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Simulating soil organic carbon stock as affected by land cover change and climate change, Hyrcanian forests (northern Iran)

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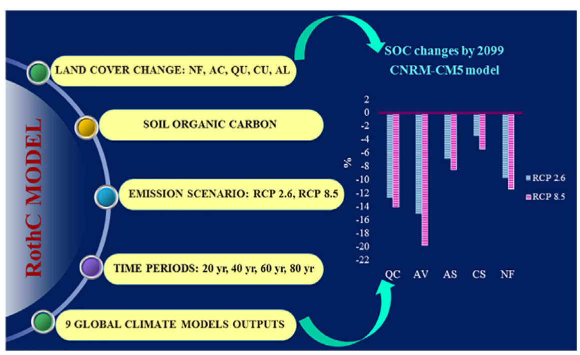
HIGHLIGHTS

- RothC model predicted the influence of future climate change scenarios in SOC stock.
- Results showed an overall decrease in SOC stocks by 2099 under climate change scenarios.
- The extents of the decrease in SOC stocks varied by different GCM models and their RCPs.
- SOC stocks losses were more significant in *Acer velutinum* plantation.

GRAPHICAL ABSTRACT



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ABSTRACT

Soil organic carbon (SOC) contains a considerable portion of the world's terrestrial carbon stock, and is affected by changes in land cover and climate. SOC modeling is a useful approach to assess the impact of land use, land use change and climate change on carbon (C) sequestration. This study aimed to: (i) test the performance of RothC model using data measured from different land covers in Hyrcanian forests (northern Iran); and (ii) predict changes in SOC under different climate change scenarios that may occur in the future. The following land covers were considered: *Quercus castaneifolia* (QC), *Acer velutinum* (AV), *Alnus subcordata* (AS), *Cupressus sempervirens* (CS) plantations and a natural forest (NF). For assessment of future climate change projections the Fifth Assessment IPCC report was used. These projections were generated with nine Global Climate Models (GCMs), for two Representative Concentration Pathways (RCPs) leading to very low and high greenhouse gases concentration levels (RCP 2.6 and RCP 8.5 respectively), and for four 20 year-periods up to 2099 (2030s, 2050s, 2070s and 2090s). Simulated values of SOC correlated well with measured data ($R^2 = 0.64$ to 0.91) indicating a good efficiency of the RothC model. Our results showed an overall decrease in SOC stocks by 2099 under all land covers and climate change scenarios, but the extent of the decrease varied with the climate models, the emissions scenarios, time periods and land covers. *Acer velutinum* plantation was the most sensitive land cover to future climate change (range of decrease 8.34–21.83 t C ha^{-1}). Results suggest that modeling techniques can be effectively applied for evaluating SOC stocks, allowing the identification of current patterns in the soil and the prediction of future conditions.

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1. Introduction

An increasing trend of the air temperature and changes in the weather conditions worldwide are denoted to as climate change. This is a major environmental and socio-economical problem and in the absence of potential mitigation and adaptation processes, climate change can affect many parts of the world, including environment, water resources, and ecosystem services (Etemadi et al., 2012).

The combustion of fossil fuels and the changes in land use and management contribute to the emission of greenhouse gases (GHGs), especially carbon dioxide (CO_2), globally increasing air temperature and enhancing climate change (IPCC, 2014). In particular, in the period 1750–2011, Land Use and Land Use Change (LULUC) are estimated to contribute with a carbon emission equal to 180 ± 80 Pg C (Ciais et al., 2013).

Climate change can significantly affect soil carbon (C), since changes in temperature, rainfall patterns and CO_2 concentrations influence C inputs to soil, and soil C decomposition (Cao and Woodward, 1998; Mosier, 1998). Recently climate change has been widely considered in order to recognize its impact on global soil organic carbon (SOC) stocks (Farzanmanesh et al., 2016; Lozano-García et al., 2017; Lu and Cheng, 2009; Smith et al., 2006; Xiong et al., 2014; Yigini and Panagos, 2016). SOC is the largest terrestrial C pool after fossil fuels, and SOC sequestration via agricultural and forestry management is important to manage and reduce greenhouse gas emissions (Jobbágy and Jackson, 2000; Sinoga et al., 2012). Different management systems can alter SOC stocks, mitigating or worsening climate change through C storage (sink) or C emissions (source) (Gottschalk et al., 2012). Prediction of SOC stocks in different ecosystem has become a key issue during the last few years, because of the possible effects of C on future climate change. On the other hand, understanding how land cover/land use and future climate change can affect SOC stocks provides useful information to improve land planning approaches (Lozano-García et al., 2017). However, in climate change studies uncertainties are high so it is essential to investigate several scenarios (Paustian et al., 2016).

Due to the high costs of field experiments, simulation models are widely used to estimate SOC stock changes in the long-term, and as decision support tools under future predicted climatic conditions (Jones and Donnelly, 2004; Mäkipää et al., 2008; Smith et al., 2006). Among the many SOC simulation models available, the Rothamsted Carbon Model (RothC) has a simpler structure than other models (Coleman and Jenkinson, 1996; Jenkinson et al., 1990), and provides accurate simulations of the measured values in different environments (Smith et al., 1997). RothC model has been used in many countries and in various ecosystems including prairie, agriculture and forest in the UK (Coleman et al., 1997), forests in Austria (Palosuo et al., 2012), Australia (Paul et al., 2003), Brazil (Cerri et al., 2007), Spain (Romanya et al., 2000) and Zambia (Kaonga and Coleman, 2008); olive groves in Spain (Nieto et al., 2010); land use and land use change in Italy (Farina et al., 2017; Francaviglia et al., 2012); and arable crops in Australia (Senapati et al., 2014), China (Guo et al., 2007; Li et al., 2016; Ludwig et al., 2010), Germany (Ludwig et al., 2007) and Kenya (Kamoni et al., 2007).

The Hyrcanian forest (from "*Hyrcania*", the Greek form of an old Iranian word to describe the region of Gorgan) is located along the southern coast of the Caspian Sea, has a total area of 1.85 million ha from the sea level up to 2800 m, and includes 80 forest woody species (*Fagus orientalis* Lipsky, *Quercus castaneifolia* C.A.M, *Alnus subcordata* C.A.M., *Acer velutinum* Boiss, *Carpinus betulus* L., *Parrotia persica* (DC) C.A.M., *Ulmus glabra* Huds, *Pterocarya fraxinifolia* (Lam.) Spach., *Populus caspica* Bornm.). Besides wood production, the forest provides many important ecosystem services including climate and water regulation, and opportunities for agriculture and tourism (Sagheb-Talebi et al., 2004).

According to the Kyoto Protocol afforestation has an important role in the mitigation of atmospheric CO_2. Forest plantations covered 184 million ha in year 2000 (116 million ha in Asia) (Nsabimana et al., 2008). Recently 200,000 ha of degraded Hyrcanian forests have been reforested with different species (Mohammadnezhad Kiasari, 2009) which may have caused changes in SOC contents in the north of Iran.

Presently, RothC has been applied under different land covers and climate change conditions in Iran (Farzanmanesh et al., 2016). Anyhow, there are no simulation studies dealing with current SOC changes, land cover change, and the effects of future climate conditions in the Middle East region of Asia.

In the case of forest management, the replacement of the natural vegetation with new plantations affects the ability to provide ecosystem services, and the maintenance of soil quality and SOC stocks. While their exploitation provides mainly wood and timber to meet the needs of a growing population, globalization and trade market, negative effects on ecosystem services can derive from the lower protection from erosion, the decrease of water regulation against floods and landslides, the loss of plant biodiversity following the fragmentation of habitats, the decrease of aesthetic and recreational components. Soil related services are strictly linked to SOC contents and stocks, which affect soil structure maintenance, soil moisture regime, organic matter decomposition and the related nutrient cycling to support plant growth, greenhouse gas emissions, and soil biota activity. In this line, the broadleafed and coniferous stands considered in the study as new plantations are supposed to differ in quantity and quality of litter input to the soil (Binkley and Giardina, 1998). The conversion from Hyrcanian forest to other types of forest covers is widespread in Iran as a consequence of the degradation of the natural forests, thus the study can be extrapolated to other forest areas with similar climatic conditions in the Middle-East region.

Thus, we used RothC model in this study to understand the response in terms of SOC stocks of the different land covers of Hyrcanian forest to the climate changes, and provide assistance in the management strategies in a long-term perspective.

The main goals of this study were: (i) to test and validate RothC as a technique for estimating SOC stocks in different land covers of Hyrcanian forest, north of Iran, and (ii) to evaluate the effects of climate change scenarios on SOC stocks using RothC.

2. Materials and methods

2.1. Study area

Darab Kola forest (a part of the Hyrcanian forest), with an area of 2612 ha, is located in the southeastern of Sari City, Mazandaran province, Iran (36°31′20″ N, 53°17′20″ E and 120–800 m a.s.l.) (Hosseini and Jalilvand, 2007) (Fig. 1). The climate is temperate humid and mean monthly temperature vary from 26.1 °C in August to 7.5 °C in February, 16.7 °C on average. Mean annual rainfall is 733 mm, with minimum and maximum monthly values in July (28 mm) and November (102 mm).

