Assessing biogeochemical and human-induced drivers of soil organic carbon to inform restoration activities in Rwanda

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Abstract

15

Land restoration is of critical importance in Rwanda, where land degradation negatively impacts crop productivity, water, food and nutrition security. We implemented the Land Degradation Surveillance Framework in Kayonza and Nyagatare districts in eastern Rwanda to assess baseline status of key soil and land health indicators, including soil organic carbon (SOC) and soil erosion prevalence. We
20 collected 300 topsoil (0-20cm) and 281 subsoil (20-50cm) samples from two 100 km^2 sites. We coupled the soil health indicators with vegetation structure, tree density and tree diversity assessments. Mean topsoil organic carbon was low overall, 20.9 g kg^{-1} in Kayonza and 17.3 g kg^{-1} in Nyagatare. Stable carbon isotope values (d13CV-PDB) ranged from -15.35 to -21.34 ‰ indicating a wide range of plant communities with both C3 and C4 photosynthetic pathways. Soil carbon content decreased with
25 increasing sand content across both sites and at both sampling depths and was lowest in croplands compared to shrubland, woodland and grasslands. Field-saturated hydraulic conductivity (K$_{fs}$) was estimated based on infiltration measurements, with a median of 76 mm h^{-1} in Kayonza and 62 mm h^{-1} in Nyagatare, respectively. Topsoil OC had a positive effect on Kfs, whereas pH, sand and compaction had negative effects. Soil erosion was highest in plots classified as woodland and shrubland. Maps of
30 soil erosion and SOC at 30-m resolution were produced with high accuracy and showed high variability across the region. These data and analysis demonstrate the importance of systematically monitoring multiple indicators at multiple spatial scales to assess drivers of degradation and their impact on soil organic carbon dynamics.

1. Introduction

35 Land degradation is inextricably linked to sustainable livelihoods and negatively impacts over 3.2 billion people each year globally (IPBES, 2018) through the loss of agricultural productivity and diminishing livelihood options for the rural poor in particular. Land degradation also adversely affects the resilience of social-ecological systems to climate change through a reduction of their adaptive

40 capacity. In other words, the combined impacts of land degradation and climate change currently represent a significant risk to global food security (Webb et al., 2017) particularly when considering positive feedback effects between processes such as more erratic and intensive rainfall and soil erosion, for example. Similarly, land degradation strongly impacts the loss of biodiversity globally, further reducing the adaptive capacity of ecosystems in the face of climate change (Gisladottir and Stocking, 2005), which means that we cannot tackle any of these global challenges in isolation.

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Efforts to avoid, reduce and reverse land degradation are therefore critical if the Sustainable Development Goals (SDGs) are to be achieved (IPBES, 2018). Furthermore, SDG 15.3, Life of Land has set ambitious targets for land degradation neutrality combining indicators of soil health and aboveground productivity (Cowie et al., 2018). Projections have also been calculated to estimate the
50 green house gas capture and soil carbon sequestration of various natural climate solutions restore degraded ecosytems, and avoid degradation altogether (Griscom et al., 2017). In line with this thinking, forest and land restoration aims to regain ecological functions, including biodiversity, improve soil health and enhance human well-being across landscapes (Chazdon, 2008; Chazdon et al., 2016). The UN Decade on Ecosystem Restoration offers promising opportunities to stimulate efforts on the ground.
55 However, ecosystems are complex and multiple biophysical and socio-economic factors need to be considered when targeting, planning, implementing and tracking restoration on the ground. This includes understanding the spatial and biogeochemical variations of the soil ecosystem, which is the foundation for biophysical land restoration efforts given its role in global net primary productivity.

60 Land degradation is a critical challenge for Rwanda, which has set a goal to achieve land degradation neutrality by 2030. In 2011, Rwanda was the first country in Africa to commit to a restoration target of degraded lands and forests under the Bonn Challenge, pledging to restore 2 million ha, corresponding to 76% of the country. Underlying causes of land degradation in the country include unsustainable farming and grazing practices, overexploitation of forests and woodlands, settlements and urbanisation
65 (Bizimana, 2018). Furthermore, Rwanda has a high average population density at 414 people per km^2 though varying by district (National Institute of Statistics of Rwanda (NISR), 2012). The majority of the country's land (70%) is devoted to subsistence agriculture, fuel wood and timber production for energy needs (National Institute of Statistics of Rwanda (NISR), 2012).

70 One of the major processes of land degradation in Rwanda is accelerated soil erosion, which is driven by unsustainable agricultural practices, particularly in steeply sloping lands (Karamage et al., 2016). This is further execrated by intense rainfall events, resulting in increased rainfall erosivity (Rutebuka et al., 2020) and the increasing energy demands of a growing population resulting in deforestation and loss of vegetation cover in general (Mukuralinda et al., 2016). Soil erosion is severe with mean national rates
75 of 250 Mg ha^{-1} yr^{-1}, and studies showing as much as 421 Mg ha^{-1} yr^{-1} in croplands (Karamage et al., 2016).

Considering that the agricultural sector contributes significantly to the national economy and that 90% of the population depends on agriculture for their livelihoods, tackling land degradation and restoring
80 degraded land is of critical importance for Rwanda. Studies suggest that investments in soil

conversation and land productivity are contributing to reduced land degradation and increased agricultural productivity in Rwanda (Bidogeza et al., 2015; Byiringiro and Reardon, 1996; Fleskens, 2007; Bizoza and De Graaff, 2012; Karamage et al., 2016). For example, various forms of terracing have been implemented across Rwanda to specifically curb the negative effects intensive farming on
85 steep slopes has on soil fertility and soil loss (Kagabo et al., 2013) and studies also show that terracing coupled with building organic matter has the potential to be financially profitable when access labour and manure is facilitated (Bizoza and de Graaff, 2012). Furthermore, there is a real need for a systems approach to sustainable agricultural intensification that spans from appropriate technologies to institutional and policy-level support (Schut et al., 2016; Vanlauwe et al., 2014). In addition, tree-based
90 ecosystem approaches have also been suggested to meet the multiple demands of farming households, including in Rwanda (Iiyama et al., 2018).

Despite these measures, about 77% of Rwanda's total surface area was estimated to be threatened by soil erosion in 2005. Studies evaluating the effects of land use change and conversion of forest to
95 agricultural land have reported a loss of soil organic matter and nitrogen while significantly increasing bulk density (Bizuhoraho et al., 2018). Spatially explicit assessments of soil erosion prevalence and soil properties such as soil organic carbon (SOC) have been missing to date for Rwanda, making the targeting and tracking of land restoration efforts difficult. Enabling better targeting and tracking of interventions will be critical given the mainstreaming of land restoration through national programmes,
100 including 708,628 ha under restoration with agroforestry reported by IUCN (Dave et al., 2019), based on an assessment of the potential for Forest Landscape Restoration (FLR) conducted in 2014 (Mukashema et al., 2014).

In particular, the Eastern Province of Rwanda has experience high deforestation. It is estimated that
105 23% of the remaining forest cover in Eastern Province was lost between 2009 to 2019 ((MOE), 2019). There is a large gap in terms of supply and demand for wood energy for cooking, which has resulted in over-exploitation and degradation of remaining tree/shrub resources. Also, prolonged droughts as a result of climate change (IPCC 2019) are not only exacerbating many of the ongoing land degradation processes in the region but have also resulted in new degradation pathways in natural and seminatural
110 ecosystems.

To address land degradation across sub-Saharan African and Rwanda in particular, the Regreening Africa project aims to restore 70,000 hectares of degraded lands and benefitting 100,000 households in Rwanda. It is part of the emerging "research in development" programmes where research is carried out
115 hand in hand with development interventions to enable actors to identify options that are locally relevant and adapted to the ecological and social contexts (Coe et al., 2014). The programme applies an 'options by context approach') in understanding the local drivers and indicators of land degradation and identifying locally relevant innovations to address them (Sinclair and Coe, 2019). A key element of the 'options by content approach' is to understand the variation in biophysical (and also socio-economic)
120 context, that includes multiple variables that may influence not only uptake of restoration approaches, but also their appropriateness and potential success. Therefore, this study was commissioned to understand the extent of land degradation across two key action districts in Rwanda, Nyagatare and

125 Kayonza and to feed this information into the learning and decision cycle of stakeholders across the project. Key aspects often missing in assessments of land degradation are the multiple scale scales as well as the interaction of multiple indicators. Therefore, there is a real need to include multiple indicators when assessing drivers of land degradation as well as soil organic carbon dynamics.

