HIGH-RESOLUTION MAPPING OF LONG-TERM SOIL ORGANIC CARBON STOCKS AND CHANGES IN MOROCCO

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[1*]Mohamed Bayad, [1]Bruno Gerard, [1]Abdellah Hamma, [2]Malcolm J. Hawkesford, [3]Eyal Ben-Dor, [4]Henry Wai Chau

[1]College of Sustainable Agriculture and Environmental Sciences, Mohammed VI Polytechnic University, Benguérir, Morocco; [2]Rothamsted Research, Harpenden AL5 2JQ, UK; [3]Remote Sensing Laboratory, Geography Department, Porter School of the Environment and Earth Sciences, Faculty of Exact Sciences, Tel Aviv University, Tel Aviv 699780, Israel; [4]Lethbridge Research and Development Centre, Agriculture and Agri-Food Canada, Lethbridge, Alberta, Canada

* Corresponding author at: College of Sustainable Agriculture and Environmental Sciences, Mohammed VI Polytechnic University, Benguérir, Morocco.

*e-mail: mohamed.bayad@um6p.ma

ABSTRACT

Soil organic carbon (SOC) is an important attribute for soil productivity and climate change mitigation. It stabilizes the soil structure and provides nutrients to the soil solution while playing a major role in carbon sequestration processes. Current regional SOC maps are not detailed enough and thus, do not support decision-making at farm and landscape and do not track long-term changes of carbon. Using large soil dataset, multispectral satellite data, climate data and machine learning approach, we created a topsoil (0-30 cm), 30m spatial resolution soil carbon stocks and temporal changes map of Morocco over the last 32 years. Our results show a total topsoil SOC stock of 3.57 Pg C, with a median SOC density of 4.98 kg C m^{-2}. The Moroccan biomes have acted as a net carbon sink in the last 32 years and absorbed an average 3.11 Mt C yr^{-1}, i.e., only 15.4% of the current anthropogenic annual carbon emissions of Morocco. However, high losses are estimated in niche areas such as the Acacia-Argania biosphere, parts of the coastal Mediterranean forest and large cropland-dominated areas due to anthropogenic pressure. The strength of sequestration is likely to diminish, if necessary, measures are not taken to protect these active carbon sinks. The present SOC mapping approach uses the largest soil C database ever recorded in North Africa and provides more accurate predictions compared to other regional studies. Our maps will help land managers and decision-makers improve climate mitigation actions and help understand trade-offs between soil carbon, biodiversity traits, and ecosystem management.

INTRODUCTION

Soil organic carbon (SOC) has received significant attention as a critical carbon pool of the terrestrial biosphere as well as a crucial soil property that governs soil health. Globally, about 2300–2500 Pg (1015g) C (60% organic and 40% inorganic) is sequestered in the top 2 m of soil, of which approximately 30% is stored in the 0-20 cm topsoil (Batjes, 1998; Paustian et al., 2016). Whilst the top 2m soil pool is hardly accessible to agroecosystem manipulation, the top 30 cm soil layer has promise as the most manipulatable layer through agroecosystem changes as it represents the root zone and the interface between the pedosphere and atmosphere. The global topsoil (0-30cm) organic carbon stocks (1500 Pg C) represent more than three times as much carbon as either the atmospheric CO_2 or the above-ground biomass. This makes the terrestrial biosphere a potential sink or source of atmospheric CO_2. Since the anthropogenic exploitation of terrestrial ecosystems can alter the SOC pool drastically (Deng et al., 2016), substantial efforts have been made to consolidate its potential role as a net sink of atmospheric CO_2. It has long been understood that ecosystem management and disturbance can affect the organic carbon stocks of the soil, and thus affect soil quality and atmospheric CO_2 emissions. Organic carbon plays a vital role in ecosystem sustainability and species occurrence and survival, which in turn control organic carbon inputs and cycling in the soil.

The dynamics of soil organic carbon are primarily influenced by the interplay of carbon inputs and residence time in the soil, which are influenced by various processes including net primary productivity, decomposition and factors such as fire and grazing, that can either facilitate or impede SOC loss or retention (Lal, 2004). At the regional scale, climatic factors and elevation play significant roles in determining soil C balance (Jobbágy & Jackson, 2000), whilst at farm and field levels, soil texture, mineralogy and topography interact with climate to shape SOC dynamics (Batjes, 1996; Bellamy et al., 2005). Temperature and precipitation regimes drive the occurrence of plant species with analogous functional traits within conspicuous areas forming biomes (Woodward et al., 2004). The species abundance, productivity, and functional traits are per se the main drivers of soil carbon inputs. Still, species interactions may also play a role in carbon dynamics (De Deyn, 2008).

Globally, there has been substantial interest in carbon sequestration in agricultural soils, not only to reach CO_2 mitigation targets, but also to enhance soil health (Frank et al., 2015; Lal, 63 2004). Carbon dioxide emissions caused by land use changes include deforestation, conversion from natural to farming ecosystems, biomass burning and drainage of wetlands for agriculture development (Lal, 2006). Some cultivated soils have lost 50-60% of the initial SOC stocks causing the release of up to 78 Pg C into the atmosphere. These losses are exacerbated by land misuse and poor soil management (Lal, 2004). Previous research showed that soil 68 organic C potential for CO_2 sequestration can be improved dramatically through ecosystem restoration strategies, smart cultivation, and improved management practices in agricultural lands. Lal (2004) recommended a range of improved management practices to enhance C stocks in agricultural soils.

Different climatic zones exhibit distinct patterns of SOC accumulation. Cold and wet climates tend to promote high primary productivity and low decomposition rates, resulting in the build-up of SOC (Batjes, 1996; Jobbágy and Jackson, 2000). Arid regions, on the other hand, typically have low SOC due to limited biomass production (Schlesinger, 1977). Tropical regions, however, display intermediate SOC levels due to their high rates of primary productivity, which offsets rapid decomposition (Houghton, 2007; Davidson et al., 2014). In temperate ecosystems, environmental and biological factors determine the persistence of SOC (Schmidt 79 et al., 2011). Houghton (2007) suggests that globally, high-latitude areas have the highest levels of SOC due to the slow decomposition caused by low temperatures and are still serving as a net sink for CO_2. The Atlas Mountains ecosystem might be potential carbon sink in North Africa as they were reported to have high SOC stocks (Sabir et al., 2020). Apart from climate, the characteristics of parent material and soil properties also influence SOC persistence. The association of SOC with minerals and the formation of soil aggregates play important roles in SOC retention (Chenu et al., 2000).

