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Effects of land cover on ecosystem services in Tanzania: A spatial assessment of soil organic carbon

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ABSTRACT

The multiple ecosystem services provided by healthy soil are well known and include soil carbon sequestration to mitigate climate change, a medium for plant and agricultural production and regulating the hydrologic cycle. Despite the wide recognition of the importance of these services, drivers of soil organic carbon (SOC) dynamics across various land uses in East Africa are poorly understood. The objectives of this study were threefold: to quantify SOC stocks across Tanzania; assess the effect of land cover and erosion on SOC; and investigate the relationship between inherent and dynamic soil properties under diverse land uses. The Land Degradation Surveillance Framework (LDSF) was used to assess the variability of ecological metrics at different spatial scales. SOC was quantified within and between different land cover types (forest, woodland, shrubland, grassland and cropland) in Tanzania. A total of 2052 soil samples from 1082–1000 m^2 plots were collected from seven 100-km^2 sentinel sites in 2010. Composite soil samples were collected at each plot from two depths (0–20 and 20–50 cm) and cumulative soil mass samples were collected to 100 cm. Soil samples were analyzed using a combination of traditional analytical laboratory methods and mid-infrared spectroscopy (MIR). Model performance of MIR spectral predictions for carbon was good, with an R^2 of >0.95 and RMSEP of 4.3 g kg^{-1}, when using an independent validation datasets. Woodland and cropland were the most frequently occurring vegetation structure types in the sampled sites, with 388 and 246 plots, respectively. Average topsoil OC (and range) was 12.4 (1.5–81.4) g C kg^{-1} (n = 1082) and average subsoil OC (and range) was 7.3 (0.64–53.8) g C kg^{-1} (n = 970) for the seven sites. Forested plots had the highest mean topsoil organic carbon concentrations (17.3 g C kg^{-1}) followed by cropland (13.3 g C kg^{-1}), for all sites included in the study, but with high levels of variability between sites. Soil mass at 30 cm was measured and these data were used to calculate carbon stocks for the different land cover types. An approach based on remote sensing was explored for the mapping of SOC stocks at 30 cm for Tanzania using Moderate Resolution Imaging Spectroradiometer (MODIS) imagery from 2012. Results indicate that the use of image reflectance for the mapping of SOC stocks has promising potential, with R^2 values ranging from 0.77 to 0.81 and RMSEP values from 0.90 to 1.03 kg m^{-2} for the three validation datasets. There is high utility of these maps for strategic land management interventions that prioritize ecosystem services.

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1. Introduction

Soil provides multiple ecosystem services, including as a medium for plant and agricultural production through maintenance of soil fertility, a filter for toxins and pollutants, a regulator of the hydrologic cycle, and potential mitigator of climate change through carbon sequestration (Brussaard, 1997; Daily et al., 1997; Lal and Bruce, 1999; Millennium Ecosystem Assessment, 2005). While the role of soil in providing these services has been documented and discussed, gaps still exist in terms of operationalizing the monitoring and quantification of these ecosystem services across diverse environments (Bello et al., 2010; Dale and Polasky, 2007; de Groot et al., 2002; Dominati et al., 2010). Globally, scientists have highlighted the importance of establishing a network of monitoring sites in order to better understand the state of natural resources, including biological diversity (Scholes et al., 2008), agricultural productivity (Sachs et al., 2010, 2012), soil properties (Makipaa et al., 2012; Richter et al., 2007; Sanchez et al., 2009; Smith et al., 2012) and land health (Vågen et al., 2012).

However, there is still a debate regarding the specific metrics to measure and monitor across space and time, as well as ways to operationalize networks of monitoring sites globally (Sachs et al., 2010, 2012; Dale and Polasky, 2007). In addition, research is still needed on the relationships between the drivers of change and the metrics

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of soil health across landscapes. However, SOC is arguably one of the most important metrics of soil health due to its contribution to well functioning ecosystems (Lal, 2010; Palm et al., 2007; Schlesinger, 1997), agricultural productivity (Lal, 2007; Miller et al., 2004; Post and Mann, 1990; Vågen et al., 2005), and its potential to mitigate climate change (Lal and Bruce, 1999), among others. The United Nations Convention to Combat Desertification (UNCCD) also stresses the importance of maintaining SOC to combat land degradation. Soil erosion is a key indicator of land degradation (Lal, 2003; Pimentel and Kounang, 1998; Vågen et al., 2013). This study aims to assess linkages between soil erosion and SOC across contrasting land cover typologies in Tanzania in order to quantify the effects of land cover on SOC, as well as interactions with soil erosion.

Soil OC dynamics have been an important research topic over the last several decades, resulting in estimates of global carbon stocks (Amundson, 2001; Jobbagy and Jackson, 2000; Post and Kwon, 2000). Other studies have focused on assessing the effects of cultivation and land use on SOC (Guo and Gifford, 2002; Miller et al., 2004; Post and Mann, 1990; Post and Kwon, 2000; Schlesinger, 1997), or understanding the complexity of SOC dynamics and climate change (Berthrong et al., 2009; Davidson et al., 2000; Johnston et al., 2004; Kirschbaum, 2000; Lal, 2004). However, gaps remain between plot-level and landscape scale assessments of SOC dynamics under different land uses, including interactions with land degradation processes.

In order to understand the drivers of changes in ecosystem health, including risks and trends over time, new tools and methods for assessing ecosystem health across diverse landscapes are needed. The Land Degradation Surveillance Framework (LDSF) is a spatially balanced, hierarchical field sampling methodology (Vågen et al., 2010a, 2010b), which has been implemented in East Africa to better understand and map land degradation indicators (Vågen et al., 2013, 2012). In addition, the LDSF has proven useful for monitoring of SOC for climate change mitigation (Vågen and Winowiecki, 2013). The current study utilizes the LDSF to assess the effects of land cover typologies on a set of soil health indicators, with an emphasis on SOC, and ecosystem services at a national scale for Tanzania, based on field sites from a diverse range of ecosystems in the country.

The overall goal of the study was to provide an example of approaches to move beyond plot-level assessments of soil and ecosystem health, which are often very detailed, and difficult to scale out beyond the domain sampled. By applying the LDSF in multiple landscapes across a wide range of climate, terrain and soil conditions and combining these measurements with remote sensing data, we show how the gap between the plot-level type assessments and coarse-scale global estimates can be bridged, focusing here on dynamic soil properties and land degradation risk factors.

