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The advantages and limitations of global datasets to assess carbon stocks as proxy for land degradation in an Ethiopian case study

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Corresponding Author:	Stefania Cerretelli UNITED KINGDOM
First Author:	Stefania Cerretelli
Order of Authors:	Stefania Cerretelli
	Laura Poggio
	Getahun Yakob
	Shiferaw Boke
	Mulugeta Habte
	Malcolm Coull
	Alessandro Peressotti
	Helaina Black
	Alessandro Gimona
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Suggested Reviewers:	Adrienne Grêt-Regamey ETH Zurich gret@ethz.ch Because of her work on the effects of mapping ecosystem services at different scales
	Grazia Zulian Joint Research Centre grazia.zulian@ec.europa.eu Because of her research on ecosystem services
	Louise Willemen University of Twente: Universiteit Twente l.l.willemen@utwente.nl Because of her work on land degradation

	Minasny Budiman University of Sydney budiman.minasny@sydney.edu.au Because of his work on soil and carbon modelling
	Sabine Grunwald University of Florida sabgru@ufl.edu Because of her work on ecosystem services and soil carbon modelling
Response to Reviewers:	

Highlights:

- Spatial variability of carbon stocks is overlooked by global datasets.
- Integration of local data is needed to obtain adequate assessment of carbon stocks.
- Care is needed when carbon stocks mapping is used to inform decision-making.
- Global datasets can be used to rank and prioritise areas for restoration purposes.

The advantages and limitations of global datasets to assess carbon stocks as proxy for land degradation in an Ethiopian case study

Stefania Cerretelli[1,2,3,4,*], Laura Poggio[2,5], Getahun Yakob[6], Shiferaw Boke[6], Mulugeta Habte[6], Malcolm Coull[2], Alessandro Peressotti[4], Helaina Black[2], Alessandro Gimona[2]

[1] Natural Resources Institute, University of Greenwich, Chatham Maritime, ME4 4TB, UNITED KINGDOM

[2] The James Hutton Institute, Craigiebuckler, AB15 8QH Aberdeen, Scotland, UNITED KINGDOM

[3] University of Trieste, Department of Life Sciences, Via Weiss 2, 34128 Trieste, ITALY

[4] University of Udine, Department of Agricultural, Environmental and Animal Science, Via delle Scienze 206, 33100 Udine, ITALY

[5] ISRIC - World Soil Information, P.O. Box 353, 6700 AJ Wageningen, THE NETHERLANDS

[6] Southern Agricultural Research Institute (SARI), P.O. Box 06, Hawassa, ETHIOPIA

[*] Corresponding author. E-mail address: S.Cerretelli@greenwich.ac.uk

Abstract

Land degradation leads to ecosystem degradation, reducing ecosystem functioning and depleting ecosystems' resilience. The majority of factors linked to land degradation are closely related with the depletion of below- and above-ground stocks of organic carbon.

Organic carbon stock is important for climate change mitigation and for restoring soil functions such as those crucial to support food security. In this study, we mapped carbon stocks to infer land degradation in a small area in the Ethiopian Great Rift Valley. The study aimed to assess carbon stock status and to identify limitations and advantages of using global data in mapping at local scale relative to using local data. Two different datasets were developed; i) a "global dataset" characterised by data from datasets with global coverage data, and ii) a "hybrid dataset" that coupled data from global datasets and soil data derived from a local survey and land cover data derived from a supervised classification of satellite images. The results showed that i) global datasets introduced inaccuracy that must be taken into account for advocating interventions at a local scale, and ii) global datasets could be used at a small catchment level for decision-making, if a simple rank of values is sufficient, but they might provide an optimistic picture of land degradation because they overestimate stocks.

Keywords: carbon stocks modelling, land degradation, Ethiopia, soil organic carbon, global datasets

1. INTRODUCTION

An increasing proportion of global agricultural land is affected by land degradation (UNCCD, 2014). Land degradation leads to ecosystem services (ESS) depletion because it negatively affects and reduces a range of ecosystem functions including soil functions (e.g. sediment retention, carbon sequestration, nutrient cycling, water retention, biomass production, delivery of important goods) (Bronick and Lal, 2005; Daily et al., 1997; Lal, 2015). It also threaten the economic resilience of the populations who depend on ecosystem functioning (Lal, 1997; MEA, 2005; Reed and Stringer, 2015; Sutton et al., 2016).

African countries, and especially sub-Saharan countries, are greatly affected by land degradation (ELD Initiative & UNEP, 2015; Nkonya et al., 2016). Ethiopia (where this study is set) is one of the countries most affected by this problem. It is particularly vulnerable to land degradation because of the very rugged terrain. Its people are vulnerable to the consequences of land degradation because the agricultural sector provides livelihoods for more than 85% of the population and accounts for more than 50% of the Ethiopian GDP (Berry, 2003; Shiferaw and Holden, 1999).

In Ethiopia, different studies assessed the total organic carbon stock (above- and below-ground organic carbon) (Bajigo et al., 2015; Belay et al., 2018a; Betemariyam et al., 2020; De Beenhouwer et al., 2016; Girmay et al., 2008; Lehtonen et al., 2020; Vanderhaegen et al., 2015; Yirga et al., 2020) stored in the ecosystem. Furthermore, several studies attempted to quantify the carbon stored in the aboveground biomass in different areas of Ethiopia, especially in forests, plantations or agroforestry systems (Amsalu and Mengaw, 2014; Denu et al., 2016; Moges et al., 2010; Solomon et al., 2017).

The majority of causes of land degradation (e.g. soil erosion, overgrazing, deforestation) are crucial factors in depleting organic carbon stocks (Lal, 2004a, 1997). In this context, organic carbon represents a crucial indicator of land degradation. More specifically, the total carbon stock of an area is the total amount of organic carbon stored in an ecosystem of that area (kg C ha^{-1}), and is usually partitioned in different pools/stocks (i.e. soil (including organic matter and belowground, dead or alive, biomass such as roots, dead wood and litter) and aboveground biomass) (Ravindranath and Ostwald, 2008). Above-and below-ground carbon stocks represent good indicators of land degradation (UNCCD et al., 2016), because they affect several ecosystem functions including soil functions (Baldock et al., 2009; Lal, 2015; Stockmann et al., 2015; Vågen et al., 2013; Wiesmeier et al., 2019). More specifically, the soil organic carbon stock is often used as an indicator of soil and land degradation because of its important role in many soil functions and soil ecosystem services provision (Lorenz et al., 2019). Therefore, the Soil Organic Carbon (SOC) stock was identified as one of the global indicators to monitor Land Degradation Neutrality (LDN) (Cowie et al., 2018; Lorenz et al., 2019; Sims et al., 2019) and to report on progress towards the Sustainable Development Goal (SDG) 15.3 (together with land cover and land productivity).

Conserving SOC and promoting its restoration is very important to compensate carbon emissions (Lal, 2006), improve nutrient cycling and water retention, and promote higher crop yields (Jobbágy and Jackson, 2000; Lal, 2015, 2004b, 2004a; Rawls et al., 2003). To make conservation and restoration operational, however, in the presence of limited resources, priority areas for interventions need to be identified with sufficient accuracy for the decision-making considered (Pandeya et al., 2016; Vihervaara et al., 2012).

The SOC modelling and mapping (together with the total organic carbon stocks assessment) is a valuable means to identify such areas, allowing decision-makers to intervene making their measures more spatially targeted and therefore more effective. This is key considering the challenges of making interventions operational in the presence of limited resources, and the need for actions to promote the important role of carbon sequestration in the global carbon cycle, climate change mitigation, land degradation alleviation, and sustaining agricultural productivity (Lal, 2004a; Scharlemann et al., 2014).

In this respect, lack of locally detailed data is a limiting factor for environmental modelling and mapping, and derived decision-making for local management; this lack is common especially in Africa (Eggen et al., 2016; Hurni et al., 2015). While, global maps/products (e.g. MODIS, ISRIC) are a potential solution and are often used, it is unclear if and when the scale, resolution, support factor of these products are adequate for local purposes. The scale and resolution dependency in modelling environmental variables has been highlighted by previous studies that found how data scale and resolution, as well as the extent and the support factor (i.e. the area over which a prediction or observation is made) affect the accuracy of the digital soil mapping (Cavazzi et al., 2013), ecosystem services modelling (Grêt-Regamey et al., 2014), and species richness and distribution mapping (e.g. Cavazzi et al., 2013; García-Callejas and Araújo, 2016; Grunwald et al., 2011). Grêt-Regamey et al. (2014) and Cerretelli et al. (2018) assessed the effect of resolution on ecosystem services mapping and found substantial differences between the results of fine and coarse resolution analyses, both aggregated to similar coarse resolution, especially when local heterogeneity was not negligible. Other studies highlighted the impact of data resolution and extent on modelling environmental factors important for understanding land degradation, such as soil erosion (de Vente and Poesen, 2005; Tan et al., 2017). A previous study (Cerretelli et al., 2018) highlighted the importance of accurate data especially for the modelling of nutrient export and retention where land cover classification was used to define nutrient loading pattern. This was not the case of the soil export (erosion) and retention modelling were global data proved to be good enough. These results showed that different outcomes or implications can rise when assessing different ecosystem services using global data. Despite these studies, there is still an important gap in knowledge regarding the impact of scale, resolution and support on the accuracy of mapping the organic carbon stock. In this paper we present a case study concentrating on how the use of different sets of data (global or local) affects local carbon estimates and related decision-making. Restoration of carbon stocks can be promoted by improved management (terracing, avoiding collection of crop residue, restrained grazing) (Gelaw et al., 2014; Rimhanen et al., 2016), as well as supporting afforestation programs and agroforestry practices (Betemariyam et al., 2020; Lehtonen et al., 2020). However, different estimates of carbon stocks could lead to different decision-making processes that might fail to support the right activities or overlook some important areas for restoration purposes.