Multiple lines of evidence indicate that climate change is altering terrestrial SOC stocks, primarily by accelerating the decomposition rate. Despite large uncertainties related to the magnitude of the losses, climate-carbon cycle feedback has an undeniably significant impact on SOC (Walker et al., 2018). Terrestrial air temperature increased by 1.03°C on average between 1919 and 2018, which could have caused an average loss of 2.5 ± 5.5% of the agricultural topsoil (0-30 cm) SOC (Poeplau & Dechow, 2023). Moreover, climate change can alter soil carbon indirectly through increasing the occurrence of wildfires. The effect of wildfires on SOC depends on various factors such as fire severity, fire frequency, vegetation type, climate, and soil properties. The immediate effect of wildfires is the combustion of above-ground vegetation, which can lead to a substantial release of CO_2 into the atmosphere. The most intuitive impact soils undergo during a fire is the loss of organic matter. Subject to fire severity, organic carbon can be volatilized, charred, or completely mineralized. Up to 15% of the burned biomass is transformed to pyrogenic organic carbon (Santín et al., 2015), whose residence time lasts from decades to millennia. In the last decade, Morocco has lost nearly 77,000 ha of land to wildfire with 32,000 ha recorded in 2022 alone. However, the impact of wildfires on SOC stock in forest ecosystems in Morocco has not been studied. The recovery of SOC in burnt forests could occur rather quickly with the natural or artificial resettlement of vegetation, due to the high productivity attributed to secondary ecological successions (Certini, 2005). Baudena et al., (2020) suggested that recurring fires could transform Mediterranean forests into shrublands, hosting flammable biomass that regrows rapidly after fire. The authors theorized that this mechanism allegedly benefits shrubland persistence and may be enhanced in the future, with an eventual aridity increase (Baudena et al., 2020). Johnson & Curtis, (2001) revealed a post-fire time effect on soil organic carbon in forest ecosystems, using a meta-analysis of 48 different studies.

Given the high importance of organic carbon as a soil health indicator and a potential global carbon sink, accurate characterization is of utmost importance. A growing body of literature has shown complementarity between remote sensing and ecosystem modelling in studying organic carbon in the biosphere (Turner et al., 2004). Conventional approaches to soil organic carbon mapping include geostatistical methods that depend greatly on soil sampling (e.g., regression kriging (Somarathna et al., 2016)), or relate SOC status solely to land use and landcover (Minelli, 2018). These methods have a major limitation as they do not allow monitoring of soil carbon status over time, without recourse to new observations. Advances in cloud computing and remote sensing have opened new horizons for spatiotemporal assessment of soil organic carbon mapping from farm to global scale. Several studies have attempted machine learning, remote sensing, climate and biological predictors for high-resolution of SOC mapping at the country scale. For example, Venter et al., (2021) produced a low uncertainty prediction model of SOC stocks in South Africa's natural soils. The authors suggested a long-term carbon change map based on the high accuracy model.

In this study, we attempted the construction of a national long-term soil organic C stocks map for Morocco. We also aimed to improve the prediction accuracy of organic carbon using a large soil dataset, Landsat satellite imagery, climate and vegetation proxies in a machine-learning workflow. This method also permitted the estimation of 32 years of SOC stocks dynamics at 30 m spatial resolution mapping. These high-resolution maps are required to understand the national trends of soil carbon stocks from landscape to national scale. The resulting maps of soil carbon stocks and changes will inform future research on the drivers impacting potential active carbon sinks and will guide restoration efforts to reverse losses while preserving ecosystem vital functions.

MATERIALS AND METHODS

Study area

Morocco comprises eight ecoregions with contrasting north-south primary productivity and precipitation gradients. These ecoregions represent four different terrestrial biomes including 1) Mediterranean Forests, Woodlands and Scrub, 2) Temperate Coniferous Forests 3) Mediterranean Grasslands and Shrublands 4) Deserts and Xeric Shrublands. The Mediterranean woodlands and forest in the north are characterized by hot and dry summers and pleasant and humid winters. North Saharan Xeric Steppe and woodland and south Sahara Desert experience low rainfall (50-100mm) in the winter and high temperatures (40-45 °C) during summer. Mediterranean Acacia-Argania dry woodlands and succulent thickets cover the northwest of the country (Fig. 1).

Soil carbon data

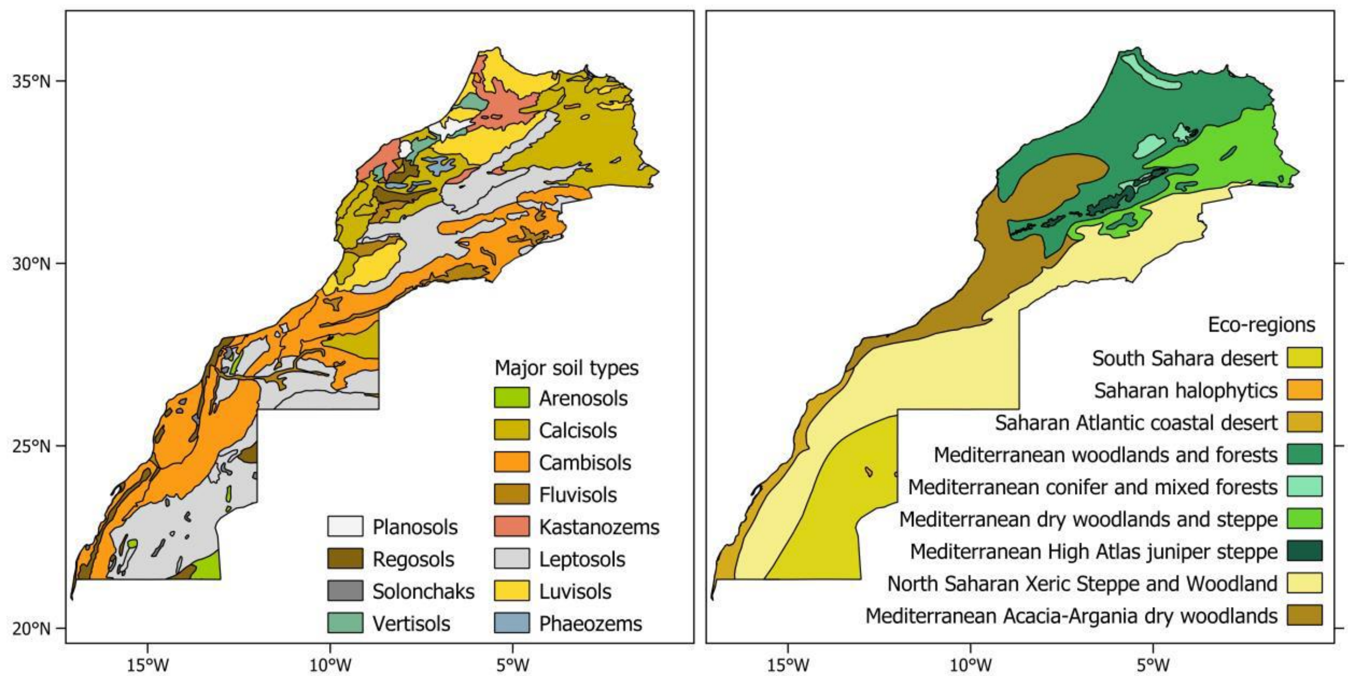

Figure 1. Major soil types (Dewitte et al., 2013) and eco-regions of Morocco (Dinerstein et al, 2017).

