro- forestry areas		−0.05	−3.96	7.00	−1.63	−4.86	4.83	−0.06	−2.42	5.37	−2.50	−13.07	7.87
Broad leaved forest		−0.34	−4.17	6.88	−2.41	−5.57	3.77	0.03	−2.36	5.55	−5.24	−15.17	5.53
Coniferous forest		0.28	−3.96	7.50	−1.37	−5.50	4.39	0.70	−2.37	6.07	0.05	−11.16	11.09
Mixed forest		6.33	−2.57	13.22	−1.38	−8.98	4.38	0.98	−2.65	6.40	−2.40	−17.71	14.02
Natural grasslands		1.51	−2.85	8.27	0.41	−3.93	5.90	−0.53	−3.84	5.09	−0.94	−11.81	10.34
Sclerophyllous vegetation		1.36	−2.83	8.22	−0.64	−4.56	5.23	−2.02	−5.10	3.00	−1.97	−12.59	9.02
Woodland scrubs		1.40	−2.63	8.54	−3.40	−7.22	2.41	1.33	−1.54	6.85	−2.08	−12.88	8.65
Salt marshes		−2.46	−14.11	4.62	−3.06	−10.86	3.74	−3.58	−7.25	2.13	−26.04	−43.47	−8.01

Table 3. Description of climate variables in the study area in projected climate change scenarios in different periods: 2040 (2011–2040), 2070 (2014–2070) and 2100 (2070–2100).