We mapped the organic carbon stocks (i.e. amount of organic carbon stored in i) the soil (SOC), ii) the biomass (aboveground and belowground), and iii) the dead organic matter) using different data sources, with different resolutions and extents. The first dataset was constituted just with data from global coverage database (e.g.: ISRIC SoilGrids, Landsat, MODIS, Global Land Cover Network), while the second dataset coupled data from global database (Landsat and MODIS), local soil data, and a supervised land cover classification. We then compared the obtained estimates of organic carbon stocks, including their accuracies, and assessed the possible consequences of the observed differences for decision-making.

The study took place in south-western Ethiopia, in the context of a project aimed at improving food security and alleviating poverty of local communities (ALTER, UK ESPA initiative). Land degradation in the study area is very severe. Mapping carbon stocks, and in particular SOC, is essential to target priority areas for restoration, and identify feasible measures to increase carbon stocks to reduce land degradation. This study assessed if global data are a good enough solution for this purpose.

2. STUDY AREA AND DATASETS

2.1. Study area

The study area consists of a hydrological subset of several sub-basins of the Bilate River, in the Ethiopian Great Rift Valley in the Halaba special *woreda* (province) with the centre located at 78° 17′N and 38° 06′E. The area has a size of approximately 480 km^2 and contains three *kebeles* (counties); Andegna Choroko, Laygnaw Arsho and Asore where the local survey was conducted (Fig 1; Cerretelli et al., 2018). The elevation ranges from 1650 to 2644 m a.s.l.. The average annual rainfall ranges from 1024 to 1243 mm yr^{-1} and the average annual temperature varies from 15 to 20 ^{0}C (WorldClim dataset 1970-2000; Fick and Hijmans (2017)).

Subsistence agriculture represents the main activity in the area. The study area is highly degraded due to intense deforestation mainly cause by population growth and by a shift from livestock to crop-based agriculture (Byg et al., 2017). Therefore, in the last decade, numerous restoration and exclosure areas were established (Byg et al., 2017), where free grazing is forbidden and biomass harvesting is controlled to restore highly degraded sites (Aerts et al., 2009).

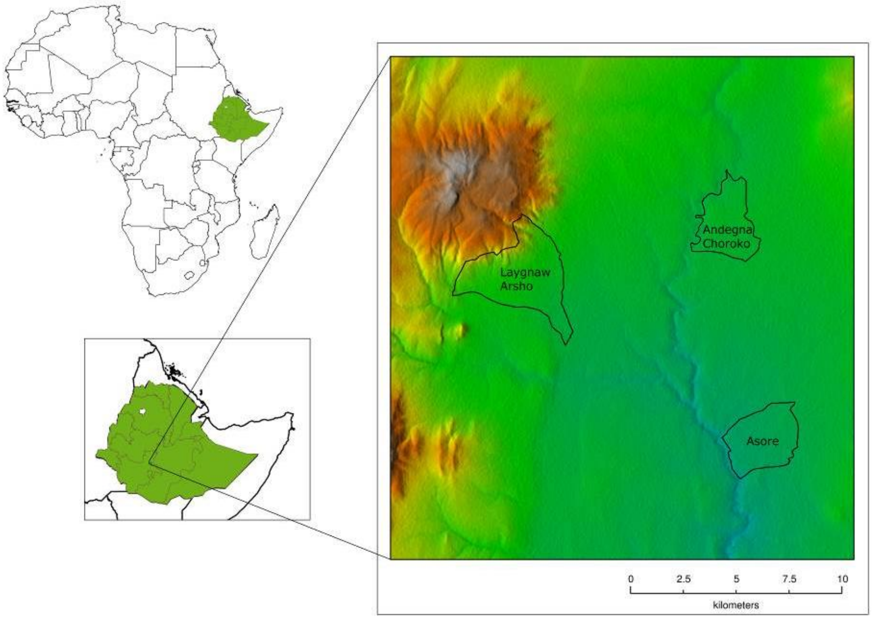

Figure 1. Study area in the Halaba special *woreda*. The polygons show the *kebeles* where the main survey was conducted.

2.2. Data sources

In this study, two datasets were used (a "global dataset" and a "hybrid dataset") each including data from different sources on soil organic carbon and land cover categories (Table 1). The "global dataset" included data (maps) just from readily available data with global coverage, and the "hybrid dataset" included global data integrated with local data (maps) on SOC, derived from interpolation of data from a local survey carried out during 2015, and on land cover derived from a locally supervised land cover classification. Global data on SOC stock is readily available from SoilGrids and the version of Hengl et al. (2017) was downloaded in May 2017 from the ISRIC (International Soil Reference and Information Centre) database (https://soilgrids.org/) and included in the "global dataset". Remote sensing datasets were used to assess and calculate biomass and to derive data for the land cover classification and interpolation of local soil properties. Remote sensing data were derived from Landsat, MODIS (Moderate Resolution Imaging Spectroradiometer), Sentinel 1, and Sentinel 2 sensors, and SRTM (Shuttle Radar Topography Mission). For further details on the global datasets used see Supplementary Information A, Section 1.

Table 1. Description of global and hybrid datasets. In brackets are reported the units of the input variables and their resolution and the date of observation in global and hybrid datasets. NDVI: Normalised Difference Vegetation Index; NPP: Net Primary Productivity; GLNC: Global Land Cover Network.

	Input variables	**Global dataset**	**Hybrid dataset**
Carbon stocks	SOC stock (t ha^{-1}) for a soil depth interval of 0-20 cm	- SOC stock map downloaded from ISRIC SoilGrids (250 m resolution; year of sampling: 1950-2014)	- SOC stock calculated from local data on bulk density, organic matter content and coarse fragment content, and mapped at 25 m spatial resolution; year of sampling: 2015)
	Organic carbon from above- and below- ground biomass (t ha^{-1})	- Landsat NDVI (30 m; years: 2013-2015) - Land cover categories from GLNC (300 m; year:	- Landsat NDVI (30 m; years: 2013-2015) - Land cover categories from

		2008)	supervised classification (30 m year: 2016)
	Organic carbon from dead organic matter (t ha^{-1})	- MODIS; NPP (~1 km; years: 2000-2015)	- MODIS; NPP (~1 km; years: 2000-2015)

2.2.1. Land cover maps

The land cover map was used together with the NDVI to infer and map the carbon stored in aboveground and belowground biomass. For this purpose, two different land cover maps were used: a land cover from a global dataset, and a land cover from a local classification. For further details on how the carbon stored in the aboveground and belowground biomass was calculated see Section 3.2.2.

Land cover map from the global database

The FAO Land Cover map of Ethiopia was derived from the Global Land Cover Network (GLNC), a global cover archive of 300 m spatial resolution (Arino et al., 2010, 2008) with few adaptations to the legend. For this study, the Ethiopian GlobCover version was downloaded from the FAO GeoNetwork database (http://www.fao.org/geonetwork/srv/en/main.home). Table 2 shows the global land cover classes occurring in the study area with a description and an approximate correspondence with the local land cover classification map classes. See the Supplementary Information A for a figure of the global land cover.

Local land cover classification

A two-step supervised classification was used to generate a local land cover dataset that was used in the hybrid dataset. 670 GPS points were selected and classified using local expertise and the support of Google Earth images. The 670 points represented different land cover categories such as degraded land, woodland, riverine areas, cropland, rangeland, forest, settlement and urban area. The points were equally distributed among the different land cover classes (approximately 85 points per land cover class). A first approximation of the local land cover classification was obtained using a classification and regression trees approach (Random Forest; Breiman (2001)) with the points and several covariates, derived from elevation, Landsat datasets and Sentinel 2 scenes.