The complexity of the ecosystem resulted in diverse soil genesis that produced variable soil types. Moroccan soils are predominantly Calcisols, Luvisols, Cambisols, Leptosols and Kastanozems (Fig. 1). Other under-represented typologies include Vertisols, Regosols, Planosols and Fluvisols. The anthropogenic impact includes a wide range of land use going rom intensive cropping in plains and plateaux to complex agroecosystems including tree cultivation and grazing in high altitudes. Cultivated land represents around 12% of the total surface area of Morocco (8.7 M ha).

Over 52,000 soil samples were collected within Fertimap project the Al-Moutmir extension program backed by Mohammed VI Polytechnic University (UM6P) and OCP Morocco. The soil sampling campaigns occurred between 2011 and 2020. Topsoil (0-30cm) was sampled from agriculture and natural ecosystems and soil organic carbon content was analyzed using the Walkley-Black oxidation method (Walkley and Black, 1934). Soil stocks were estimated using 162 the following equation.

$$SOC\ stock\ (kg\ C\ m{-}2) = SOC\ concentration\ (g\ kg{-}1) \times BD\ (g\ cm{-}3) \times d\ (cm)$$

Prediction covariables and modelling

Where $SOCconcentration$ is organic carbon concentration and BD is bulk density that was not measured but estimated using a linear pedo-transfer function inferred from Ruehlmann & Körschens (2009). The coarse elements percentage was not considered because of the lack of this data.

The covariates used represent proxies for climate, surface biomass, and topography as determining factors of SOC stocks. In natural ecosystems, SOC is more likely to be controlled by environmental variables (e.g., climate, biomass, topography). In cultivated land, SOC dynamics are also strongly impacted by anthropogenic factors, which include tillage, cropping rotation, irrigation, residue management, etc. Temporal dynamics of Landsat data (e.g., NDVI) may inform on cropping intensity and even crop classification. Surface reflectance time series from Landsat 5, 7, and 8 were used from 1990 to 2022. Landsat surface reflectance (L2SR) data archives provided by USGS were atmospherically corrected by the Land Surface Reflectance Code. Clouds, cloud shadow and snow were masked using 'QA_PIXEL' band. Surface reflectance data from the tree sensors was harmonized using the cross-calibration method from Roy et al., (2016). Annual median and variance composites of NDVI and reflectance from all bands were calculated and tested as predictors.

The environmental covariates include mean climate water deficit, precipitation, Palmer Drought Severity Index, minimal temperature, and maximal temperature form the TerraClimate dataset provided by the University of California Merced (Abatzoglou et al., 2018). Topographic used predictors are data elevation, slope, and aspect are provided by NASA, USGS, and JPL-Caltech (Farr et al., 2007). Topographic diversity index derived from ALOS provided by Conservation Science Partners (Theobald et al., 2015). The Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) and leaf area index (LAI) derived from the AVHRR sensor onboard the NOAA satellite (Claverie et al., 2014). Net primary productivity derived from MODIS and provided by NASA's Land Processes Distributed Active Archive Center (LP DAAC). Two- and 5-year median aggregates of all the predictors, prior sampling dates, were tested for predicting SOC stocks using a random forest algorithm. The used predictors are summarized in Table 1. After several iterations, the best model was adopted, and some variables were excluded because of their non-availability for the whole of the studied 32 years period and their low impact on model accuracy. All the predictors used for the final model extend from over the whole study period (1990-2022). The data processing and modelling workflow is summarized in Figure 3.

The random forest model hyperparameters *ntree* and *mtry* were set to 500 and the square root of the number of variables, respectively. A 30% sampling points subset was used for model validation. Models' prediction accuracy was evaluated using the coefficient of determination (R2) and root mean scare error (RMSE). The variables' importance of the random forest model is derived from the sum of decreases in the Gini impurity index, to see what predictors are more relevant in SOC stocks prediction.

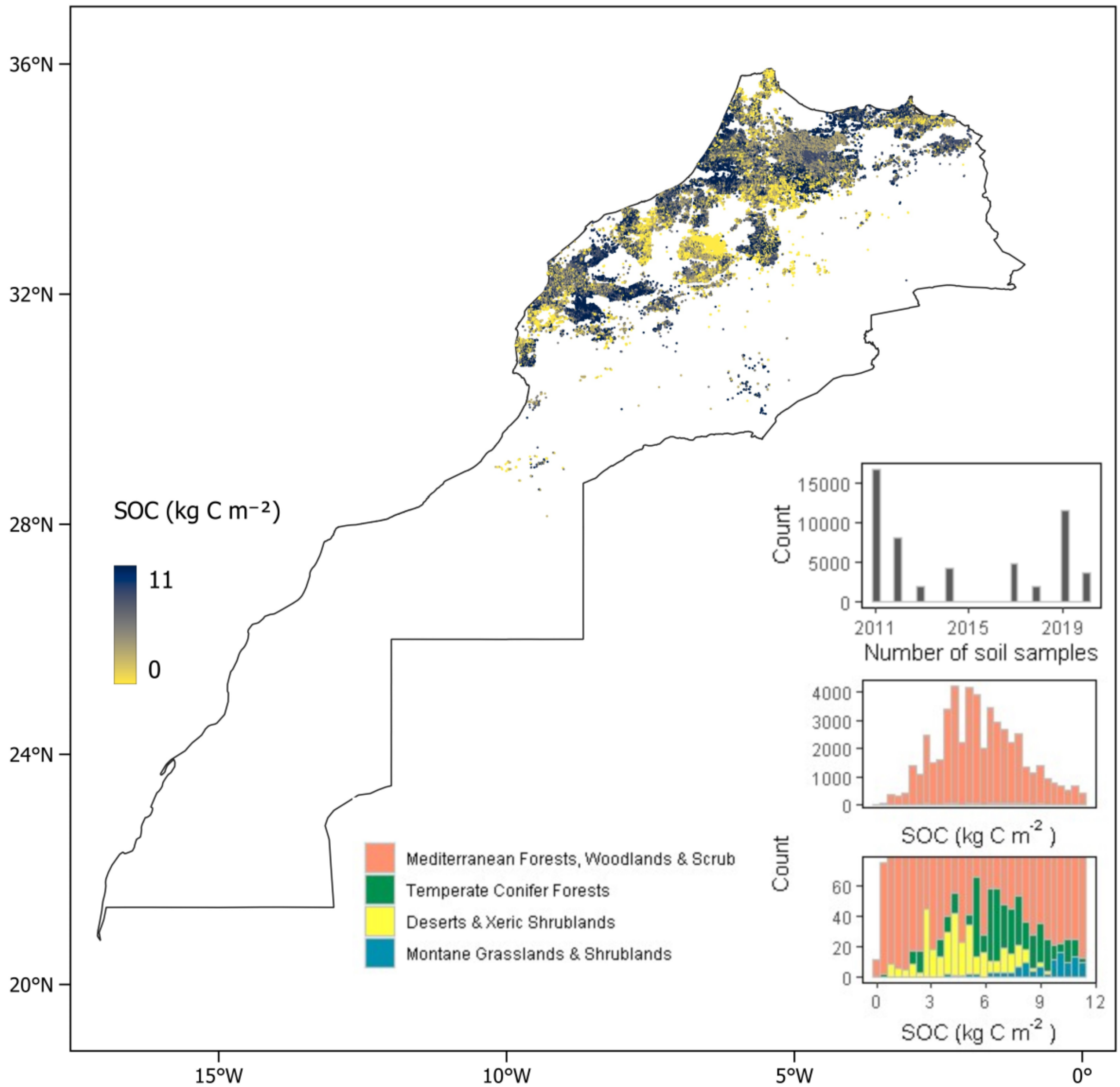

Figure 2. Distribution map of soil sampling across Morocco. Sampling points are colored by SOC values (kg C m^{-2}). Insert plots represent count of samples per years and distribution histograms of SOC (kg C m^{-2}) per biomes.

