Received: 29 September 2022 | Accepted: 2 November 2022

DOI: 10.1111/gcb.16551

Global Change Biology WILEY

RESEARCH ARTICLE

Smallholder farms have and can store more carbon than previously estimated

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Funding information
International Fertilizer Development Center and USAID, Grant/Award Number: AID-BFS-IO-15-00001; United States Agency for International Development, Grant/Award Number: AID-OAA-A-13-00006

Abstract

Increasing soil organic carbon (SOC) stocks is increasingly targeted as a key strategy in climate change mitigation and improved ecosystem resiliency. Agricultural land, a dominant global land use, provides substantial challenges and opportunities for global carbon sequestration. Despite this, global estimates of soil carbon sequestration potential often exclude agricultural land and estimates are coarse for regions in the Global South. To address these discrepancies and improve estimates, we develop a hybrid, data-augmented database approach to better estimate the magnitude of SOC sequestration potential of agricultural soils. With high-resolution (30 m) soil maps of Africa developed by the International Soils Database (iSDA) and Malawi as a case study, we create a national adjustment using site-specific soil data retrieved from 1160 agricultural fields. We use a benchmark approach to estimate the amount of SOC Malawian agricultural soils can sequester, accounting for edaphic and climatic conditions, and calculate the resulting carbon gap. Field measurements of SOC stocks and sequestration potentials were consistently larger than iSDA predictions, with an average carbon gap of 4.42 ± 0.23 Mg C ha^{-1} to a depth of 20 cm, with some areas exceeding 10 Mg C ha^{-1}. Augmenting iSDA predictions with field data also improved sensitivity to identify areas with high SOC sequestration potential by 6%—areas that may benefit from improved management practices. Overall, we estimate that 6.8 million ha of surface soil suitable for agriculture in Malawi has the potential to store 274 ± 14 Tg SOC. Our approach illustrates how ground truthing efforts remain essential to reduce errors in continent-wide soil carbon predictions for local and regional use. This work begins efforts needed across regions to develop soil carbon benchmarks that inform policies and identify high-impact areas in the effort to increase SOC globally.

KEYWORDS
carbon sequestration, climate change mitigation, geographically weighted regression, iSDA, smallholder agriculture, soil carbon, sub-Saharan Africa

1 | INTRODUCTION

Carbon is among the most consequential and contentious substances on earth. Responsible for much of human wellbeing through powering economic activity, it is also the greatest threat to global biodiversity and ecosystem function by driving global climate change (IPCC, 2022). Carbon sequestration in agriculture offers a means to address this threat while also supporting food security. While some agricultural practices such as soil cultivation and residue removal contribute to soil carbon depletion (Martínez et al., 2008; Paustian, Collier, et al., 2019), agricultural soils also may have more potential than natural lands to sequester carbon with changes in management (Six et al., 2002). Agricultural soils with higher soil organic carbon (SOC) tend to be more productive and better able to withstand climate change-enhanced shocks than those with lower SOC (Droste et al., 2020; Oldfield et al., 2019; Williams et al., 2016). However, human activity has caused an estimated loss of 133 Pg C since the beginning of agriculture (Sanderman et al., 2017), around 10% of remaining global stocks (Scharlemann et al., 2014; Walker et al., 2022). In a win–win scenario, sequestering carbon to increase SOC stocks in agricultural soil mitigates climate change and enhances the adaptation capacity of agriculture.

Unfortunately, a soil's potential to sequester carbon is highly variable and difficult to predict. The potential for sequestering carbon has two components. The first is the rate at which carbon can accumulate in a soil. Global estimates of rates vary widely within agricultural lands, for example, between 0.9 and 4.8 Pg C year^{-1} (Griscom et al., 2017; Zomer et al., 2017); at the field scale, published C sequestration rates in surface soils range from +0.4% to +17.6% per year, depending on region, climate, management, and baseline (Corbeels et al., 2019). The second component, the quantity that a soil might accumulate, is the difference between the current stock and the potential stock—the carbon gap. The potential stock is limited by climate, edaphic, and critically, management factors that can be altered to increase potential stocks. In general, cropped soils have lower potential carbon stocks than uncropped soils of the same series (Matus, 2021; Minasny et al., 2017). Although the sequestration potential of agricultural soils is limited per unit area, agriculture is the dominant land use globally, so quantifying and locating agricultural carbon gaps is essential for climate change mitigation. Those locations with large carbon gaps are likely to have higher potential storage rates than those with smaller gaps and are more likely to benefit agronomically from increases in carbon stocks (Corbeels et al., 2019; Six et al., 2002). As a result, large-gap sites are high priority for carbon sequestration interventions.

Yet, predicting carbon gaps on agricultural lands remains so difficult that agricultural soils continue to be excluded from high-profile estimates of the global potential to sequester carbon (Walker et al., 2022). Identifying large-gap soils requires accurate, high-resolution soil maps to estimate current stocks and a robust method to estimate potential stocks. This is especially true in the Global South, where widespread, small-scale management amplifies variation in existing carbon stocks of old, management-sensitive soils (Snapp, 2022). Maps estimating soil carbon stocks have improved over the past decade to predict stocks at field-scale (30 m) resolution (Hengl et al., 2015, 2021). However, prediction models still are generated at the continental scale; as a result, these maps may not be accurate or precise at policy-relevant scales of fields to nations (Ewing et al., 2021). Investment in field-scale soil carbon data to better understand and manage sequestration on cultivated lands may overcome this (Beillouin et al., 2022). The other major challenge is setting a standard or goal. One approach is based on texture, which is used to estimate the total organic carbon that could associate with fine silt and clay particles (Hassink, 1997), although this value is still sensitive to management (Fujisaki et al., 2018) and also excludes large, management-sensitive pools such as particulate organic matter. Alternatively, nearby natural lands are used as a primary data source for mapping stocks or estimating potentials (Guillaume et al., 2022; Kempen et al., 2019). While land use change from agriculture to natural lands may allow a field to reach the ecological potential of carbon stocks, such a tradeoff with food production likely is unacceptable. Estimating a field's potential carbon stock assuming continued agricultural management avoids this tradeoff but lacks an obvious standard.

We propose solutions to these dual challenges of map accuracy and the estimation of sequestration potential of agricultural soils, with Malawi as a case study. For the first, we create a national adjustment to the International Soils Database (iSDA) maps of Africa using a dataset of 1160 fields, as suggested by Hengl et al. (2021). For the second, we borrow a benchmarking approach from the soil health literature (Karlen et al., 2019; Nunes et al., 2021) to estimate the sequestration potential of Malawian agricultural soils within edaphic and climatic contexts. Based on previous experience (Ewing et al., 2021), we expected: (a) that SOC stocks would be higher and more variable than predicted by iSDA; (b) that soils would show a greater potential for carbon sequestration than predicted by iSDA; and (c) that adjusting iSDA could mitigate these biases and aid the identification of fields with high storage potential. The outcomes are high-resolution maps of current and potential SOC stocks and SOC gaps at 30 m resolution to support targeted investments in locations where carbon sequestration has the most storage potential. We conclude by discussing the continued need for sampling to verify carbon sequestration and carbon gaps and the utility of this approach for (a) setting local to regional policy goals and (b) directing investment toward those areas with the greatest potential to sequester carbon.