Climate change	TDJF (˚C)				TJJA (˚C)				PPT(mm)			
scenario	Baseline	2040	2070	2100	Baseline	2040	2070	2100	Baseline	2040	2070	2100
BCCR-BCM2-A1B												
Low	4.6	4.9	5.8	6.3	19.7	19.5	21.0	21.9	357.0	308.0	290.0	282.0
High	13.5	13.6	14.3	14.8	27.1	26.9	28.3	29.4	2304.0	1625.0	1376.0	1257.0
Mean ± SD	10.1 ± 1.6	10.3 ± 1.5	11.2 ± 1.4	11.7 ± 1.4	25.1 ± 1.0	24.9 ± 1.0	26.3 ± 1.0	27.5 ± 1.1	761.8 ± 218.8	589.1 ± 154.8	529.2 ± 134.2	484.2 ± 121.7
BCCR-BCM2-A2												
Low	4.6	5.1	5.5	6.4	19.7	19.8	20.6	22.4	357.0	303.0	291.0	269.0
High	13.5	13.8	14.0	14.9	27.1	27.2	27.9	30.0	2304.0	1571.0	1368.0	1199.0
Mean ± SD	10.1 ± 1.6	10.4 ± 1.5	10.8 ± 1.4	11.8 ± 1.4	25.1 ± 1.0	25.2 ± 1.0	26 ± 1.0	28.1 ± 1.1	761.8 ± 218.8	577.1 ± 149.4	510.1 ± 132.8	470.7 ± 117.5
BCCR-BCM2-B1												
Low	4.6	5.2	5.1	5.7	19.7	20.0	20.4	20.9	357.0	311.0	293.0	295.0
High	13.5	13.9	13.5	14.1	27.1	27.4	27.9	28.4	2304.0	1709.0	1380.0	1456.0
Mean ± SD	10.1 ± 1.6	10.5 ± 1.5	10.2 ± 1.4	11.0 ± 1.4	25.1 ± 1.0	25.5 ± 1.0	25.9 ± 1.0	26.4 ± 1.0	761.8 ± 218.8	597 ± 160.4	519.6 ± 132.8	545.4 ± 140.5
CNRMCM3-A1B												
Low	4.8	5.5	4.1	4.4	19.7	18.3	19.7	22.3	303.0	189.0	145.0	138.0
High	13.7	13.7	14.5	15.0	27.1	27.8	28.8	31.0	1861.0	1701.0	1375.0	1306.0
Mean ± SD	10.3 ± 1.6	10.4 ± 1.2	11.3 ± 1.4	11.7 ± 1.4	25.2 ± 1.0	25.9 ± 1.0	27 ± 1.1	28.9 ± 1.2	614.5 ± 178.2	624.4 ± 167.8	539.6 ± 137.7	511.9 ± 131
CNRMCM3-A2												
Low	4.8	2.5	4.2	4.7	19.7	18.1	20.1	23.6	303.0	172.0	124.0	142.0
High	13.7	13.6	14.5	15.1	27.1	27.6	29.2	32.3	1861.0	1645.0	1338.0	1301.0
Mean ± SD	10.3 ± 1.6	10.3 ± 1.5	11.3 ± 1.4	11.9 ± 1.4	25.2 ± 1.0	25.8 ± 1.0	27.3 ± 1.1	30 ± 1.2	614.5 ± 178.2	615.6 ± 165	521.5 ± 132.4	510.4 ± 130
CNRMCM3-B1												
Low	4.8	2.9	3.0	3.8	19.7	18.6	19.4	19.3	303.0	164.0	170.0	144.0
High	13.7	13.9	13.9	14.3	27.1	28.0	28.7	28.5	1861.0	1488.0	1544.0	1391.0
Mean ± SD	10.3 ± 1.6	10.6 ± 1.5	10.6 ± 1.5	11.1 ± 1.4	25.2 ± 1.0	26 ± 1.0	26.7 ± 1.1	26.6 ± 1.0	614.5 ± 178.2	572.3 ± 150.7	586.4 ± 154.3	542.1 ± 140.1
ECHAM5-A1B												
Low	4.6	4.8	5.7	7.2	19.6	20.7	22.3	23.3	341.0	316.0	290.0	299.0
High	13.6	13.5	14.3	15.5	27.0	28.0	29.7	31.6	2232.0	1653.0	1428.0	1374.0
Mean ± SD	10.1 ± 1.6	10.2 ± 1.5	11.1 ± 1.5	12.6 ± 1.4	25 ± 1.0	26 ± 1.0	27.7 ± 1.1	29.4 ± 1.3	738.2 ± 210.1	602.9 ± 158.8	534.3 ± 138.1	536.8 ± 137.7
ECHAM-A2												
Low	4.6	4.7	5.7	6.9	19.6	20.8	21.9	23.5	341.0	316.0	309.0	277.0
High	13.6	13.6	14.3	15.3	27.0	28.2	29.2	31.7	2232.0	1653.0	1530.0	1263.0
Mean ± SD	10.1 ± 1.6	10.1 ± 1.5	11.1 ± 1.5	12.3 ± 1.4	25 ± 1.0	26.2 ± 1.0	27.3 ± 1.1	29.6 ± 1.3	738.2 ± 210.1	602.9 ± 158.8	566.3 ± 147.7	487.1 ± 125.7
ECHAM-B1												
Low	4.6	5.1	5.5	6.0	19.6	20.6	21.3	22.9	341.0	318.0	309.0	307.0
High	13.6	13.7	14.0	14.6	27.0	27.8	28.4	30.0	2232.0	1662.0	1582.0	1469.0
Mean ± SD	10.1 ± 1.6	10.3 ± 1.5	10.7 ± 1.5	11.3 ± 1.4	25 ± 1.0	25.8 ± 1.0	26.5 ± 1.0	28.1 ± 1.1	738.2 ± 210.1	609.8 ± 160.9	577.9 ± 151.9	542 ± 140.6

Table 4. Measured and modelled soil organic C (SOC) content (Mg ha^{-1}) under different climate scenarios (BCCR-BCM2, CNRMCM3 and ECHAM5), and results of the Kolmogorov-Smirnov test.

Soil depth (cm)	N	Measured SOC		BCCR-BCM2 Modelled SOC			CNRMCM3 Modelled SOC			ECHAM5 Modelled SOC			Kolmogorov–Smirnov test (*p*)
		Mean	SD	Mean	SD	*R*	Mean	SD	*R*	Mean	SD	*R*	
0–25	1504	30.51	28.11	31.36	29.93	0.9889	31.70	26.89	0.9892	31.48	26.90	0.9892	< 0.01
25–50	1033	19.66	19.18	19.82	18.60	0.9898	19.88	18.60	0.9898	19.87	18.59	0.9898	< 0.01
50–75	600	15.65	14.67	15.87	14.31	0.9912	15.92	14.31	0.9912	15.88	14.31	0.9912	< 0.01
0–75	1504	51.25	47.55	54.48	38.82	0.8840	52.51	38.66	0.8850	54.47	38.88	0.8840	< 0.01

[a] Correlation is significant at the 0.01 level.