The validated random forest model was used to predict SOC stocks based on satellite and the environmental predictors from 1990 to 2022. The predictor variables were aggregated in 5-year median and used as inputs of random forest to predict annual SOC stocks (Fig. 3). The annual predictions served as basis for estimation of long-term average stocks and changes. The carbon stock changes were estimated using the Sen's slope (Sen, 1968) of the predicted stock time series at each pixel. This method has been used by Venter et., (2021) to estimate long-term SOC stocks temporal dynamics and the changes were estimated as:

ΔSOC (%) = s÷$SOCLTA$×100216

where s is the Sen's slope and $SOCLTA$ _is long-term average C stocks of the considered pixel.

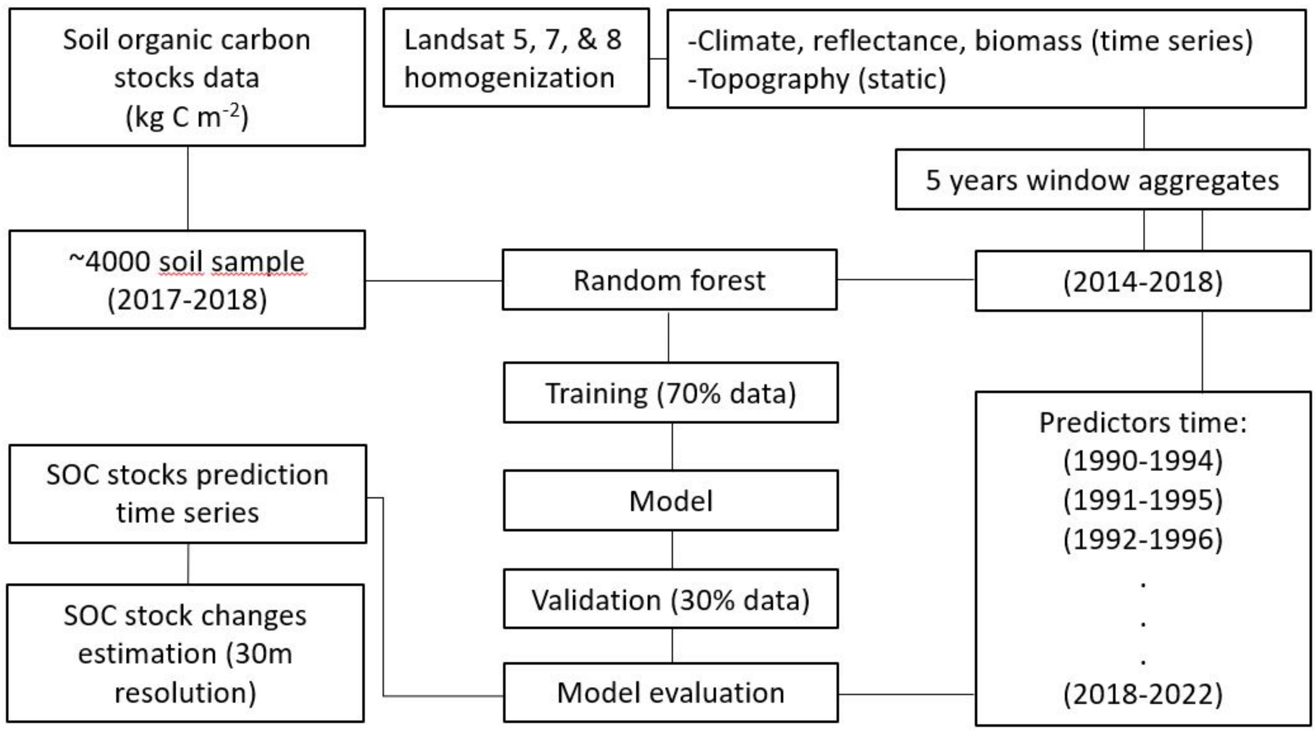

Figure 3. Workflow diagram that summarizes the data preparation and modelling framework.

RESULTS

Results indicate a total SOC stock of 3.57 Pg C in the years 2018 and a long-term 32-year average stock of 3.94 Pg C. This provides an estimate of the overall carbon storage capacity in the assessed area (~700,000 km^2) over all Moroccan biomes. The soil C stocks had an average 227 of 5.14 kg C m^{-2} and a median of 5.12 kg C m^{-2} (Table 2, and Table S1). This metric provides insights into the typical carbon content per unit area and helps in assessing the baseline SOC levels in Moroccan ecosystems.

This study reveals significant variations in SOC stocks distribution between northern-west and southern regions simulating the north-south climate gradient (Fig. 4 and Fig. S2). The northwestern and High Atlas areas exhibited higher carbon stocks, compared to the eastern and southern Saharan eco-regions. This highlights the strong impacts of climate and ecosystem characteristics in determining SOC stocks at the regional level.

The analysis demonstrates variations in long-term average SOC stocks across different biomes. The temperate conifer forest ecosystems show the highest SOC content per surface area, with a median of 6.06 kg C m^{-2}, followed by mountain grasslands and shrublands with 5.14 kg C m^{-2}, and Mediterranean forests woodlands & scrub areas with 5.31 kg C m^{-2}, while the deserts and xeric shrublands had the lowest SOC concentrations (4.76 kg C m^{-2}).

Table 1. Climate, biomass and topographic variables that were used to model SOC stock in Morocco.

Category	Spatial resolution (meter)	Predictors
Climate	4638	Mean annual precipitation
		Annual climate water deficit
		Palmer drought severity index
		Minimal temperature
		Maximal temperature
Biomass	5566	FAPAR Mean
		LAI Mean
	500	Net primary productivity
	30	Red band reflectance
		Green band reflectance
		Blue band reflectance
		Shortwave infrared band 1 reflectance
		Shortwave infrared band 2 reflectance
		NDVI median NDVI variance
		NDVI 10th percentile
		NDVI 90th percentile
Topographic	30	Elevation
		Slope
	270	Topographic diversity index

Using climate and remote sensing time series data allowed to derive historic estimates of the spatiotemporal dynamic changes of C stocks in Morocco. Model outputs indicated a 0.08% net increase in SOC stocks over 32 years (1990-2022). Whilst the findings suggest an overall slim increase in SOC stocks, the strongest changes were observed in the Mediterranean Forest, Woodlands and Scrub biome. Losses were observed in large parts of the Mediterranean Acacia-Argania dry woodlands and succulent thickets and Mediterranean woodlands and forests ecoregions (Fig. 5 and Fig. S3). While Desert and Xeric Shrublands experienced the smallest dynamics in SOC stocks, temperate conifer forest and montane grasslands and shrublands biomes showed the most important net increase in Morocco, indicating sequestration of 1.2×10^{-2} kg C m^{-2} and 1.1×10^{-2} kg C m^{-2}, respectively.