In this paper we applied a systematic approach to the collection of soil health and land degradation indicators, including the use of consistent laboratory procedures, using the Land Degradation
130 Surveillance Framework (LDSF) (Vågen et al., 2013; Leigh Winowiecki et al., 2016). We assessed the relationship between inherent soil properties such as texture and SOC, as well as the influence of various soil properties on field-saturated hydraulic conductivity, in addition to human-induced processes such as soil erosion. We also assess the current status of vegetation structures across the landscape, including assessing tree densities and tree species diversity, which are often considered key
135 indicators of restoration. We present spatially explicit assessments and maps of SOC for eastern Rwanda and explore key biogeochemical and human-induced driver of SOC across landscapes in the eastern part of the country. Specific objectives of this study were to: 1) Assess soil and land health parameters across the action sites; 2) Understand the drivers of SOC dynamics; 3) Develop hot-spot maps of soil erosion and soil organic carbon for interventions.

140 **2. Methods**

2.1. Site Description

Nyagatare is the largest dairy district in Rwanda and is characterised by two main seasons: one long dry season and a short rainy season. Its annual average temperature varying between 25.3 and 27.7 °C, and receives an annual rainfall of 827 mm, however predictability of rainfall has decreased overtime. The
145 average altitude is 1513m. It consists of gently sloping hills separated by low granitic valleys. The vegetation type was originally savannah vegetation and some gallery forestry. From 2009 to 2019, the deforestation and afforestation rates were 34% and 18%, respectively (MoE, 2019). The major economic activity is subsistence farming while the main source of cooking energy is fuel wood. Multiple crops are cultivated in Nyagatare including, maize, beans, groundnut, cassava, irish potatoes,
150 banana, yams, among others. Some areas have been cultivatetd for 100 years with major conversion events in 1973 and 1995.

Kayonza district has a mean altitude of 1428 m while mean annual rainfall is 919 mm (NISR, 2012)
155 From 2009 to 2019, the deforestation and afforestation rates were 20% and 6% respectively (MoE, 2019). It is prone to long drought events with two principal seasons, a long dry period and a short rainy season. Both districts are heavily impacted by agriculture. Crops cultivated in Kayonza include beans, banana, cassava, maize, irish potatoe, sorghum, cocoa yams, among others. Most of the area has been cultivated for over 50 years, with mining activities also taking place.
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2.2. Field Sampling using the Land Degradation Surveillance Framework

The LDSF was developed by the World Agroforestry (ICRAF) in response to the need for consistent field methods and indicator frameworks to assess land health in landscapes. The framework has been applied in projects across the global tropics (Vågen et al., 2016; Vågen and Winowiecki, 2020, 2019)
165   and is currently one of the largest land health databases globally with more than 30,000 observations, The LDSF uses a hierarchical sampling design to assess multiple geo-referenced indicators at multiple scales, e.g., each 100 km^2 site is stratified into 16-1km^2 clusters each containing 10-1000 m^2 plots and 4-100 m^2 subplots (L. Winowiecki et al., 2016). This multi-scale, randomized sampling design enables robust analysis of drivers of degradation as well as the production of predictive maps of soil health
170   indicators, for example soil organic carbon (Vågen et al., 2018).

Measurements took place at the plot and subplot levels. For example, vegetation structure at the plot level was classified using the FAO Land Cover Classification System (LCCS), which was developed in the context of the FAO-AFRICOVER project (Di Gregorio, A., and Jansen, 2000). In the LDSF, trees
175   are classified as woody vegetation above 3.0m tall. All trees were counted and identified to species level in each of the four subplots, per plot. Soil erosion was scored and classified in each subplot (n=4) per plot. Soil samples were collected at 0-20 cm (topsoil) and 20-50 cm (subsoil) depth by combining samples from the four subplots per LDSF plot into one composite sample at the plot level.

180   Infiltration capacity was measured at three plots per cluster in each site using single ring infiltrometers (Bouwer, 1986) to assess variation across land uses and soil types. Soil infiltration capacity into dry soils follows a predictable temporal pattern: it is high in the early stages of infiltration and tends to decline gradually as the soil moisture content increases until it eventually approaches a nearly constant rate known as steady-state infiltration capacity (Horton, 1940). This steady-state rate is independent of
185   the initial soil water content and approximates the soil's saturated hydraulic conductivity. Infiltration measurements were carried out at the center of each plot using a metal cylinder with an inner diameter of 15.6 cm and 20 cm in height for two hours and a half to ensure capturing steady-state conditions.

Field-saturated hydraulic conductivity (Kfs) (Reynolds and Elrick, 1990) was calculated from the
190   infiltration data using the analytical formula proposed by (Nimmo et al., 2009). First, infiltration rates were corrected for non-constant falling head and subsurface lateral spreading effects. For each plot, an asymptotic function was then fitted to its corrected infiltration curve using the *nls.multstart* package in R (Padfield and Matheson, 2018) to obtain the asymptote, which represents Kfs.

195   The effects of soil and land use and land cover variables on Kfs were assessed with linear mixed effects models using the *lme4* (Bates et al., 2015) package in R. Random effects intercept models were fitted using the lmer function, with random intercept for each level of site and for each level of cluster within site (nested grouping factors).

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2.3. Laboratory Methods

Upon collection, all soil samples were processed locally, air-dried and ground to pass through a 2-mm sieve. Further grinding was conducted on a subsample using a Retsch motor grinder to attain a particle size between 20 and 53 microns. This subsample was analyzed in triplicate for MIR absorbance using the Tensor 27 HTS-XT from Bruker Optics located at the ICRAF Soil–Plant Spectral Diagnostics Laboratory in Nairobi, Kenya. The measured wavebands ranged from 4000 to 601 cm^{-1} with a resolution of 4 cm^{-1}. Processing of the MIR spectra included computing the first derivatives computed using a Savitsky-Golay polynomial smoothing filter implemented in the locpoly function of the KernSmooth R package (Wand, 2015) as outline in Terhoeven-urselmans et al., (2010).

Wet chemistry reference analysis was conducted on 10% of the collected soil samples. Soil samples with both MIR spectra and associated wet chemistry data were used to develop the MIR prediction models for the various soil properties (Vågen et al., 2016). pH was analyzed in a 1:2 H_2O mixture that was shaken for 30 min at moderate speed on a horizontal shaker then let stand for 20 min before reading on a Eutech Cyberscan 1100 pH meter. Exchangeable bases were extracted using a Mehlich- 3 method after five minutes on a reciprocating shaker. The filtrate was analyzed for base cations: potassium (K), calcium (Ca), magnesium (Mg) and sodium (Na) on ICP OES (Model-Thermo iCAP6000 Series) at Crop Nutrition Laboratory Services in Nairobi, Kenya. Total nitrogen, organic carbon and stable carbon isotopes (d13C)were measured by dry combustion using an Elemental Analyzer Isotope Ratio Mass Spectrometry (EA-IRMS) from Europa Scientific after removing inorganic C with 0.1 N HCl, at the IsoAnalytical Laboratory located in the United Kingdom.

2.4. Prediction of soil properties from MIR soil spectroscopy

We used the random forest (RF) algorithm to predict soil properties based on MIR absorbance spectra for the two sites in Rwanda. In this approach, many decision trees are built based on a random subset of the input MIR spectra and these trees are combined to predict the different soil properties. The RF models were based on the full library of soil samples with associated soil reference data for each soil property. The number of reference samples used for model development and testing were 10,820 for SOC, 7,305 for soil pH, 4,322 for soil texture and 1,657 for d13C. In training the prediction models, we randomly selected 70% of the samples for each soil property, keeping the remaining 30% out for testing of the models. We then calculated R^2 and Root Mean Square Error of Prediction (RMSEP) values for the training and test dataset to assess model performance.