2 | METHODS

2.1 | Study locations, sampling, and data acquisition

Data were collected from 1160 smallholder fields as part of the Africa RISING project (Tu et al., 2022). Sites were selected by stratified random sampling from two villages within each of eight extension planning areas in three districts. The villages span the

variation in soil conditions across Malawi (Figure 1). Soils were collected in 2016 as previously described (Ewing et al., 2021). Briefly, samples were collected to a depth of 20 cm and composited from eight locations per field. Samples were air-dried, sieved to 2 mm, and stored until analyses. Total carbon and nitrogen concentrations were measured with a Leco Tru-Mac CN Analyzer (Leco Corporation). pH was measured in a 1:2 soil:water slurry. Texture was measured using the micropipette method (Burt et al., 1993). Soils were assumed to be free of carbonates due to generally acidic conditions; this was confirmed on a subset ($n = 148$) of samples which were assessed for carbonates by change of mass upon acidification with 1 M hydrochloric acid (Allison & Moodie, 2016). In 2020, 74 of these sites were revisited to measure soil bulk density. Five centimeter diameter cores were carefully taken per field

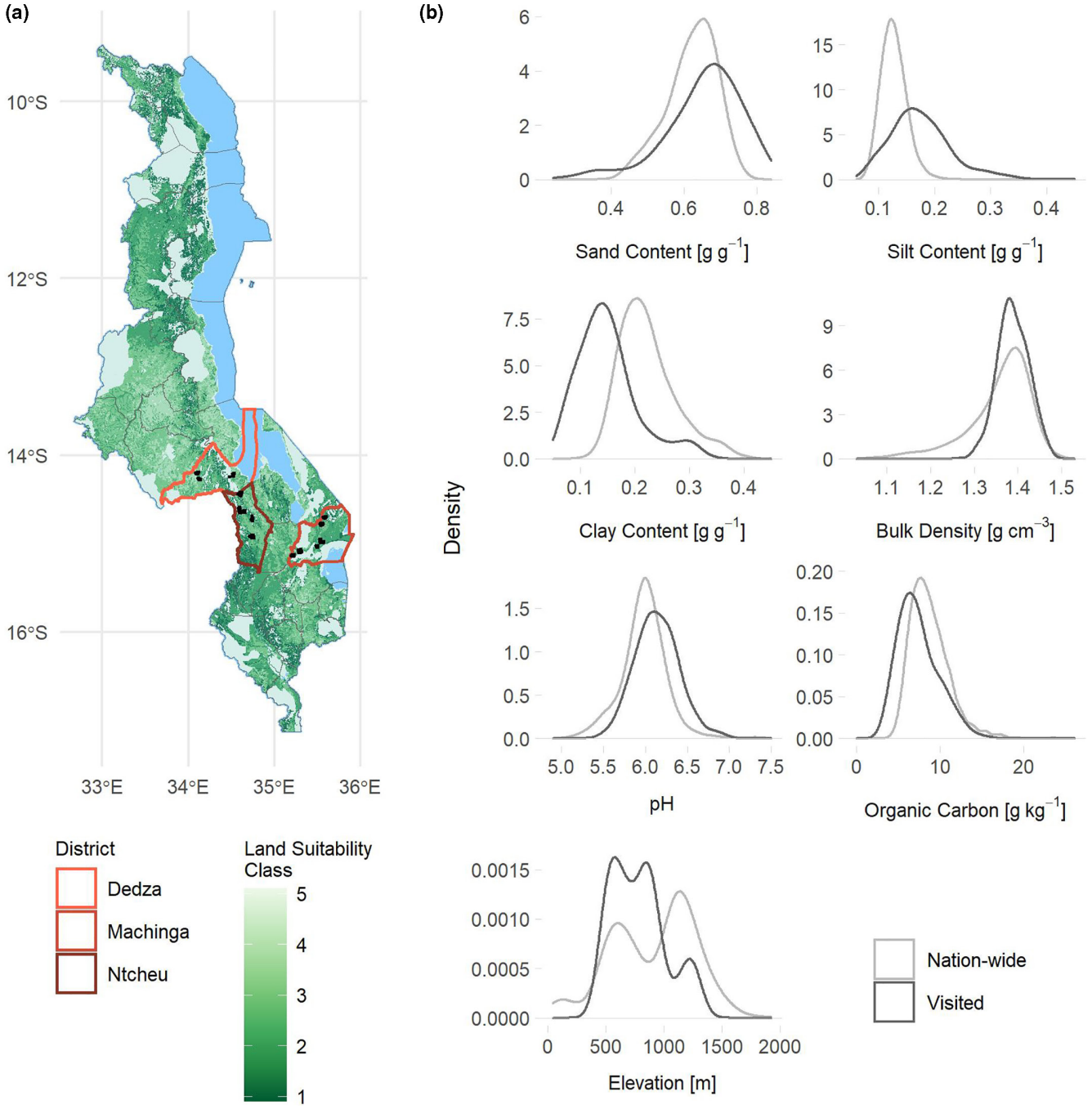

FIGURE 1 (a) Sample locations against a backdrop of land suitability for agriculture (Li et al., 2017). Lower numbers and darker colors indicate higher suitability. Black dots are sample locations and districts containing those points are highlighted in color. Panel (b) shows distributions of soil properties at visited fields (black) or across Malawi based on 5000 randomly selected points (gray). All properties are estimated from iSDA or the SRTM-90 digital elevation model. Densities indicate the proportion of points along the *x*-axis. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

to avoid compaction, three from the row and three from the interrow to account for management-induced differences in these locations. The six cores were then composited, oven dried, and weighed.

Layers of estimates for soil properties in Malawi were downloaded from the Innovative Solutions for Digital Agriculture database (iSDA; www.isda-africa.com; Hengl et al., 2021) following OpenLandMap instructions (https://gitlab.com/openlandmap/africa-soil-and-agronomy-data-cube) within *R* 4.0.2 for Malawi and transformed to SI units. Soil properties were mass fractions of total carbon, organic carbon, sand, silt, clay, plus bulk density, pH, and carbon stocks for the 0–20 cm depth. Agricultural suitability classes were acquired from Li et al. (2017). Malawi political boundaries were acquired from Database of Global Administrative Areas (www.gadm.org). Elevation (SRTM 90 m) and MODIS reflectance indices were acquired via Google Earth Engine (Didan & Huete, 2015; Jarvis et al., 2008).