Table 2. Random Forest SOC stocks model analytical metrics including R2 and RMSE (kg C m^{-2}) and number of observations (n) used in the training and validation. The first model uses the predictors described in Table 1 (except green and blue bands) aggregated from 2017-2018. The second model uses the same predictors as the first model from the 2014-2018 period but excluded net primary productivity.

Model	Year	n	RMSE	R2	n	RMSE	R2
1	2017-2018	4473	1.086	0.734	2025	1.395	0.491
2	2014-2018	4478	1.035	0.729	2025	1.393	0.493

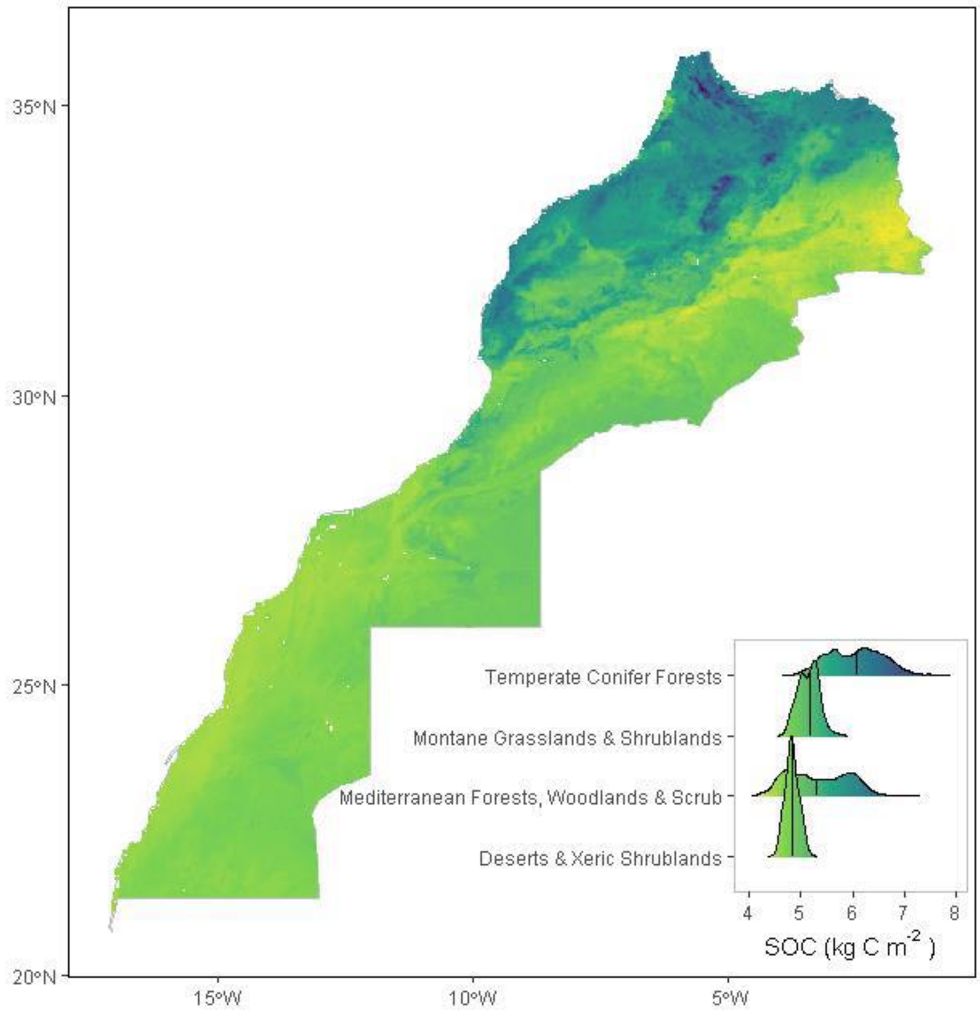

Figure 4. Long-term (1990-2022) average SOC stocks (kg C m^{-2}) map. Insert plot represent SOC stocks frequency distribution over biomes in Morocco.