The derived land cover classification was subsequently verified and manually modified using Google Earth images as background. Several classified polygons categories were changed, based on local knowledge of the area, to differentiate between land cover classes that in the automated classification were confused (e.g. degraded land, restoration land and croplands) due to their similar reflectance spectrum. Polygons derived from the classification and characterised by mixed semi-natural vegetation and agroforestry were differentiated from the forested areas. Areas characterised by small settlements and cropland alongside them were also individuated and differentiated from Halaba urban area or farmland areas. The resulted classification was visually validated by local experts. Table 2 shows the local land cover classes' description and an approximate correspondence with the global land cover classes (see Section 2 of Supplementary Information A for further details and the figure of the derived land cover classification map).

Table 2. Description of "global" land cover (LC) classes derived from the FAO GlobCover of Ethiopia, and description of local land cover classes obtained through a supervised land cover classification.

Global LC class	Description	Percentage of study area (%)	Corresponding local LC class
14	rainfed cropland	54.6	5
20	mosaic cropland (50-70%)/vegetation (grassland/shrubland/forest) (20-50%)	17.1	3
30	mosaic vegetation (grassland/shrubland/forest) (50-70%)/ cropland (20-50%)	7.7	2
60	open (15-40%) broadleaved deciduous forest/woodland (>5m)	0.1	1
110	mosaic forest or shrubland (50-70%)/grassland (20-50%)	0.9	NA
130	closed to open (15%) shrubland (<5m)	19.6	NA
150	sparse (<15%) vegetation-sparse woody vegetation/herbaceous sparse vegetation.	0.2	NA

Class Local LC	Description	Percentage of study area (%)	Corresponding global LC class
1	Forests and exclosures in the riverplain	2.5	60
2	Forests and farmland in hilly area (mixed semi-natural and agricultural areas)	13.4	30

3	Settlements and farmland alongside settlements	18.7	20
4	Degraded land	9.5	NA
5	Farmland	53.0	14
6	Halaba, bigger villages and paved streets	1.5	NA
7	Riverine areas	0.6	NA
9	Grassland, graze land	0.8	NA

2.3. Local survey

Local soil data were derived from 354 soil samples (for 0-20 cm of soil depth) collected during a local survey carried out in the study area in 2015, in areas with different land cover types and management strategies. The samples were collected from: i) different fields of 75 households in the three *kebeles* (selected from a household survey to represent three wealth categories); ii) 108 semi-natural sites and farmland sites, and iii) 6 restoration sites of different ages. 201 samples were collected in farmland areas, while 153 were collected in semi-natural, restoration, and exclosure sites. The farmland samples were collected from home garden, nearby field and far field of the 75 selected households to infer different management and input strategies. Non-agricultural areas were selected using a random probabilistic approach weighted by semi-natural area (previously identified using morphological features and land cover classes). The soil survey covered an area of about 400 km^2.

The SOC amount (stock) was derived from data on soil organic matter (SOM) content, bulk density, and volume of coarse fragments of the 354 samples collected (see Section

3.2.1). The soil depth interval of 0-20 cm was chosen to match it with the AfSIS Technical Specifications for Soil Health Surveillance (http://africasoils.net) that were used in the Ethiopian Soil Information Service (EthioSIS), an Ethiopian initiative to gather and analyse soil samples at a national level to develop extensive soil fertility maps. The 0-20 cm depth interval was a pragmatic choice because the local soil survey did not have bulk density data for the second soil depth interval (20-50 cm as defined by the soil survey protocol). A soil depth interval of 0-20 cm was therefore chosen for this study. The soil depth interval considered the mineral soil (as in the SoilGrids, where the organic layers on top of mineral soils were removed) since the O horizon was absence in our soil samples. A bulk density corer was used to collect soil cores used to determine bulk density. An Edelman auger was used to collect composite samples of 500 g used to determine organic matter and soil texture. For the composite sample a "W" sampling design was used.

3. METHODS

The procedure used to assess carbon stocks and analyse the obtained results was characterised by three main steps: i) data collection to derive the "global" and the "hybrid" datasets; ii) mapping of organic carbon stocks by calculating the three carbon pools (carbon from total living biomass, carbon from dead organic matter, and SOC); iii) statistical analysis for comparing the two sets of results (global and hybrid). The methodology was similar to that used by Cerretelli et al. (2018).

3.1. Local soil property maps

Local soil properties maps, in particular SOM percentage and bulk density, were obtained through an interpolation process using an extension of the scorpan-kriging approach (McBratney et al., 2003). More in detail, a hybrid geostatistical Generalized Additive Models (GAM; Wood (2006)), combining GAM with kriging (Poggio and Gimona, 2017, 2014) was used. Several covariates (17) mainly based on remote sensing data (DEM, Landsat, Sentinel 1, and Sentinel 2 derived maps) were used. A prediction grid of 25 m x 25 m resolution for the first 20 cm of soil depth was obtained (see Supplementary Information A for further details).

3.2 Carbon stocks assessment

Three different organic carbon pools were considered to assess the total organic carbon stock:

i) soil organic carbon;

ii) carbon from total living biomass (aboveground and belowground biomass);

iii) carbon from dead organic matter.

The next sections provide details about assessing each of the three pools.

3.2.1. Soil organic carbon

Global soil organic carbon stock data

The SOC stock data, expressed in t ha^{-1} for six depth intervals (0-5 cm, 5-15 cm, 15-30 cm, 30-60 cm, 60-100 cm, 100-200 cm), was downloaded from the SoilGrids 250m availed by ISRIC – World Soil Information (International Soil Reference and Information Centre) (https://soilgrids.org/) (Hengl et al., 2017). The SoilGrids dataset is a collection of soil property maps at 250 m spatial resolution. It was produced using digital soil mapping techniques based on machine learning algorithms (Hengl et al., 2017). The SOC stock for 20 cm depth was derived by summing the stock of the two first SoilGrids layers of 0-5 cm and 5-15 cm, and just the stock of the first 5 cm (one third of the total depth interval) of the third layer (15-30 cm), assuming a constant SOC stock throughout the layer. This weighted average calculation was suggested by the trapezoidal formula indicated by Hengl et al. (2017). Accordingly, the total amount for the 0-20 cm depth interval was obtained as follow:

$$SOC_{stock} = SOC_{d1} + SOC_{d2} + \frac{1}{3} SOC_{d3} \quad (1)$$

where:

SOC_{stock} = soil organic carbon stock (t ha^{-1})

SOC_{d1-d3} = soil organic carbon at 0-5 cm (SOC_{d1}), 5-15 cm (SOC_{d2}), and 15-30 cm (SOC_{d3}) depth interval.

Local soil organic carbon stock

The SOC stock for the hybrid dataset was calculated using the following equations, based on the assumption that the carbon content of SOM is 58% (Van Bemmelen, 1890). This proportion has been largely used in literature for obtaining SOC content from the SOM content because it provides a reasonable estimate for most purposes (Baldock and Nelson, 2000; Stockmann et al., 2013).

$$SOC_{\%} = OM \times 58_{\%} \quad (2)$$

$$SOC = SOC_{\%} \times BD \times (100_{\%} - VS_{\%}) \times SDT \times 100 \quad (3)$$

where:

$SOC_{\%}$ = soil organic carbon content (%)

OM = organic matter content (%)

SOC = amount (stock) of soil organic carbon for a certain depth (t ha^{-1})

BD = bulk density (g cm-3)

VS = volume of stones – coarse fragments (%)

SDT = soil depth thickness (cm)

3.2.2. Carbon from total living biomass

Equations that estimate plant biomass from NDVI index were used for calculating the total living biomass of four different vegetation types to characterise the land cover classes mapped in the study areas; grassland: Devineau et al. (1986), forest: Gizachew et al. (2016), shrubland: Pereira et al. (1995), and cropland: Thenkabail et al. (2002). The coefficient of correlation of the four equations ranges from 0.50 to 0.98. Table 3 summarises the equations used. In Table 3 we reported the biomass in different conditions (wet weight aboveground biomass – wAGB, and dry weight aboveground biomass - AGB) because the different equations estimate either wet weight aboveground biomass (for cropland), or dry weight aboveground biomass (for grassland and shrubland). The wAGB represents the sum of AGB and moisture content. Moreover, the equation used for the forest estimates directly the total living biomass (sum of dry weight of aboveground and belowground biomass).