2.5. Landscape level mapping of soil erosion and SOC

Using LDSF soil and baseline data from a total of 30,853 sites in 40 countries, including the two sites included in this study, random forest models were developed to predict and spatially assess SOC and soil erosion prevalence across eastern Rwanda. The approach we followed in this study is described in Vågen et al. (2013), but applying Landsat 8 rather than Landsat 7 satellite imagery. Given that all LDSF plots are georeferenced we can extract the Landsat 8 spectral band values for each plot in the database

and link these to field observations of soil erosion and MIR predicted SOC, respectively. This allows us to develop predictive models for assessments of these variables across larger landscapes.

3. Results

3.1. Vegetation structure and diversity in theLDSF plots sampled

Field surveys took place between October and November 2018. In total, 155 plots were sampled in Kayonza and 149 plots were sampled in Nyagatare. Sixty-eight percent of the sampled plots in Kayonza were classified as cultivated and 89% in Nyagatare. Other vegetation structure classes included shrubland, woodland and grassland. Median tree densities were similar for each site (25 tree ha^{-1}), though average tree density was higher in Nyagatare (120 tree ha^{-1}) compared to Kayonza (68 tree ha^{-1}). Overall this level of tree density is low, and the higher tree densities only occurred in woodlots of *Eucalyptus spp.* (Figure 1). In total 62 unique tree species were identified in the two LDSF sites. The most common species was: *Eucalyptus spp.*, followed by *Grevillea robusta*, *Euphorbia tirucalli*, *Ricinus communis*, *Mangifera indica*, *Carica papaya* and *Senna spectabillis* (Figure 2). Differences were observed between the two LDSF sites, most notably that *Jatropha curcas* was only found in Kayonza and *Senna singueana* was only found in Nyagatare. (Figure 2). In summary, 48 unique species were observed in Kayonza and 39 species in Nyagatare. This level of tree diversity is considered quite low, with a low occurrence of most species and few indigenous species. For example, 171 (56%) of the sampled plots had *Eucalyptus spp.*, including 125 of the cropland plots (53%).

3.2. MIR prediction results for soil properties

Prediction performance was good for the soil properties included in the study, including for the prediction of d13C, as summarised in Table 1. The prediction model performance for d13C is similar to that reported by (Winowiecki et al., 2017) when predicting d13C based on near-infrared (NIR) spectroscopy. Figure 3 shows predicted versus measured SOC and d13C, respectively, for Nyagatare and Kayonza, showing good model performance across a wide range of SOC and d13C, respectively.

3.3. Soil properties and erosion prevalence

Soil properties for top and sub soil samples for Kayonza (n= 151, 136) and Nyagatare (n= 149, 145) LDSF sites are presented in Table 2. Density plots for the soil variables demonstrate the variability between and within the sites (Figure 2). Overall, pH values were low across the two sites, with mean topsoil pH in Kayonza being 5.65 and 5.89 in Nyagatare. This level of pH can potentially limit agricultural production. Both sites had low overall exchangeable bases (Ca, K, Mg, Na), especially considering that 8 cmol$_c$ kg^{-1} is considered critically low for agricultural productivity. For example, Kayonza had slightly higher clay content and lower sand content compared to Nyagatare. Correspondingly, Nyagatare had higher topsoil OC content (20.9 g kg^{-1}) compared to Kayonza 17.3 g kg^{-1}). Figure 5 shows the relationship between sand content and SOC content, with SOC increasing

with decreased sand content, for both sites and both depths (Figure 5). In addition, topsoil OC was lowest in the cropland plots compared to the other vegetation classes, even given the high variation.
275   Average d13C was -18.9 ‰ in Kayonza and -19.2 ‰, in Nyagatare, which indicates that these are mixed C3-C4 systems. We also assess the variation of stable carbon isotopes across the vegetation structure classes (Figure 6). Even woodland plots, which are generally *Eucalyptus* plantations, were previously cultivated, hence the mixed signal.

280   Kayonza had higher soil erosion prevalence with 45% of the plots considered severely eroded, compared to 27% of the sampled plots in Nyagatare. The dominate erosion categories were rill and sheet. Severe erosion was more prevalent in woodland (91%), shrubland and grassland (77%), compared to cropland (25%). This is most likely given the high prevalence of terracing in the region as well as the location of the cropping fields compared to woodland and bushland. For example the
285   average slope for the plots classified as cultivated was seven degrees compared to 19 degrees for the other vegetation classes.

3.4. Infiltration capacity

Median topsoil field-saturated hydraulic conductivity (Kfs) in Kayonza was 76 mm h^{-1}, whereas in Nyagatare it was 62 mm h^{-1} (Figure 7). In Kayonza, Kfs was not only higher but also more variable than
290   in Nyagatare, with an interquartile range (upper quartile – lower quartile) of 77 mm h^{-1} and 42 mm h^{-1}, respectively.

Results from the linear mixed effects models showed that topsoil SOC content had a positive effect on Kfs, whereas pH and sand content had a negative effect. The presence of root depth restrictions above
295   20 cm depth also had a negative effect on Kfs. The effect of vegetation structure on Kfs could not be assessed, as most of the plots where infiltration was measured were on cropland.

3.5. Soil mapping

Soil erosion prevalence was predicted with a high degree of accuracy using Landsat 8 satellite data,
300   with an out-of-bag prediction error of 14%. The receiver operator characteristics (ROC) curve also indicates good model performance with the area under the ROC curve (AUC) calculated at 0.86. These results are expected given results from previous studies using remote sensing to predict erosion (Vågen et al., 2013; Vågen and Winowiecki, 2019). Soil erosion prevalence was mapped at 30-m resolution for 2018. Hotspots of erosion are shown in red/yellow for each of the maps below. This map shows high
305   spatial variability in erosion across eastern Rwanda as well as hotpots for interventions.

The prediction model performance for SOC was also good, with an R^2 of 0.82 based on the out-of-bag prediction results from the random forest model (Figure 9). The map of SOC shows high variation of SOC across eastern Rwanda, with higher SOC in the western part and lower SOC moving east until the
310   wetlands, which have higher SOC. Both LDSF sites located between this gradient of SOC values. These

maps can be used to track SOC overtime and in response to interventions. There is higher SOC in wetlands and in lower lying areas, including along rivers and less carbon in the more intensively cultivated areas in the northeastern part of Nyagatare district, for example.

315   4. Discussion

There is a real need for developing a robust set of soil and land health indicators for monitoring ecosystem restoration interventions over time and across multiple scales. By conducting multi-scale assessments of land and soil health across landscapes, we are able to provide analysis at the farm level, across landscapes to inform ecosystem health investments. However, landscapes are complex and linear
320   relationships do not always exist, therefore addressing the complexity across the interactions of multiple indicators is important.

Healthy soil is the foundation for functioning ecosystems, including sustainable agricultural systems, rangelands, wetlands and forests. It is a prerequisite for land-based ecosystem restoration. However,
325   there are inherent soil properties, such as those influenced by parent material, for example, that can limit the ability of the soil to store or sequester carbon. These data showed a strong relationship between inherent soil properties, such as sand content, and SOC. The trend of decreasing SOC with increasing sand content in these data was also observed in the LDSF data from Tanzania (Winowiecki et al., 2016). As expected, SOC content had a positive effect on Kfs. Topsoil SOC in Kayonza was higher than in
330   Nyagatare, and so was Kfs. Sand content, pH and soil compaction had a negative effect on Kfs. This indicates the complexity in determining hydrologic controls. However, when infiltration of water into the soil is poor (slow), surface runoff increases, leading to increased soil erosion. Therefore understanding how to better manage soil to increase infiltration rates is an important restoration intervention.
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Soil erosion was more prominent in the woodland, shrubland and grassland plots compared to the cropland plots. The same trend was seen with SOC content, lower SOC in cropland plots compared to the other vegetation classes. Given the croplands are managed, there is high potential to improve soil health, including increasing SOC through improved management practices.
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In the case of the two districts in eastern Rwanda, both Nyagatare and Kayonza had low overall soil pH and exchangeable bases. While SOC content hovered around the 20 g kg^{-1} threshold set for temperate regions, we were not able to compare these sites with naturally vegetated, undisturbed sites, as all of the
345   plots in both LDSF plots were on cultivated or heavily managed sites. This was also re-enforced by the mixed C3-C4 signal in the d13C data, none of the soil samples from the plots exhibited dominant C3 or C4 photosynthetic pathways.