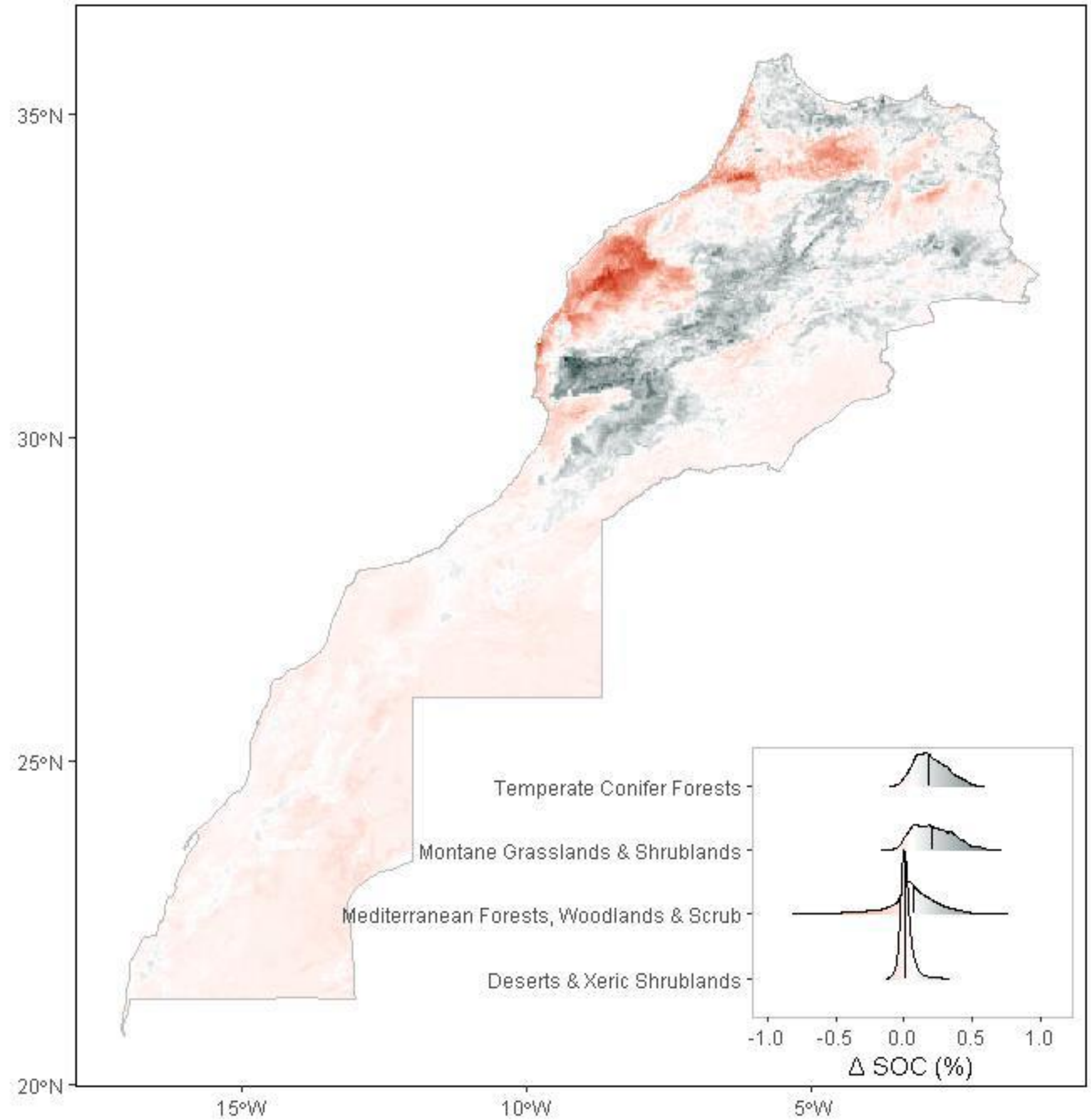

Figure 5. Long-term (1990-2022) average SOC changes (%) map. Insert panel shows SOC change frequency distribution in different biomes.

Model performance uncertainty

The variables importance values in the random forest prediction model showed that the drought severity index was the most influential in determining SOC, followed by temperature (Min, Max), elevation and primary productivity (Fig. 6 and Fig. S1). Vegetation dynamics captured by high-resolution NDVI contributed equally to the prediction compared to LAI and precipitation proxies (Fig. 6). The variables importance changed slightly when option for two instead of four-year aggregation period of the predictors (Fig. S1).

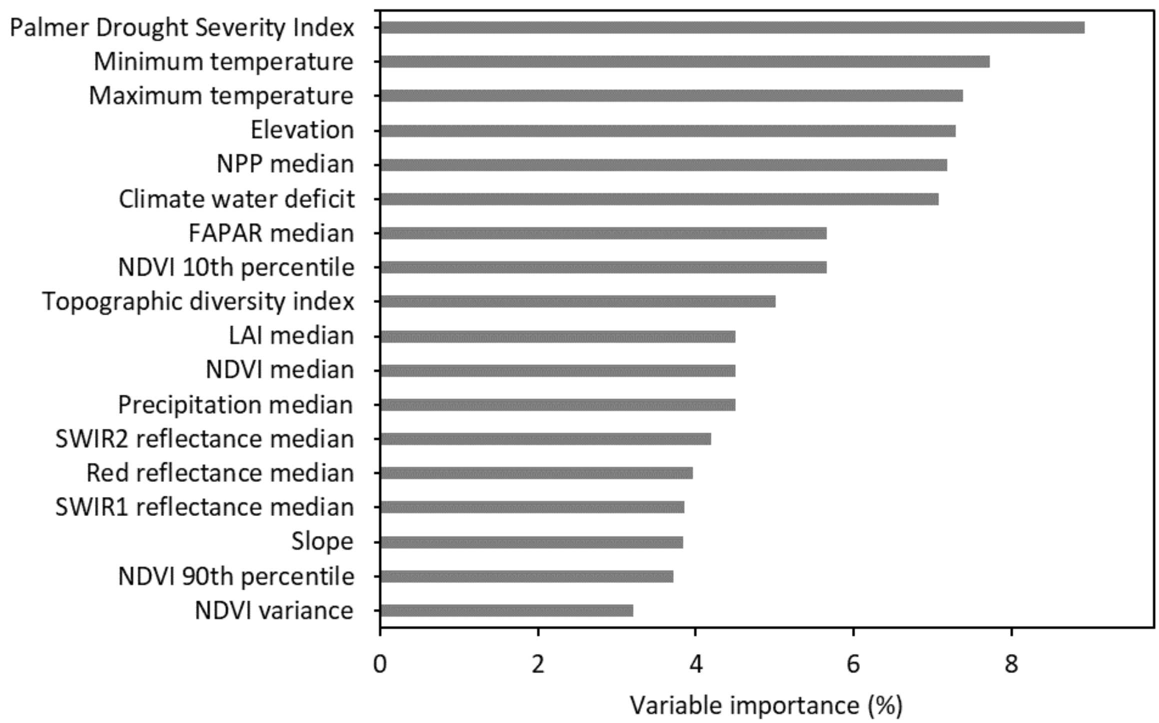

Figure 6. Random forest model variables importance (%) from the first model, derived from the sum of decrease in Gini impurity index.

SOC prediction performance was evaluated using the RMSE and R2 of the random forest model. The model validation had an R2 of 0.49 and RMSE 1.39 kg C m^{-2}. The model showed an R2 of 0.73 and RMSE 1.08 kg C m^{-2} with the training set (Table 2, Fig. 7). Long term change estimates were not validated because of the lack of repeated records in the same sampling locations. However, soil C stock times series estimates were compared with the measured values over 8 years (Fig. 8).

Although the model uncertainty was highly variable over space and time, in general, the error values showed unimodal distribution. When validated against measures from different years, the random forest model had a median absolute error 0.13 kg C m^{-2} (Q1=-1.32; Q2= 1.47). Model error was unevenly distributed over space, with the highest inaccuracy recorded in the montane grasslands and shrublands. The model underestimated SOC stocks in these biomes, which include the High Atlas and Mediterranean dry woodland and steppe eco-regions (Fig. 8). The model uncertainty varied between years, with the highest inaccuracies recorded in 2012, 2014, and 2020 (0.99, 0.95, and 0.88 kg C m-2, respectively) (Fig. 8 and Fig. S4). The lowest uncertainties were observed in 2013, 2017 and 2018, where median absolute error values were lower than 0.17 kg C m^{-2}.

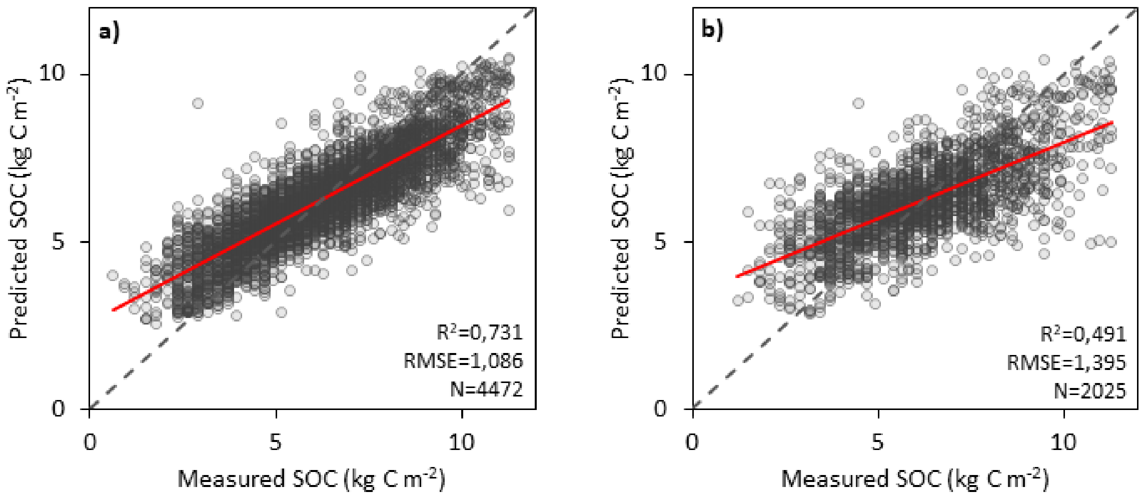

Figure 7. Scatter plots of predicted versus measured SOC stocks (kg C m^{-2}) with (a) training and (b) test datasets plot). Predictors include all variables shown in Fig. 6 aggregate from 2017-2018 time period.