Table 3. Equations used to calculate the biomass. wAGB = wet aboveground biomass (t ha^{-1}). AGB = dry aboveground biomass (t ha^{-1}). BGB = dry belowground biomass (t ha^{-1}) calculated as in Kuyah et al. (2012) (R^2 = 0.95). TLB = total living biomass (above- and below-ground biomass) (t ha^{-1}). The symbol "-" identifies the unused equations for each vegetation type (e.g. for the forests we applied only the TLB equation).

	wAGB (t ha^{-1})	**AGB (t ha^{-1})**	**BGB (t ha^{-1})**	**TLB (t ha^{-1})**
Forest	-	-	-	$280.93 \times NDVI - 84.22$ (Gizachew et al., 2016)
Grassland	-	$\frac{(0.216 \times (100NDVI)^{1.7})}{100}$ (Devineau et al., 1986)	$0.49 \times AGB^{0.923}$ (Kuyah et al., 2012)	$AGB + BGB$
Shrubland	-	$2.923 + 21.486 \times NDVI$ (Pereira et al., 1995)	$0.49 \times AGB^{0.923}$	$AGB + BGB$
Cropland	$(0.186e^{3.6899 \times NDVI}) \times 10$ (Thenkabail et al., 2002)	$wAGB \times 0.905$	$0.49 \times AGB^{0.923}$	$AGB + BGB$

To obtain the dry weight of the aboveground cropland biomass, the moisture content (9.5%) was removed (Table 3). This moisture content was obtained through a literature review on moisture content in cropland residues (Ben-Iwo et al., 2016; Frear et al., 2005; Guo et al., 2016; Lam et al., 2007; Mani et al., 2004; McKendry, 2002). Even though different crops could differ in the moisture content, we assumed that 9.5% represents a good average proportion for all cropland types, based on literature review.

The total living biomass (t ha^{-1}) was calculated for the four different vegetation types (e.g. grassland, forest, shrubland, and cropland). The four values were applied in different proportions to characterise the biomass of each global and local land cover class (Table 4). This was necessary because the land cover classes represent a mosaic of different land cover categories, due to the high heterogeneity of the Ethiopian landscape, and to the difficulties of distinguishing between different categories such as cropland and degraded land, forest and cropland around settlements. The estimation of the proportion of each vegetation type in the land cover classes was based on visual inspection of high-resolution satellite images (Google Earth) and supported by local expertise and local vegetation surveys. Table 4 illustrates different proportions of total living biomass previously obtained using the four regression equations reported above (Table 3), applied for each land cover class. For example, for the areas classified as forest classes (global land cover class 60 and hybrid land cover class 1), we derived the biomass by adding at the biomass obtained using the equation for forest environment (Gizachew et al., 2016) 30% of the biomass obtained using the equation for grassland environment (Devineau et al., 1986), based on the assumption that grassland biomass is also present in the forests, as supported by local expertise of the study area and local vegetation surveys.

For the class representing the settlements and the croplands (local class 3 and global land cover class 30), we assumed the presence of biomass from cropland (60%), grassland (29.5%) and forest (15%), because the class is characterised by a mosaic of mixed vegetation and crops. We derived the proportions based on the heterogeneity of the class; they were then justified by local expertise, satellite images investigation and local surveys. Refer to Tables 2 for the characterisation of the land cover classes.

Table 4. Proportions of total living biomass obtained through the four regression equations reported in Table 3, applied in each land cover class.

		Short LC class description	Eq. forest	Eq. grassland	Eq. shrubland	Eq. cropland
Global land cover classes	14	Farmland	-	15%	-	85%
	20	Cropland and semi-natural vegetation	15%	29.5%	-	60%
	30	Semi-natural vegetation and cropland	45%	28.5%	-	40%
	60	Forest	100%	30%	-	-
	110	Shrubland and grassland	30%	58%	30%	-
	130	Shrubland	-	30%	100%	-
	150	Sparse vegetation	30%	79%	-	-
Local land cover classes	1	Forest	100%	30%	-	-
	2	Semi-natural vegetation and cropland	45%	18.5%	-	40%
	3	Cropland, settlements, and semi-natural vegetation	15%	29.5%	-	60%
	4	Degraded land	20%	60%	-	20%
	5	Farmland	-	15%	-	85%
	6	Cities and paved streets	-	50%	-	-
	7	Riverine areas	-	50%	-	-
	9	Grassland	10%	93%	-	-

Finally, the dry weight of the total living biomass (t ha^{-1}) was multiplied by 0.475 to obtain the carbon content stored in the total living biomass (IPCC, 2006; Magnussen and Reed, 2004). This conversion factor is considered a reasonable estimate of carbon stored in above- and below-ground living biomass. It is an assumption largely used in literature in case there is not data from a survey (Cañellas et al., 2017; Magnussen and Reed, 2004; Propastin and Kappas, 2010; Rieger et al., 2015).

3.2.3. Carbon from dead organic matter

The amount of carbon from dead organic matter was derived from the Net Primary Productivity map downloaded from the MODIS database, which considers a period range of 2000-2015, assuming that the system was in equilibrium (MOD17A3, https://lpdaac.usgs.gov/products/mod17a3v055/). This method derives from the fundamental implicit assumption that, when the living biomass per unit surface in an ecosystem is stationary, i.e. it reaches a growth plateau, to each gram of new organic carbon incorporated by production corresponds a gram of biomass shed as dead matter, thus resulting in a dynamic equilibrium (Hogarth, 2015; Ohtsuka et al., 2005; Schlesinger and Bernhardt, 2013; Woodwell and Whittaker, 1968).

3.3. Statistical analysis and software used

The estimates obtained with the “global” and the “hybrid” datasets were compared to highlight possible implications in mapping carbon stocks using data at different spatial and temporal resolutions, and obtained from radically different sampling and modelling approaches.

The following steps were performed in the analysis:

- since the resolution of the global and hybrid results (e.g. carbon stocks estimates) were 250 m and 30 m, respectively, to compare the two sets of results, the maps obtained using the hybrid dataset were resampled at 250 m resolution using the nearest neighbour resampling algorithm;
- zonal statistics (mean, median, and sum) at land cover and sub-catchment level were obtained (see Supplementary Information A on how the sub-catchment map was derived). The sub-catchment represents a useful geographical unit for conservation or management strategies implementation at a local decision-making process because hydrologically self-contained;
- side by side comparison of mapped estimates;
- statistical comparison between “global” and “hybrid” results:
    - linear regressions were run at pixel and at sub-catchment level to identify the correlation among the two sets of results (“global” and “hybrid” results);
    - Kendall correlation coefficient (rank correlation analysis) was used to identify the association between paired samples;
    - qq-plot (quantile-quantile plot; a graph where the quantiles of two distributions (e.g. global and hybrid results) are plotted against each other). If both sets of quantiles came from the same distribution, the qq-plot will show a set of points forming an approximately straight line;

As an indicator of land degradation, the SOC of the two different datasets (global and hybrid) were compared to identify possible implications of using SOC estimates as proxy for land degradation. Zonal statistics were calculated to estimates the SOC at land cover level. The local land cover classification was used because of the major level of detail and accuracy (as compared to the global land cover classification), and also because it contained a land cover class defined as degraded land.

Moreover, the root-mean-square error (RMSE) was calculated between the SOC data measured at the sampled points and the SOC maps resulting from the global dataset (SoilGrids prediction) and the hybrid dataset (local predictions).

Carbon stocks was calculated using QGIS (version 3.0.0) and GRASS GIS (version 7.4.0) software (GRASS Development Team, 2017; QGIS Development Team, 2017). R software (version 3.4.0) (R Core Team, 2017) was used for the statistical analysis. The packages used were: “raster” (Hijmans, 2015), “rgrass7” (Bivand, 2015), “rasterVis” (Perpiñán-Lamigueiro and Hijmans, 2013).

4. RESULTS

4.1. Carbon stocks assessments

The calculated total organic carbon stocks ranged from 56 to 134 t ha^{-1} with both mean and median of 76 t ha^{-1} in the global case, and from 4 to 118 t ha^{-1} with a mean of 46 t ha^{-1} and a median of 44 t ha^{-1} in the hybrid case. In the global case, in the three pools, the carbon stocks ranged from 50 to 92 t ha^{-1} (mean 63 t ha^{-1}), from 0 to 53 t ha^{-1} (mean 7 t ha^{-1}), and from 4 to 10 t ha^{-1} (mean 6 t ha^{-1}) in the soil, biomass, and dead organic matter, respectively. While in the hybrid case, the carbon stocks ranged from 0 to 84 t ha^{-1} (mean 31 t ha^{-1}), from 0 to 68 t ha^{-1} (mean 9 t ha^{-1}), and from 4 to 10 t ha^{-1} (mean 6 t ha^{-1}) in the soil, biomass, and dead organic matter, respectively, thus with the vast majority in the soil. In the global case, the relative contribution to the total carbon stocks was 82.9%, 9.2%, and 7.9% in the soil, living biomass, and dead organic matter pools, respectively. In the hybrid case, the relative contribution was 67.4%, 19.6%, and 13.0% in the soil, biomass, and dead organic matter pools, respectively. The linear regression models between the two distributions of organic carbon stocks (obtained using the global dataset or the hybrid dataset) showed good correlation at sub-catchment level (tons per sub-catchment) with R^2 of 0.96, while a R^2 of 0.40 at pixel level. The R^2 between the two sets of results was 0.52 if the means per sub-catchment in t ha^{-1} are correlated.

Furthermore, the two sets of results showed fair rank correlation at pixel level with a rank correlation coefficient of 0.42. The coefficient was 0.43 if the median amounts of carbon stocks per sub-catchment (t ha^{-1}) are correlated.