350   Tree planting is in the global spotlight as a restoration activity that has high potential for climate change mitigation, while provide multiple other ecosystem services (Bastin et al., 2019). In Rwanda, there are multiple tree planting campaigns from the Government as well as within the Development Sector. However, overall tree densities in both districts were low as was species diversity. In addition, the species inventory indicated that mostly exotic species were recorded. These findings are similar to what was found as most common agroforestry species in other regions of Rwanda (Bucagu et al., 2013;

355   Iiyama et al., 2018). These results highlight the opportunity for the strategic inclusion of useful and appropriate tree species that fulfill multiple ecosystem benefits, including the inclusion of indigenous tree species on farm.

By applying a consistent indicator frameworks such as the LDSF, which combines systematic field

360   measurement with and innovative laboratory methods and advanced data analytics, we are able to conduct spatial assessments of SOC and other land health indicators at multiple spatial scales, with high accuracy and application for not only targeting but tracking changes overtime. For example, by mapping SOC at 30-m resolution, we are able to pick up spatial patterns related to both land management and inherent soil properties, tot identify drivers of degradation.

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5.   Conclusions

Rwanda is one of the most progressive countries in the region in terms of acknowledging the important of land restoration for sustainable livelihoods in the country. It has set ambition targets over the next decade, aiming to restore more than 76% of its land area. Given the importance of the agricultural sector

370   in the country and widespread land degradation due to a combination of deforestation and unsustainable agricultural practices, there is a need for evidence to support the targeting of land restoration efforts, as well as the tracking of the effectiveness of such interventions over time. In addition, by combining systematic field based surveys with earth observation data, we can model and map SOC concentrations with high accuracy, allowing us to track interventions overtime.

375

In this paper we have shown the importance of understanding both biogeochemical and human-induced drivers of indicators important for land restoration, such as soil organic carbon. We argue that there is an urgent need for systematic assessments of soil organic carbon, as well as aboveground biodiversity (e.g., tree diversity), combined with hydrologic properties, along with other indicators of land

380   degradation such as soil erosion, that are spatially explicit and allow for targeted interventions across landscapes. This will not only ensure that appropriate interventions for land restoration are implemented, but also provide the evidence base to religiously assess their effectiveness.

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6. Data Availability

All LDSF data are posted here:
390 https://data.worldagroforestry.org/dataverse/icraf_soils

7. Sample Availability

All soil samples are logged and barcoded at the ICRAF Soil-Plant Spectral Diagnostics Laboratory at
395 World Agroforestry (ICRAF) in Nairobi, Kenya.

8. Team List

See acknowledgements and author list.

9. Author Contribution

400

LW and TGV co-led the conceptualization, writing and analysis. AM and AlexM led the coordination
of the field work and contributed to the writing. PM contributed to collection of field data and
interpretation. EBN and AlexM contributed to interpretation of the results. SC contributed to the
conceptualization and contextualization. ATB contributed to the analysis, in particular to the infiltration
405 analysis and modeling as well as the writing. LW prepared the manuscript with contributions from all
co-authors.

10. Competing Interest

"The authors declare that they have no conflict of interest."
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11. Disclaimer

The views expressed in this paper do not necessarily reflect the views of the donors who funded thisi
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11.2.   Acknowledgements

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Table 1: Prediction model performance metrics for the prediction of soil properties from MIR spectroscopy included in the study.

Soil property	R^2		RMSEP	
	Training	Testing	Training	Testing
SOC	0.99	0.92	1.3	3.3
d13C	0.97	0.72	0.8	1.8
pH	0.97	0.84	0.2	0.4
Sum of exchangeable bases	0.96	0.84	3.9	8.2
Sand	0.98	0.84	3.1	8.9
Clay	0.98	0.82	3.5	10.1

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Table 2: Soil properties for top and sub soil samples at the two LDSF sites (SD = standard deviation, ExBases is exchangeable bases) .

Site	Depth	N	Mean SOC	SD SOC	Mean d13C	SD dC13	Mean pH	SD pH	Mean ExBaes s	SD ExBas es	Mean Sand	SD Sand	Mean Clay	SD Clay
	cm		g kg^{-1}		‰				cmol$_c$ kg^{-1}		%			
Kayonza	0-20	151	20.9	8.83	-18.9	1.15	5.65	0.68	10.3	8.69	19.8	9.29	58.4	11.5
	20-50	136	16.9	7.96	-18.4	1.26	5.65	0.65	10.6	9.10	19.4	9.27	60.6	11.4
Nyagatare	0-20	149	17.3	6.07	-19.2	0.92	5.89	0.54	8.74	4.80	30.0	10.2	44.5	10.5
	20-50	145	13.3	5.49	-18.7	0.97	5.88	0.55	8.44	5.77	30.0	10.5	45.8	11.4

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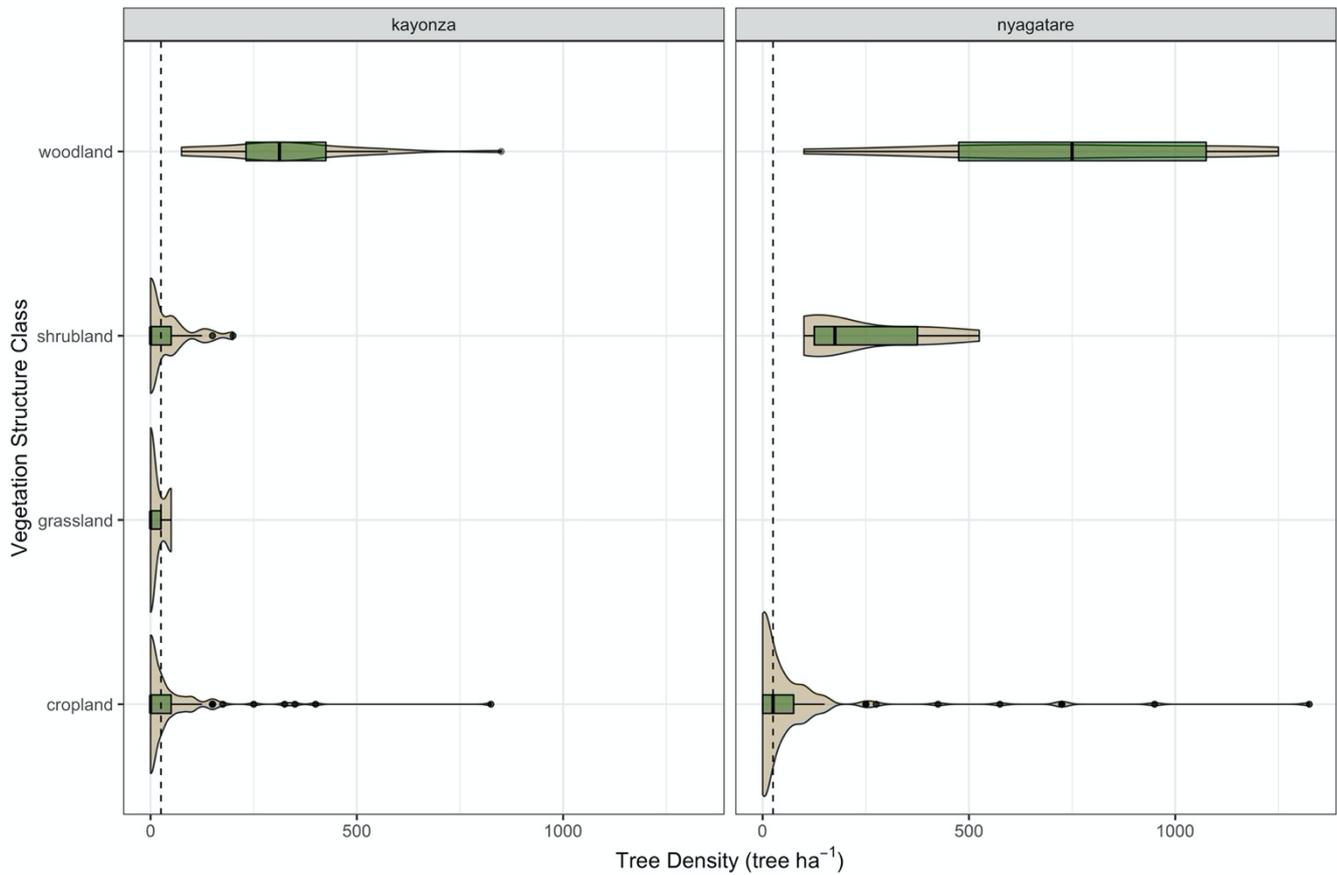
Figure 1: Violin plots showing the variation in tree densities across the vegetation classes at both LDSF sites. The dotted line is the median (25 tree ha^{-1}).