Vågen and Winowiecki (2013) used Landsat ETM + to predict SOC stocks in four case studies from East Africa, showing the potential of remote sensing for mapping of SOC at moderate to high resolution. In the

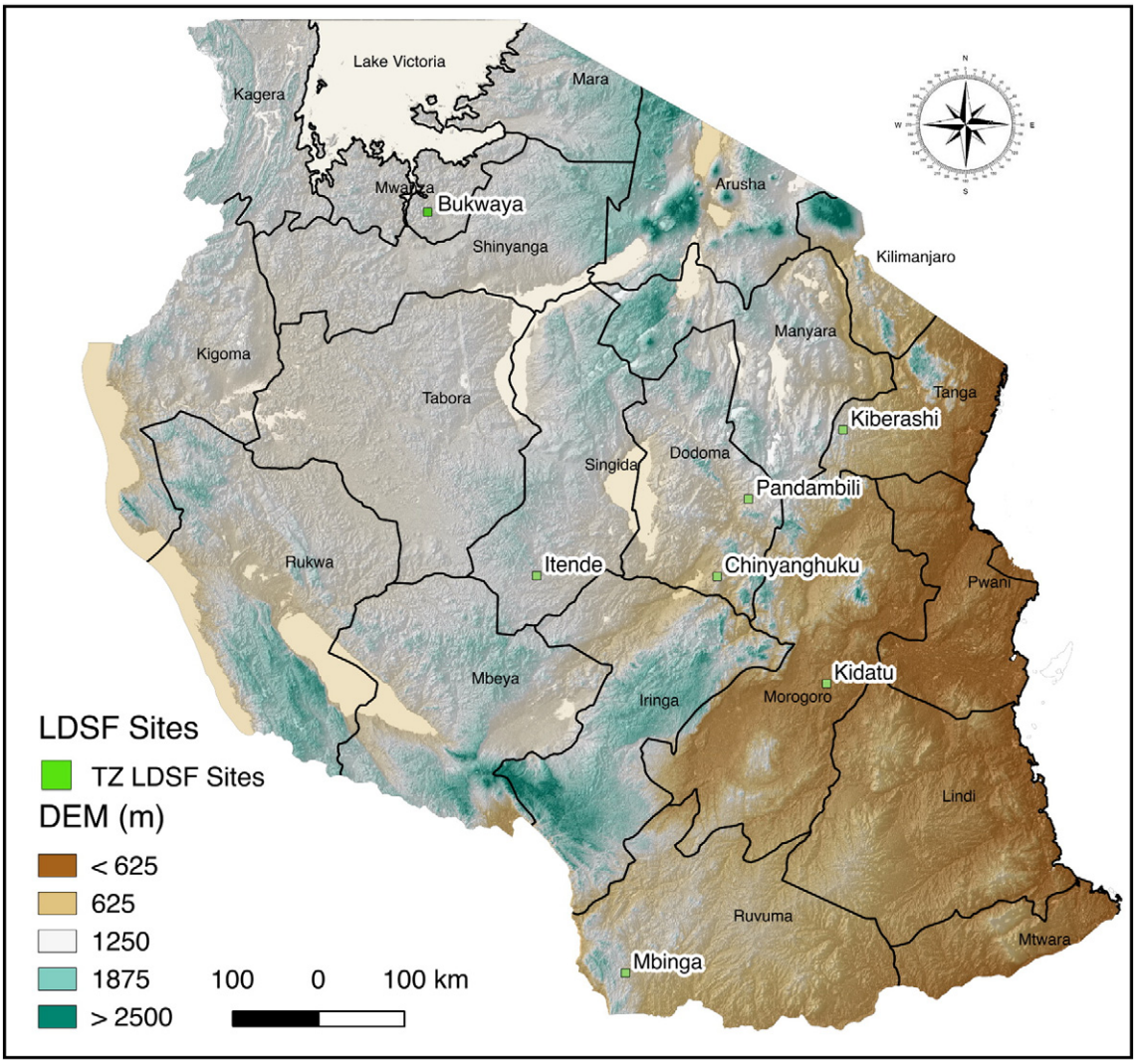

Fig. 1. Location of the seven LDSF sites in Tanzania used in this study overlaid on a digital elevation model.

current paper we explore the use of MODIS for modeling and mapping of SOC stocks at moderate spatial resolution (500 m) for Tanzania. While granularity is lower when using MODIS, compared to for example Landsat, it has a higher number of spectral bands than Landsat, has been shown to be radiometrically stable, and images are collected on a daily basis. Further, the spatial scale offered by MODIS (500 m pixel resolution) makes it well suited for assessments of soil properties at regional (e.g. district) to national, continental and global scales.

The specific objectives of the study were threefold: 1) to assess the effect of land cover and erosion on SOC across Tanzania; 2) to investigate the relationship between inherent and dynamic soil properties under diverse land uses; and 3) to develop maps of SOC stocks to guide site-specific land management strategies.

2. Materials and methods

2.1. Land health surveys

The Land Degradation Surveillance Framework (LDSF) was used to assess multiple land health metrics simultaneously at seven sites across Tanzania. These sites were part of a larger sampling effort within Phase I of the Africa Soil Information Service (AfSIS) project, which sampled 62 sites across sub-Saharan Africa (SSA). Sites were randomly stratified by the Koeppen–Geiger climatic zone (Kottek et al., 2006; Vågen et al., 2010a, 2010b). The seven sites sampled in Tanzania were within the Aw (equatorial dry winter) Köppen–Geiger climate zone (Kottek et al., 2006). The elevations of the sites ranged from 281 to 2090 m (Fig. 1), while mean annual precipitation (MAP) ranged from 665–1421 mm. Two of the sites were located within protected areas (Kidatu and Itende), Pandambili was a private grassland for livestock grazing and the remaining sites were dominated by smallholder mixed crop-livestock systems. Native vegetation of the southern sites was Miombo Woodland (White, 1983). These sites represent the dominant agroecological zones of Tanzania, with the exception of highland farming systems.

Each site was 100 km^2, divided into 16–1 km^2 clusters with 10–1000 m^2 randomly distributed sampling plots per cluster and 4–100 m^2 subplots per plot. Observations and measurements were made at both the plot and subplot levels. This method has been described previously in Vågen et al. (2010a, 2010b), Vågen and Gumbritch (2012) and Vågen et al. (2013).