2.2 | Estimation of carbon stocks and storage potential

All analyses were performed in *R* 4.1.1 (R Core Team, 2021). Unless noted, graphs and maps were made using *ggplot2*, geospatial analyses were conducted with *sf*, *terra*, and *stars*, and other statistics were completed using base functions (Hijmans, 2022; Pebesma, 2018, 2022; Wickham, 2016). Geospatial analyses were conducted in the WGS84(2007) datum, while maps were projected in NAD83 UTM Zone 36S. Code for adjusting iSDA layers, deriving benchmarks, evaluating prediction error, and predicting potentials is available on Zenodo at https://doi.org/10.5281/zenodo.

We used an equivalent-depth approach to estimate and compare carbon stocks at all measured sites (Rovira et al., 2022). We first derived a pedotransfer function to predict soil bulk density at those sites where bulk density was not measured. Properties were selected using stepwise linear regression to minimize Akaike information criterion (AIC; Bozdogan, 1987). Potential properties were soil texture, total carbon, elevation, slope, and pH. The resulting function was:

$$\text{Bulk Density} = 1.29 - 0.00722 \times \text{SOC} + 0.344 \times \text{Sand}, \quad (1)$$

where SOC is measured in g kg^{-1} soil and sand in g g^{-1} soil. This pedotransfer function performed comparably to other published regressions based on root mean squared error calculated with 10-fold cross-validation (Table S1) and had a relative prediction error of 6.3%.

We next estimated potential carbon stocks at field sites using quantile regression. The approach assumed that soils with similar properties and with identical long-term management should support similar carbon concentrations. First, we identified climate and edaphic properties that were associated with total soil carbon using LASSO penalized regression in *glmnet* (Friedman et al., 2010). Potential properties included soil texture, elevation, mean annual precipitation, and mean land surface temperature; these were chosen due to their low sensitivity to management relative to other parameters like soil pH and crop canopy reflectance. Only soil texture and elevation had important associations with soil carbon.

We then identified the 80th percentile of SOC concentrations across these gradients of soil properties using the function *rq*() from *quantreg* (Koenker, 2022). By this definition, 20% of soils were determined to have a carbon gap of zero Mg ha^{-1}. The 80th percentile was selected as feasible yet ambitious, a classification that is admittedly arbitrary. For comparison, Idowu et al. (2009) use a 75th percentile as a minimum "ideal" level of indicators such as organic matter where more is generally better. Soil class-based benchmarking in France found a threefold increase in national carbon sequestration potential when using the 95th percentile versus the 80th percentile (Chen et al., 2019).

Finally, we calculated carbon stocks and potential carbon stocks at field sites using the pedotransfer function and quantile regression relationships. Carbon gaps were calculated as the difference between potential and current carbon stocks.

We compared these calculated stocks, potential stocks, and gaps with those predicted by iSDA. We calculated iSDA carbon stocks based on bulk density and soil organic carbon due to the known lack of carbonates. The quantile regression relationship to estimate potential carbon concentrations was also re-derived using iSDA predictions of soil properties. We finally assessed iSDA's predictive power by comparing it to empirical measurements.

2.3 | Regional adjustment of iSDA stock estimates

To extrapolate our SOC stock estimates to unmeasured locations we derived regional adjustments to iSDA soil properties. We compared three methods for this (Figure S1), all of which allowed a second-order polynomial relationship between iSDA estimates and field measurements of soil properties. The first, a "stationary, top-down" approach, simply correlated empirical and iSDA carbon stocks and assumed that this relationship was stationary across the study area. The second approach relaxed the assumption of stationarity and instead used geographically weighted regression (GWR) to derive local relationships between iSDA and empirical carbon stocks—hereafter, "GWR, top-down." This was implemented using the *gwr.basic*() function in *GWmodel* (Lu et al., 2014). Neighborhoods were defined adaptively with 138 neighboring points using a Gaussian kernel and the *bw.gwr*() function with great circle distances. Finally, a "stationary, bottom-up" approach began by deriving adjustments to iSDA predictions of texture, bulk density, and carbon concentrations, and then re-calculating stocks and storage potential from these corrected component layers.

For each approach, we used cross validation to adjust iSDA values and assess prediction quality. Cross-validation groups were geographically defined as each of eight extension planning areas. Prediction quality indices included root mean squared prediction error (RMSPE), the coefficient of determination (R^2), and spatial

autocorrelation of error (Moran's *I*) (Moran, 1950). R^2 was calculated to test a 1:1 prediction:observation relationship:

$$R^2 = 1 - \left(SS_{error} \times SS_{total}^{-1}\right), \quad (2)$$

where SS_{error} is the sum of squared prediction errors and SS_{total} is the sum of squared, mean-centered data. Negative values of R^2 are possible under this definition and indicate that predictions are less reliable than the average of the empirical data. Moran's *I* was calculated based on inverse distance weighting using *Moran.I*() of *ape* which also tested significance using permutation (Paradis & Schliep, 2019).

We further evaluated adjusted iSDA stocks for their ability to identify locations with large gaps—those field sites with the top 25th percentile of carbon gaps. Classification of sites as high potential sites was assessed by calculating sensitivities, specificities, and accuracies, by calculating receiver–operator characteristics with the *roc*() function of *pROC* (Robin et al., 2011), and by correlation among methods. Here, significance was tested using permutation and errors calculated by bootstrapping ($n = 999$).

Finally, we used the best-performing iSDA correction to predict carbon stocks, potential carbon stocks, and carbon gaps across Malawi. The best performing model was that with low overall prediction error, low spatial autocorrelation of prediction error, and high classification accuracy.

3 | RESULTS

3.1 | Estimation of carbon stocks, potential stocks, and gaps

To estimate the continued utility of local measurements of carbon stocks, we first compared iSDA predictions of carbon stocks to those we measured in the field. We found iSDA stocks were consistently larger by 28.1 ± 0.4 Mg C ha^{-1} ($p < .001$) due to a substantial amount of inorganic carbon in iSDA predictions. In contrast, none of the soils we sampled contained inorganic carbon. This, combined with the low potential to manage soils to increase inorganic carbon, led us to focus on the comparison between measured SOC and iSDA-predicted SOC.