Table 5. Changes in SOC stocks at different soil depths in different SRES (A1B, A2 and B1) and global climate models (BCCR-BCM2, CNRMCM3 and ECHAM5) in the period 2000–2100.

Soil section (cm)	A1B			A2			B1		
	BCCR-BCM2	CNRMCM3	ECHAM5	BCCR-BCM2	CNRMCM3	ECHAM5	BCCR-BCM2	CNRMCM3	ECHAM5
0–25	−0.3 %	−3.3 %	−2.1 %	−0.9 %	−4.8 %	−2.9 %	−0.6 %	−3.7 %	−3.1 %
25–50	−1.3 %	−3.4 %	−3.5 %	−2.0 %	−4.9 %	−4.2 %	−0.6 %	−0.6 %	−2.9 %
50–75	2.9 %	2.9 %	4.6 %	3.2 %	3.3 %	4.2 %	1.7 %	1.6 %	2.4 %
0–75	−8.2 %	−9.4 %	−7.5 %	−9.9 %	−13.0 %	−12.2 %	−6.5 %	−3.4 %	−10.8 %

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Fig. 1. Study area.

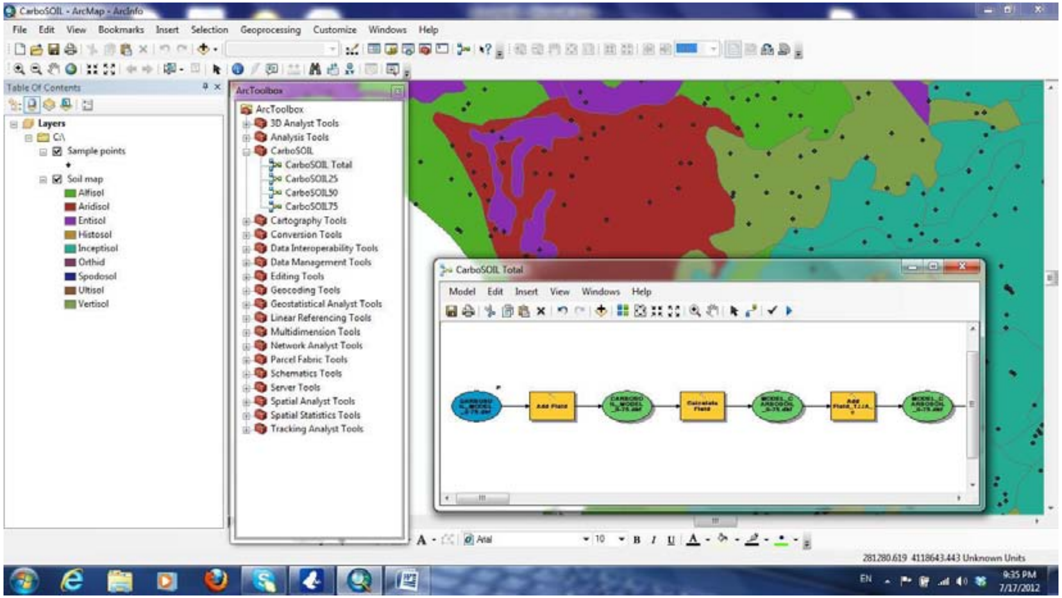

Fig. 2. Interface of CarboSOIL model tool in ArcGIS 10.