Specific land health metrics measured included: soil erosion patterns; tree and shrub densities; management practices, slope and land cover. The latter was classified following the FAO Land Cover Classification System (LCCS) e.g., forest, woodland, shrubland, grassland and cropland (Di Gregorio and Jansen, 1998). Erosion prevalence was scored and classified at each subplot (e.g., none, gully, sheet or rill). Soil samples were collected from two depths per subplot: topsoil (0–20 cm) and subsoil (20–50 cm). Subplot topsoil samples were combined to form one composite topsoil sample for the plot and the same was followed for the subsoil samples. These are referred to as standard soil samples. Soil health metrics measured on the standard soil samples included: SOC, total nitrogen, exchangeable bases and pH. Cumulative soil mass samples were taken from subplot one from two depths (0–20 and 20–50 cm) at all plots and from four depths (0–20, 20–50, 50–80 and 80–100 cm) at one third of the plots, using the methods described in Vågen and Winowiecki (2013) and Vågen et al. (2010a, 2010b). In short, soil samples were collected using an auger and a cumulative mass sampling plate. All of the soil from each depth

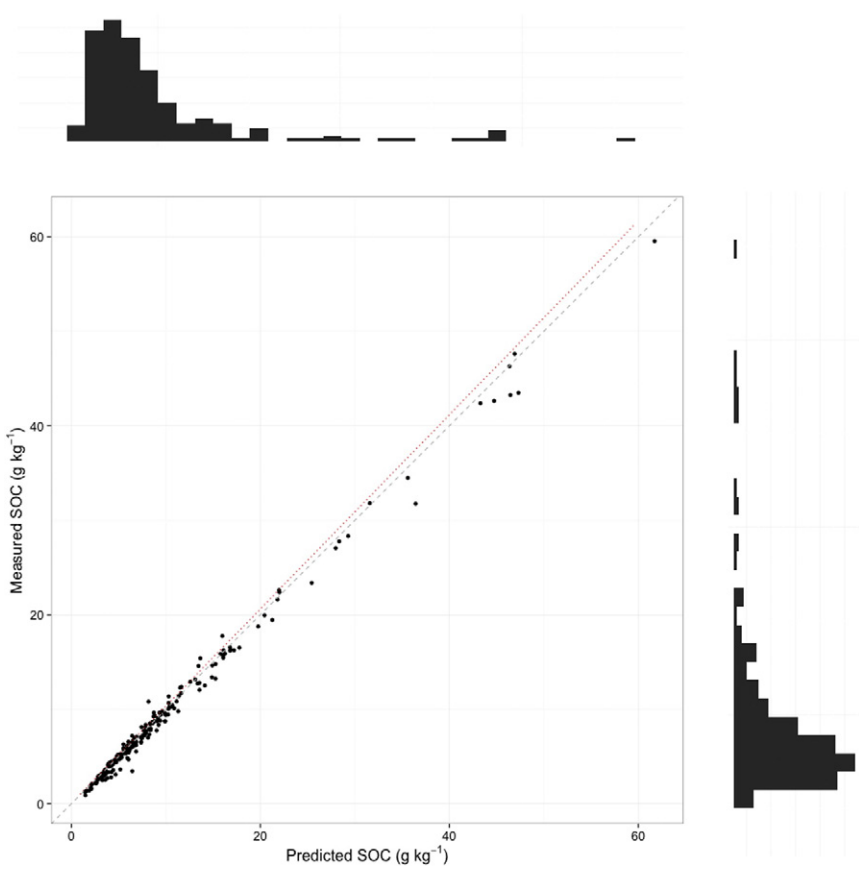

Fig. 2. Measured vs. predicted SOC based on mid-infrared spectra for the 32 reference samples for each site (n = 7). R^2 is >0.95.

Table 1
Baseline information of soil and land health variables for the 1082 plots sampled within the seven LDSF sites in Tanzania. The mean is presented with the range (between brackets). Soil variables are for topsoil (0–20 cm) only.

Site Name (# of plots)	Elevation (m)	Slope (degrees)	SOC (g kg^{-1})	TN (g kg^{-1})	pH	ExBases (cmol$_c$ kg^{-1})	Sand (%)	MAP (mm)	Tree density (tree ha^{-1})	Erosion (%)	Cultivation (%)
	---------Mean (range)---------							Mean			
Bukwaya (n = 150)	1197 (1139–1285)	1.7 (0–11.5)	8.1 (1.52–39.5)	0.58 (0.17–3.37)	6.8 (5.8–8.4)	13.5 (1.5–52.8)	63 (9–83)	949	2	59	75
Chinyanghuku (n = 154)	901 (770–1212)	15.0 (0–39.5)	10.5 (3.2–36.4)	0.96 (0.35–3.13)	7.0 (6.2–8.4)	11.8 (5.0–74.4)	52 (10–74)	641	221	98	13
Itende (n = 152)	1224 (1165–1369)	3.8 (0–38)	8.1 (2.9–35.2)	0.49 (0.17–2.47)	6.2 (5.1–8.2)	5.1 (2.2–24.2)	59 (7–80)	797	517	45	0
Kiberashi (n = 155)	1134 (973–1455)	7.4 (1–24.5)	13.7 (2.9–50.9)	1.03 (0.23–4.79)	6.0 (5.0–6.8)	8.7 (2.0–23.1)	48 (8–89)	832	298	49	18
Kidatu (n = 160)	316 (281–355)	0.9 (0–7.5)	8.2 (2.5–25.1)	0.50 (0.21–1.50)	6.2 (5.6–6.8)	4.8 (1.7–18.5)	64 (11–84)	1421	239	1.3	0
Mbinga (n = 156)	1001 (872–1231)	9.8 (1–37.5)	29.7 (8.5–81.4)	2.01 (0.52–5.19)	5.7 (4.9–6.4)	6.9 (2.4–19.0)	20 (6–36)	1323	196	48	48
Pandambili (n = 155)	1096 (1019–2090)	0.6 (0–2.75)	8.0 (3.7–21.0)	0.74 (0.33–1.25)	6.3 (4.9–8.6)	12.8 (3.1–97.8)	53 (10–82)	665	48	6	10

increment was collected and transported to the laboratory for weighing and processing.

2.2. Soil laboratory analyses

Standard soil samples were air-dried and initially sieved to 2 mm for standard laboratory analysis, while all samples analyzed using mid-infrared (MIR) reflectance were ground to <100 μm with an agate mortar and pestle, according to procedures described in Terhoeven-Urselmans et al. (2010). Cumulative soil mass samples were air dried and weighed to capture the weight of the entire sample (including both the coarse fragments (>2 mm) and the fine fraction (<2 mm)). Cumulative soil mass samples were then sieved to 2 mm and coarse fragments were weighed and weights were recorded. Subsamples were oven dried to calculate the gravimetric water content, which was used to calculate the oven-dried fine soil weight of each depth increment (0–20, 20–50, 50–80 and 80–100 cm).