In 1987, some parts of this forest were "clear-cut", and then afforested by the Forests and Rangelands Organization of Iran (FROI) in 1991. The dominant forest types, which were planted at a spacing of 2×2 m, included cypress (*Cupressus sempervirens* var. *horizontalis*), maple (*Acer velutinum* Bioss.), alder (*Alnus subcordata* C.A. Mey.), oak (*Quercus castaneifolia* C.A. Mey.) and red pine (*Pinus brutia* Ten.).

The woody species in the natural forest are Persian iron wood (*Parrotia persica* C. A. Meyer), European hornbeam (*Carpinus betulus* L.), oak (*Quercus castaneifolia* C.A. Mey.), maple (*Acer velutinum* Bioss.), and alder (*Alnus subcordata* C.A. Mey.). Herbaceous vegetation in the natural forest includes cowslip (*Primula veris* L), johnson grass (*Sorghum halepense* (L.) Pers.), nettle (*Urtica dioica* L.), and eagle fern (*Pteridium aquilinum* (L.) Kuhn).

In this study, five different land covers were compared: maple plantation (AV: with 15 ha area), alder plantation (AS: with 7 ha area), oak plantation (QC: with 20 ha area), cypress plantation (CS: with 4 ha area) and a natural forest as native vegetation (NF). These plantations are a sample of land cover change in the natural area of Hyrcanian forest,

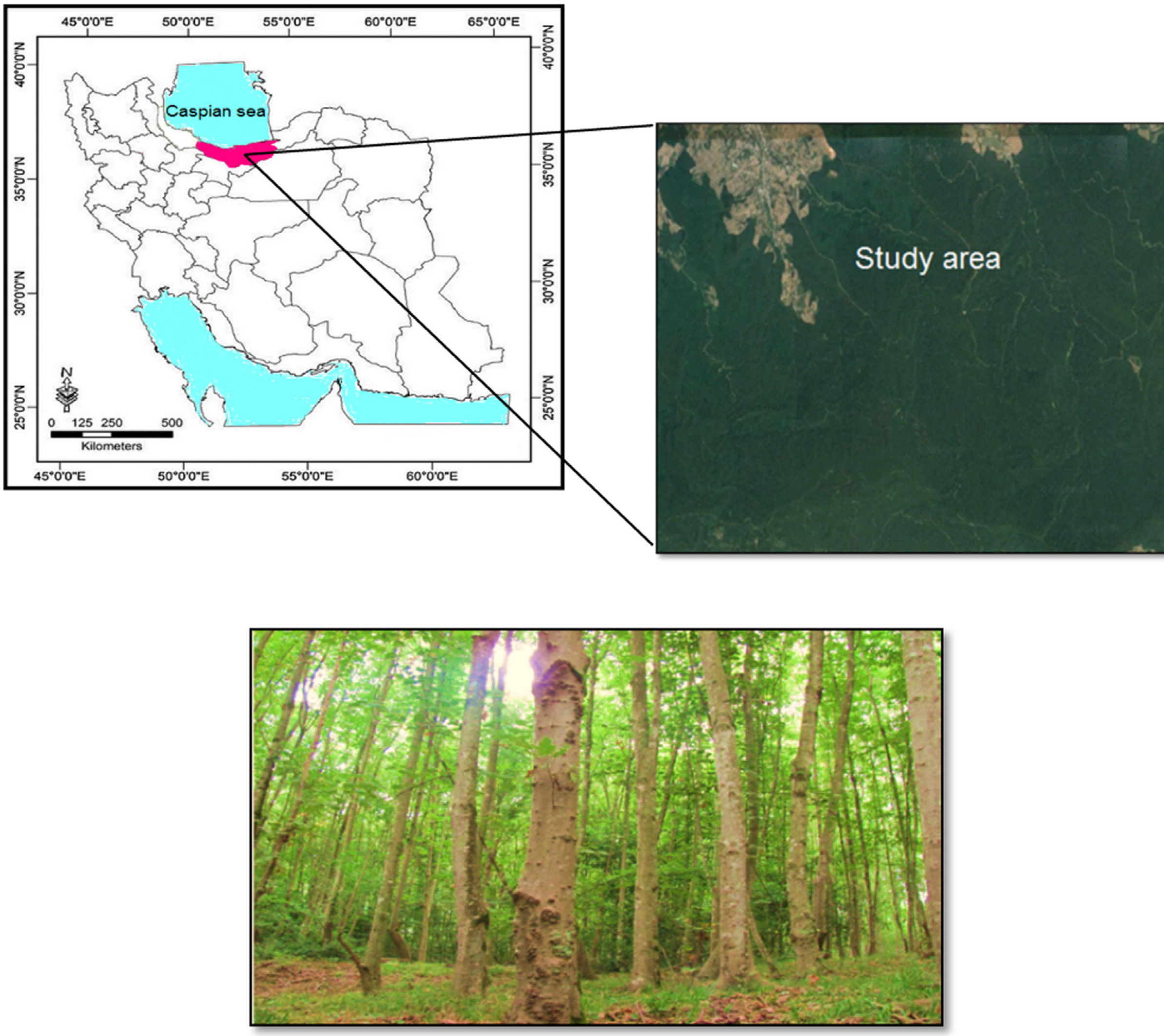

Fig. 1. Location of the Darab Kola Forest, located in the central Caspian region of northern Iran. This site falls within the Hyrcanian forest zone.

north of Iran, needing a comparative evaluation between planted and natural forests. Thus, we compared a needle-leaved plantation and three broad-leaved plantations with a natural forest, since the most of new plantations in Hyrcanian forest have been done with these species.

Soil samples were collected from the top 0–20 cm layer in November 2015 and 2016 before the onset of the rainy season. Thirty five soil replicates (seven replicates for each land cover) were sampled using a random method; each replicate was sampled at the four corners of a square-shaped area of 25 m^2, and then combined into a composite sample. To decrease the border effects for each land cover, the outer rows were not considered during sampling. In addition, SOC data of 2007 year was taken from Kooch et al. (2012) and Mohammadnezhad Kiasari (2009).

Soil reaction was measured using an Orion Ionalyzer Model 901 pH meter, total organic C and total N were measured by the Walkey and Black and the Kjeldahl methods respectively (Kjeldahl, 1883; Walkley and Black, 1934), bulk density was measured by the clod method (Plaster, 1985) and soil texture was determined by the hydrometer method (Day, 1965).

The soils are brown forest soils, classified as Cambisols according to IUSS Working Group WRB (2015). Main soil characteristics are shown in Table 1.

Soil organic C stocks were calculated with the formula:

$$SOC = C\,(\%) \times Bd \times d \qquad (1)$$

where SOC indicates the organic carbon stock (t C ha^{-1}); C is the percentage of organic carbon content; Bd is the bulk density (g cm^{-3}); d is thickness (cm).

2.2. RothC model

RothC-26.3 (Coleman and Jenkinson, 1996) is a model to simulate the turnover of organic C in non-waterlogged topsoils as affected by soil type, temperature, moisture and plant cover. The data used in the model are: monthly rainfall and open pan evaporation or potential evapotranspiration (mm), monthly air temperature (°C), percentage of clay, the ratio Decomposable Plant Material/Resistant Plant Material of the incoming plant material to soil, monthly soil cover (whether the soil is bare or vegetated), monthly input of plant residues (t C ha^{-1}), monthly input of FYM (t C ha^{-1}) if any. In this model, soil organic C is split into four active compartments including Decomposable Plant Material (DPM), Resistant Plant Material (RPM), Humified Organic matter (HUM), and Microbial Biomass BIO, and one small inert organic matter (IOM) fraction (resistant to decomposition) (Jenkinson and Coleman, 1994; Jenkinson et al., 1987, 1990, 1992). The model has two types of simulations: "direct" that uses the known input of organic C to the soil to determine the SOC stock, and "inverse" when the organic matter input is unknown, that calculates the organic C input required to keep the stock of SOC for a known combination of soil, DPM/RPM, land management and weather data (Coleman and Jenkinson, 1996).

Table 1
Main soil physical and chemical properties in the different land covers (means ± standard deviation).

Land cover[a]	Organic carbon (%)	Nitrogen (%)	Bulk density (g cm^{-3})	pH	Sand (%)	Silt (%)	Clay (%)
Acer velutinum	2.3 ± 0.57	0.18 ± 0.07	1.33 ± 0.05	7.0 ± 0.68	26.0 ± 10.77	39.6 ± 11.08	34.4 ± 7.40
Alnus subcordata	2.6 ± 0.36	0.21 ± 0.12	1.37 ± 0.05	7.0 ± 0.33	25.2 ± 7.42	42.0 ± 14.0	32.8 ± 16.03
Quercus castaneifolia	2.4 ± 0.30	0.16 ± 0.01	1.32 ± 0.04	7.0 ± 0.95	22.4 ± 6.78	47.6 ± 6.22	30.0 ± 10.43
Cupressus sempervirens	3.2 ± 0.24	0.17 ± 0.01	1.24 ± 0.03	7.7 ± 0.24	21.2 ± 9.65	38.4 ± 3.28	40.4 ± 7.26
Natural forest	2.4 ± 0.29	0.17 ± 0.03	1.45 ± 0.05	7.5 ± 0.53	34.2 ± 7.69	42.8 ± 5.76	23.0 ± 15.49

[a] $n = 7$ in each land cover.