Table 3. Long-term (32 year) mean and median SOC stocks and net change estimations by biomes in Morocco as estimated from the random forest model.

Biome	Mean SOC stocks (kg C m^{-2})	Median SOC stocks (kg C m^{-2})	SOC stock (Pg C)	Net change (%)	Net change (kg C m^{-2})
Deserts & Xeric Shrublands	4.77	4.76	1.91	0.012	5.7 10^{-4}
Temperate Conifer Forest	6.07	6.06	0.08	0.196	1.18 10^{-2}
Montane Grasslands & Shrublands	5.14	5.14	0.04	0.215	1.1 10^{-2}
Mediterranean Forests Woodlands & Scrub	5.19	5.17	1.91	0.056	2.9 10^{-3}
Total	5.14	5.12	3.94	0.079	4 10^{-3}

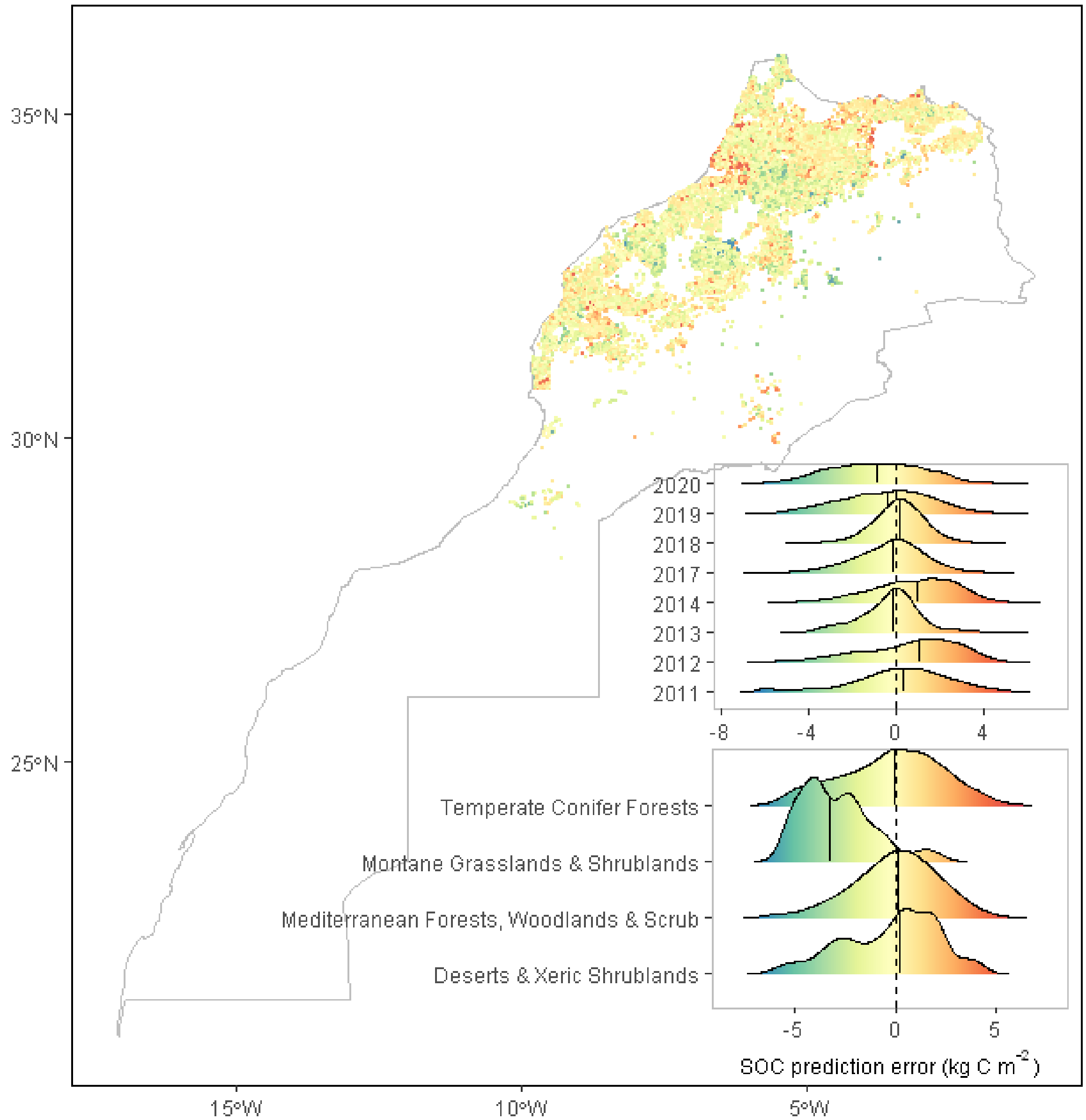

Figure 8. Spatial distribution map of the Random Forest error calculated as difference between predicted and measured SOC stocks (kg C m^{-2}).

Table 4. Long-term (32 year) mean and median SOC stocks estimations by eco-regions in Morocco as estimated from the random forest model.

Eco-region name	Biome name	Mean SOC (kg C m^{-2})	Median SOC (kg C m^{-2})	SOC stock (Pg C)
Saharan Atlantic coastal desert	Deserts & Xeric Shrublands	4.66	4.65	9.8 1013
South Sahara Desert	Deserts & Xeric Shrublands	4.82	4.82	5 1014
Mediterranean conifer and mixed forests	Temperate Conifer Forests	6.07	6.06	7.9 1013
Mediterranean High Atlas juniper steppe	Montane Grasslands & Shrublands	5.13	5.14	3.8 1013
Mediterranean Acacia-Argania dry woodlands and succulent thickets	Mediterranean Forests, Woodlands & Scrub	5.19	5.09	5.7 1014

DISCUSSION

Using climate and remote sensing predictors we estimated the soil C stock dynamics over a 32-year period in Morocco. Our mapping method uses a large soil database, 30 m resolution satellite data, climate and morphological data. This allowed the i) assessment of spatial dynamics of soil carbon from paddock to national scale, ii) estimation of the magnitude of topsoil stocks in Morocco at 0-30 cm, and iii) to step back on time to get historical estimates of soil C and thus, assess long-term C changes. Accessing this amount of detail is impossible with lower resolution maps, due to the substantial variability of soil properties from farm to pedon scale. While the SOC long term changes map was based solely on the spatial changes of the environmental proxies, it informs on change drivers, as well as potential increases in certain areas, as influenced by their inherent climate and edaphic features. This will give land managers a useful tool to detect and reverse losses using appropriate actions.