A subset of 32 standard top and subsoil samples were analyzed for carbon, nitrogen, pH, exchangeable bases and texture. pH was analyzed in a 1:1 H_2O solution and exchangeable bases were analyzed using a Melich-3 extraction at the Crop Nutrition Laboratory (www.cropnuts.com) in Nairobi, Kenya. Total nitrogen and organic carbon were analyzed using dry combustion at the IsoAnalytics Laboratory (http://www.iso-analytical.co.uk). Texture measurements were conducted using a laser diffraction particle size analyzer after shaking each soil sample for 4 min in a calgon solution at the World Agroforestry Centre Plant and Soil Spectroscopy Laboratory in Nairobi, Kenya (http://worldagroforestry.org/research/land-health/spectral-diagnostics-laboratory).

2.3. Mid-infrared spectroscopy

Infrared spectroscopy is a well-established methodology for predicting important soil properties such as soil organic carbon (SOC), pH, base cations and texture (Brown, 2007; Madari et al., 2006; Reeves et al., 2006; Shepherd and Walsh, 2002; Terhoeven-urselmans et al., 2010; Vågen et al., 2006). All soil samples were analyzed for MIR absorbance and spectra were uploaded to the main MIR spectral database at the World Agroforestry Centre (ICRAF), which contains over 80,000 soil spectra. The measured wavebands ranged from 4000 to 601 cm^{-1} with a resolution of 4 cm^{-1}. Processing of the mid-infrared (MIR) spectra followed the procedures outlined in Terhoeven-Urselmans et al. (2010), with first derivatives computed using a Savitzky–Golay polynomial smoothing filter implemented in the *locpoly* function of the *KernSmooth* R package (Wand and Ripley, 2008). A global random forest (RF) prediction model was used to predict the soil properties for this study based on a calibration dataset of 5600 soil samples. The 32 standard reference top and subsoil samples from each site were used to validate (test) the performance of the global RF model. Random forest modeling is an ensemble modeling approach, where many weak learners (decision trees) are combined or bagged to predict an outcome, SOC in this case (Breiman, 2001).

2.4. Statistical analysis

As mentioned in the description of the sampling design, the LDSF datasets used in this study are hierarchical or nested, which has implications for the analysis of the effects of land use and erosion on SOC. In short, methods are needed that permit errors to be structured according to the spatial hierarchical nature of the sampling scheme. Linear mixed-effects (LME) (Pinheiro et al., 2013; Pinheiro and Bates, 2000) models represent a class of models that is well suited for this kind of analysis by not only providing the ability to make generalizations about the data at each level of scale (plot, cluster and site), but also improve estimates of effects that account for the spatial nesting of the input data. We

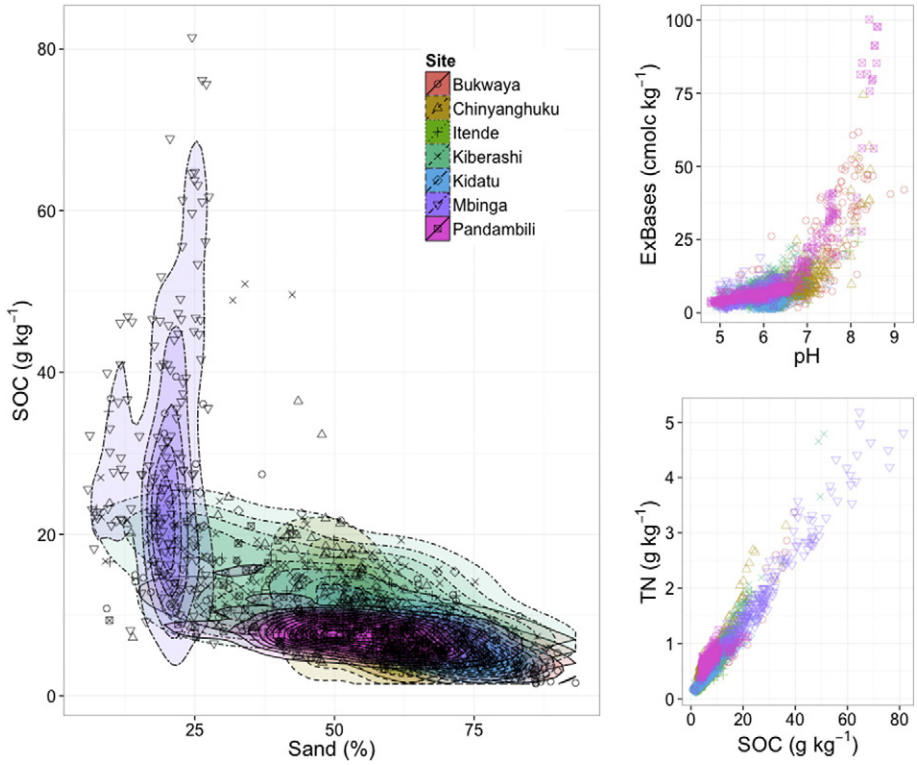

Fig. 3. Two-dimensional density estimation showing the relationship between SOC and sand for topsoil samples (n = 1082), density cluster by sites (left panel). Relationship between exchangeable bases and pH (upper right). Linear relationship between total nitrogen (TN) and SOC (lower right).

modeled the effects of land use and soil erosion on SOC by using a LME model with ln(SOC) as dependent variable, land use and erosion as independent variables, and sampling clusters, site and depth as random effects. All calculations and statistical analyses were conducted using R statistics (R Core Team, 2014) and KNIME (Berthold et al., 2007).

2.5. Soil organic carbon stocks

Soil organic carbon stocks to 30 cm (mSOC30) were calculated by multiplying the soil mass for each depth increment by the associated SOC to get the cumulative mass of carbon by depth in each profile. This was then scaled based on the diameter of the auger used in order to express this mass in kg C m^{-2}. Then a linear mixed-effects model (Pinheiro et al., 2013; Pinheiro and Bates, 2000) was fitted to the cumulative SOC mass with random intercepts and slopes at each plot, as described in Vågen and Winowiecki (2013) and the stocks of SOC were predicted to 30 cm depth for each profile. The development of this model included soil mass samples from the seven Tanzania LDSF sites (n = 1082 plots) as well as LDSF sites outside of Tanzania. The inclusion of the additional samples allowed us to build a more robust model for the prediction of SOC stocks to 30 cm (mSOC30).