2.3. Model parameterization and data inputs

Long-term (1984–2005) observed daily data of air temperature, precipitation, and open pan evaporation were taken from Gharakheill climate station of the Meteorological Organization of Iran (IRIMO), and then the average of monthly temperature, rainfall, and open pan evaporation were calculated. IOM value (t C ha^{-1}) was calculated using the formula IOM $= 0.049 \times$ $SOC^{1.139}$, where SOC is expressed in t C ha^{-1} (Falloon et al., 1998). The DPM:RPM ratio in this study was set to the default value of 0.25 for woodlands in all plantations as reported in Coleman and Jenkinson (1999).

To evaluate SOC stocks in different treatments, the model must be calibrated using a treatment with SOC at equilibrium, so the model baseline was established with the natural forest as the potential native vegetation.

Briefly, RothC was run to equilibrium in inverse mode for the natural forest, and to fit the simulations to measured data, the model was run under the mean weather and soil conditions of the natural forest for 10,000 years. The plant C input was adjusted iteratively until the modeled values of SOC stock at equilibrium matched the measured starting values. To achieve the SOC content of 69.68 t C ha^{-1} measured in the natural forest, a C input to the soil of 3.85 t C ha^{-1} was required. Clay (%) and IOM content were 23% and 6.16 t C ha^{-1} respectively.

To simulate SOC in the new forest plantations, and to match as close as possible the SOC contents previously measured in 2007, 2015 and 2016, specific management files were created: the model was run starting from the equilibrium conditions for the natural forest, and then up to the sampling date in 2016 for the new plantations. Thereafter, the effects of future climate change described below were modeled for four 20 year-periods on SOC stocks in the different plantations.

2.4. Climate change scenarios

Climate predictions used in the study were derived from nine Global Climate Models (GCMs) and two CO_2 Representative Concentration Pathways (RCPs) available from the IPCC Data Distribution Center site (www.ipcc-data.org), used respectively in the Fifth Assessment IPCC report (Plattner et al., 2009) and in the World Climate Research Programme's Fifth Coupled Model Intercomparison Project (Taylor et al., 2009).

A baseline and future climate conditions were investigated. The baseline climate was derived from the daily data of the 1984–2005 period, and the RCP 2.6 and RCP 8.5 future climate scenarios were built from the predicted climatic parameters of the 2020–2099 period. In this study we used nine Global Climate Models (GCMs) (Table 2). The LARS-WG model was used for downscaling the nine GCMs output on daily data of Gharakheill meteorological station. LARS-WG is a stochastic weather generator based on the series weather generator (Racsko et al., 1991) with an exhaustive explanation being given in Semenov et al. (1998).

The RCP 2.6 is developed by the IMAGE modeling team (Integrated Model to Assess the Global Environment), and leads to very low GHG concentration levels. First its radiative forcing level reaches 3.1 W/m^2 mid-century ("peak" scenario), and returns to 2.6 W/m^2 by 2100 by reducing GHG and pollutants emissions during the time (Van Vuuren et al., 2007).

The RCP 8.5 is developed by the MESSAGE modeling team (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) and the IIASA (Integrated Assessment Framework at the International Institute for Applies Systems Analysis), Austria. In this scenario GHG emissions increase over time, and leads to high GHG levels, based on the A2r scenario (Riahi et al., 2007).

A schematic illustration of the experimental approach is shown in Fig. 2.

The simulations were projected on four time periods with the nine GCM models:

- 2030s: mean climate change for the period 2020–2039, with 428.50 (RCP 2.6) and 448.19 (RCP 8.5) CO_2 concentrations (ppm);
- 2050s: mean climate change for the period 2040–2059, with 442.05 (RCP 2.6) and 539.66 (RCP 8.5) CO_2 concentrations (ppm);
- 2070s: mean climate change for the period 2060–2079, with 437.46 (RCP 2.6) and 674.55 (RCP 8.5) CO_2 concentrations (ppm);
- 2090s: mean climate change for the period 2080–2099, with 426.40 (RCP 2.6) and 841.19 (RCP 8.5) CO_2 concentrations (ppm).

2.5. Statistical analyses

The predictive performance of the RothC model is reported in the results section using the relevant statistical indices R-squared (R^2), Mean Absolute Error (MAE) and Root Mean Square error (RMSE) as shown in the following equations:

$$R^2 = \frac{\left(\sum_{i=1}^{n}\left(S_i - \overline{O}\right)\left(O_i - \overline{O}\right)\right)^2}{\sum_{i=1}^{n}\left(S_i - \overline{S}\right)^2 \sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2} \tag{2}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|o_i - s_i|}{n} \tag{3}$$

$$\mathrm{RMSE} = \left[\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2\right]^{1/2} \tag{4}$$

where S_i and O_i represent the i^{th} predicted and observed values respectively, $\overline{S}$ and $\overline{O}$ the average predicted and observed SOC values respectively, and n the total number of observations.

3. Results

3.1. Climate change and emission scenarios

The CO_2 concentration was 360 ppm in the baseline (1984–2005 period) climate scenario, and an increase in CO_2 concentration compared with baseline was shown for the four time periods both in the RPC 2.6 and in the RPC 8.5.

Downscaled results of changes in temperature and precipitation for four future time periods using LARS-WG method compared with the baseline climate (1984–2005) are given in Figs. 3–6.

The results predict an increase in future temperature relative to the baseline period (1984–2005) with all the GCM models, in both emission scenarios, but the increase of temperature was higher in the RCP 8.5. For example, in CNRM-CM5 model the mean temperature would increase

Table 2
Overview of selected Global Climate Models (GCMs).

No.	Model	Spatial resolution (Longitude × Latitude)	Institution
1	CNRM-CM5	1.41 × 1.4	Centre National de Recherches, France
2	EC-EARTH	1.125 × 1.122	EC-EARTH consortium
3	GISS-E2-H	2.5 × 2.0	NASA Goddard Institute for Space Studies
4	GISS-E2-R	2.5 × 2.0	
5	MIROC-ESM	2.81 × 1.77	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute
6	MIROC-ESM-CHEM	2.81 × 1.77	for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
7	MIR-CGCM3	1.125 × 1.125	
8	MPI-ESM-LR	1.875 × 1.85	Max Planck Institute for Meteorology (MPI-M)
9	MPI-ESM-MR	1.875 × 1.85	

by 1.82, 2.37, 2.44 and 2.47 °C, respectively for 2030s, 2050s, 2070s and 2090s future periods in the RCP 2.6. Conversely, in the RCP 8.5, the mean temperature would increase by 1.43, 2.70, 4.03 and 5.59 °C respectively.

The projection on future rainfall patterns is very complex and uncertain since precipitation involves local processes of larger complexity than temperature, and projections are usually less robust than those for temperature (Giorgi and Lionello, 2008). GCM models indicated different results for precipitation in the four time periods. In MIROC-ESM-CHEM model the amount of precipitation would increase by 21.83%, 58.91%, 30.57% and 52.28%, respectively for 2030s, 2050s, 2070s and 2090s in the RCP 2.6. While in MPI-ESM-LR model the amount of precipitation would decrease by 13.06%, 4.60%, 1.99% and 1.32% respectively in the RCP 2.6.

3.2. Baseline carbon storage and modeling results

Running the model in inverse mode, RothC calculated the annual organic C inputs to soil needed to attain SOC stocks in the natural forest. Modeled annual inputs in the different land covers ranged from 2.65 to 5.09 t C ha^{-1} year^{-1} (Table 3).

In this study, SOC stocks considerably differed across land covers. The highest accumulation of SOC occurred under the *Alnus subcordata* and the *Cupressus sempervirens* plantations (71.24 t C ha^{-1} and 79.42 t C ha^{-1} respectively) measured in 2016 following land cover change from the natural forest (69.68 t C ha^{-1}) to the new plantations. However, SOC stocks were sharply lower in the *Acer velutinum* and the *Quercus castaneifolia* plantations (61.51 t C ha^{-1} and 63.36 t C ha^{-1} respectively).

Soil organic C stocks in *Cupressus sempervirens* and *Alnus subcordata* plantations increased by 9.74 t C ha^{-1} and 1.56 in t C ha^{-1} respectively in comparison with the natural forest, and decreased by 8.17 t C ha^{-1} and 6.32 t C ha^{-1} in the *Acer velutinum* and *Quercus castaneifolia* plantations respectively in 2016.

In forest ecosystems, the soil C is determined by the balance between the litter input and the soil heterotrophic respiration. The change of soil C in the different land covers was estimated by RothC model. As shown in Table 3, there was a good agreement among the measured and modeled data by RothC for the period 1989–2016, as shown by the low percent deviation.