The maps in Fig. 2 (a and b) show the spatial distribution of carbon stocks obtained using the global dataset (Fig. 2a), and the hybrid dataset (Fig. 2b). The latter results (obtained with the hybrid dataset) showed more spatial variability, and lower carbon stocks (t ha^{-1}) in the whole area compared to the first results (obtained with the global dataset). This aspect is quite clear from the density plot and the scatter plot in Fig. 2c and 2d; the two graphs show how the spatial distribution of the two results (global and hybrid) differed in the estimates range and in the variability. The distribution of the estimates of the global dataset (in blue) showed overall higher estimated and lower variability as compared to the distribution of the hybrid results (in red) (Fig. 2c). This aspect is also shown by the scatter plot in Fig. 2d.

The lower estimates of carbon stocks with the hybrid dataset are shown also in the qq-plots in Fig. 3 both at pixel resolution (Fig. 3a), and at sub-catchment resolution (Fig. 3b). At pixel resolution (Fig. 3a), the difference between the quantile of the distribution of the estimates of the hybrid and the global datasets was high especially at lower estimates. The difference between the quantiles of the distribution decreased at higher estimates, showing better agreement at high estimates. Moreover, also at higher quantiles, the qq-plot at pixel level (Fig. 3a) shows that the global dataset obtained higher values of carbon stocks. At sub-catchment resolution (Fig. 3b) the difference remained constant throughout the quantiles, with lower estimates using the hybrid dataset.

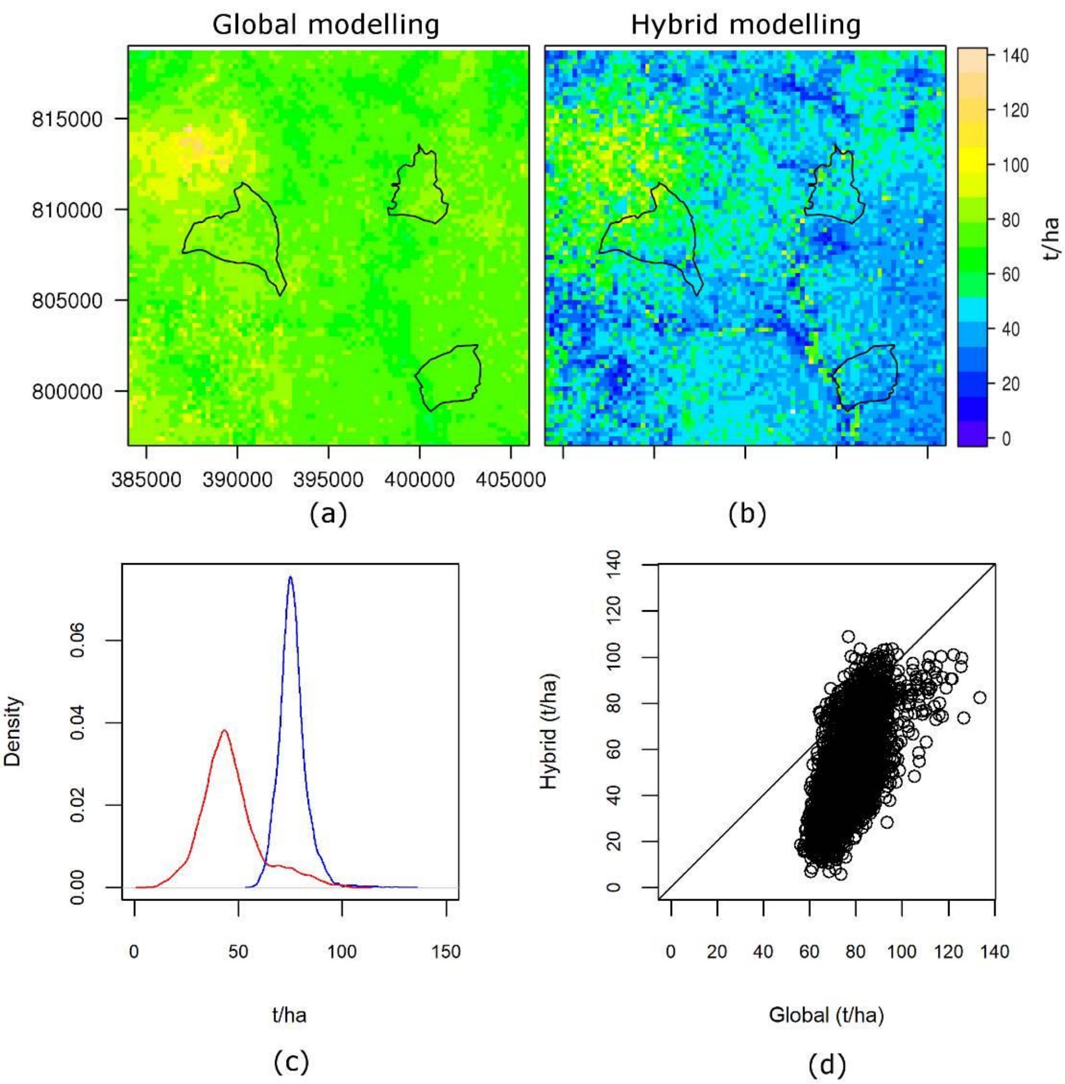

Figure 2. Carbon stocks (t ha^{-1}) obtained using the global dataset (Fig. 2a) and the hybrid dataset (Fig. 2b) (the black polygons show the kebeles where the survey was concentrated). Fig. 2c shows the density plot of the global (blue) and the hybrid (red) results (carbon stocks estimates at pixel level). Fig. 2d shows the scatter plot of global against hybrid results (at pixel level).

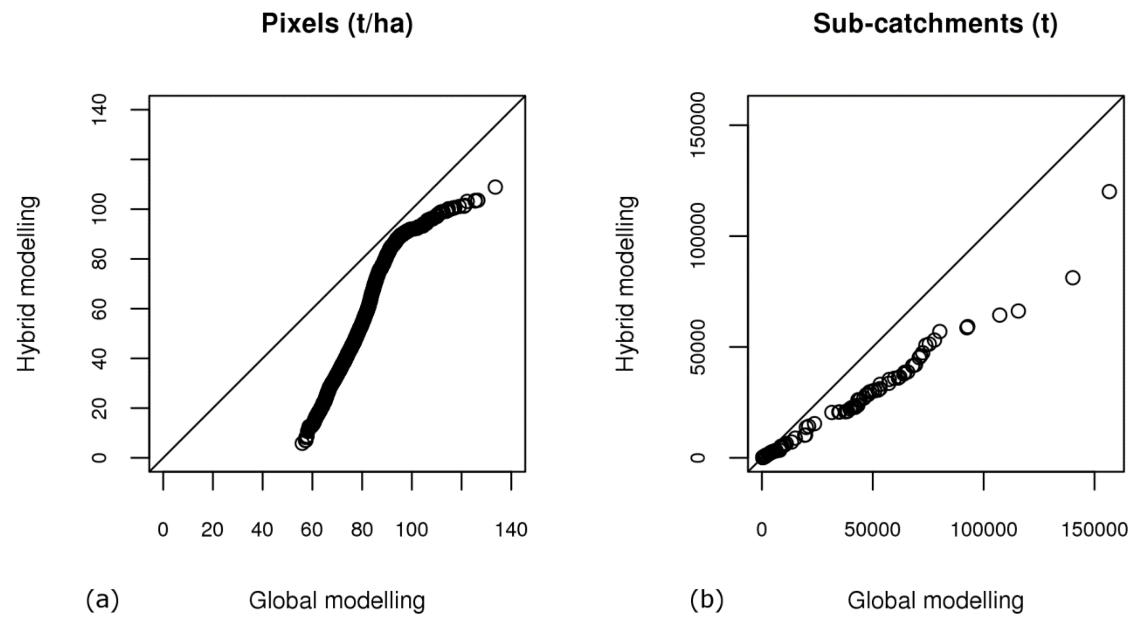

Figure 3. Quantile-quantile plots (qq-plots) between global and hybrid results of carbon stocks at pixel (a) and sub-catchment (b) level.

When aggregated by land cover classes different estimates were obtained with different datasets (e.g. global and hybrid datasets). The bar plots in Fig. 4 show the mean value of carbon stocks (t ha^{-1}) summarised by global (Fig. 4a) and local (Fig. 4b) land cover classes. The results obtained from the global dataset are shown in blue colour and the results obtained from the hybrid dataset are shown in green colour. The higher estimates obtained by the global dataset at pixel level (Fig. 3) were also confirmed at land cover level; in fact, the blue bars are in all land cover classes higher compared to the green bars. The mean value of carbon stocks (t ha^{-1}) per local land cover class (Fig. 4b) was higher in the class 2 in both estimates of the global and the hybrid dataset. Class 2 of the local land cover corresponds to cultivated area with semi-natural vegetation and agroforestry practices in the western hilly areas. Its mean carbon stocks was also higher compared to the mean carbon stocks estimated for the class 1 (forests and exclosures located especially in the proximity of the river, that underwent restoration activities in the past years).