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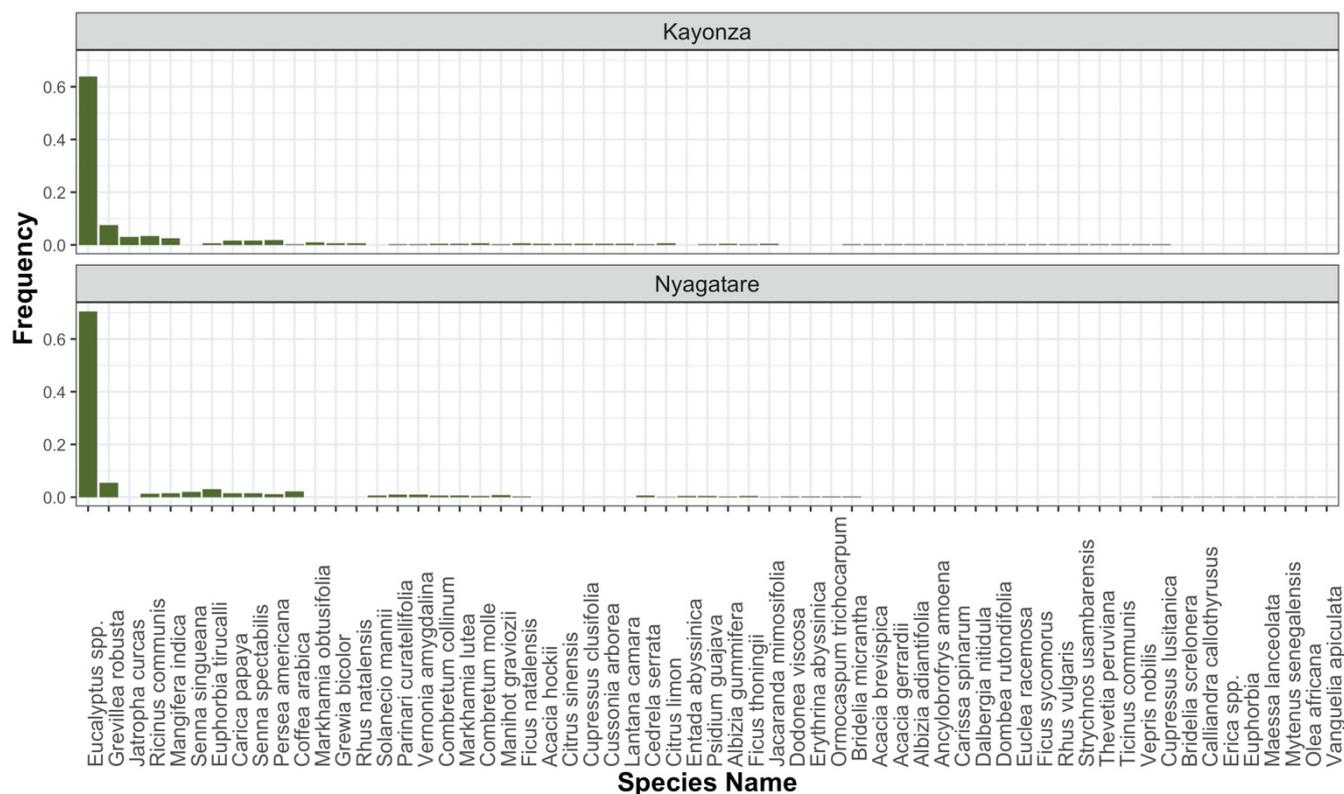
Figure 2: Tree species across the two LDSF sites. Sixty-two different species were recorded, with low occurrence of most species, and few indigenous tree species.
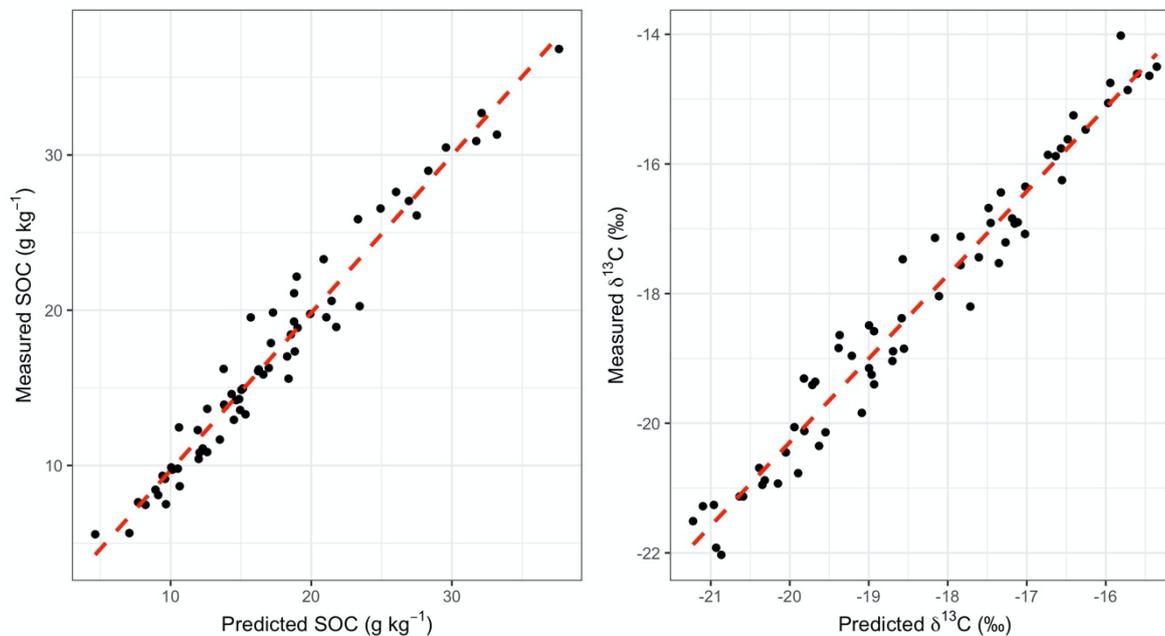
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Figure 3. Predicted vs measured SOC and d13C based on MIR spectra for the two sites included in the study.
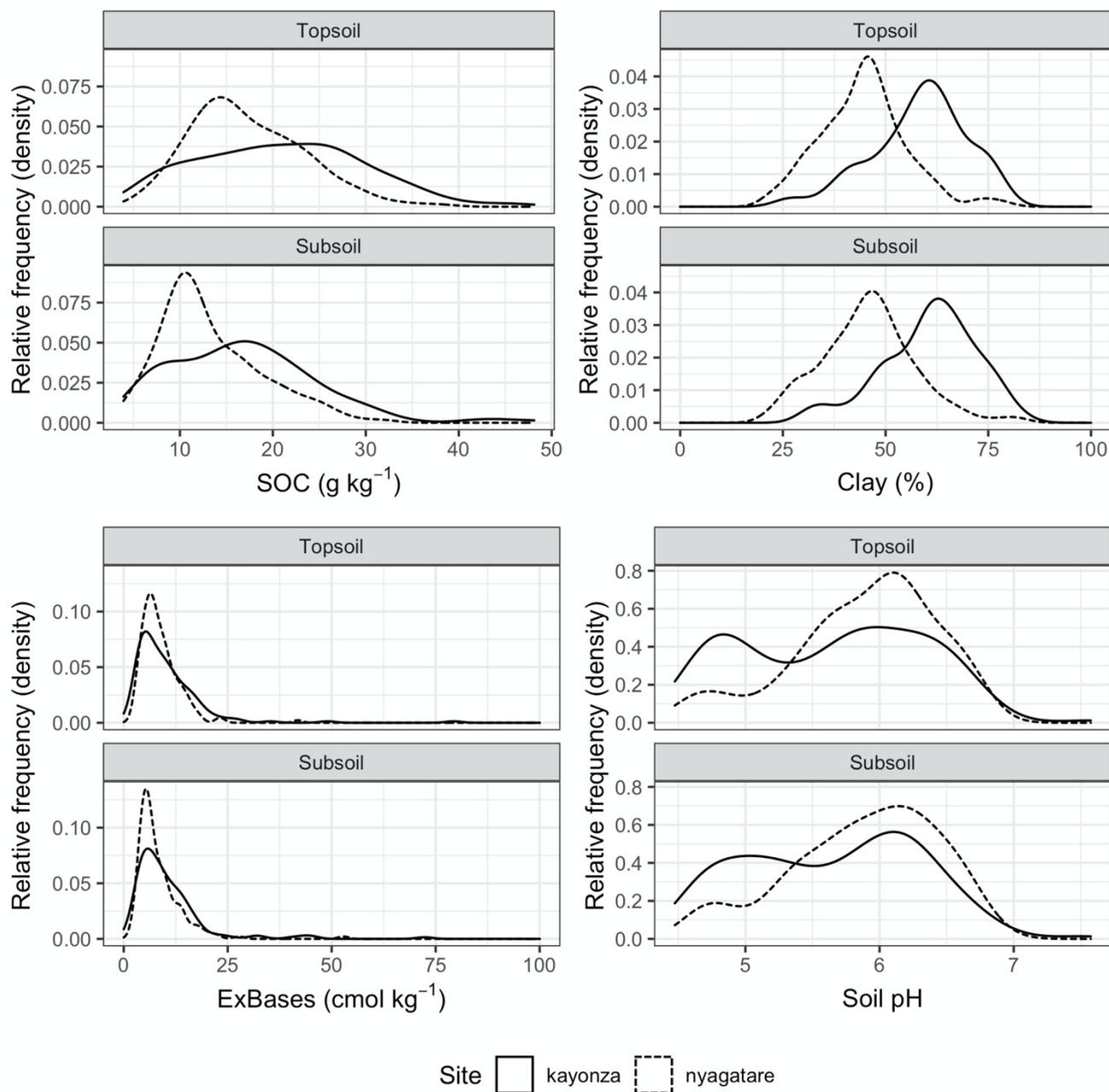
Figure 4: Density plots of soil organic carbon (SOC), clay, exchangeable bases (ExBases), and pH for the top and sub soil samples at Kayonza and Nygatare.
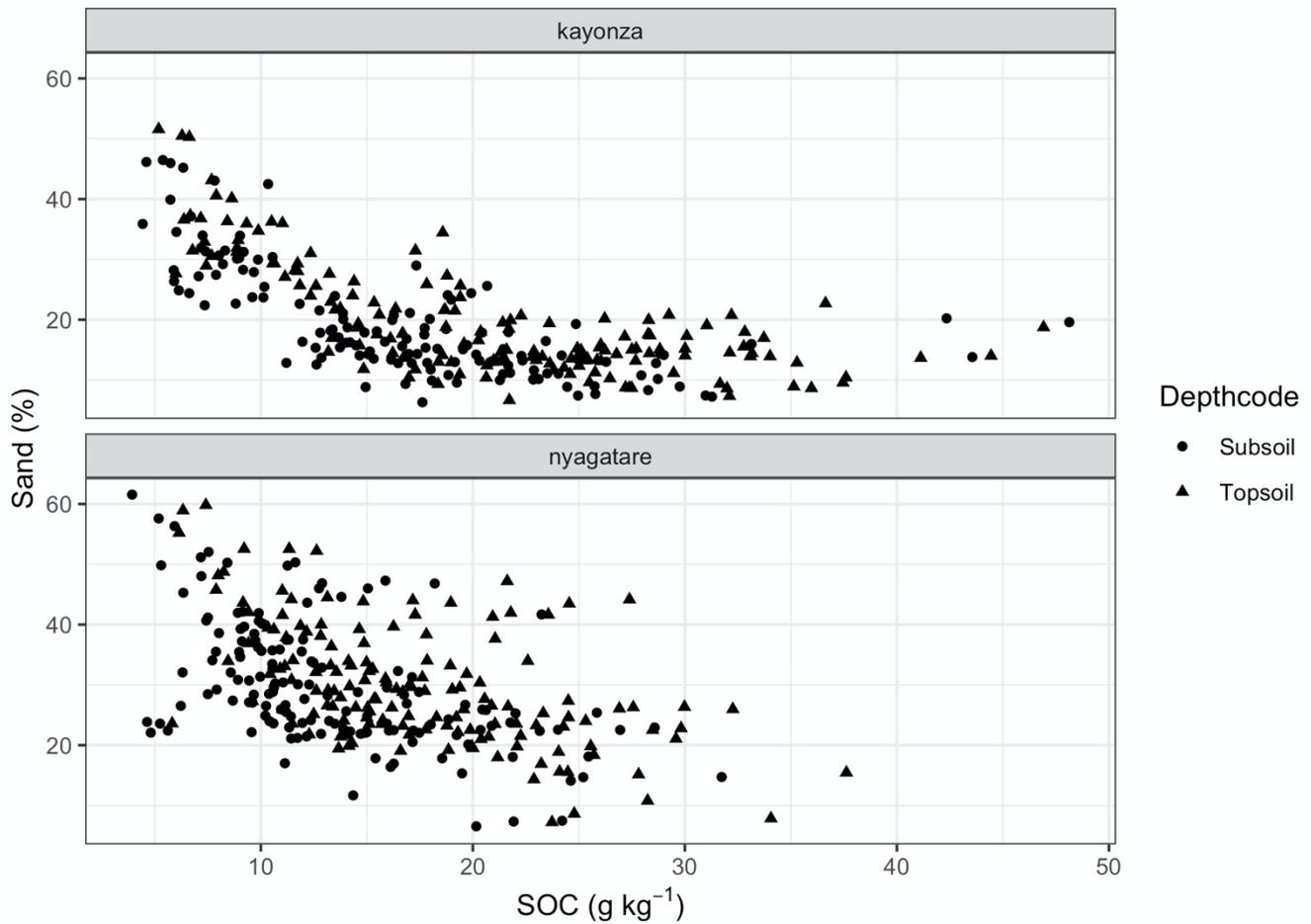
Figure 5: Relationship between sand content and soil organic carbon (SOC) for both top and sub soil samples at Kayonza nnd
575 **Nyagatare LDSF sites.**