Results showed that C stock modeled in the *Alnus subcordata* and *Cupressus sempervirens* plantations increased by 2.11 t C ha^{-1} and 8.71 t C ha^{-1} respectively compared with the natural forest. Conversely, a marked SOC decrease was modeled in the *Acer velutinum* plantation with 9.14 t C ha^{-1}, and the *Quercus castaneifolia* plantation with 5.42 t C ha^{-1}. The highest modeled SOC stocks were shown in the *Alnus subcordata* (71.79 t C ha^{-1}) and the *Cupressus sempervirens* plantations (78.39 t C ha^{-1}), and the lowest in the *Acer velutinum* and the *Quercus castaneifolia* plantations (60.53 t C ha^{-1} and 64.25 t C ha^{-1} respectively).

The simulated SOC stocks with the different Global Climate Models (GCMs) and Representative Concentration Pathways (RCPs) are presented in Tables 4 and 5. Two graphical examples are given in Figs. 7 and 8 for the CNRM-CM5 model. In our study, the projected decrease in SOC stocks was 0.44–17.04 t C ha^{-1} and 0.67–21.83 by 2099 respectively in the RCP 2.6 and RCP 8.5. The highest decrease, equal to 21.83 t C ha^{-1}, was predicted by MIROC-ESM-CHEM (RCP 8.5), and the lowest decrease by GISS-E2-H (RCP 2.6) with 0.44 t C ha^{-1}.

In the *Acer velutinum* and *Quercus castaneifolia* plantations, a sharp SOC decrease was observed after 2090s compared with the baseline values in 2016, even with no changes in land management or soil C inputs. But the SOC change in the other plantations (*Alnus subcordata* and *Cupressus sempervirens*) was lower in all scenarios. For example in the *Alnus subcordata* plantation SOC decreased by 2.83–7.65 t C ha^{-1}; in the *Cupresuss sempervirens* plantation by 0.44–6.02 t C ha^{-1}; in the *Acer velutinum* plantation by 10.72–14.30 t C ha^{-1}; and in the *Quercus castaneifolia* plantation by 6.83–10.81 t C ha^{-1} in the GISS-E2-H model.

Table 6 shows some results of predicted total SOC stock changes in t of C for the different land covers considering the surface of the

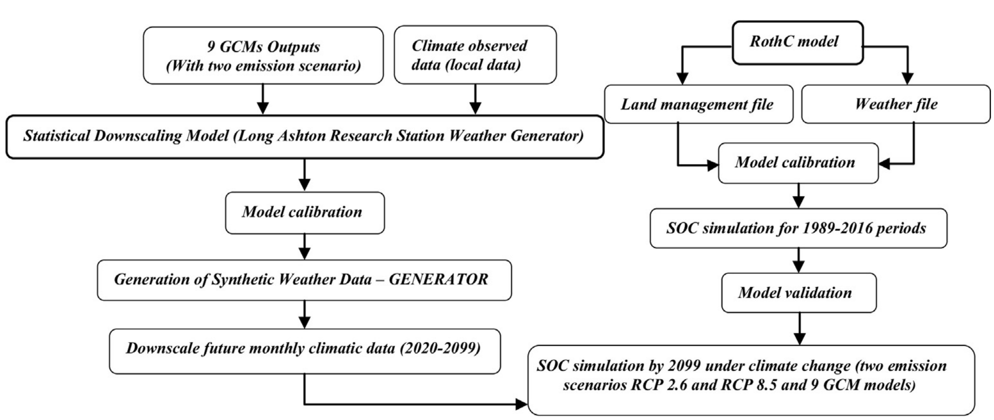

Fig. 2. Schematic illustration of the experimental approach.

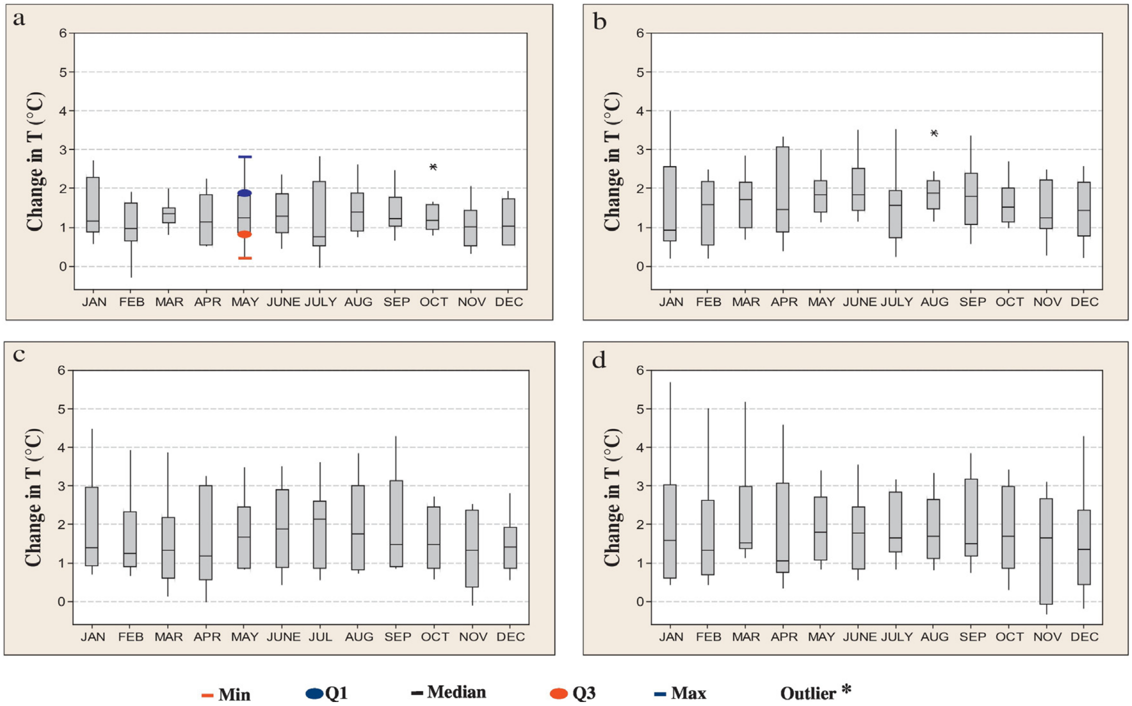

Fig. 3. Box plot of changes in temperature with climate change scenario for 9 Global Climate Models (GCMs) in 2020–2099 compared with the base period under RCP 2.6. a) 2020–2039; b) 2040–2059; c) 2060–2079; d) 2080–2099.

plantations. SOC stock will decrease by 83.2–315.0 t C in *Quercus castaneifolia* plantation, by 125.1–327.45 t C in *Acer velutinum* plantation and by 16.7–192 t C in natural forest. In the *Cupressus sempervirens* and the *Alnus subcordata* plantations, SOC will increase in MPI-ESM-MR model (RCP 2.6) and decrease by 21.0–126.42 and 2.68–72.56 t C (respectively in *Alnus subcordata* and *Cupressus sempervirens* plantations) in the other models at the end of simulation period.

4. Discussion

4.1. Model validation

The RothC model has been validated in many countries, such as Australia, Brazil, Ireland, India, Italy, and France (Cerri et al., 2003; Francaviglia et al., 2012; Liu et al., 2011; Senapati et al., 2014; Xu et al.,

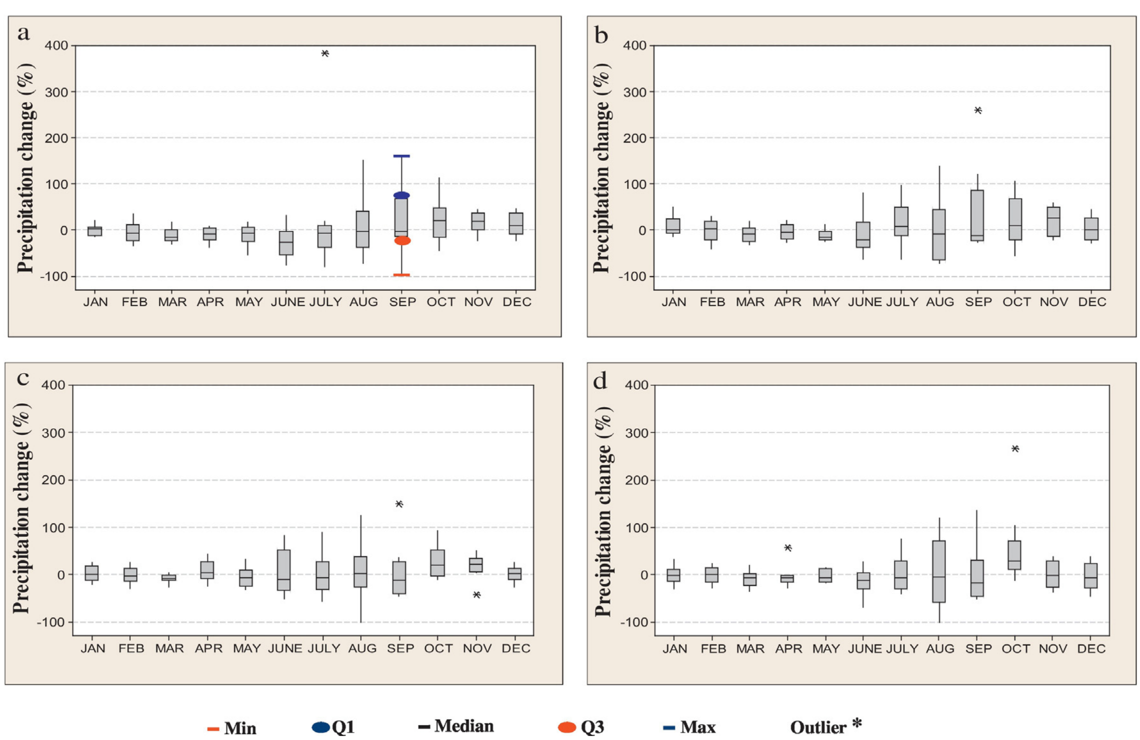

Fig. 4. Box plot of changes in precipitation with climate change scenario for 9 Global Climate Models (GCMs) in 2020–2099 compared with the base period under RCP 2.6. a) 2020–2039; b) 2040–2059; c) 2060–2079; d) 2080–2099.