Previous attempts to estimate soil C magnitudes in different areas of Africa showed inaccuracies due to the low resolution of the maps employed and insufficient soil data. For example, the estimation of SOC stocks by Henry et al., 2009, who used DSMW, ISRIC and ETOPOS maps at a 1:5M scale, showed estimates of 2.87 and 2.23 Pg C (0-30cm) for South Africa and Morocco, respectively. However, Venter et al., 2001 quantified 5.59 Pg C in South Africa, using a large national soil database and a high-resolution mapping approach. The magnitude of our estimation of topsoil C stocks was at 3.94 Pg C in Morocco (711,000 km^2), which seems in accordance with other studies in the Mediterranean region–e.g., Spain (505,000 km^2), which is predominantly Mediterranean Forests, Woodlands, and Scrub, has a SOC stock of 3.3 Pg C (Calvo de Anta et al. 2020). These high variabilities and inaccuracies in regional studies, show the inadequacy of small-scale maps in quantifying the spatially highly dynamic soil carbon.

The level of accuracy of our model (RMSE = 1.36 kg C m^{-2}) is higher than some regional maps and national studies. Examples include subtropical maps such as South Africa (RMSE = 2.45 kg C m^{-2}, Venter et al.2021). Even when the model was tested against independent past data points, it still yielded low uncertainty for most past years, except for 2012, 2014, and 2020, when absolute errors were 0.99, 0.95, and 0.88 kg C m^{-2}, respectively (Fig. 8). Coupled with high-resolution multispectral data from Landsat, the large number of samples representing different ecosystems in Morocco clearly strengthened the accuracy of the model.

SOC stocks by biomes and ecozones

Sabir et al. (2020) attempted to quantify soil C in different agro-ecozones in Morocco and estimated high SOC levels in the Middle Atlas (mean of 4.55, min. 0.15, max. 9.81 kg C m^{-2}), followed by the Rif zone (mean of 4.13, min. 0.3, max. 7.71) that intersects with both Mediterranean conifer and mixed forest and Mediterranean woodlands and forest eco-regions. The authors estimated the lowest soil C concentrations in the Acacia-Argania dry woodlands (mean 2.14, min. 0.7, max. 3.93 kg C m^{-2}), and the Sahara Desert (mean of 0.18, min 0.15, max. 0.24 kg C m^{-2}). Boulmane et al., (2010) reported SOC stocks of 5.6-8 kg C m^{-2} in the forest green belt in the Middle Atlas Mountains. Sabir et al. 2004 also reported high C (10.5 kg C m^{-2}) values in the *Quercus suber L.* forest in northern Morocco. These values agree with the high median (6 kg C m^{-2}) found in the present study, in the Mediterranean conifer and mixed forests.

Changes in soil carbon stocks

It has long been appreciated that management and land-cover changes can alter the amount of organic carbon sequestered in the soil (Laganière et al., 2010), which subsequently affects both soil quality and atmospheric CO^2 fluxes (Powers et al., 2011). Land use change can cause a change in surface biomass and an associated disturbance in soil C stocks. Ecosystem changes can occur naturally or be the result of anthropogenic pressures. Each ecosystem has a potential carbon-carrying capacity and an equilibrium carbon status defined by inherent climate and edaphic characteristics. The soil carbon cycle is disturbed by land use changes until a new equilibrium is eventually attained in the ecosystem. Throughout this procedure, alterations in soil C stocks might have occurred, either as a sink or as a source of carbon. We estimated a 32-years average changes in soil carbon stocks at 0.08% (3.11 Mt C) in Moroccan topsoil. This average annual gain represents only 15.4% of the anthropogenic carbon emissions reported at 0.02 Pg C in 2021 in Morocco (Crippa et al., 2022). Nevertheless, the current annual anthropogenic carbon emissions represent only 5 per-mille (‰) of the topsoil stocks, indicating the substantial potential of the soil organic C pool to offset CO_2 emissions in Morocco. Over the 32-year period studied; Moroccan biomes constituted a net carbon sink. Soil carbon change magnitude at the regional scale is limited by climate and edaphic criteria. However, a net carbon sink is observed currently in the terrestrial biosphere of the northern hemisphere. De Vries et al., (2006) reported that for European forests, net carbon capture is in the range of 100 to 150 Mt C yr^{-1}. Similarly, Heath et al., (1993) suggested that temperate forest produces a net sink of 205 Mt C yr^{-1}. Our estimation shows the highest soil carbon increase in the Mediterranean conifer and mixed forests in the north and Mediterranean High Atlas juniper steppe (including Anti-Atlas) eco-regions. The highest losses we estimated were in the Acacia-Argania dry biosphere, the Gharb Forest in the northwest of Morocco and large parts of the Prerif Mediterranean woodland and forest. Losses in the Gharb Forest were estimated at 21% (3000 ha) in the last 20 years (Hansen et al., 2013). The Prerif areas have lost up to 8% of the forest in the last 20 years. Net losses observed in the Prerif areas (Taounate region) are likely related to climate and anthropogenic pressures. In the first decade of the century, more than half a million olive and carob trees were planted in this area. Still, these efforts are still not enough to reverse carbon losses.

For the Acacia-Argania woodlands, le Polain de Waroux et al., (2012) reported a net decrease of tree density of 44.5% between 1970 and 2007. Consequently, this area will continue to act as a carbon source until a new equilibrium is reached. Although this endemic species is well adapted to the Mediterranean dry climate in Morocco, anthropogenic pressure presented by overgrazing and use as fire fuel are the main causes of this decline (Le Potain de Waroux et al., 383 2012). Croplands around the world are losing massive soil carbon stocks depending on their initial state and a high-loss area was the cropland in the coastal plain in the Settate region. Similar net carbon sink patterns were also observed at the country scale (Janssens et al., 2005), where areas with a high prevalence of cultivated land tended to be a carbon source, whilst forest and grassland-dominated areas acted as net terrestrial carbon sinks (Janssen et al., 2005). In the future, the Northern Hemisphere will maintain a role as a carbon sink, although the upward trends are likely to be decreased (Canadell et al., 2007; Zaehle et al., 2007). Although our estimates of carbon changes are consistent with the theoretical dynamics of Soil C, given the land use changes and anthropogenic pressures, future work should validate the change trend map using repeated measurements from the current sampling locations.

CONCLUSION

The present work provides the first high-resolution dynamic map of topsoil carbon in Morocco. This national map provide accurate and valuable insights onto the soil carbon magnitudes in north African Biomes and an estimate of the C stock changes in the last 32 years. The map could be used as a soil carbon stock watch that will support CO_2 mitigation actions. Generally, Moroccan biomes are still acting as net carbon sink. However, high losses were estimated in ecological niches such as the dry Acacia-Argania ecoregion, which undergoes relentless anthropogenic pressure. Using this high-resolution map, different stakeholders should take an important leap forward in identifying carbon source areas and target appropriate remedial actions, whilst understanding trade-offs between ecosystems management, biodiversity, and soil carbon. The extensive database has the potential for future applications, including the modelling of how climate changes affect carbon sequestration in Morocco.

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