A library of remote sensing surface reflectance spectral data extracted from the Moderate Resolution Imaging Spectroradiometer (MODIS) platform for plots with data on mSOC30 in East Africa (n = 2747) and a prediction model for mSOC30 was developed using Random Forests (Breiman, 2001), with mSOC30 as the dependent variable and MODIS reflectance bands as predictors. This approach is similar to the one used for Landsat by Vågen et al. (2013) and Wiesmeier et al. (2010). The RF model was fitted to MODIS tiles covering Tanzania and predictions of SOC stocks to 30 cm depth were made for the whole country for 2012. Prediction model performance was done using 3-fold cross-validation without replacement, or by randomly drawing 2/3 of the samples for calibration and using the remaining 1/3 for validation and repeating this procedure three times with independent calibration/validation datasets in each run.

3. Results and discussion

3.1. Mid-infrared predictions

Prediction models using MIR spectra performed well. Fig. 2 shows the relationship between measured and predicted SOC for the 32 reference samples in each of the seven sites. This is consistent with a number of previous studies (Ben-Dor and Banin, 1995; Brown et al., 2006; Shepherd and Walsh, 2002). The R^2 for the prediction of SOC from MIR was >0.95 (RMSEP = 4.3 g kg^{-1}) indicating a good fit overall, with similar results for TN (RMSEP = 0.03%), exchangeable bases (RMSEP = 1.5 cmol$_c$ kg^{-1}), pH (RMSEP = 0.2) and sand (RMSEP = 4.5%).

3.2. Baseline assessment

The seven LDSF sites that were sampled in 2010 totaled 1082–1000 m^2 plots.

Table 1 shows a summary of key biophysical metrics for each of the sites surveyed, including topographic characteristics, soil properties, climate, tree densities, erosion and land use. The Itende site had the highest tree densities with an average of 517 trees ha^{-1}, while Bukwaya had virtually no trees on average for the site. Cultivation in the sites ranged from 0% in the protected areas to 75% in Bukwaya, with Mbinga having 48% cultivated area. Both Mbinga and Kiberashi represent areas with relatively recent and ongoing conversions from Miombo woodlands. Erosion prevalence was extremely high in Chinyanghuku, where 98% of the plots surveyed had severe erosion (i.e. erosion in three or more subplots within each LDSF plot) due to a combination of high grazing pressure, compaction of sandy soil and some cultivation (10%). Pandambili and Kidatu had low erosion prevalence (Table 1). We later explore the relationship between soil erosion and SOC

dynamics in these sites. Overall, the seven LDSF sites had high variability of the soil and land health metrics.

3.3. Dynamic and inherent soil properties: identifying constraint envelopes

Maintenance of soil fertility is an important supporting service as it is necessary for ecological functions and overall productivity of the system. However, there are inherent soil properties that can limit the extent to which the soil can provide these services. These limitations form constraint envelopes, which are important to understand in order to manage for agricultural productivity. Table 1 shows the measured ranges in important soil fertility indicators such as SOC, TN, pH, exchangeable bases and sand for each site. We use thresholds for assessing soil fertility deficiencies of nitrogen and base cations in agricultural systems based on suggestions from Ndakidemi and Semoka (2006). For example, using a threshold of 2.0 g kg^{-1} nitrogen content in agricultural soil, only 7% of the topsoil samples were at or above this level, indicating low overall N content across all seven sites. With regard to exchangeable bases, 38% of the topsoil samples were at or below the critical level of 8 $cmol_c$ kg^{-1}. It will be important to assess the impact of particular management strategies on each of these soil fertility indicators, as even woodland and forests are impacted by human activities, such as charcoal production, firewood collection and grazing.

The overall mean SOC values were 12.4 g kg^{-1} for topsoil (0–20 cm) and 7.4 g kg^{-1} for subsoil (20–50 cm). Mbinga had the highest SOC, while Kidatu had the lowest SOC on average. A threshold of 20 g SOC kg^{-1} soil is often used as a critical value below which the stability of soil aggregates is affected, which is, however, based on studies in temperate regions (Loveland and Webb, 2003). Only the Mbinga site showed SOC values that generally surpass the threshold value. The other sites had average SOC values below the 20 g C kg^{-1}, with Kidatu having the lowest average SOC (e.g., below the threshold of 10 g C kg^{-1} for extremely low SOC levels) (Loveland and Webb, 2003).

The variance components from the applied lme model for SOC showed that variation is greater between sites then within sites, indicating that future sampling should focus on sampling additional sites to better understand SOC dynamics. Overall, concentrations of SOC decrease with increasing sand content in the study sites (Fig. 3, left panel), showing the importance of inherent soil properties such as texture on SOC dynamics in these systems. Furthermore, this graphic illustrates that high contents of sand can limit the soils' capacity to store SOC, e.g., high sand content creates a constraint envelope for SOC. The estimated densities (contour lines in Fig. 3, left panel) also confirms the strong grouping according to site observed in the lme model for SOC, with Mbinga having higher SOC overall and also lower sand contents. In fact, Mbinga is the only site where the majority of the sampling plots have less than 25% sand. However, despite the narrow range in sand content in this site, SOC varies from <10 to ~80 g kg^{-1}. Itende, Bukwaya and Pandambili have low SOC overall and higher sand content, the latter also having low variability in SOC, while Kiberashi has a high range of sand content.

In Fig. 3 (top-right panel) we show the relationship between exchangeable bases and pH, with colors according to site. The variations in pH and exchangeable bases across the sites are large, particularly in