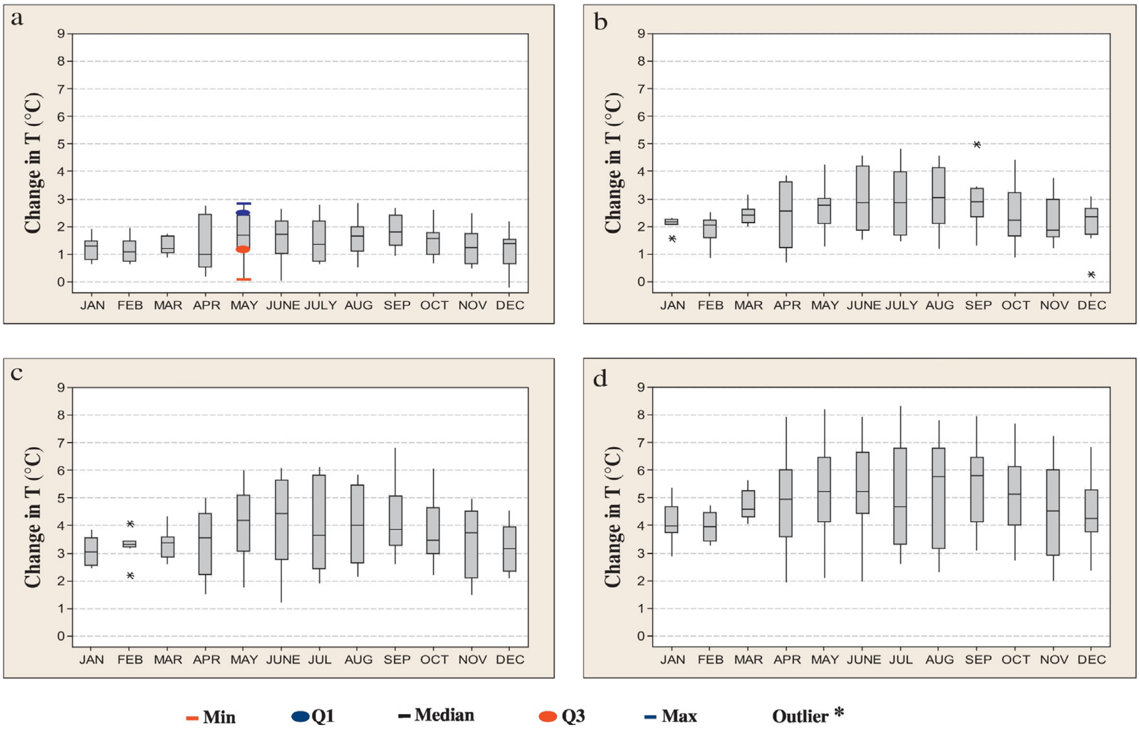

Fig. 5. Box plot of changes in temperature with climate change scenario for 9 Global Climate Models (GCMs) in 2020–2099 compared with the base period under RCP 8.5. a) 2020–2039; b) 2040–2059; c) 2060–2079; d) 2080–2099.

2011). Validation results of each plantation based on three different criteria are shown in Table 7. The R^2, RMSE and MAE between all predicted and measured values of soil organic C were used to assess the performance of RothC model. RMSE can vary from 0 to a large positive value, where zero RMSE indicates a perfect model simulation with no difference between simulated and observed data. RMSE and MAE show the similarity relationship, so the lower values indicate a best simulation performance. The total simulation error in terms of RMSE ranged from 1.79 to 4.22. Mean absolute error (MAE) ranged from 1.62 to 2.92. *Cupressus sempervirens* and *Acer velutinum* plantations had the lowest and highest values of RMSE and MAE respectively. Moreover, the higher values of R^2 represent the higher similarities among simulated and measured data. The coefficient of determination (R^2) ranged within 0.63–0.90. The results of statistical parameters analyses

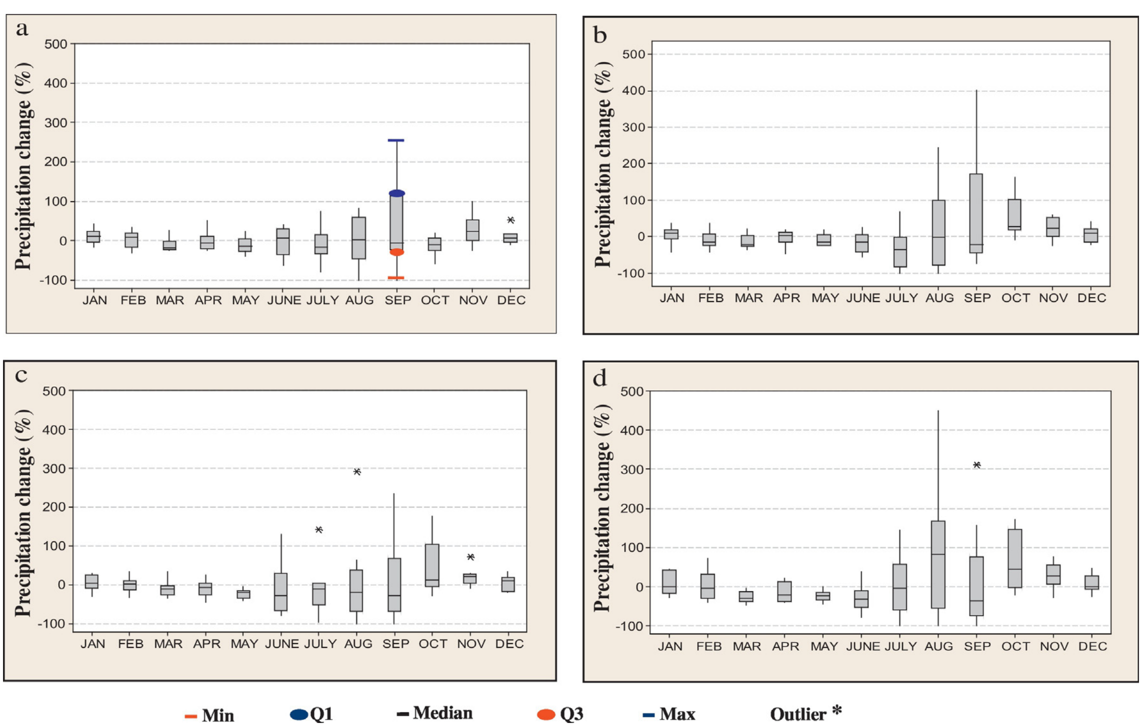

Fig. 6. Box plot of changes in precipitation with climate change scenario for 9 Global Climate Models (GCMs) in 2020–2099 compared with the base period under RCP 8.5. a) 2020–2039; b) 2040–2059; c) 2060–2079; d) 2080–2099.

Table 3
Input data, measured and modeled SOC in 2016 in the different land covers (means ± standard deviation).

Land cover[a]	Clay (%)	Soil carbon inputs (t C ha^{-1})	IOM (t C ha^{-1})	SOC measured (t C ha^{-1})	SOC modeled (t C ha^{-1})	Deviation[b] (%)
Acer velutinum	34.4 ± 7.40	2.65	5.34 ± 1.19	61.51 ± 12.93	60.53	−1.58
Alnus subcordata	32.8 ± 16.03	4.18	6.31 ± 1.00	71.24 ± 10.49	71.79	0.78
Quercus castaneifolia	30.0 ± 10.43	3.15	5.52 ± 0.76	63.36 ± 8.42	64.25	1.41
Cupressus sempervirens	40.4 ± 7.26	5.09	7.14 ± 0.84	79.42 ± 8.49	78.39	−1.29
Natural forest	23.0 ± 15.49	3.84[c]	6.16 ± 0.90	69.68 ± 8.68	69.68	0.0

SOC: soil organic carbon; IOM: inert organic matter.
[a] $n = 7$ in each land cover.
[b] Deviation calculated as [100 × (modeled − measured) / measured].
[c] Model run to the equilibrium in "inverse mode".

indicated a better prediction for *Cupressus sempervirens* plantation rather than the other plantations since *Cupressus sempervirens* plantation had the highest values of R^2, and the lowest RMSE and MAE.