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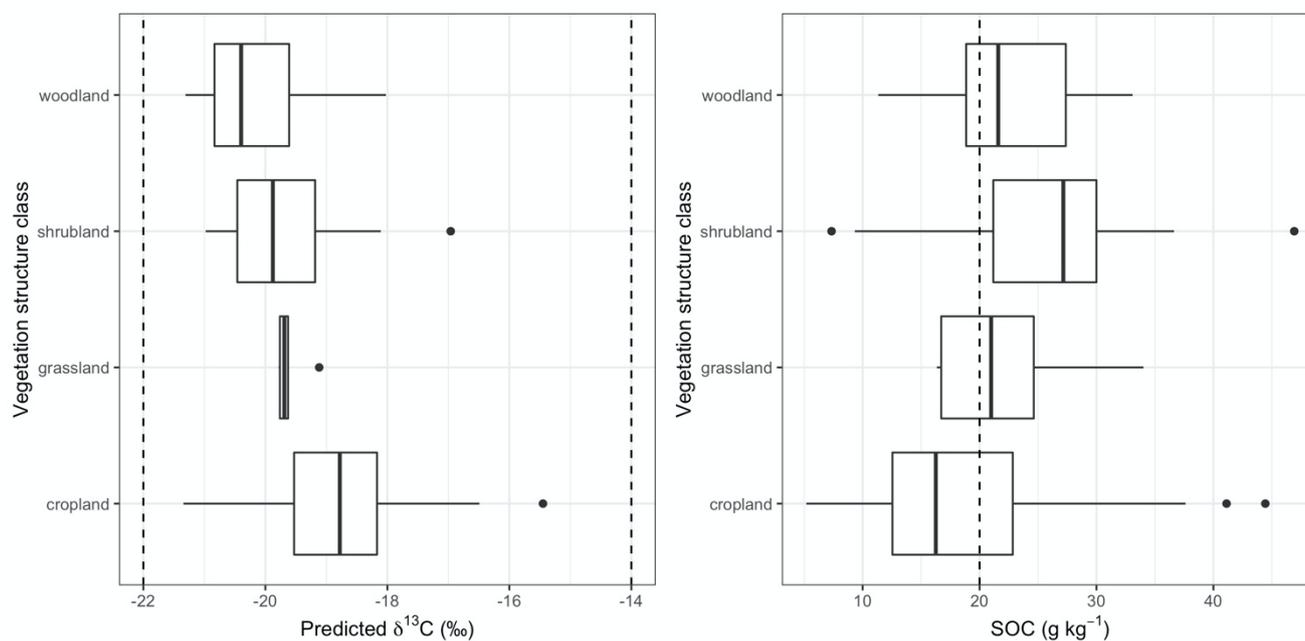
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Figure 6: Boxplots of d13C values in topsoil and topsoil OC content for each vegetation structure class. Dotted vertical lines at -22 and -14 ‰ indicate the C3 and C4 dominated systems, respectively. The dotted line at 20 g kg⁻¹ SOC is to indicate a threshold for agricultural productivity in humid areas.