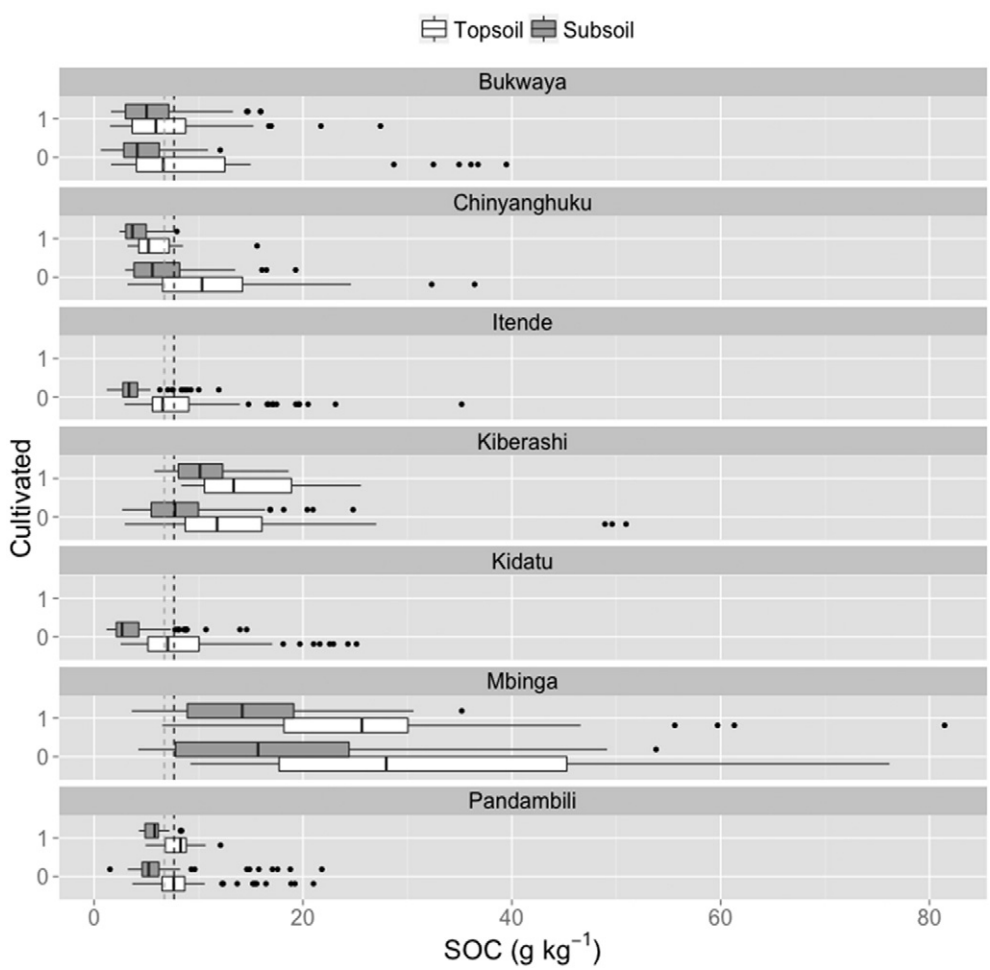

Fig. 4. Variation of soil organic carbon (SOC) concentrations for each site in cultivated (1) and cultivated (0) plots, for both topsoil (0–20 cm, n = 1082) and subsoil (20–50 cm, n = 970). Ablines indicate the modeled intercept for mean SOC values (cultivated = 6.7 g kg^{-1} and non-cultivated = 7.7 g kg^{-1}).

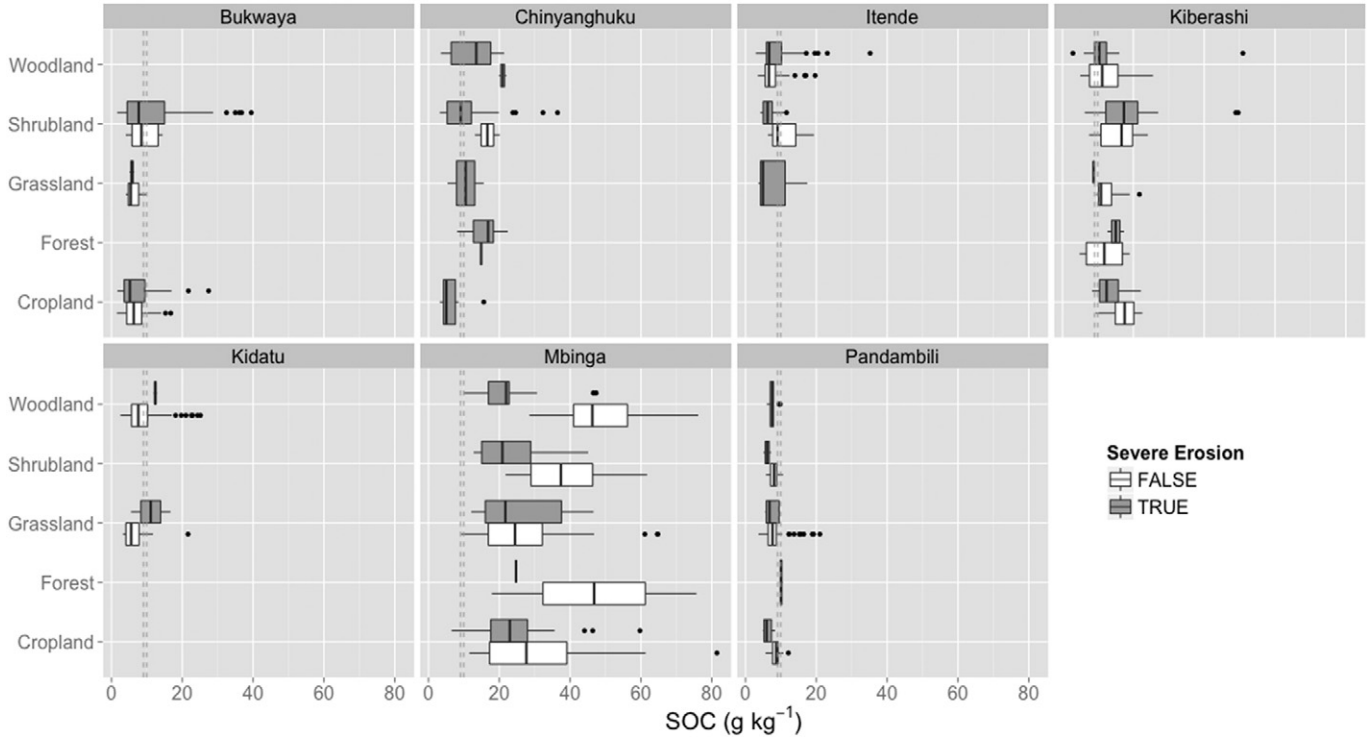

Fig. 5. SOC content in eroded and non-eroded plots for each land cover typology within each site.

Pandambili where pH ranges from ≤5 to >8. Mbinga has the lowest levels of variability in pH and exchangeable bases, with higher levels of acidity than the other sites. As shown in the lower-right panel in Fig. 3, there is a linear relationship between TN and SOC in the study sites.

Understanding these relationships is important when conducting cross-site analysis, as systems within different textural domains, for example, are likely to respond very differently to management and hence require different management options. For example, Fig. 3 shows that soils in sites with high sand are limited in terms of how much carbon they can store, while sites such as Mbinga have large potential for increasing SOC through management or reforestation. Finally, these relationships can be used to identify key thresholds for productivity, including low levels of exchangeable cations (bases) or other types of soil constraints such as acidity.