4.2. Predictions of SOC under climate change scenarios

It has been predicted that the increasing levels of atmospheric CO_2 and other GHGs will result in increased temperature and altered rainfall patterns (Gorissen et al., 2004). In climate change studies, various uncertainty sources that can be related to GHG emissions, climatic drivers, etc. (Van Vuuren et al., 2012), may affect future climate simulations; and in addition, these uncertainties may affect SOC dynamics in simulation studies. The results of the present study revealed that GCMs uncertainties in simulation of SOC for the case study area are high. Moreover, the results showed relevant differences between both future time periods and the land covers. Therefore, use of just a single GCM model for future climate change surveys may be misleading.

Table 4
Present (A), and simulated (B to E) soil organic carbon stocks in t C ha^{-1} in the RCP 2.6 scenario and the future time periods (2030s, 2050s, 2070s and 2090s). Changes in t C ha^{-1} yr^{-1} are shown in brackets.

Land cover	2016	Time periods	CNRM-CM5	EC-EARTH	GISS-E2-H	GISS-E2-R	MIROC-ESM	MIROC-ESMCHEM	MIR-CGCM3	MPI-ESM-LR	MPI-ESM-MR
QC	A 63.36	B 20–39	62.37 (−0.05)	61.50 (−0.09)	62.39 (−0.05)	61.53 (−0.09)	61.38 (−0.10)	58.35 (−0.25)	61.73 (−0.08)	62.67 (0.03)	61.89 (−0.07)
		C 40–59	58.67 (−0.12)	60.06 (−0.08)	59.32 (−0.10)	60.38 (−0.07)	59.52 (−0.10)	53.40 (−0.24)	59.31 (−0.10)	57.33 (−0.15)	61.37 (−0.05)
		D 60–79	56.82 (−0.11)	58.23 (−0.08)	57.78 (−0.09)	58.53 (−0.08)	56.96 (−0.11)	52.91 (−0.17)	57.31 (−0.10)	57.23 (−0.10)	60.51 (−0.04)
		E 80–99	55.29 (−0.10)	58.94 (−0.05)	56.53 (−0.08)	57.31 (−0.07)	56.20 (−0.09)	49.46 (−0.17)	55.87 (−0.09)	57.08 (−0.08)	59.20 (−0.05)
		E-A	−8.07	−4.42	−6.83	−6.05	−7.16	−13.9	−7.49	−6.28	−4.16
AV	A 61.51	B 20–39	58.19 (−0.14)	57.42 (−0.20)	58.20 (−0.16)	57.45 (−0.20)	57.32 (−0.20)	54.65 (−0.34)	57.62 (−0.19)	58.45 (−0.15)	57.77 (−0.18)
		C 40–59	54.04 (−0.18)	55.22 (−0.15)	54.61 (−0.17)	55.50 (−0.15)	54.76 (−0.16)	49.27 (−0.30)	54.57 (−0.17)	52.88 (−0.21)	56.37 (−0.12)
		D 60–79	51.62 (−0.12)	52.88 (−0.14)	52.49 (−0.15)	53.15 (−0.13)	51.77 (−0.16)	48.01 (−0.22)	52.07 (−0.15)	51.94 (−0.15)	54.89 (−0.11)
		E 80–99	49.69 (−0.11)	52.87 (−0.10)	50.79 (−0.13)	51.48 (−0.12)	50.49 (−0.13)	44.47 (−0.21)	50.20 (−0.14)	51.22 (−0.12)	53.17 (−0.10)
		E-A	−9.52	−8.64	−10.72	−10.03	−11.02	−17.04	−11.31	−10.29	−8.34
AS	A 71.24	B 20–39	71.08 (−0.01)	70.00 (−0.62)	71.11 (−0.01)	70.04 (−0.06)	69.85 (−0.07)	66.11 (−0.25)	70.28 (−0.05)	71.45 (0.01)	70.49 (−0.04)
		C 40–59	68.34 (−0.07)	70.15 (−0.03)	69.16 (−0.05)	70.56 (−0.02)	69.48 (−0.04)	62.05 (−0.23)	69.19 (−0.05)	66.64 (−0.11)	71.77 (0.01)
		D 60–79	67.61 (−0.06)	69.34 (−0.03)	68.79 (−0.04)	69.70 (−0.02)	67.75 (−0.05)	63.10 (−0.13)	68.2 (−0.05)	68.22 (−0.05)	72.15 (0.01)
		E 80–99	66.89 (−0.05)	71.50 (0.003)	68.41 (−0.03)	69.37 (−0.02)	68.05 (−0.04)	59.82 (−0.14)	67.61 (−0.04)	69.20 (−0.02)	71.67 (0.01)
		E-A	−4.35	0.26	−2.83	−1.87	−3.19	−11.42	−3.63	−2.04	0.43
CS	A 79.42	B 20–39	78.88 (−0.03)	77.62 (−0.09)	78.92 (−0.02)	77.66 (−0.09)	77.45 (−0.10)	73.078 (−0.31)	77.95 (−0.07)	79.32 (−0.01)	78.19 (−0.06)
		C 40–59	77.00 (−0.06)	79.18 (−0.01)	77.96 (−0.04)	79.67 (0.01)	78.39 (−0.02)	69.81 (−0.24)	78.04 (−0.03)	74.98 (−0.11)	81.09 (0.04)
		D 60–79	77.23 (−0.04)	79.24 (−0.003)	78.61 (−0.01)	79.66 (0.004)	77.37 (−0.03)	72.18 (−0.12)	77.93 (−0.02)	78.03 (−0.02)	82.54 (0.05)
		E 80–99	77.21 (−0.03)	82.66 (0.04)	78.98 (−0.005)	80.10 (0.01)	78.58 (−0.01)	69.03 (−0.13)	78.04 (−0.02)	79.98 (0.007)	82.76 (0.04)
		E-A	−2.21	3.24	−0.44	0.68	−0.84	−10.39	−1.38	0.56	3.34
NF	A 69.68	B 20–39	68.82 (−0.04)	67.81 (−0.09)	68.85 (−0.04)	67.86 (−0.09)	67.68 (−0.1)	64.18 (−0.27)	68.08 (−0.08)	69.17 (−0.02)	68.27 (−0.07)
		C 40–59	65.79 (−0.10)	67.46 (−0.05)	66.55 (−0.08)	67.85 (−0.04)	66.83 (−0.07)	59.78 (−0.25)	66.57 (−0.08)	64.20 (−0.14)	68.99 (−0.02)
		D 60–79	64.56 (−0.08)	66.20 (−0.06)	65.68 (−0.07)	66.54 (−0.05)	64.70 (−0.08)	60.19 (−0.16)	65.13 (−0.07)	65.11 (−0.07)	68.86 (−0.01)
		E 80–99	63.48 (−0.08)	67.80 (−0.02)	64.92 (−0.06)	65.83 (−0.05)	64.56 (−0.06)	56.76 (−0.16)	64.15 (−0.07)	65.63 (−0.05)	68.01 (−0.02)
		E-A	−6.2	−1.88	−4.76	−3.85	−5.12	−12.92	−5.53	−4.05	−1.67

QC: *Quercus castaneifolia*; AV: *Acer velutinum*; AS: *Alnus subcordata*; CS: *Cupressus sempervirens*; NF: Natural Forest.

Table 5
Present (A), and simulated (B to E) soil organic carbon stocks in t C ha^{-1} and in the RCP 8.5 scenario and the future time periods (2030s, 2050s, 2070s and 2090s). Changes in t C ha^{-1} yr^{-1} are shown in brackets.