Measurements of SOC stocks were consistently larger than predictions across all extension planning areas within the study region, by 8.7 ± 1.0 Mg C ha^{-1} on average (Figure 2a). Average current stocks ranged from 18.7 ± 1.3 Mg C ha^{-1} in Nsanama (Machinga district) to 48.8 ± 3.7 Mg C ha^{-1} in Linthipe (Dedza). We further wanted to identify how much carbon soils could store under optimal, agricultural management. In general, higher elevation and finer textured soils contained more SOC, in agreement with previous studies (Matus, 2021; Figure 3). Using dataset-specific quantile regression equations (Table S2), we found that potential carbon stocks in agricultural soils also were larger

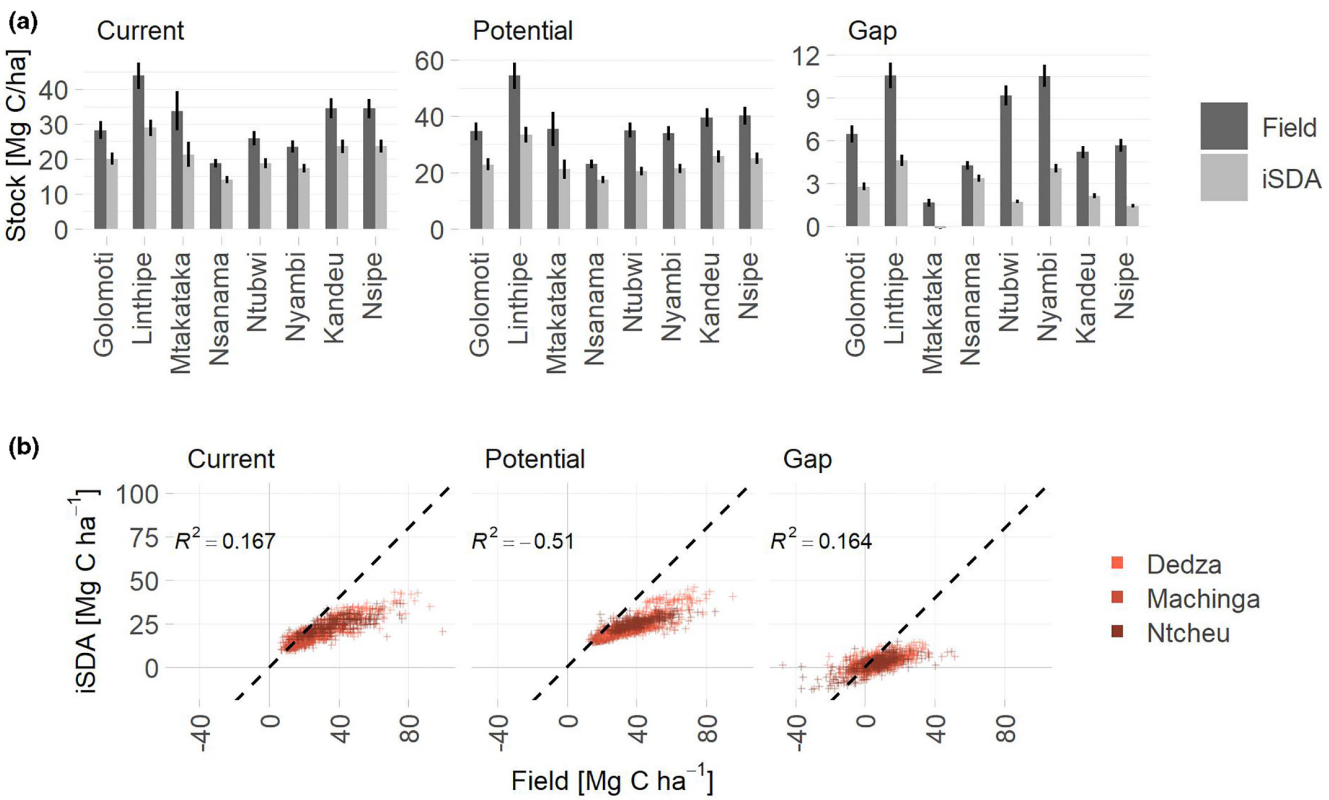

FIGURE 2 Field-measured and iSDA-predicted SOC stocks, potential SOC stocks, and the resulting gap in SOC stocks at sampled locations across the 0–20 cm depth. (a) Means and standard errors within each extension planning area; (b) measured and predicted stocks at each sample location. R^2, coefficient of determination for prediction quality. The dashed lines represent a 1:1 relationship.

than iSDA predicted and averaged within extension planning area were as high as 54.4 ± 4.6 Mg C ha^{-1} in Linthipe (Dezda). Finally, we found a consistently large gap between current and potential SOC stocks that was substantially higher than iSDA predicted (4.42 ± 0.23 Mg C ha^{-1}) and exceeded 10 Mg C ha^{-1} in Linthipe and Nyambi (Machinga). Investigation at the field level revealed an underprediction of current and potential SOC stocks and gaps in the iSDA dataset, especially in fields with more than 20 Mg C ha^{-1}. This was consistent across the sampled region (Figure 2b) and consistent with previous, independent ground truthing of continental soils databases based on remote sensing (Ewing et al., 2021).

3.2 | Local adjustments to iSDA predictions

While iSDA predicted carbon stocks poorly (R^2 = .162; Table 1), predictions were correlated with measured stocks (Pearson's r = .69). Therefore, we tested whether a local adjustment to iSDA values derived from local sampling and additional environmental covariates could improve iSDA predictions of stocks, potential stocks, and gaps at unmeasured agricultural fields. Prediction errors at unobserved extension planning areas for top-down adjustment methods, including the geographically weighted method, were significantly but only slightly correlated across space (Moran's I: 0.09–0.22, p < .001). Closer inspection indicated that the spatial scale of variation in iSDA prediction errors was at the level of extension planning area or smaller and this variation is minor compared to overall prediction error.

In terms of raw correlation, the top-down, stationary adjustment method was both the simplest and the best means to predict SOC gaps: It had the lowest RMSPE (8.23 Mg C ha^{-1}), the highest R^2 (.383), and prediction error had the smallest spatial autocorrelation (I = 0.135). For predicting SOC stocks and potential stocks, the top-down, geographically weighted model was slightly more parsimonious than the stationary model by all measures. Both top-down adjustments reduced prediction errors of stocks and potential stocks by 40%–55% and reduced prediction errors of gaps by 14%. The bottom-up adjustment method performed worse than both top-down methods, but still was more accurate than the unadjusted iSDA predictions for predicting stocks and potential stocks.

This improvement in prediction of the magnitude of carbon stocks with an iSDA adjustment translated to better identification of sites with large SOC gaps (Table 2). We defined these fields as those with gaps in the top 25th percentile and they accounted for 50% of the total SOC sequestration potential across sampled