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Modelling soil organic carbon stocks in global change scenarios

M. Muñoz-Rojas et al.

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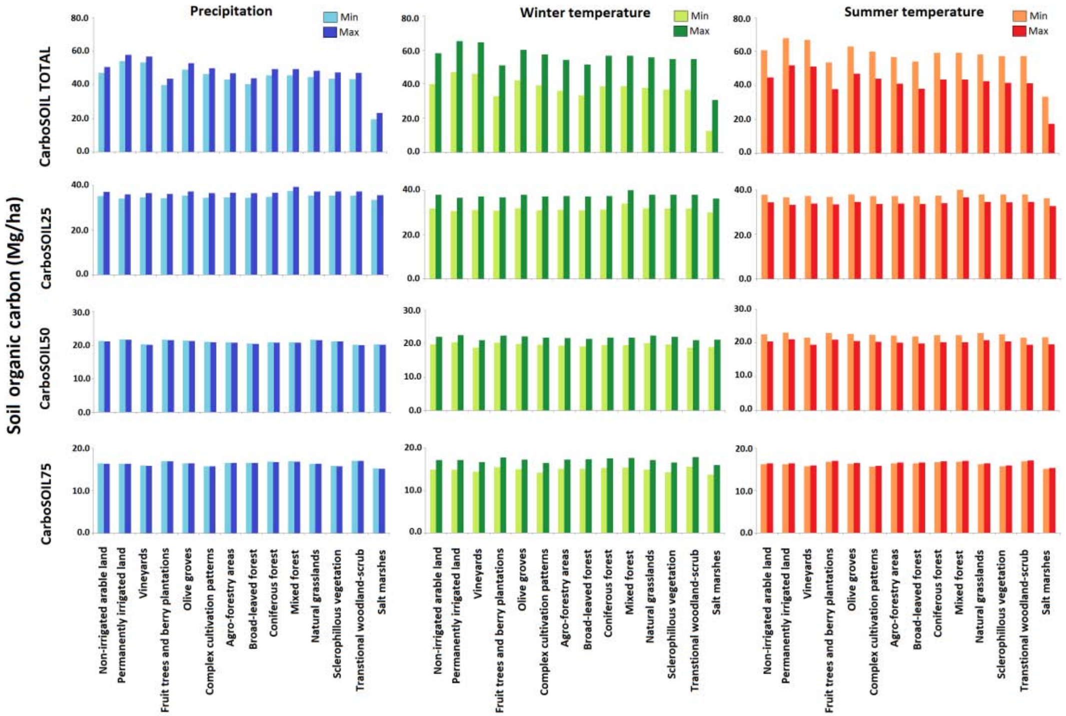

Fig. 3. Sensitivity analysis of CarboSOIL model for climate variables (annual precipitation, mean winter temperature and mean summer temperature) at different soil depths 0–25 (CARBOSOIL25), 25–50 (CARBOSOIL50), 50–75 (CARBOSOIL75) and 0–75 cm (CARBOSOIL TOTAL).