Land cover	2016	Time periods	CNRM-CM5	EC-EARTH	GISS-E2-H	GISS-E2-R	MIROC-ESM	MIROC-ESM-CHEM	MIR-CGCM3	MPI-ESM-LR	MPI-ESM-MR
QC	A 63.26	B 20–39	61.07	61.82	61.08	62.84	61.03	58.07	61.30	63.93	58.54
			(−0.11)	(−0.08)	(−0.11)	(−0.03)	(−0.11)	(−0.26)	(−0.10)	(−0.03)	(−0.24)
		C 40–59	58.22	59.32	57.30	59.66	58.58	52.59	58.01	59.61	54.19
			(−0.12)	(−0.10)	(−0.15)	(−0.09)	(−0.11)	(−0.26)	(−0.13)	(−0.093)	(−0.22)
		D 60–79	57.15	55.46	54.00	58.28	55.10	48.27	55.05	56.42	54.21
			(−0.10)	(−0.13)	(−0.15)	(−0.08)	(−0.13)	(−0.25)	(−0.13)	(−0.11)	(−0.15)
		E 80–99	54.48	51.60	52.55	56.41	51.51	47.61	50.97	53.26	51.99
			(−0.11)	(−0.15)	(−0.13)	(−0.09)	(−0.14)	(−0.19)	(−0.15)	(−0.13)	(−0.14)
		E-A	−8.88	−11.76	−10.81	−6.95	−11.85	−15.75	−12.39	−10.1	−11.37
AV	A 61.51	B 20–39	57.04	57.70	57.05	58.59	57.01	54.4	57.24	59.54	54.81
			(−0.22)	(−0.19)	(−0.22)	(−0.14)	(−0.22)	(−0.35)	(−0.21)	(−0.09)	(−0.33)
		C 40–59	53.60	54.58	52.79	54.91	53.91	48.54	53.42	54.91	49.97
			(−0.19)	(−0.17)	(−0.21)	(−0.16)	(−0.19)	(−0.32)	(−0.20)	(−0.16)	(−0.28)
		D 60–79	51.87	50.46	49.11	52.92	50.12	43.96	50.05	51.32	49.17
			(−0.16)	(−0.18)	(−0.20)	(−0.14)	(−0.18)	(−0.29)	(−0.19)	(−0.16)	(−0.20)
		E 80–99	48.97	46.46	47.21	50.69	46.38	39.68	45.89	47.96	46.69
			(−0.15)	(−0.18)	(−0.17)	(−0.13)	(−0.18)	(−0.27)	(−0.19)	(−0.16)	(−0.18)
		E-A	−12.54	−15.05	−14.3	−10.82	−15.13	−21.83	−15.62	−13.55	−14.82
AS	A 71.24	B 20–39	69.46	70.40	69.48	71.67	69.41	65.77	69.75	73.03	66.34
			(−0.099)	(−0.04)	(−0.09)	(−0.02)	(−0.09)	(−0.27)	(−0.07)	(−0.09)	(−0.24)
		C 40–59	67.87	69.19	66.72	69.55	68.31	61.06	67.59	69.42	63.02
			(−0.08)	(−0.05)	(−0.11)	(−0.04)	(−0.07)	(−0.25)	(−0.09)	(−0.04)	(−0.20)
		D 60–79	68.09	65.87	64.15	69.40	65.46	57.29	65.44	67.01	64.69
			(−0.05)	(−0.09)	(−0.12)	(−0.03)	(−0.10)	(−0.23)	(−0.10)	(−0.07)	(−0.11)
		E 80–99	65.88	62.24	63.59	68.24	62.16	53.18	61.50	64.26	62.97
			(−0.07)	(−0.11)	(−0.09)	(−0.04)	(−0.11)	(−0.22)	(−0.12)	(−0.09)	(−0.10)
		E-A	−5.36	−9.00	−7.65	−3.00	−9.08	−18.06	−9.74	−6.98	−8.27
CS	A 79.42	B 20–39	76.99	78.08	77.01	79.58	76.93	72.69	77.32	81.18	73.35
			(−0.12)	(−0.07)	(−0.12)	(0.01)	(−0.124)	(−0.33)	(−0.10)	(0.09)	(−0.30)
		C 40–59	76.52	78.04	75.15	78.42	77.03	68.66	76.18	78.21	70.93
			(−0.07)	(−0.03)	(−0.11)	(−0.02)	(−0.059)	(−0.26)	(−0.08)	(−0.03)	(−0.21)
		D 60–79	77.85	75.14	73.20	79.32	74.69	65.33	74.71	76.45	74.03
			(−0.03)	(−0.07)	(−0.10)	(−0.001)	(−0.078)	(−0.23)	(−0.08)	(−0.05)	(−0.09)
		E 80–99	76.01	71.70	73.40	78.75	71.64	61.28	70.87	74.05	72.73
			(−0.04)	(−0.10)	(−0.07)	(−0.01)	(−0.097)	(−0.22)	(−0.11)	(−0.67)	(−0.08)
		E-A	−3.41	−7.72	−6.02	−0.67	−7.78	−18.14	−8.55	−5.37	−6.69
NF	A 69.68	B 20–39	67.31	68.19	67.33	69.37	67.27	63.86	67.58	70.64	64.40
			(−0.12)	(−0.07)	(−0.12)	(−0.01)	(−0.12)	(−0.3)	(−0.10)	(−0.05)	(−0.26)
		C 40–59	65.32	66.58	64.23	66.94	65.73	58.84	65.06	66.84	60.69
			(−0.11)	(−0.08)	(−0.14)	(−0.07)	(−0.10)	(−0.27)	(−0.11)	(−0.07)	(−0.22)
		D 60–79	64.99	62.94	61.29	66.26	62.54	54.74	62.51	64.03	61.70
			(−0.08)	(−0.11)	(−0.14)	(−0.06)	(−0.12)	(−0.25)	(−0.12)	(−0.09)	(−0.13)
		E 80–99	62.53	59.12	60.33	64.76	59.04	50.48	58.41	61.04	59.72
			(−0.09)	(−0.13)	(−0.12)	(−0.06)	(−0.13)	(−0.24)	(−0.14)	(−0.11)	(−0.12)
		E-A	−7.15	−10.56	−9.35	−4.92	−10.64	−19.2	−11.27	−8.64	−9.96

QC: *Quercus castaneifolia*; AV: *Acer velutinum*; AS: *Alnus subcordata*; CS: *Cupressus sempervirens*; NF: Natural Forest.

According to this study, in general, the RCP 8.5 scenario provided a warmer climate in the future and predicted a more critical condition compared to the RCP 2.6 scenario. Among the nine GCMs, CNRM-CM5, MIROC-ESM and MIROC-ESM-CHEM models showed more extreme climate change simulations for temperature than the other models in both emission scenarios. GCMs precipitation predictions showed a broad

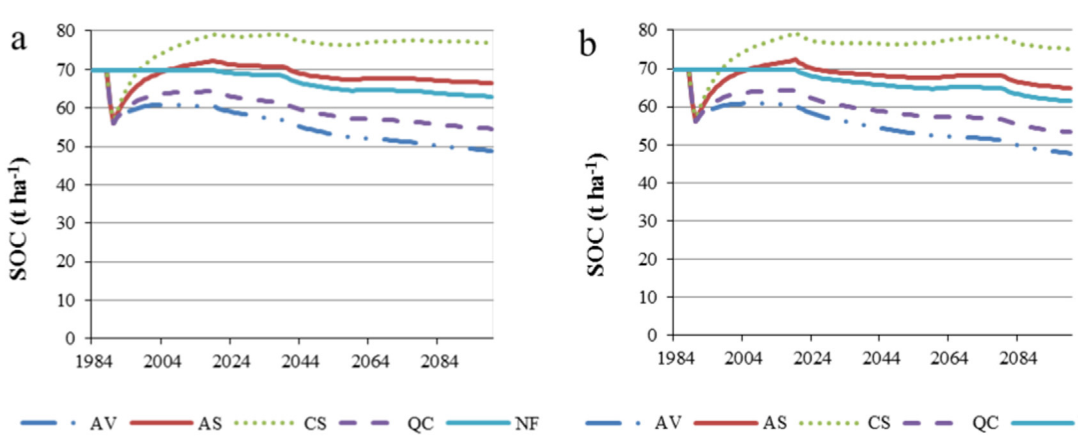

Fig. 7. Simulation of soil organic carbon dynamics under CNRM-CM5, a: RCP 2.6, b: RCP 8.5. QC: *Quercus castaneifolia*; AV: *Acer velutinum*; AS: *Alnus subcordata*; CS: *Cupressus sempervirens*; NF: Natural Forest.

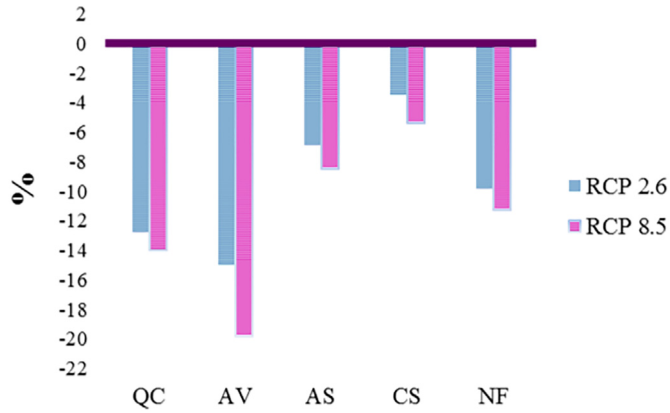

Fig. 8. Soil organic carbon changes in 2090s under the two emission scenarios (RCP 2.6 and RCP 8.5), CNRM-CM5 model for each land cover. QC: *Quercus castaneifolia*; AV: *Acer velutinum*; AS: *Alnus subcordata*; CS: *Cupressus sempervirens*; NF: Natural Forest.

range. Maximum changes in precipitation in the future periods compared to the base period were observed in MIROC-ESM-CHEM (40.89% and 50.14% respectively in RCP 2.6 and RCP 8.5 emission scenarios), and MIR-CGCM3 (14.20% and 19.20% respectively in RCP 2.6 and RCP 8.5 emission scenarios) models in both emission scenarios, and MIROC-ESM model, 26.13% in RCP 8.5.