3.4. Effect of cultivation on SOC content

Fig. 4 shows SOC variation in cultivated (1) and non-cultivated (0) plots for top- and subsoils in each site. The effect of cultivation is site specific. For example, Kiberashi had slightly higher topsoil OC in cultivated plots compared to non-cultivated plots, while Mbinga and Chinyanghuku had higher SOC in non-cultivated plots, and Bukwaya had very little difference. This site specificity complicates models when trying to assess the effect of cultivation on SOC and needs to be accounted for in the model. For example, taking a simple average of SOC in cultivated plots for all sites gives a value of 13.8 g kg^{-1}, largely due to the high levels of SOC in Mbinga, which has almost 50% cultivation. In contrast, the model intercept for cultivated plots in the LME model was 7.7 g kg^{-1}, with an overall decrease in SOC of 1 g kg^{-1} relative to non-cultivated areas. These results show the complexity involved in assessing the effects of cultivation on SOC across diverse landscapes due to factors such as climate and management (Miller et al., 2004; Ogle et al., 2005), original C:N ratios in uncultivated soil, soil type, and litter quality (Post and Mann, 1990).

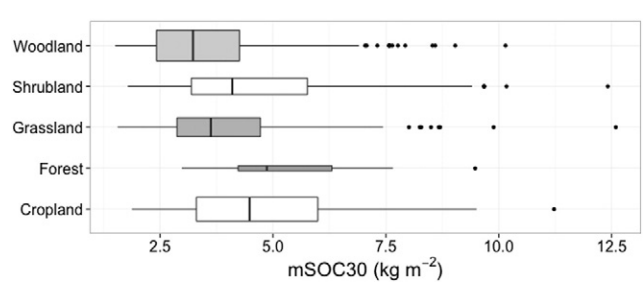

Fig. 6. Boxplot of SOC stocks to 30 cm (mSOC30) by land cover typology. The width of the boxplot reflects the number of samples in each typology.

3.5. SOC dynamics, land cover typologies and soil erosion

Of the plots surveyed, 388 were classified as woodland, 246 as cropland, 219 as grassland, 202 as shrubland and 27 as forest. Forested ecosystems had the highest SOC ($p < 0.05$) when compared to the other vegetation structure types across all sites (Fig. 5). Croplands had similar SOC to grasslands and shrublands overall. As expected, subsoils had lower SOC than topsoils under all land cover types, however shrubland and woodland have the strongest decrease with depth on average. The small difference in sand content across most of the sites, except Mbinga, helps explain why we do not see much difference in SOC between vegetation cover types. For example, Pandambili has extremely low variability overall due to the high sand contents. Consequently, Mbinga had the highest levels of variability in SOC between vegetation cover types (Fig. 5).

Land degradation is generally considered to have negative impacts on the functioning of ecosystems, including their ability to deliver important ecosystem services such as agricultural productivity. We assessed the effects of erosion on SOC for the study sites and different land cover typologies discussed previously using the LME model described in Section 2.4. Non-eroded plots ($n = 619$) had higher SOC (mean = 9.9 g kg^{-1}) than eroded plots ($p < 0.05$), with an overall decrease of 0.92 g kg^{-1} SOC in eroded areas relative to non-eroded

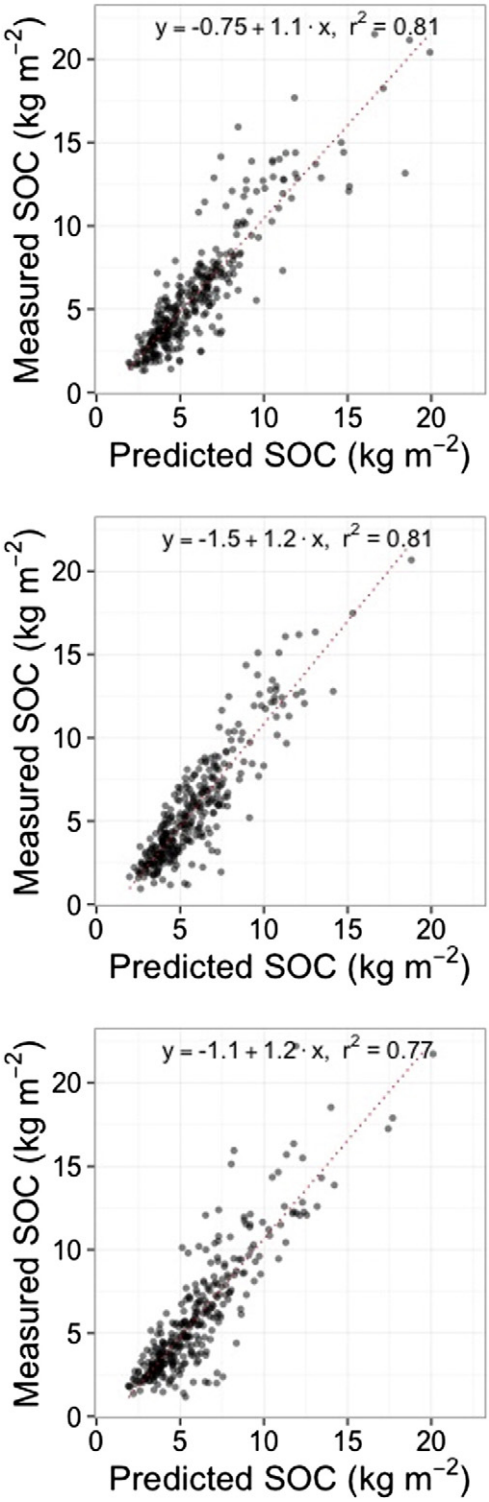

Fig. 7. Prediction model results for mSOC30 (kg m^{-2}), based on three separate cross-validation runs using MODIS reflectance for 2012.

areas. This effect might seem small, but the effects of erosion are strongly site specific and sites such as Mbinga had losses of SOC in eroded plot of 10.7 g kg^{-1} on average across all land cover types. In contrast, Kiberashi had similar SOC concentrations in eroded and non-eroded plots. The latter site was recently converted from natural forest at the time of the field surveys reported here. Further, the largest reductions in SOC by vegetation structure were found in forested ecosystems, croplands and shrublands, respectively. Grasslands have very low erosion prevalence. The results of the LME model analysis on the effects of soil erosion on SOC within individual sites and vegetation structure types within sites are summarized in Fig. 5, highlighting the importance of considering land degradation when quantifying the effects of land cover on SOC dynamics.

3.6. SOC stocks to 30 cm

Stocks of SOC to 30 cm were relatively low for all sites, except for forested plots in Mbinga. Hence, there were no significant differences between land cover classes (Fig. 6). We hypothesize that this lack of difference in SOC stocks by land cover is partially due to the uneven distribution and low sample size for forested plots, the low overall stocks in the sampled sites and large variability within croplands (due to management impacts and varying times since conversion). It is also important to mention that most of the land cover classes in this sample set are impacted by human activities, for example, woodlands and forests are used for charcoal production, firewood collection and grazing.