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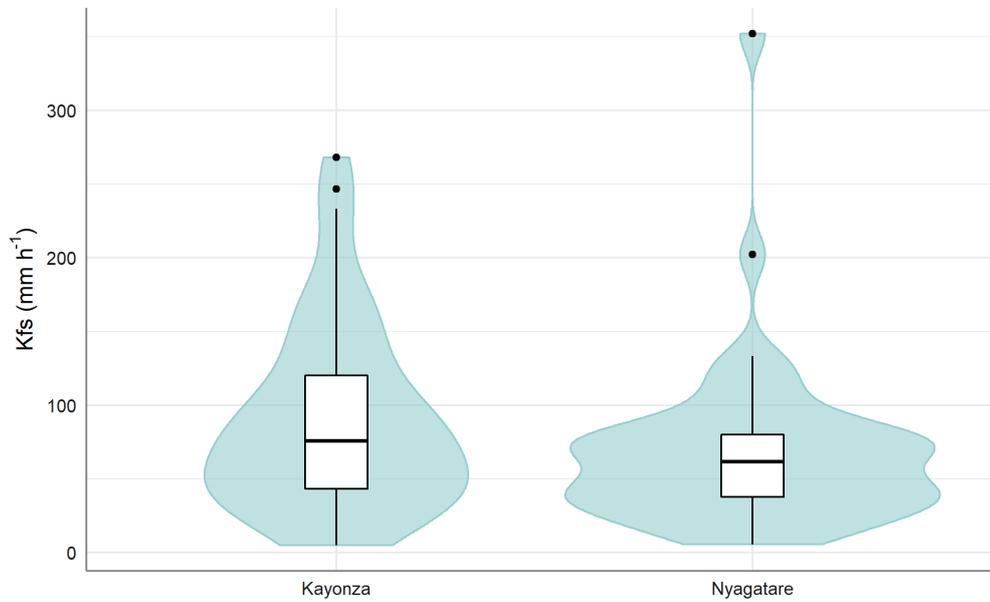
Figure 7: Box and violin plots of field-saturated hydraulic conductivity (Kfs) for each LDSF site. The three horizontal lines in the box plot show the lower quartile, the median, and the upper quartile. Whiskers extend to the outer-most data point that falls within 1.5 box lengths. The violin plots show the distribution of the Kfs data.