Apart from class 60 (open (15-40%) broadleaved deciduous forest/woodland (>5m)), which is represented by a very small area (~0.1% of the whole area), there was lower variability of estimates of carbon stocks among land cover classes if global dataset was used, as compared to the estimates by the hybrid dataset (Fig. 4).

Among mean estimates of the global and local land cover classes that can be compared, differences in the range of 12%-48% were found, with higher values in all cases in the global estimates (Table 5). For details on the corresponding land cover classes refer to Table 2.

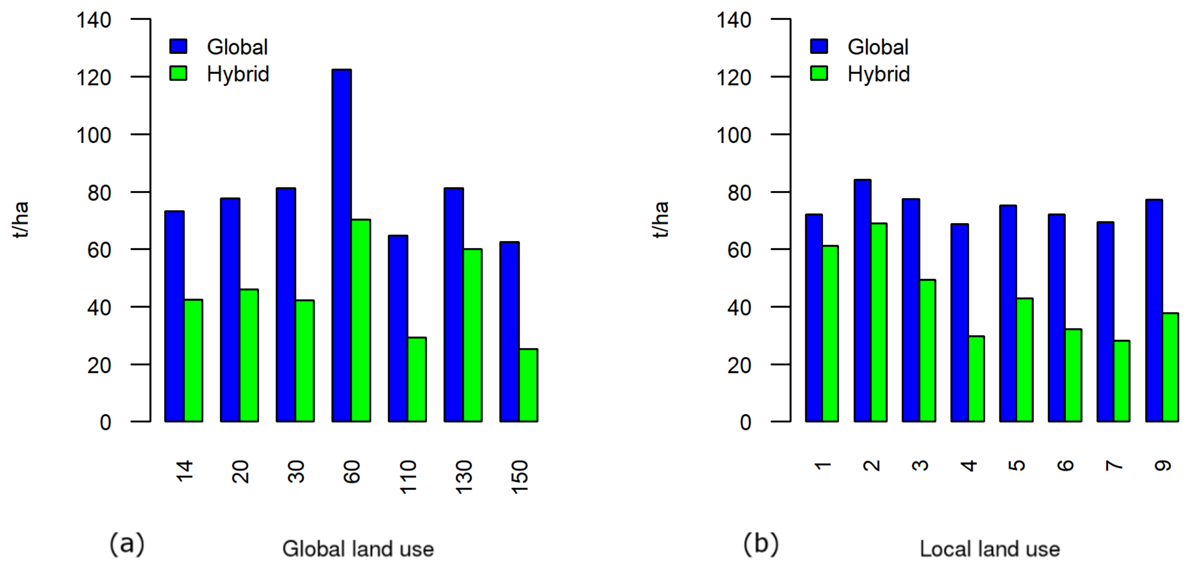

Figure 4. Bar plots of mean carbon stocks (t ha^{-1}) per global (a) and local (b) land cover classes. In blue the results obtained using the "global" dataset and in green the results obtained using the "hybrid" dataset.

Table 5. Mean values per corresponding global and local land cover classes obtained using the global and the hybrid datasets, respectively. The last column shows the percentage difference obtained using the two datasets if the corresponding global and local LC classes are considered.

Brief LC description	**Global LC**		**Local LC**		**% difference**
	Class	**Mean (~ha t^{-1})**	**Class**	**Mean (~ha t^{-1})**	
Farmlands	14	73	5	42	42%
Farmlands and mixed semi-natural vegetation	20	78	3	49	37%
Mixed croplands and vegetation	30	81	2	71	12%
Forests	60	122	1	63	48%

4.2. Soil organic carbon in the two datasets

In the whole area, the SOC stock ranged from 49.7 to 91.7 t ha^{-1} (mean = 62.9, median = 62.9, standard deviation = 4.37, variance = 19.1, coefficient of variation = 7.0%) for the global dataset, and from 0 to 84.4 t ha^{-1} (mean = 31.2, median = 31.1, standard deviation = 8.36, variance = 69.9, coefficient of variation = 26.8%) for the hybrid dataset. Fig. 5 shows the maps of SOC stock used in the global dataset (Fig. 5a), and the one produced using the local data (Fig. 5b), the difference between the global and hybrid SOC (Fig. 5c), and the qq-plot between global and hybrid SOC (Fig. 5d). Fig. 5c shows that, in the whole area, the SOC stock of the global dataset was higher than the SOC stock of the hybrid dataset. Fig. 5d also shows that the difference between the quantile of the distribution of the global and hybrid SOC was high for the whole distribution. In Fig. 6 the bar plots show the minimum (Fig. 6a), and median (Fig. 6b) values of SOC (t ha^{-1}) summarised by local land cover classes. In all classes, the SOC of the global datasets was higher than the SOC of the hybrid dataset, for the minimum, and median values. In particular, in the local land cover class 4 (degraded land) the SOC minimum, median, and maximum values were 49.7, 59.3, and 77 t ha^{-1} in the global dataset, and 0, 21.1, and 49.7 t ha^{-1} in the hybrid dataset. Ultimately, the bar plots suggest that the spatial variability was lower in the global SOC estimates compared to the hybrid SOC estimates.

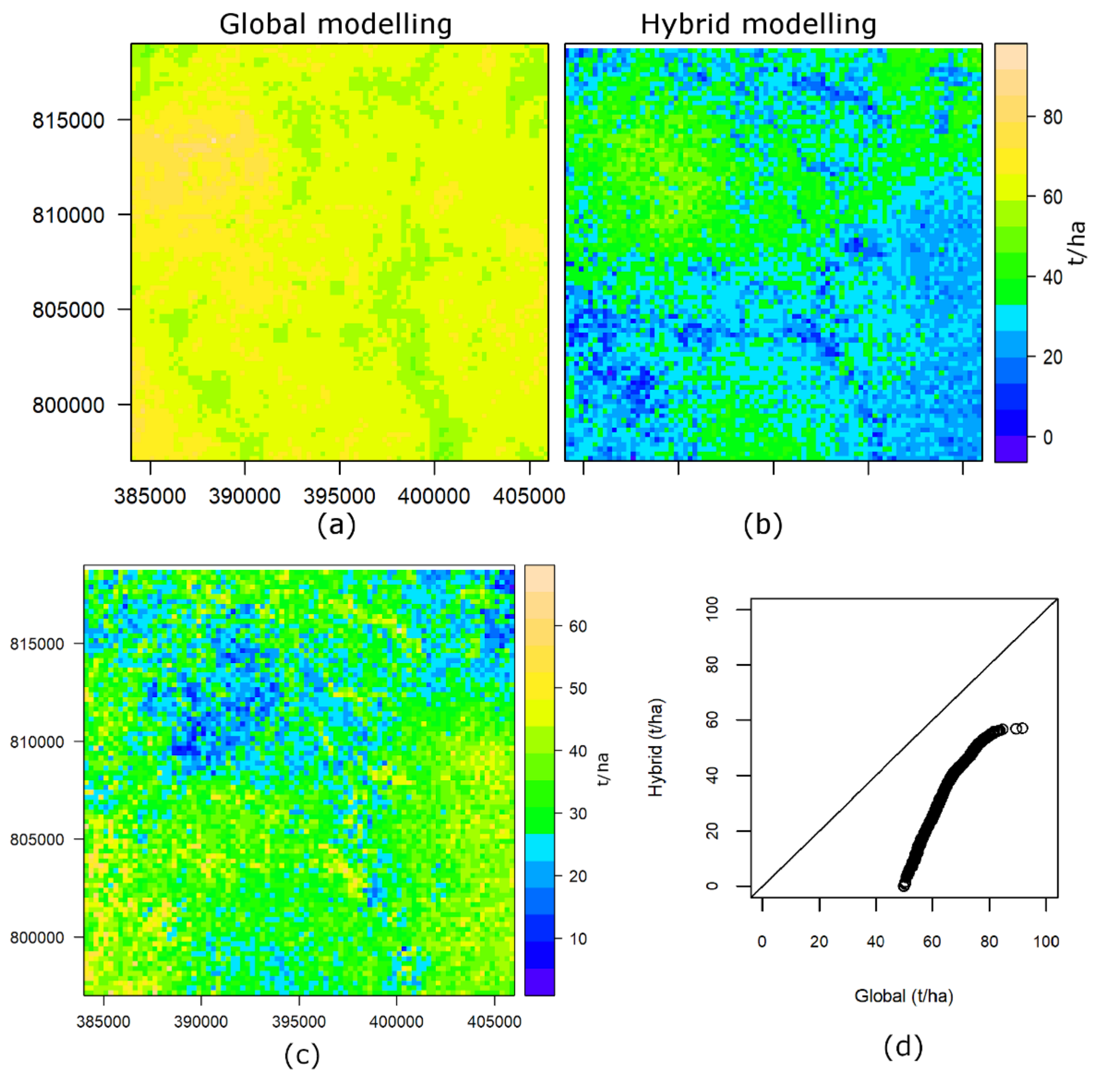

Figure 5. Soil organic carbon (t ha^{-1}) of the global dataset (a) and the hybrid dataset (b), the difference between soil organic carbon (t ha^{-1}) of the global and the hybrid dataset (c), and quantile-quantile plot (qq-plot) between global and hybrid SOC (d).