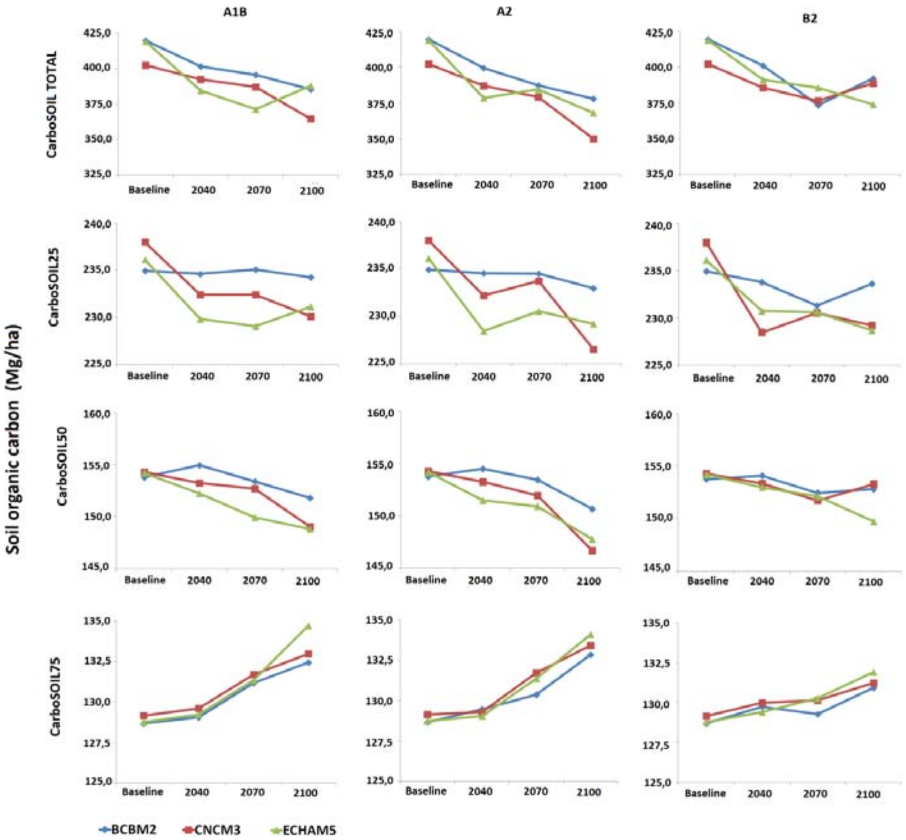

Fig. 4. Soil organic C stocks in climate change scenarios for each GCM and SRES in different periods (2040, 2070 and 2100) at different soil depths 0–25 (CARBOSOIL25), 25–50 (CARBOSOIL50), 50–75 (CARBOSOIL75) and 0–75 cm (CARBOSOIL TOTAL).

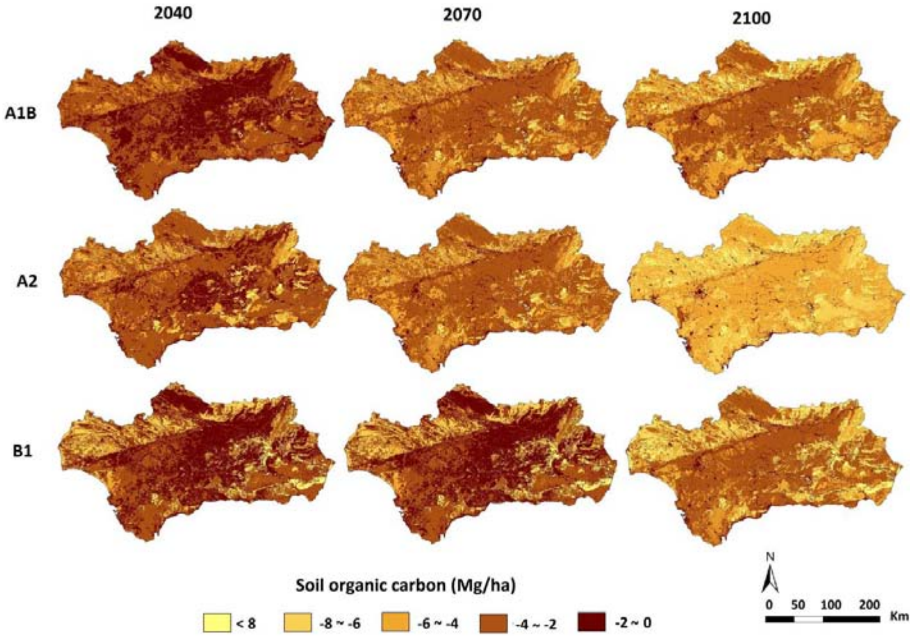

Fig. 5. Spatial distribution of changes in soil organic carbon content (Mg ha^{-1}) in Andalusia (Southern Spain) for different SRES scenarios and different periods (2040, 2070, 2100).