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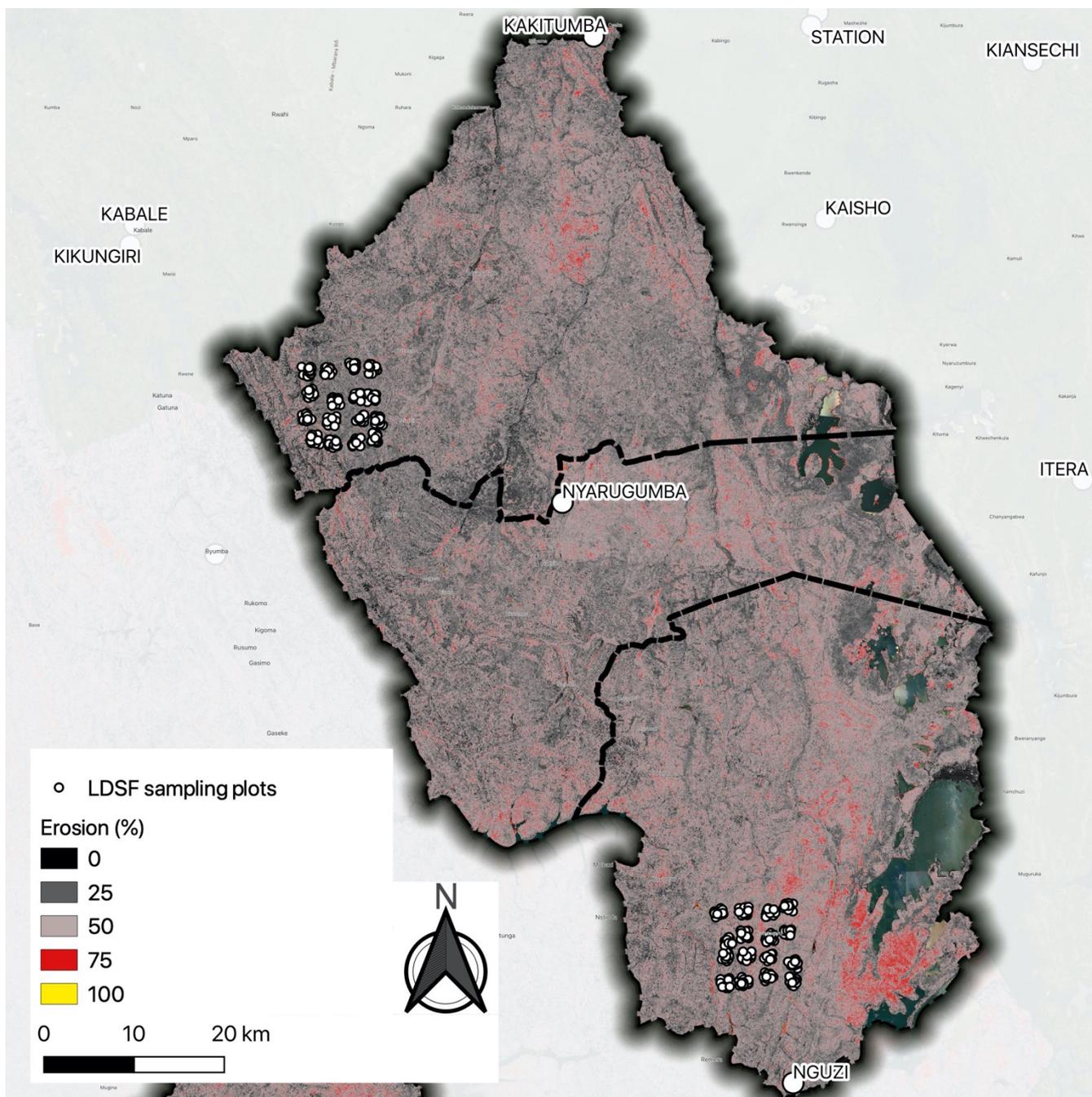
Figure 8:Map of soil erosion prevalence (%) predicted based on Landsat 8 satellite imagery and field data from the LDSF plots.
620 **The two LDSF sites are also shown on map (Nyagatare in the north and Kayonza in the south), with the sampling plots shown as white circles..**
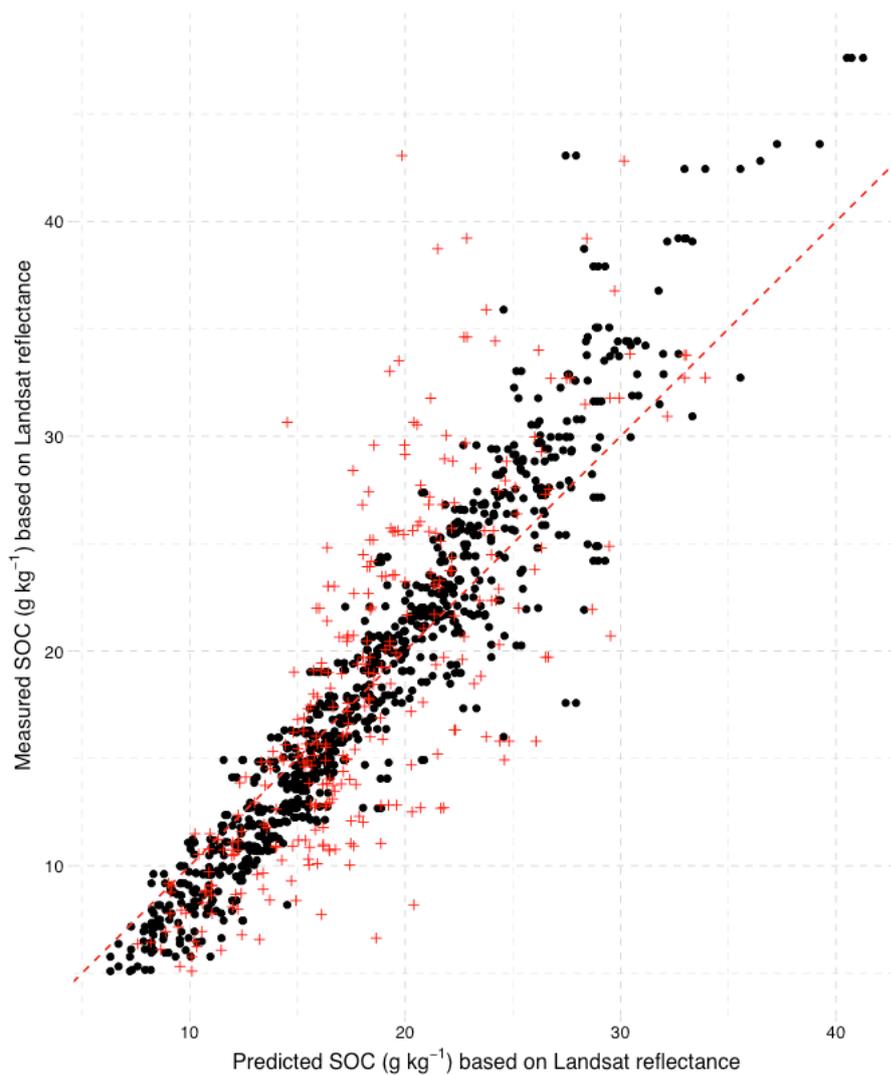
625 **Figure 9. Predicted vs measured SOC based on predictions made from Landsat 8 reflectance for the two study sites. The black dots are training data, while the red crosses show independent validation results.**
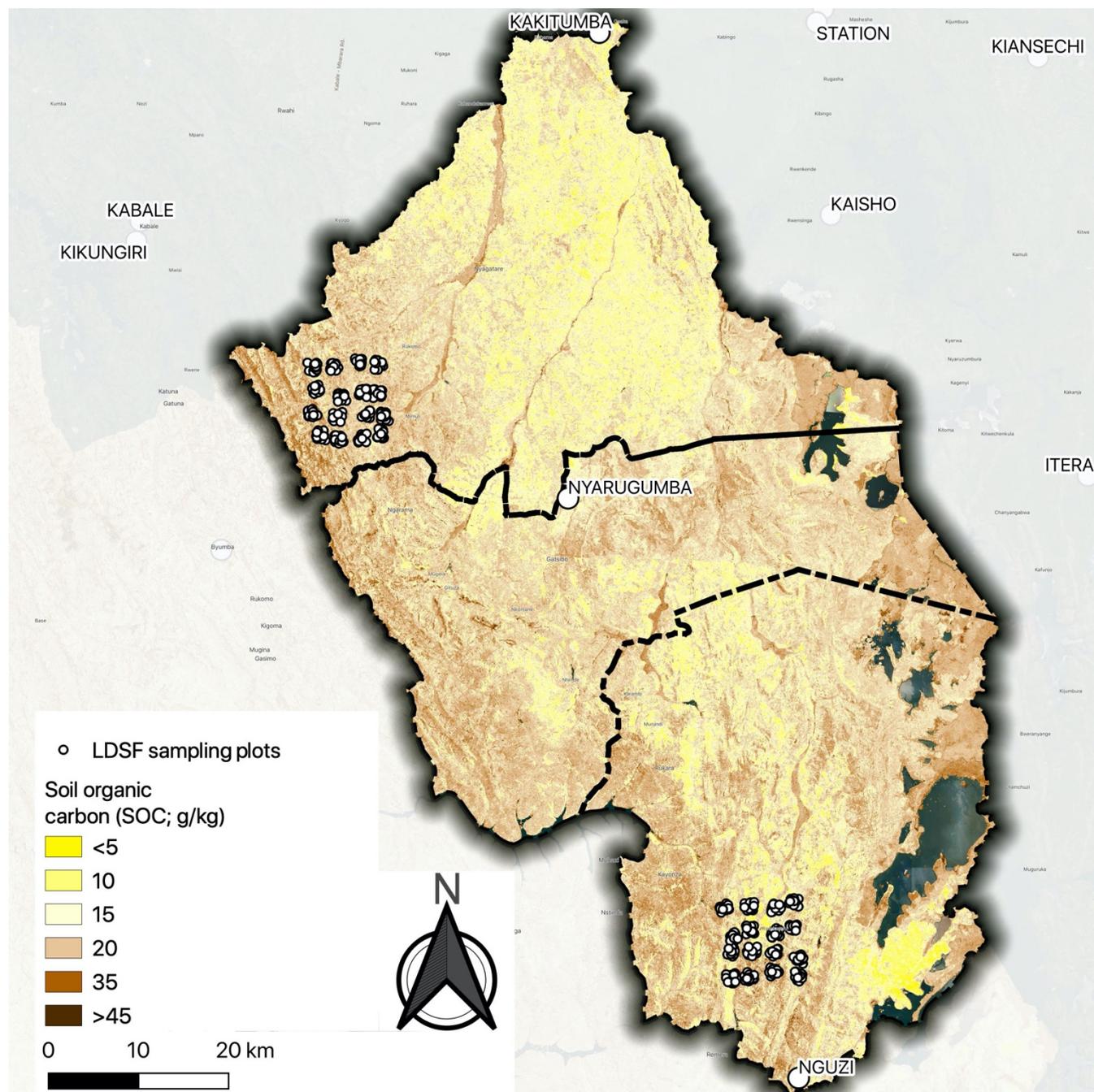
Figure 10. Map of soil organic carbon (SOC) predicted based on Landsat 8 satellite imagery and soil data from the LDSF plots. The two sites are also shown on map (Nyagatare in the north and Kayonza in the south), with the sampling plots shown as white circles.

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