The model results suggest an overall decrease in SOC stocks by 2099 as a consequence of changes in land cover and climate, but in the *Alnus subcordata* and *Cupressus sempervirens* plantations this decrease was lower. The lower decrease of SOC in *Alnus subcordata* (1.87–18.06 t C ha^{-1}) and *Cupressus sempervirens* (0.44–18.14 t C ha^{-1}) plantations compared to *Acer velutinum* (8.34–21.83 t C ha^{-1}) and *Quercus castaneifolia* (4.16–15.75 t C ha^{-1}) plantations can be related to the distinct quality of the plant material from different forest types (Lal et al., 1995).

Cupressus sempervirens plantation has a higher litter deposition on the soil surface, and a lower decomposability of plant residues due to changed litter quality (for example, higher C:N ratio) of needle-leaves in comparison with broad-leaves, so *Cupressus sempervirens* plantation shows higher SOC (Kooch et al., 2012).

Also Mao et al. (2010) results show that the presence of N-fixing species can increase content of SOC in forest plantations, so the high content of soil organic C in soils of the *Alnus subcordata* plantation is due to the presence N-fixing species.

SOCs in the *Alnus subcordata* and *Cupressus sempervirens* plantations were 53.18–71.67 t C ha^{-1} and 61.28–82.76 t C ha^{-1} respectively at the end of simulation (80 yr) compared to 50.48–68.01 t C ha^{-1} in the natural forest, i.e. about 5% higher in the *Alnus subcordata* and 12% higher in the *Cupressus sempervirens* plantations.

Acer velutinum plantation had the lowest SOC among the other land covers. C stocks were 39.68–53.17 t C ha^{-1} after 80 years, and about 78% lower in comparison with the natural forest. We can conclude that *Acer velutinum* plantation, with a C decrease in the range 8.34–21.83 t C ha^{-1}, was more sensitive to climate change compared to the baseline value of 2016.

Table 7
RothC validation results for soil organic carbon from the plantations.

Statistical factor	*Quercus castaneifolia*	*Acer velutinum*	*Alnus subcordata*	*Cupressus sempervirens*
R^2	0.834	0.862	0.636	0.909
RMSE	2.83	4.22	2.22	1.79
MAE	2.57	2.92	1.98	1.62

The natural forest, *Cupressus sempervirens* and *Alnus subcordata* plantations were not highly sensitive to climate change, and the natural forest had a low decrease compared to the 2016 baseline during the 80 years simulation (1.67–19.2 t C ha^{-1}). After "80 yr" C stocks were in the range 50.48–68.01 t C ha^{-1}.

Some GCM models marked a different trend in *Cupressus sempervirens* plantation and *Alnus subcordata* plantation (RCP 2.6). In both scenarios, the SOC had an annual decrease in all GCMs, except EC-EARTH and MPI-ESM-MR models in *Alnus subcordata* plantation, and EC-EARTH, MPI-ESM-MR, GISS-E2-R and MPI-ESM-LR models in *Cupressus sempervirens* plantation only in RCP 2.6. A minor increase (0.34 t C ha^{-1} on average) was predicted in *Alnus subcordata* plantation, while this increase in *Cupressus sempervirens* plantation was 1.95 t C ha^{-1}.

A lower decrease was observed in the RCP 2.6 scenario. MIROC-ESM-CHEM showed the highest decrease after 80 years in all the land covers and scenarios, and the lower decreases were observed in the MPI-ESM-MR and GISS-E2-R respectively in the RCP 2.6 and RCP 8.5 scenario.

Considering the surface of plantations, *Cupressus sempervirens* plantation showed the lowest decrease and *Acer velutinum* plantation the highest decrease at the end of simulations.

Some studies have shown increased SOC decomposition at warmer temperatures (Dalias et al., 2001; Holland et al., 2000), but in these conditions decomposition can also be slowed by decreased soil moisture (Gottschalk et al., 2012). Rampazzo Todorovic et al. (2014) concluded that the future scenarios for the forest sites show a slightly higher increase of SOC accumulation compared to past and present stocks, probably due to a combination of higher temperatures, lower precipitation, and drier soil conditions. On the other hand Köchy et al. (2015) stated that both the increase in global temperatures and the decrease of precipitations, may result in an overall decrease in the SOC stock.

Results of Francaviglia et al. (2012) showed that with increased temperature and decreased precipitation SOC accumulation was very different in the future climate change projections. In particular, in the land uses with high soil C inputs SOC increased, and in the land uses with low soil C inputs SOC decreased in the future.

Acer velutinum plantation had the highest losses of soil organic C from 0.1 to 0.27 t C ha^{-1} yr^{-1} in comparison with the other land covers. *Cupressus sempervirens* plantation had the lowest losses of SOC from 0.005 to 0.22 t C ha^{-1} yr^{-1}, and in some of GCMs in RCP 2.6, result showed that *Cupressus sempervirens* can maintain or even increase SOC by 0.56 to 3.34 t C ha^{-1} yr^{-1} from the initial value.

Results in this research shows that the land cover effect is more relevant than climate change. Our results are similar with other simulation studies clearly denoting that land use/cover can affect soil organic C content more strongly than climate change in Italy and Europe (Farina

Table 6
Predicted total soil organic carbon stock changes in t of C for the different land covers.

Land cover	Area (ha)	RCP 2.6		RCP 8.5	
		MPI-ESM-MR	MIROC-ESM-CHEM	GISS-E2-R	MIROC-ESM-CHEM
QC	20	−83.2 (−4.16 × 20)	−278.0 (−13.9 × 20)	−139 (−6.95 × 20)	−315 (−15.75 × 20)
AV	15	−125.1 (−8.34 × 15)	−255.6 (−17.04 × 15)	−162.3 (−10.82 × 15)	−327.45 (−21.83 × 15)
AS	7	3.01 (0.43 × 7)	−79.94 (−11.42 × 7)	−21 (−3.00 × 7)	−126.42 (−18.06 × 7)
CS	4	13.36 (3.34 × 4)	−41.56 (−10.39 × 4)	−2.68 (−0.67 × 4)	−72.56 (−18.14 × 4)
NF	10	−16.7 (−1.67 × 10)	−129.2 (−12.92 × 10)	−49.2 (−4.92 × 10)	−192.0 (−19.2 × 10)

QC: *Quercus castaneifolia*; AV: *Acer velutinum*; AS: *Alnus subcordata*; CS: *Cupressus sempervirens*; NF: Natural Forest.

et al., 2011; Francaviglia et al., 2012; Yigini and Panagos, 2016). Farina et al. (2011) indicated that the effect of management practices on the C balance could prevail on climate change. Francaviglia et al. (2012) stated that the changes in land use affected significantly SOC stocks, with a lower effect to be ascribed to climate change scenarios. According to Yigini and Panagos (2016) differences in SOC stocks were higher among land covers than among climate change scenarios.

To determine SOC content and stocks, some studies have focused on both topsoil and subsoil (Jobbágy and Jackson, 2000; Parras-Alcántara et al., 2015); when predicting the impacts of future climate change scenarios on soil organic C in the long term, Lozano-García et al. (2017) and Muñoz-Rojas et al. (2015) stated that climatic factors and soil use and management mainly affect SOC in the surface layers compared with the depth.

In summary, results showed a SOC decrease in the topsoil under future climate scenarios and with the conversion from natural forest to the other land covers, which are remarkable in the 2099 time period. Our results are in agreement with Jones et al. (2005), Lozano-García et al. (2017) and Muñoz-Rojas et al. (2015, 2017). However, the amount of this decrease varies according to species and forests types.

Early prediction of SOC changes is crucial to reach a sustainable management in order to reduce SOC loss. RothC model suggested that soils under *Cupressus sempervirens* and *Alnus subcordata* plantations could accumulate more soil organic C than *Acer velutinum* and *Quercus castaneifolia* plantations (with low SOC contents), be more effective for mitigation of future climate change in Hyrcanian forests, and represent a key economic driver for land cover restoration in degraded Hyrcanian forests.

5. Conclusions

With the simulation results of the RothC model, we can achieve useful information in relation to land cover and future climate changes. Our results indicated the RothC model can adequately predict the SOC stocks at Hyrcanian forests. The conversion of a prior natural forest to *Cupressus sempervirens* and *Alnus subcordata* plantations resulted in a sharp increase in the SOC stock, but with a lower effect to be attributed to future climate change. The IPCC climate change scenarios considerably affect the soil C stocks in the different land cover in Hyrcanian forest ecosystem. The RothC simulation showed that the SOC stocks decreased considerably with increasing temperatures. The extent of this decrease varies in RCP 2.6, RCP 8.5 and among GCM models, but the response of soil organic C to future climate change was relatively less evident than land cover change. Our results point out that the use of a simulation approach is reasonable and cost-effective in comparison with long-term monitoring requiring expensive measurements. Simulation models combined with SOC inventory data can be considered as the most advanced tools of reporting and management planning. In addition, many other factors affecting SOC content in future climate change scenarios, including age of plantations, different soil depths, and land use scenarios can be evaluated with simulation approaches to improve management decisions.

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