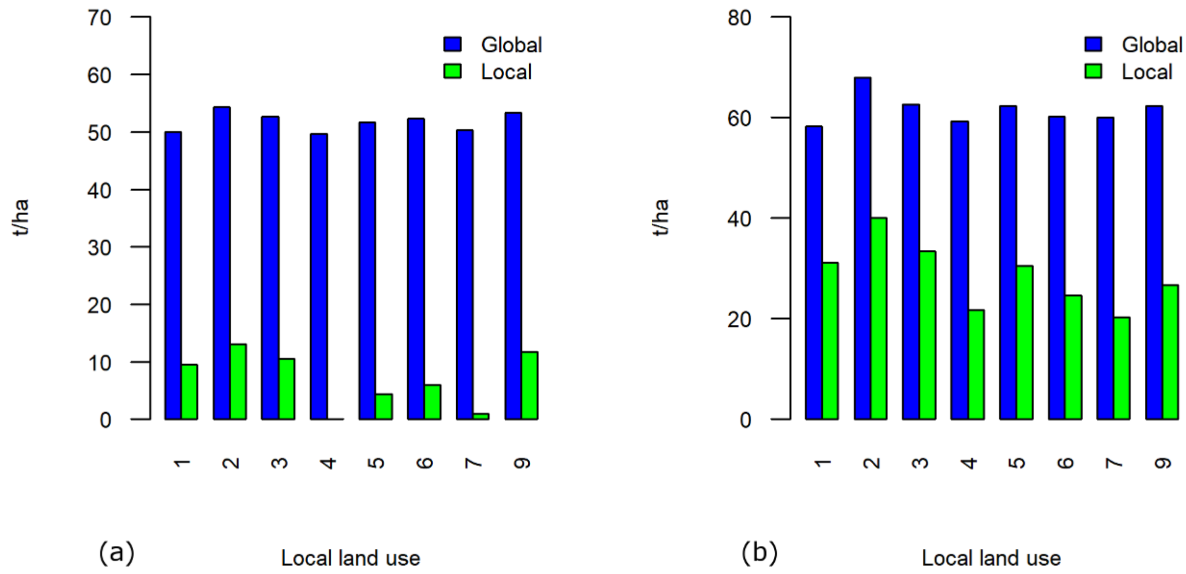

Figure 6. Bar plots of minimum (a), and median (b) values of SOC (t ha^{-1}) per local land cover classes. In blue the SOC value of the “global” dataset and in green the SOC value of the “hybrid” dataset.

The R^2 between the observed SOC values and the SOC predictions of the interpolation used in the hybrid dataset was 0.88. The R^2 decreased to 0.33 if the same map resampled to 250 m was used. A R^2 of 0.08 was found between the observed values and the SOC derived from the SoilGrids (used in the global dataset).

The RMSE calculated between the observed values and the SOC predictions of the interpolation used in the hybrid dataset was 4.1 t ha^{-1} (if the map of 25 m resolution was used in the analysis). The RMSE increased to 9.6 t ha^{-1} if the same map resampled to 250 m resolution was used. The RMSE calculated between the observed values of SOC and the SOC predictions in the global dataset was instead 31.9 t ha^{-1}. This, as expected, demonstrated that local estimates were much closer to the observed values.

5. DISCUSSION

While it should be borne in mind that the carbon stocks mapping used in our study is not dynamic and is simplistic, this limitation does not affect the validity of the comparison of the results obtained using different datasets being studied here.

The data used clearly produced a difference in estimates. The fair correlation at pixel level and the difference in the estimates of carbon stocks using global and hybrid datasets were mainly due to i) the difference in soil datasets (SOC stock was considerably lower when calculated from local data compared to the global data), and to ii) the difference in land cover datasets (organic carbon in biomass was lower when calculated from the local land cover map compared to when calculated from the global land cover map). Besides, the difference in the time scale of the local land cover classification (obtained using data of 2015) and the Ethiopia GlobCover database (obtained using data of 2005) likely affected the estimations of the carbon from biomass in the two models. Keeping in mind that land cover changes over ten years might affect the estimations, we think that a land cover map of 300 m resolution is not adequate to infer land cover changes in a small area.

A similar discrepancy was also present for the SOC, since the hybrid dataset used data from 2015, while the data used in the global SoilGrids prediction were collected from 1950 to 2014 (Hengl et al., 2015). This likely led to different estimates of SOC due to the dynamic nature of soil processes or possible land degradation exacerbation. The overestimation obtained using the global dataset might also be the result of a lack of data-points in our study area. In fact, despite the utilisation of more than 1500 Ethiopian profiles for deriving the SoilGrids maps (Batjes et al., 2017), no soil profiles were located in our region of interest. The sparse data representativeness and the time difference of the samples used in the two predictions (global and local SOC) were the main driver of different estimates of SOC, and subsequently of carbon stocks. Furthermore, the discrepancies may also reflect differences in sampling and laboratory analysis (of organic carbon content, bulk density, and coarse fragments content) and even in the calculations of stocks. The SoilGrids version used in this study might generally overestimate soil organic carbon stocks due to the data used to map bulk density, including North American legacy data (especially from the USA), in which the bulk density was calculated without oven-drying the soil samples. This issue is resolved in the current version (2.0) of SoilGrids (de Sousa et al., 2020). However, these factors did not affect the main objective of this study, which was to identify possible limitations and drawbacks or advantages of using global or local datasets to map carbon stocks. Furthermore, the global datasets, using legacy data, could overlook the presence of soil carbon restoration and rehabilitation measures. However, the restoration of SOC after rehabilitation activities is a long process (Mekuria et al., 2011) that a ten-year frame difference would not dramatically affect the results. Overall, the observed discrepancies between the organic carbon stocks assessed using the two different datasets may be because the global dataset is produced not using any data originating from the study area and/or reflects past times (Arino et al., 2008; Hengl et al., 2015). Decision-making is influenced by such differences and it is recommended to collect and use local and up-to-date data where possible. Lesser accuracy (showed by the difference in RMSE of the carbon stored in the soil) is not necessarily a systematic problem of global datasets compared to local datasets. It is also reasonable to assert that, in different areas, with different land cover conditions as well as biophysical factors, the same analysis and the same global datasets (e.g. SoilGrids) could provide local underestimates, instead of overestimates. Over larger areas this results in good estimates of the mean. However, the local estimates could still be affected by non-negligible errors, and it is important to understand the implications for decision-making.

Our estimates of organic carbon stocks obtained using the hybrid dataset as well as the global dataset were lower than those found in other areas in Ethiopia. For example, Vanderhaegen et al. (2015) found total organic carbon stocks of ~70±12 t ha^{-1} in maize field systems, ~77±10 t ha^{-1} in grazing lands, and up to 337±121 t ha^{-1} in natural forest and coffee agroforestry areas. De Beenhouwer et al. (2016) estimated total organic carbon stocks ranging from 219±23 t ha^{-1} to 413±56 t ha^{-1} in an agroecosystem dominated by natural forest, coffee extensive cultivations, and more intensive agroecosystem and intensified shade plantation systems. Bajigo et al. (2015) reported total carbon organic stocks of 51±0.7 t ha^{-1}, 86±20 t ha^{-1} and 448±43 t ha^{-1} in home gardens, parklands, and woodlots, respectively. The SoilGrids estimates for Ethiopia are probably the result of data available from Ethiopia exceeding our estimates for the study area. However, these quantitative comparisons should be taken carefully due to different techniques of biomass measurements, different modelling approaches as well as soil sampling depths. In fact, in our study, the SOC stock was calculated for 20 cm of soil depth, while in most of the other studies a standardised soil depth of 30 cm was used.

In both datasets, there were also potential sources of underestimation of carbon stored in the living biomass because the NDVI (used to calculate the biomass) was derived from Landsat images of dry periods. Furthermore, the quality of the global land cover likely introduced possible errors in the biomass calculation. Hence, a remote sensing approach that permits to classify the landscape should be used to derive a reliable and detailed land cover dataset. In fact, the better accuracy of the land cover mapderived from the supervised classification and used in the hybrid dataset likely led to more reliable results. This was also found in our previous study (Cerretelli et al., 2018), in which the results were mainly affected by the quality of the land cover classification used in the modelling. Moreover, the carbon derived from the total living biomass might have been underestimated because the equation used to calculate the belowground biomass (Kuyah et al., 2012) was derived from woody biomass, while our study comprehended also grassland or mixed vegetation areas. However, this extension did not affect the validity of the comparison between the different results obtained using different sets of data, because the same bias can be applied in both sets of results (global and hybrid results).