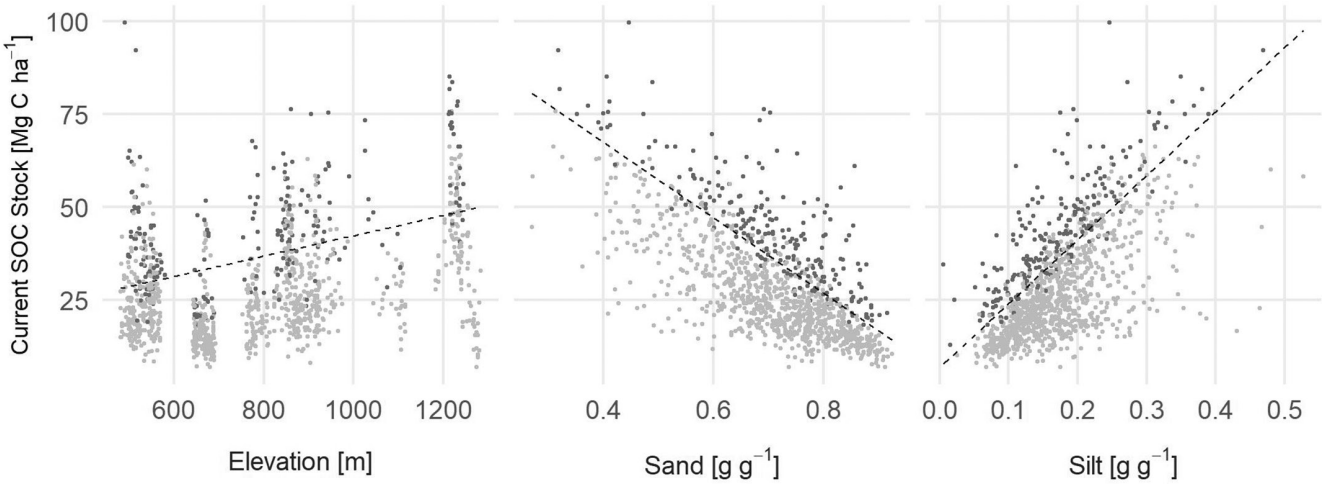

FIGURE 3 Measured SOC stocks across gradients of elevation, measured silt, and measured clay content. Black points indicate fields that are at carbon storage potential, at or above the 80th percentile using quantile regression. Gray points indicate fields that could sequester more carbon. The dashed line approximates this 80th percentile across the indicated gradient.

TABLE 1 Prediction characteristics of iSDA adjustments

	Current stock			Potential stock			Current gap		
Adjustment method	RMSPE	R^2	Moran's I	RMSPE	R^2	Moran's I	RMSPE	R^2	Moran's I
iSDA	13.23	.167	0.239*	16	−.51	0.28*	9.581	.164	0.19*
Stationary (Top-down)	7.999	.696	0.107*	7.765	.644	0.222*	8.228	.383	0.135*
GWR (Top-down)	7.871	.705	0.089*	7.592	.66	0.217*	8.325	.369	0.159*
Bottom-up	8.083	.689	0.083*	9.418	.477	0.379*	9.741	.136	0.308*

*p < .001.

TABLE 2 Ability of iSDA adjustments to identify large-gap[a] sites

Adjustment method	Sensitivity		Specificity		Accuracy	
	Mean	Error	Mean	Error	Mean	Error
iSDA	0.517	0.064	0.881	0.021	0.808	0.022
Stationary (Top-down)	0.55	0.064	0.888	0.02	0.821	0.022
GWR (Top-down)	0.54	0.064	0.886	0.02	0.816	0.022
Bottom-up	0.442	0.063	0.867	0.023	0.776	0.024

Note: Bootstrapped standard errors ($n = 999$). All $p < .001$.
[a]Sites with the top 25% largest gaps.

locations (Figure S2). iSDA identified high-gap sites with an accuracy of 0.81 ± 0.02 and a sensitivity of 0.52 ± 0.06. While better than expected if randomly selected ($p < .001$), the moderate sensitivity indicates that half of identified sites did not have large SOC gaps. The stationary, top-down adjustment's accuracy was 0.82 ± 0.02 with a sensitivity of 0.55 ± 0.06, again better than random selection ($p < .001$) and 6% more sensitive than iSDA. The GWR model performed similarly to the stationary model, while the bottom-up model performed worse than unadjusted iSDA. Still, all methods gave similar classifications, with nearly identical AUC and classification agreements for at least 88% of fields (Figure S2).

With field data corrections of iSDA, we generated updated predictions of carbon stocks, potential carbon storage, and the subsequent carbon sequestration potential in agricultural land in Malawi (Figure 4) and errors of these estimates (Figure S3). Overall, we estimated that the 6.8 million ha of land suitable for agriculture in Malawi has the potential to hold 274 ± 14 Tg SOC in the top 20 cm of soil, an increase of 33 ± 14 Tg C from current stocks, with changes in land management but not land use. These estimates are larger than those predicted by iSDA by 53% for potential stocks and 89% for SOC gaps (Figure 5; Figure S4). These maps highlight that much of the agricultural land in central and southwestern areas of Malawi is near our definition of saturated for soil organic carbon, while the northwest, southeast, and pockets of the Dedza district have high sequestration potential of greater than 15 Mg C ha^{-1}. While carbon stocks and gaps are negatively correlated ($r = -.43$), some carbon-poor soils including lakeshore, low altitude areas in southern Malawi also have low carbon sequestration potential. These observations have implications for directing the investment in practices that build soil carbon and setting expectations for potential increases in agronomic production and stability that accompanies increases in soil organic matter.

3.3 | Recommended approach for regional improvements to iSDA carbon stock predictions

Based on these results, we recommend the top-down, stationary approach for developing regional adjustments to iSDA SOC stock predictions in agricultural lands (Figure S1). First, evaluate the relationship between iSDA predictions and empirical measurements of SOC stocks, where iSDA predictions are based on iSDA predictions of both SOC concentrations and bulk density. Next, identify edaphic and climatic factors that define soils with similar SOC-limiting properties—here, elevation and iSDA-predicted soil texture—through variable selection—here, by LASSO regularized regression. Use the selected factors to develop a quantile regression relationship between iSDA SOC stocks and the covariates at the threshold of choice, which thus represents an expected upper limit or potential of carbon stocks given soil covariates (here, the 80th percentile). With this quantile regression relationship, predict potential carbon stocks across the region of interest and then calculate carbon gaps as the difference between current and potential stocks, with a floor of zero. An Rmarkdown notebook (Xie et al., 2019) demonstrating this workflow is included in the supplementary information.

4 | DISCUSSION

Carbon sequestration happens at the scale of management. In smallholder agriculture, management occurs in fields often smaller than 1 ha (Snapp, 2022). Incentivizing carbon sequestration is more efficient with knowledge of which fields have the potential to store carbon and how large those carbon gaps are. However, a recent synthesis of 192 meta-analyses of SOC highlighted the lack of SOC data at local scales and limited numbers of studies in the global south (Beillouin et al., 2022). Our findings emphasize the persistence of this challenge and demonstrate a solution. Overall, we found that iSDA underestimated the current carbon stocks in Malawian agricultural fields, the potential carbon stocks of these fields, *and* the amount of carbon that could be sequestered as organic matter in these soils. Adjusting iSDA revised the value of filling carbon gaps in Malawi upwards by USD 1375 ha^{-1} on sampled fields, based on a carbon price of USD 85 per ton of CO_2e, the price in the European carbon credit market as of August 3, 2022 (https://carboncredits.com). Scaling this across Malawian land suitable for agriculture, we estimate the value of the 33 Tg carbon gap to be USD 10.4 billion. Revising these carbon gaps is consequential for organizations investing in green development strategies because the value of these strategies is essential to the socioeconomic viability of carbon-based development strategies (Polak & Snowball, 2019).