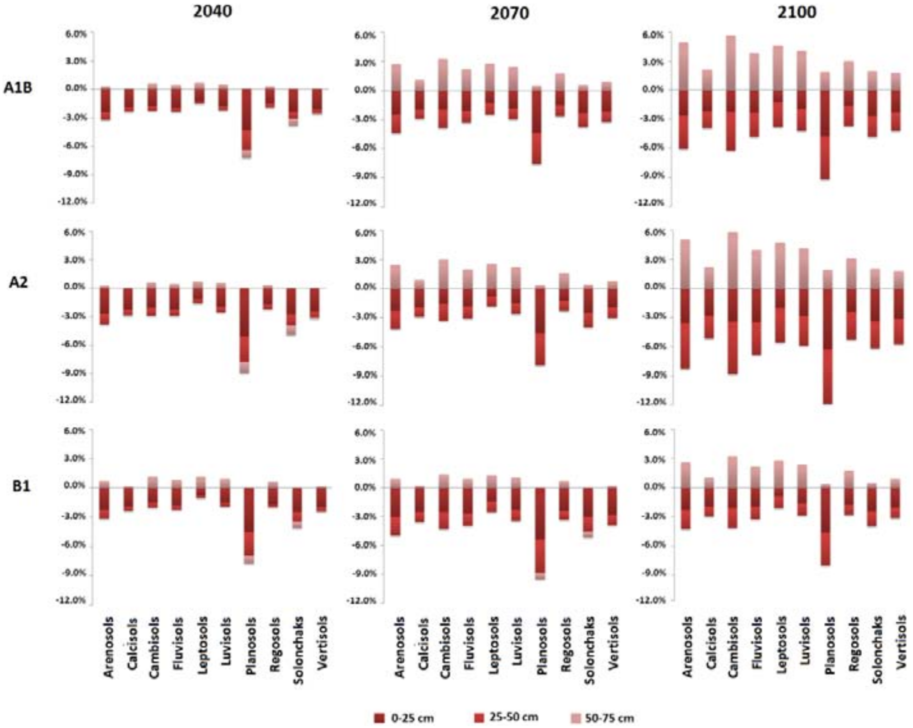

Fig. 6. Soil organic C stocks in climate change SRES scenarios in different periods (2040, 2070 and 2100) for each soil type at different soil depths (0–25, 25–50, 50–75 cm).

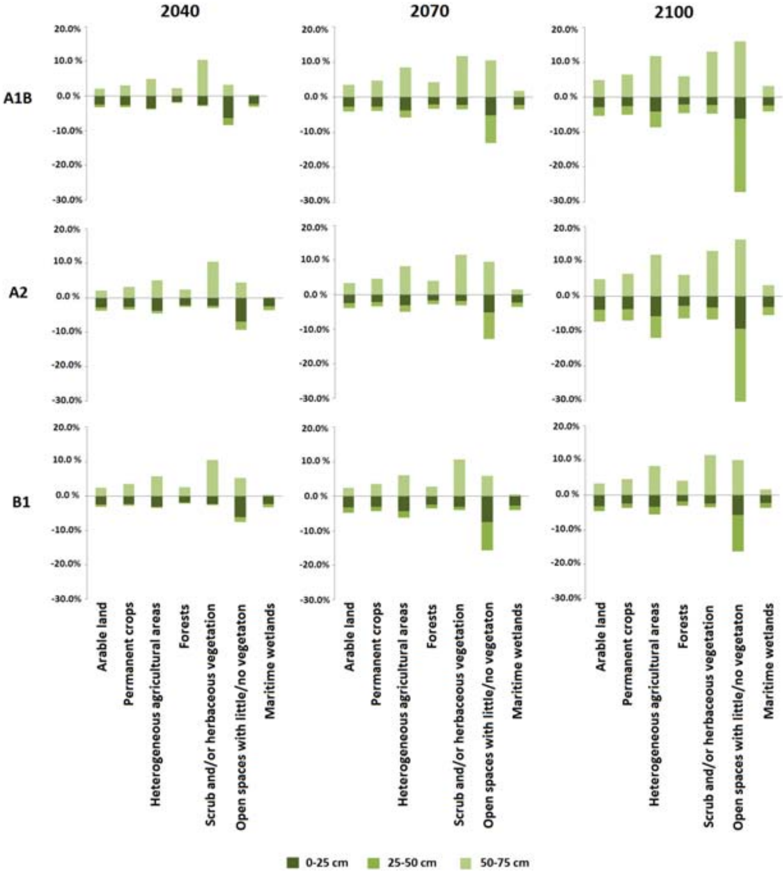

Fig. 7. Soil organic C stocks in climate change SRES scenarios in different periods (2040, 2070 and 2100) for each land use at different soil depths (0–25, 25–50, 50–75 cm).