Validation prediction results for mSOC30 were good overall, with R^2 values ranging from 0.77 to 0.81 and RMSEP values from 0.90 to 1.03 kg m^{-2} for the three validation datasets, when we averaged predictions by cluster (i.e. to the 500 m pixel size of the MODIS platform) (Fig. 7). We fitted the resulting model to MODIS tiles covering Tanzania (Fig. 8), producing a map of SOC stocks to 30 cm depth for the country. Estimates of SOC stocks were highest in forested ecosystems around Mt Kilimanjaro and Mt Meru, in the Uluguru mountains south of Morogoro, parts of West Usambara mountains and in the south-eastern lowland (coastal) areas. For example, estimated SOC stocks to 30 cm in the West Usambaras ranged from around 6 kg m^{-2} in agricultural systems to 17 kg m^{-2} in forested ecosystems. The latter is comparable to results reported by Munishi and Shear (2004) who reported between 20.9 ± 10 kg m^{-2} from a study in the Usambara mountains and 14.8 ± 5.3 kg m^{-2} on average for 0–30 cm in the Uluguru mountains (Munishi and Shear, 2004). A recent study in a forested system along a transect up Mt. Hanang reports about 5.31 kg m^{-2} (Swai et al., 2014). Areas on granitic parent material with semi-arid climates, such as in Central Tanzania have lower predicted SOC stocks. These areas have also been undergoing significant transformations in recent decades due to increasing population pressure and agricultural expansion. The median estimated SOC stock for Tanzania is 6 kg m^{-2} based on the predicted map (Fig. 8), which translates into a total of 5.7 Pg C for Tanzania as a whole (assuming an area for the country of 945,203 km^2).

4. Conclusions

Landscapes are complex and exhibit high levels of variability in soil properties, land degradation status, vegetation cover and land use. In order to quantify ecosystem services, including provisioning, supporting and regulating services provided by soils, systematic measurements that address this complexity, along with large sample sizes, are needed. This study demonstrated the use of systematic sampling across randomized sites in Tanzania and offered analytical approaches for dealing with grouping effects as well as the high levels of variability between sites, for example in topsoil OC content in cultivated and non-cultivated areas.

The current study presented approaches that may help bridge the gap between plot-level and landscape scale assessments of SOC dynamics by sampling soil variability at nested spatial scales, allowing for the incorporation of scaling effects into statistical models. The results of the study show an overall decrease in SOC as a result of cultivation, but with high variability between sites. Erosion also had a negative influence on SOC. Furthermore; a map of SOC stocks was developed at a resolution of 500 m for Tanzania. This map can be used to assess current SOC stocks in the country in a spatially explicit way and for targeting strategic interventions aimed at increasing soil carbon sequestration.

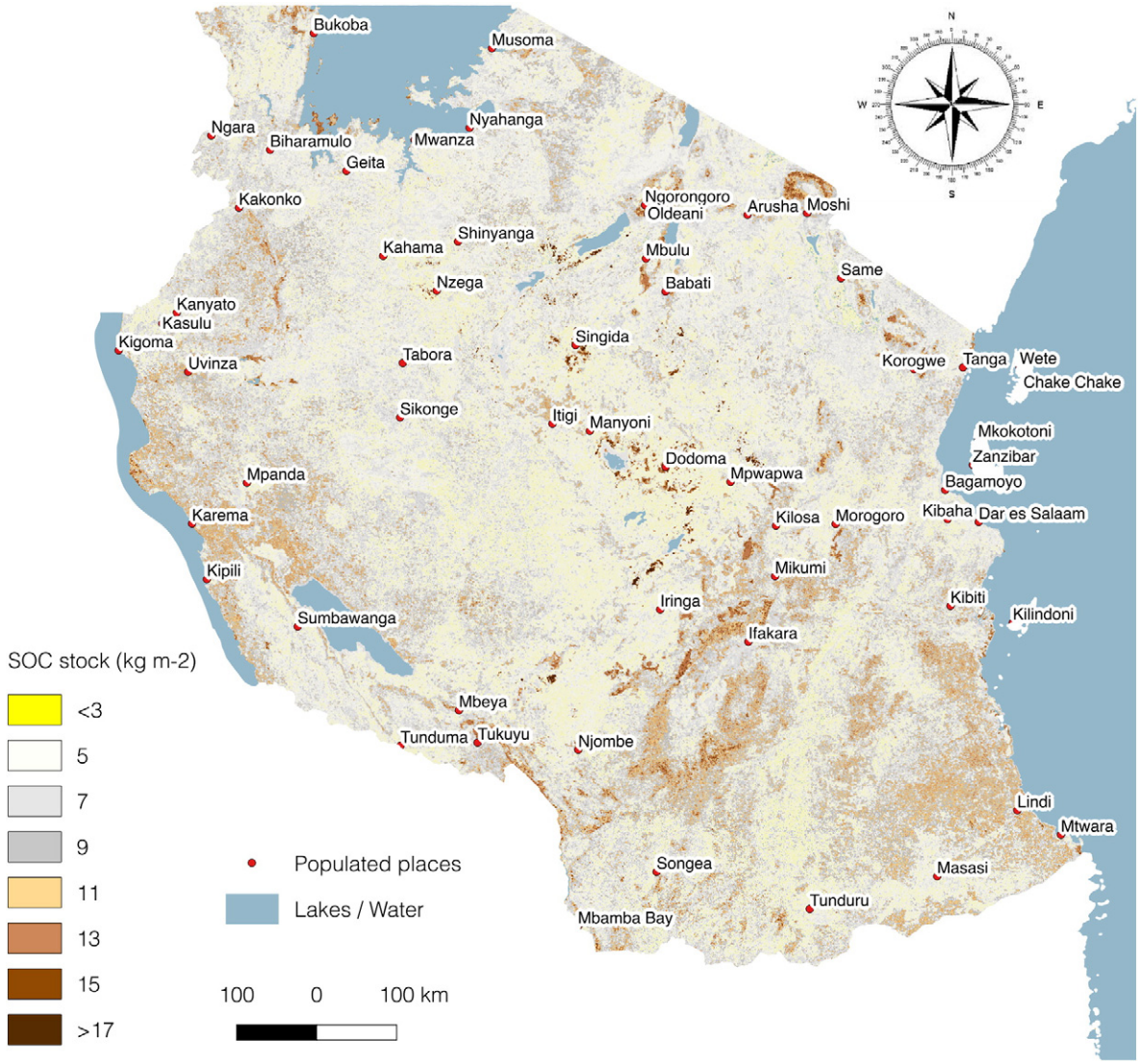

Fig. 8. Map of SOC stocks to 30 cm (mSOC30) in kg m^{-2} for Tanzania using MODIS Imagery.

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