We begin this discussion by emphasizing the continued, global need for sampling to estimate carbon stocks and gaps at local and regional scales to inform policy, investment, and management. We

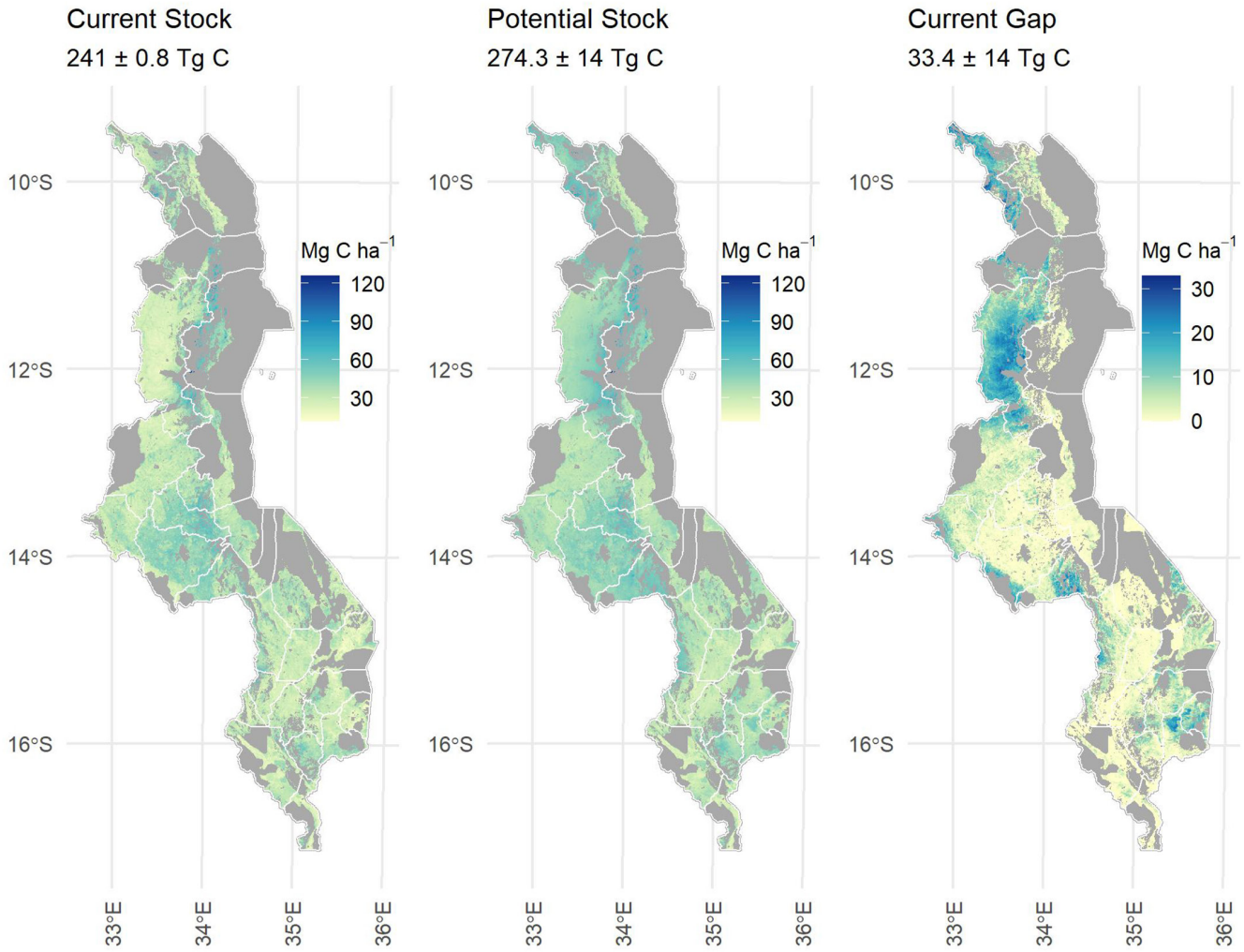

FIGURE 4 Maps of carbon stocks, potential stocks, and sequestration potential in agricultural soils in Malawi. Gray areas mask water or land not suitable for agriculture (category 5 of Li et al., 2017). Map lines delineate study areas and do not necessarily depict accepted national boundaries.

then discuss efficient ways to estimate potential stocks and gaps by setting context-specific benchmarks. We conclude by developing scenarios that highlight the policy implications of updated estimates of stocks and gaps in Malawi within the context of national and global emissions and potential sequestration rates.

4.1 | In-field estimates of soil carbon remain essential for policy, management, and interventions

We found that iSDA, which as of writing provides the highest resolution predictions of soil properties in Africa, was able to identify fields with high storage potential in its current form—if stocks are recalculated using iSDA predictions for bulk density and SOC. However, adjusting iSDA slightly improved sensitivity and resolved a systematic underestimation of SOC gaps. Armed with such identifications of fields, we expect that policies and entrepreneurial activity aimed at improving carbon stocks or capturing carbon credits will be more effective at targeting farmer–partners. Additionally, local adjustments to regional databases can provide an accurate prediction of carbon stocks and gaps within administrative districts.

Still, adjustments to regional databases do not obviate the need for on-site sample collection for quantifying carbon sequestration potential in agricultural soils at the field scale. Rather, such sampling remains an important component of farmer engagement toward increasing SOC stocks. One reason for the difficulty in accurately predicting carbon stocks and gaps—even with datasets augmented with locally collected data—may be that in this region, management varies from plot to plot; as a result, land degradation can be both extreme and highly asymmetric at the scale of tens of meters due to soil's sensitivity to management practices (Li et al., 2017; Moebius-Clune et al., 2011; Snapp, 1998; Tittonell et al., 2005). Continued sampling therefore serves multiple purposes. The first is scientific, to aid the development of regionally specific databases to use in benchmarking to estimate carbon gaps. Additionally, local sampling will validate whether fields

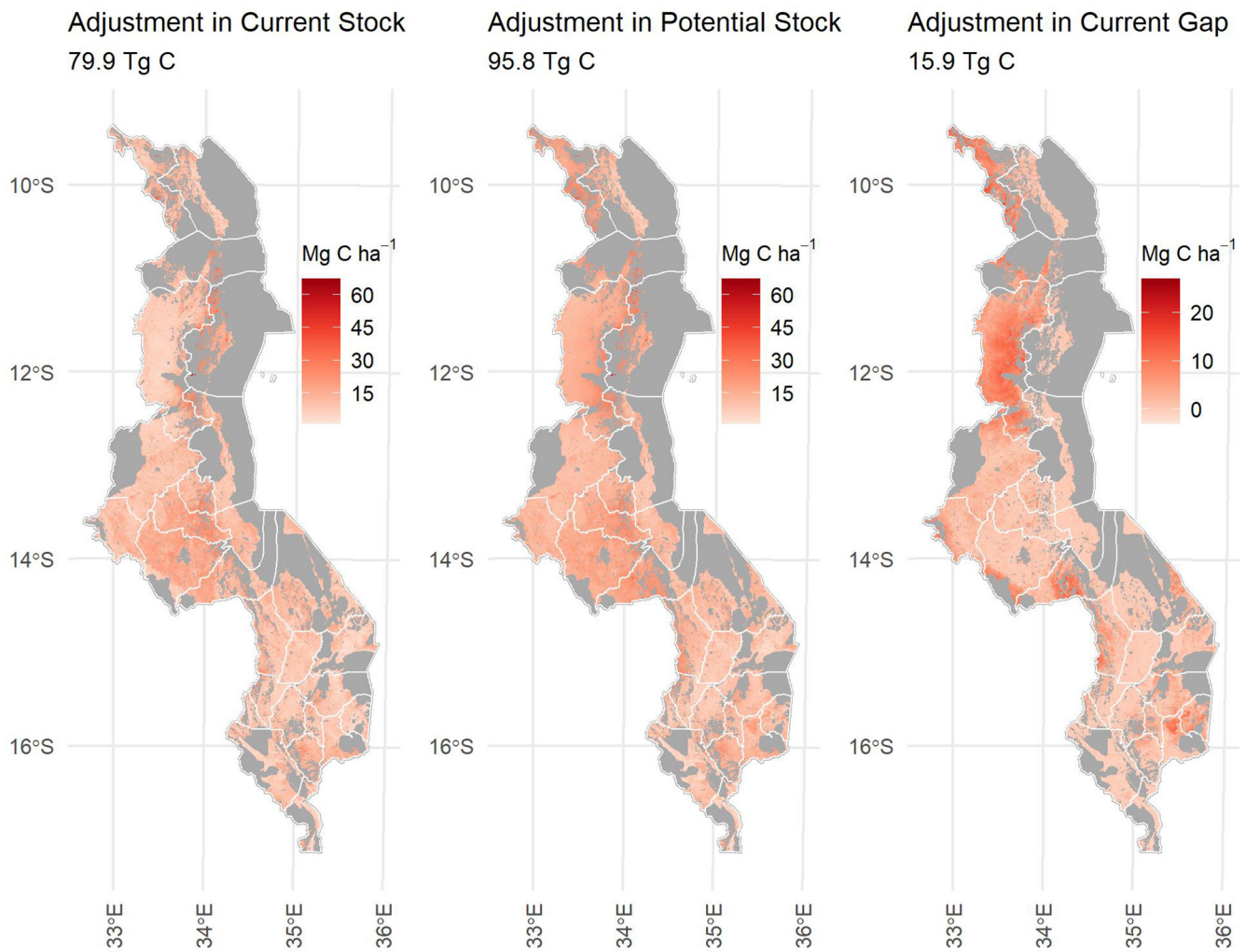

FIGURE 5 Upward adjustment in stocks, potential stocks, and organic carbon gaps from iSDA predictions by the stationary, top-down method. Gray areas mask water or land not suitable for agriculture (category 5 of Li et al., 2017). Map lines delineate study areas and do not necessarily depict accepted national boundaries.

predicted to have large carbon gaps do have large carbon gaps, allowing quantification of the monetary value of carbon sequestration, improving decision making, and facilitating farmer buy-in (Maynard et al., 2022). Repeated sampling will validate successful carbon sequestration and identify practices that sequester carbon in smallholder settings.

Repeated, standardized, field-scale sampling is increasingly feasible in logistically challenging and poorly financed settings. Regarding the type and quantity of measurements, bulk density, texture, and SOC are required at multiple sites to develop iSDA adjustments and carbon storage benchmarks. Texture estimates might be estimated using touch by well-trained technicians (Salley et al., 2018). Bulk density, while labor intensive, varied by around 15% in this study. This sampling can be minimized; in this study, 6.4% of sampled fields were used to adjust iSDA bulk density, which was sufficient to improve iSDA's relative prediction error of bulk density to 7%. Alternatively, locally valid pedotransfer functions might be used to predict bulk density. Finally, the equivalent-mass approach is preferred for tracking changes in SOC stocks with management, which obviates recurring bulk density measurements (Mikha et al., 2013; Rovira et al., 2022). Soil carbon, meanwhile, is increasingly easily estimated using non-destructive, in situ methods. For example, a field-portable and low-cost reflectometer predicted carbon in these same soils with relatively high precision (R^2 = .57–.69 depending on supplementary data; Ewing et al., 2021). These advances dramatically lower the cost of future studies quantifying carbon stocks, creating benchmark sequestration goals, and critically, tracking and verifying progress toward meeting those goals.

4.2 | Benchmarking to predict carbon sequestration potential

The quantification of carbon storage potential is a difficult problem. A combination of edaphic, climatic, biological, and management factors combine to lead to different equilibrium amounts of carbon. In general, converting land from natural areas to

agriculture leads to a rapid loss of carbon until a new equilibrium is reached (e.g. Moebius-Clune et al., 2011). This depletion of SOC with land use change suggests that carbon stocks pre-conversion represent the carbon storage potential. While the natural lands comparison is common in the scientific literature, it is unrealistic using current technology because it implies a massive return of agricultural land to unmanaged or pastureland, with dramatic food security and farmer welfare implications. Additionally, a return to original, unmanaged habitat may not lead to a full restoration of carbon stocks due to, for example, crossing soil degradation thresholds (Gao et al., 2011). Finally, the "natural" state of land use may not maximize soil carbon stocks.

In contrast, we set achievable, data-driven goals for carbon sequestration in agricultural lands using benchmarking. Quantile regression enabled us to predict potential SOC stocks and carbon gaps within an agricultural context and tempered by edaphic and climatic factors. In effect, we identified fields that are approaching carbon saturation, presumably due to carbon sequestering management practices, and used these best examples to set goals for remaining fields. Similar benchmarking of soil health parameters has proven effective for directing management interventions to mitigate soil degradation (Chen et al., 2019; Nunes et al., 2021). For acting upon benchmarking results, it is acknowledged that soil C sequestration in tropical farming systems faces challenges, including rapid SOC loss under intensive cultivation with minimum organic residue return; a loss exacerbated at high temperatures (Fujisaki et al., 2018; Moebius-Clune et al., 2011). At the same time, studies have identified locally effective practices that increase SOC (Cheesman et al., 2016; Corbeels et al., 2019; Luedeling et al., 2011; Nord et al., 2022). Conservation agriculture in Southern Africa involves fine-tuning of practices to fit local conditions, including minimum tillage, crop diversity and management practices, and consistently delivers gains in SOC and soil function (Cheesman et al., 2016). Assessments conducted through on-farm research and monitoring of cultivated lands in Malawi point to residue return, organic manures and compost, and crop diversity as positive determinants of SOC (Snapp et al., 2018; Tu et al., 2022). West Africa is a particularly challenging environment with sandy soils and high temperatures, yet the same suite of practices promote SOC gain in medium- to long-term field experiments (Nord et al., 2022).Context is important for interpreting benchmarking systems as they do not necessarily translate well across regions or cropping systems (Roper et al., 2017). While our sites were limited to maize cropland in south-central Malawi, they captured the range of edaphic conditions in the country in which 44% of annual agricultural land is devoted to maize (Figure 1; Malawi Ministry of Agriculture and Food Security—Planning Department, 2016), which bolsters our confidence in iSDA adjustments and benchmarks. However, a Malawian adjustment may not be valid in neighboring countries; indeed, a preliminary analysis suggests that Tanzania requires a very different iSDA adjustment (Nord et al., unpublished). Explaining this, iSDA was built with different training data depending on availability, data which tend to vary among countries and was collected using varying methods (Hengl et al., 2021). Future studies in other regions of Malawi should validate the iSDA corrections and carbon benchmarks, particularly within specific types of cropping systems, with locally collected data. Studies external to Malawi might use the method described here to develop country-specific adjustments and benchmarks.

4.3 | Sustainability implications of updated estimates of carbon stocks and sequestration potentials

We estimate that Malawian agricultural soil can sequester 33.4 Tg C, offsetting 122 Mt of CO_2e. For context, in 2019, Malawi was responsible for 19.2 Mt CO_2e of emissions. How quickly might these carbon gaps be closed and what benefits might it provide? In the following scenarios, we provide estimates based on the aspirational, four-per-mille (0.4%) per year increase in stocks above current levels in those soils with carbon gaps (Minasny et al., 2017). This rate has been achieved in a majority of studies in sub-Saharan Africa for agroforestry systems, and in some cases, annual cropping (Corbeels et al., 2019). The highest success in studies that combine multiple conservation agriculture practices including reduced tillage, residue retention, and rotation diversification (Cheesman et al., 2016). Additionally, CO_2e offsets are assumed to be worth USD 85 per ton as described above.

If all agricultural land with carbon gaps were immediately to begin sequestering carbon at 0.4% per year, Malawi can expect an initial sequestration rate of 0.51 Tg C year^{-1}, offsetting 9.7% of its total, 2019 emissions (Climate Watch Historical GHG Emissions, 2022) and generating USD 160 million in CO_2e offsets. After just 15 years, 50% of Malawian agricultural land would reach storage potential while sequestering approximately 7.1 Tg C, offsetting 26 Mt CO_2e emissions and generating USD 2.2 billion.

Of course, implementing these conservation practices across all of Malawian agricultural land immediately is unrealistic. A more strategic approach might focus on the most degraded soils. Because these soils tend to have the largest carbon gaps and also the lowest productivity potential, restoring carbon has disproportionately large benefits to both climate mitigation and food security (Corbeels et al., 2019). For example, Burke et al. (2020) found that soils in Malawi with lower than 9.4 g SOC kg^{-1} soil were so degraded as to likely be unresponsive to fertilizer. This leads to agronomic productivity challenges and may limit carbon fixation by plants, which can reduce carbon sequestration (Schlesinger, 2000). After adjusting iSDA predictions of organic carbon concentrations, we estimate that 47% of land suitable for agriculture in Malawi falls into this non-responsive category. Restoring these soils to the 9.4 g SOC kg^{-1} soil threshold (Burke et al., 2020), for example by residue addition and diversification with leguminous crops, would sequester 22 Mt CO_2e over a median of 42 years. Research on smallholder farms in Malawi has shown this could well alleviate climate risks to food security and likely improve farmer livelihoods

(Burke et al., 2022; Snapp et al., 2018). Because degraded soils often sequester carbon proportionally faster with proper management than soils near carbon saturation (Castellano et al., 2015), these results might be realized in substantially less time.

5 | CONCLUSIONS

Global interest in tackling food security and climate change has never been higher, as evidenced by the continued development of carbon offset markets and increasingly generous aid programs to support agricultural development in food-insecure regions. Building soil carbon is well-known to address both challenges. Accurate predictions of carbon stocks and storage potential are critical to this. Our collective knowledge of where soil stores carbon is more precise and accurate than ever thanks to remote measures. Nonetheless, this study highlights how ground truthing remains an essential component of policy and intervention by reducing errors in continental-scale predictions of soil carbon. Relevant soil carbon benchmarks are essential to framing policies and locating high-value areas for investment and interventions.

Effective benchmarking depends on the development of a regional database of agricultural soils, which this work begins. Such a database might follow the model of continental iSDA, which aggregates data from across government, nonprofit, and for-profit stakeholder sources (Hengl et al., 2021), but in contrast with iSDA's extensive reliance on legacy data, focus specifically on contemporary samples collected recurrently from agricultural soils. Such a momentous data collection effort could be facilitated by advancements in soil testing and data aggregation through smartphone-enabled crowdsourcing and low cost, field-portable instrumentation (Ewing et al., 2021; Herrick et al., 2013; Kelly et al., 2022). Doing so could create a robust and broad set of ground measures from samples taken across the region (Paustian, Collins, et al., 2019; Snapp, 2022). Beyond sub-Saharan Africa, this information could be incorporated into continental and global databases to support work in agriculture broadly, and carbon investment specifically.

Understanding the potential for carbon storage is critical not only for smallholders in Malawi, but also for global adaptation and mitigation of climate change. Higher carbon soils would likely improve smallholder productivity which, when coupled with payments for carbon storage, could also increase household economic security, enhancing overall wellbeing in a country where over 80% of people live in rural areas (Malawi National Statistical Office, 2016).

ACKNOWLEDGMENTS

We thank many team members for their dedication in collecting field data, including Emmanuel Jambo, Hannah Livuza, and Edward Mzumara. We thank Dr. Dan TerAvest and Dr. Sharon Schneider for comments on earlier drafts. This study was funded by the United States Agency for International Development Grant AID-OAA-A-13-00006, as part of the Feed the Future Initiative project Africa Research in Sustainable Intensification for the Next Generation with support from the International Institute of Tropical Agriculture. The research was also supported through a Michigan State University contract under International Fertilizer Development Center and USAID under the Prime Agreement No. AID-BFS-IO-15-00001. Mention of trade names or commercial products in this publication is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the U.S. Department of Agriculture. The USDA is an equal opportunity provider and employer.

CONFLICT OF INTEREST

The authors report no conflict of interest.

DATA AVAILABILITY STATEMENT

Source data, scripts, and results are available on Zenodo at https://doi.org/10.5281/zenodo.7392437.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Ewing, P. M., Tu, X., Runck, B. C., Nord, A., Chikowo, R., & Snapp, S. S. (2023). Smallholder farms have and can store more carbon than previously estimated. *Global Change Biology*, *29*, 1471–1483. https://doi.org/10.1111/gcb.16551