The mean of the carbon stocks in the whole study area for hybrid results was ~40% smaller than the mean for global results. We found that lower carbon stocks values were more overestimated by the global dataset than higher carbon stocks values, if the results obtained using the hybrid dataset are used as reference. Therefore, if global datasets are used quantitatively, e.g. to compare thresholds, decision-makers might not focus on the best areas or might underestimate the carbon depletion. For example, areas having low carbon stocks (i.e. carbon stocks lower than 50 t ha^{-1}) would be completely missed by the global dataset. The global dataset proved to be not adequate and spatially detailed also for selecting priority land cover classes for carbon stocks enhancement purposes, while the hybrid dataset could give better indications on where to intervene for increasing carbon stocks. However, the rank correlation analysis at sub-catchment resolution showed a fairly good correlation of the mean estimates (t ha^{-1}) with a rank correlation of 0.43. Therefore, global datasets proved to be adequate for targeting or prioritising sub-catchments based on their rank distribution. Both models made point-support predictions. When aggregating point-support data using different regions (e.g. sub-catchments or land cover classes) care should be taken because of the well-known modifiable areal unit problem (MAUP) (Jelinski and Wu, 1996; Openshaw and Taylor, 1979). Several studies highlighted the importance of the spatial scales, the extents and the support of estimates when modelling environmental properties (Cavazzi et al., 2013; Grunwald et al., 2011; Poggio et al., 2010). Accordingly, care should be taken because aggregation in different areal units could lead to unreliable findings. This aspect was also highlighted by Grêt-Regamey et al. (2014) who found that ecosystem services mapping is affected by the mapping resolution. These results are corroborated by Verhagen et al. (2016) who found that heterogeneity is often important when mapping different ecosystem services. This aspect was also true in our study which showed different agreements between the estimates of the global and the hybrid datasets, based on the different scales of aggregation used in the comparison analysis (pixel or sub-catchment level). The role of global datasets is prominent in countries with limited access to soil survey data. Our study suggested that these global datasets can be useful, provided their limitations and inaccuracies are understood, despite their potential for error in the numerical values of carbon stocks estimates. Such potential could lead to underestimation of the need for restoration in some regions, and mis-targeting of conservation measures, if based on quantitative estimates, because of the lower accuracy of the carbon stocks maps derived when using only global datasets. This study agrees with Vihervaara et al. (2012) who stressed how ecosystem services mapping needs detailed datasets to estimate variation at local level that could be relevant at a decision-making perspective.

More in detail, in our study, the mean value of carbon stocks (t ha^{-1}) was lower in the forests and exclosures in the riverplain (land cover class 1) than in the cultivated area with semi-natural vegetation and agroforestry practices in the western hilly area (land cover class 2). These results are in contrast with the expectation that forest areas store more carbon than semi-natural vegetation areas (Sisay et al., 2017; Solomon et al., 2017). However, this was mainly due to the characteristic of the land cover class 1, which embodies exclosures and plantations but not natural forests. These areas underwent intense grazing and exploitation before reafforestation programs were implemented (Byg et al., 2017; Yirdaw et al., 2014). Moreover, areas in proximity of the river (where land cover class 1 is mainly located) are highly prone and subjected to water-driven soil erosion (Cerretelli et al., 2018). Therefore, we think that land cover class 1 stores less carbon than land cover class 2 because of the high erosion rates and the long history of overgrazing and overexploitation. Only recently, these areas were subjected to afforestation programs and exclosure establishments (Yirdaw et al., 2014). Our study suggested that carbon stock restoration through afforestation programs takes time as already reported by many Ethiopian studies (Belay et al., 2018b; Mekuria et al., 2011). In addition, the exclosure areas, despite strict regulations, were subjected to uncontrolled and forbidden grazing and biomass harvesting (Byg et al., 2017; personal observation).

In order to halt and reduce carbon depletion, especially in the cropland areas, some measures can be suggested: afforestation practices, terraces and contour strips to reduce erosion, reduced removal of crop residues, restrained grazing, reduced tillage, manure application, agroforestry practices (Betemariyam et al., 2020; Gelaw et al., 2014; Lal, 2005; Lehtonen et al., 2020; Rimhanen et al., 2016). These practices and measures proved to be important to restore carbon stocks in other areas. We think that supporting and promoting such practices could contribute to increase carbon in the soil and biomass, and overall reduce land degradation (Betemariyam et al., 2020; Dagnachew et al., 2020; Gelaw et al., 2014; Lemenih et al., 2006; Rimhanen et al., 2016; Welemariam et al., 2018). Afforestation practices (such as exclosure establishment) should be implemented especially in already degraded areas (e.g. local land cover class 4), where cultivation, as well as grazing, is not an option anymore.

The need for attention when using global coverage datasets was also shown by the comparison between the SOC estimates of the global dataset and the SOC estimates derived from the local soil survey. In fact, the global SOC was about 50% higher than the hybrid SOC, if the mean value for the whole area is considered. This aspect could have implications at decision-making level, if SOC estimates are used as an indicator of land degradation to support and monitor land degradation neutrality and Sustainable Development Goal 15.3 (Lorenz et al., 2019; Sims et al., 2019). Furthermore, the analysis of the SOC stock per land cover map class showed that the global datasets failed to differentiate between different land cover classes. Our study showed that selecting certain areas for restoration purposes using the SOC as an indicator of land degradation (among other factors) would be difficult if based only on the absolute values of global datasets. These considerations are valid for our study area and for the global datasets considered. The same cannot be implied in other areas or if other global datasets are used. However, in the absence of dense sampling, this problem is expected to persist even if the size of the grid cell of global datasets is decreased.

The SOC map obtained using the soil survey data (used in the hybrid dataset) showed low estimates in the degraded land. Therefore, our results confirmed that SOC stock can be used as an indicator and proxy for land degradation. However, almost no variability at landscape level (land cover class level) was shown by the global SOC, considering both the minimum and the median value per land cover class. Already degraded areas might remain overlooked if global datasets are used as decision-making for restoration or conservation programs. Although SOC can indicate land degradation, many other factors (e.g. land productivity, land use and land cover changes, socio-economic aspects) should be included in the assessment to keep the complexity of land degradation drivers and factors into consideration (Lorenz et al., 2019). The integration of several factors that affect changes in SOC should be included in the soil and land degradation modelling in order to limit possible inaccuracies in the SOC estimates. Indeed, a major implication of these results, if confirmed elsewhere, is that global estimates of land degradation obtained with global datasets are likely to be optimistic compared to the actual situation on the ground. However, this will likely improve in Ethiopia when the EthioSIS dataset will be globally and easily available and will be used to distribute soil properties and resources maps. Nonetheless, global data can be extremely useful if properly utilised: our results on carbon stocks indicate that, for national-level, and even regional-level prioritisation of areas to restore (e.g. within REDD+ or the 4 per mille initiative (Minasny et al., 2017)), “global” data are likely to suffice if ranked values or distribution quantiles are used. Instead, when the actual values are needed it is preferable to use locally produced models. Therefore, if watersheds with lower carbon stocks must be selected for restoration activities, the global datasets proved to be good enough. Nonetheless, within those areas, to benefit local communities, local data are likely to be needed to refine spatial prioritisation. This aspect is particularly important to support poverty eradication strategies that account for benefits and dis-benefits, as well as trade-offs between different ecosystem services and/or between groups of people (Byg et al., 2017).

Conclusions

To summarise, global datasets overall provided higher values of organic carbon stock in soil (e.g. SOC) and biomass, but the estimates were less accurate as compared to the values obtained from local surveys. The lower accuracy of the global dataset (mainly concerning the soil organic carbon) was likely due to the use of legacy data and the lack of representative data points for the study area. Therefore, if there is a lack of representative data for a selected area or the global datasets are derived from old legacy data, we recommend the integration of global data with data from a local survey. Furthermore, global datasets provided estimates with lower spatial variability, making it difficult to select small areas, based on absolute values, for restoration prioritisation. These aspects should not be negligible if carbon stocks modelling or soil organic carbon are used as supports of decision-making processes.

However, global estimates of organic carbon stocks could be used as one of the proxies for land degradation, at the level of relatively small areas, such as small sub-catchments. Therefore, global estimates could be appropriate when, rather than the numerical values, a simple rank of those estimated values per ha is sufficient.

In conclusion, both the global and the hybrid carbon estimates were higher in the western hilly area that is characterised by a mix of agroforestry, woodland, and farmland patches. This suggests that further implementation of restoration and afforestation projects as well as agroforestry practices could be a key intervention to foster carbon sequestration.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: