Land Use Capability Analysis for Agricultural Land Planning in Niger

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Abstract

Smallholder agriculture is a major source of income and food for developing nations. With more frequent drought and increasing scarcity of arable land, land use planning can be used to better allocate land resources to support regional agricultural activity. To support this objective, we used the Land Capability Classification (LCC) system to map the basic limitations to agricultural use of land. The LCC is a stepwise hierarchical land assessment system that can be used to understand factors that limit land use potential. We carried out our assessment in the Dosso region of Niger. Using two public soil data sets, Food and Agriculture Organization Harmonized World Soil Database and International Soil Reference and Information Center (ISRIC) SoilGrids, and a modified version of the LCC, we developed 250 m gridded maps of LCC values across the region. To validate the LCC maps, we interpolated soil physical data from 1308 field sites in the Dosso region and created LCC maps based on these interpolated data. We find that across the region, land is very severely limited for agricultural use by available water-holding capacity (AWC) which limits dry season agricultural potential, especially without irrigation, and requires more frequent irrigation where supplemental water is available. If the AWC limitation is removed in the LCC algorithm (i.e. simulating the use of sufficient irrigation or a much higher and more evenly distributed rainfall than is received by the Dosso region), the dominant regional limitations become less severe and more spatially varied.

Key Words

land capability classification - drought - land degradation - vulnerability - agriculture

1. INTRODUCTION

Worldwide, there are over 800 million people who are chronically undernourished (FAO, 2017). Africa has the highest prevalence of people who are chronically hungry with undernourishment rates in sub-Saharan Africa (SSA) at 23% (FAO, 2017). Food insecurity is driven by complex interactions of socioeconomic and environmental factors and is exacerbated in places with low adaptive capacity; conditions that are common in smallholder agricultural settings (Connoly-Boutin & Smit, 2016). In SSA, there are a variety of threats to food security occurring at varying scales and magnitudes of severity which enhances the need for multi-faceted interventions (IPCC, 2014).

The projected increases in global temperatures signal that climate-related drivers will persist and likely increase in severity across SSA if greenhouse gas emissions remain uncurbed (Serdeczny et al., 2017). Average temperatures in Africa are projected to rise faster than the global average with some of the highest increases in temperature to be experienced by the Sahel region (Welborn, 2018). Changing precipitation can include increases in the prevalence of events such as prolonged droughts or intense rainfall and floods which can irreparably damage crops (Ogwang et al., 2018). Small-scale agricultural operations face increasing challenges as the industry is highly sensitive to climate change and extreme weather events (Williams et al., 2018). In Africa, only 6% of cultivated land is irrigated (NEPAD, 2013). While 8% of natural disasters globally can be attributed to drought, drought accounts for 25% of natural disasters in Africa (Gautam, 2006). Heat stress and drought conditions threaten the productivity of crops globally through negative impacts on plant growth, physiology and reproduction (Yordanov et al., 2000; Barnabas et al., 2008; Prasad et al., 2017). Extreme climate shocks also have an impact on nutrition and food security which can, in turn, have an effect on conflict (Brown et al., 2020). Furthermore, the severity of damage caused by drought is often unpredictable as it is a function of rainfall, water-holding capacity of the soil, and water losses through evapotranspiration (Fahad et al., 2017; Wildemeersch et al., 2015).

Land degradation further increases the sensitivity of agroecological systems to extreme climate events (Gisladottir & Stocking, 2005). Improving soil fertility in SSA requires farming systems approaches that prioritize addressing barriers across socioeconomic and biophysical aspects (Stewart et al., 2020). About 52% of global agriculture area is affected by land degradation including “soil salinization, acidification, soil crusting and sealing, compaction, organic matter decline, nutrient imbalance, loss of biodiversity and pollution” (Pereira & Bugonovic, 2019). It is estimated that 3.2 billion people worldwide are negatively impacted by the degradation of the land surface with a disproportionate effect falling on those who already face poverty (IPBES, 2018; Barbier & Hochard, 2018). Roughly 40% of land degradation has occurred in developing countries and these countries are projected to experience 78% of the global dryland expansion and 50% of the population growth by 2100 (Huang et al. 2015). In addition, efforts to feed a rapidly growing human population have typically involved agricultural intensification which often speeds up land degradation (Kopittke et al., 2017). Since prevention of land degradation is preferable to restoration of degraded land, land management strategies should attempt to prevent further damage (IPBES, 2018).

In parts of SSA, there is limited adaptive capacity which inhibits the ability to quickly respond to changing climate and land use conditions and prevent adverse effects from hitting vulnerable populations (IPCC, 2014). Adaptation strategies are pertinent to the long-term improvement of livelihoods in Africa due to the high prevalence of climate-related risks. There are a number of methods aimed at improving adaptive capacity of farming systems which address a variety of the drivers of food insecurity. Irrigation infrastructure can potentially alleviate some of the stress brought on by water scarcity through removing the reliance on increasingly variable rainfall (Stringer et al., 2009). Climate resilient tolerant crops and varieties can be used in lieu of crops which are prone to drought and heat stresses (Hadebe et al., 2017) and stone lines and grass bands can be used to reduce erosion and store water thus improving resilience to drought (Traore et al., 2020). To avoid or reverse land degradation, there are land management strategies such as agroforestry systems and integrated crop and livestock systems which can be utilized (IPBES, 2018; Cowie et al., 2018). Efforts to increase adaptive capacity is a top priority in responding to climate-related variability (Welborn, 2018).

Land use planning and management are considered foundational strategies for increasing adaptive capacity (Webb et al., 2017). These strategies aid in the effort to protect or restore soil health and soil fertility for food security, economic growth and national security (Herrick et al., 2019). In the face of increasing drought prevalence, land use analysis can be used to spatially assess agricultural suitability using a variety of physical and social factors. If coupled to strategic planning processes, these efforts could potentially mitigate climate and degradation related risks if combined carefully with appropriate economic and social interventions. A simple, and widely used approach to land use planning is the Land Capability Classification system (LCC). LCC is a land potential evaluation system that identifies land suitable to cropping or grazing land use and the associated physical limitations to productivity risks of degradation and has been used to identify and implement management interventions to improve agricultural productivity and sustainability (Abd-Alla Gad, 2015; Tiruneh, 2015). Using LCC provides the flexibility to assess constraints to agriculture at any scale and in any location where sufficient data is available. In addition, we can modify the limitations considered in LCC calculations to fit the landscape or crop in/ question (Quandt et al., 2020). For example, flooding would not be a limiting factor if a farmer was growing flood resistant rice varieties but would be a limitation if growing maize.

In this study, we create gridded LCC assessments for agriculture in the Dosso region of southwest Niger; an area that is important for regional food security. Further, there is significant interest from the Government of Niger and several research and development organizations. We built assessments using two publicly-available global soil map datasets and compared these assessments to LCC estimates based on field data thus demonstrating the opportunities and limitations of using different types of soil maps where field data are unavailable. The use of these public datasets for spatial assessments of agricultural suitability provides support for land-use planning and management in areas which are data scarce. It also allows increased scale of assessment to investigate larger areas of land since this soil data is available globally.

2. METHODS

2.1. *Study Site Description*

The Dosso region of Niger (Figure 1) is the southwestern tip of the nation on the border of Benin and Nigeria. Niger is in the Sahel region of Africa, the ecoclimatic and biogeographic zone of transition nestled between the Sahara Desert and the Sudanian Savanna. Over half of the

Sahelian region relies directly or indirectly on agriculture for employment and more than 95% of the agriculture in the Sahel is rain-fed (Potts et al., 2012).

2.2 Land Capability Classification

The LCC framework groups soils based on their limitations to their use for agricultural production (see Table 1 for breakdown of classes). The LCC system parses land into eight classes based on factors that may limit current production, as well as the sustainability of future production. It identifies limiting factors that must be managed (see Table 2 for limiting factors) to reduce degradation risk, increase production, or both. These classes can be used to support land use planning decisions, technology targeting, and can serve as the first step in determining specific crop and crop production system suitability. Furthermore, determining the limitations of soils provides information about potential interventions which could be used to improve soil capability.

To create LCC assessments, an LCC value was calculated for each spatial unit. The full process is described in the supporting information but briefly, the overall LCC value was taken by first calculating an LCC value for each of the subclasses (Table 2). The maximum of the subclass LCC values (reflecting the most severe limitation) was taken to be the overall LCC value and the subclasses with values that were equal to the maximum value are denoted as primary limitations. We examined both primary and secondary limitations in the results to examine the shift that occurs if a primary limitation is addressed through management.

In this study, i) we use three separate data sets, including two publicly available soil map products, to create gridded maps of LCC for the Dosso region; and ii) we compare the results of the field data-based product to the two soil map products for both LCC designation and identification of the primary limitation.

2.3 ***Data and Spatial Scale***

LCC requires a set of soil attributes as input variables. The variables needed for the calculation of LCC are outlined in the supporting information. The two publicly-available soil datasets we use are Food and Agriculture Organization (FAO) 30 arc-second (~1 km) Harmonized World Soil Database (HWSD) and International Soil Reference and Information Center (ISRIC) 250m SoilGrids data (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009; Hengl et al., 2017). HWSD is a global traditional soil map product based on available local and national soil maps. One or more soils is associated with each soil mapping unit and the average percent contribution of each soil is estimated for each unit. SoilGrids predicts soil attributes using global covariates and common algorithms fitted with local data to develop spatial models of soil properties. Instead of predicting what “soil” will occur at a location, it independently predicts each soil property at each depth for each pixel (Sanderman et al., 2017; Zomer et al., 2017).

Slope was calculated by using the “Spatial Analyst Tool Surface Slope” in ArcGIS environment with the most recently available Sentinel-2 12.5 m resolution Digital Elevation Model (DEM). We chose to start with 12.5 m resolution slope data in order to investigate the effect of high resolution slope on LCC values. High resolution DEM data was aggregated out to 250 m at subsequent steps in analysis to improve processing speeds as initial analysis results informed that 12.5 m resolution soil data did not provide much additional variation in LCC assessments due to the lower resolution of soil data used.

Both of the publicly-available datasets lack some of the variables which are needed for LCC analysis thus modifications were made to the LCC algorithms to incorporate whichever attributes do exist. For more information on data attributes used, please refer to the supporting information.

2.4 *Field Data*

2.4.1 *Study site*

The soil fertility survey was conducted in the Dosso region located 13°02'46"N and 3°11'50"E in Niger. Mean annual rainfall in the region is 635 mm and varies from 350 mm in the Northern part to 800 mm in the Southern part of the region with strong intra and inter annual variation (ANADIA2, 2018). The soils derived from three major soil groups i.e. the ferruginous soils, the hydromorphic soils and the newly developed soils from alluvial deposits (Annou, 2000).

2.4.2 *Soil sampling location*

The soil sampling covered the entire Dosso region, except a few locations in the upper North, owing to security threats during the sampling period. A random stratified approach was used for selection of soil sampling locations. Soil properties characteristics from clay content and soil organic carbon grids (ISRIC, 250 m resolution) and climate characteristics from DEM (SRTM, 90 m resolution) were used to determine soil fertility related influences between the different areas, and based on these influences, random samples were generated between the grids to determine the most ideal locations for sampling. Road networks (open street data) were used to determine accessibility and a buffer of 3 km used to get locations to sample. A total of 1305 sampling points were selected (Figure 1B).

Surface soil was collected by means of a stainless steel auger at approximately 20 cm deep. At each geo-referenced sampling location, a composite soil sample was obtained from 10 soil cores randomly collected in a 10 m-radius around the main sampling point. The samples were air-dried at room temperature, sieved through a 2 mm mesh and stored in paper bags for subsequent chemical analysis.

2.4.3 *Laboratory analysis*

Soil pH, total N and total organic carbon were determined by NIR spectroscopy, based on a calibration from wet chemistry methods using 100 samples, and the associated R^2 values. Phosphate and exchangeable bases (Ca, K, Na and Mg) and B were extracted with the Mehlich 3 method and determined by inductively coupled plasma optical emission spectroscopy (ICP-OES, Mehlich, 1984). Sulfate was determined by the Ca-sulfate procedure (Bashour, 2007) and micronutrients (Cu, Mn, Zn and Fe) were analyzed by the EDTA method (Hughes et al., 1996).

2.5 Spatial Analysis -

Three distinct data products were created with soil input data from interpolated Field Data, FAO HWSD, and ISRIC SoilGrids. We calculated LCC on a per-pixel basis in order to generate spatial assessments of LCC values. All maps are 250 m in resolution. Where input data was not 250 m in resolution, resampling was used to either increase resolution (HWSD resampled from 1 km to 250 m) or aggregated from lower resolution (DEM slope resampled from 12.5 m to 250 m resolution via averaging). The area of the Dosso Reserve was excluded from LCC maps as it is not considered potential agriculture land.

In order to create a gridded field dataset from the original point data collected, we interpolated each soil attribute using ordinary kriging. For more information on the kriging process, please refer to the supporting information. We interpolated field data at 250 m resolution in order to match the resolution of the other two LCC assessments. Because the average distance between field sites is 2,742 m, the 250 m resolution provided sufficient coverage without multiple points falling within the same pixel.

LCC algorithms were based on those used in the Land-Potential Knowledge System mobile application (LandPKS) which provides non-soil scientists with the ability to determine LCC through a mobile interface. The algorithms used in this study were developed based on a review of the LCC implementations throughout the world, and represent a consensus approach to LCC (see supporting information for full outline of algorithms) (Quandt, 2020). Where direct replication could not be achieved due to constraints of the available attributes, modifications were made with help from the LandPKS team. In addition to calculating LCC using all variables, we also calculated LCC without the primary limitations.

3. RESULTS

Our investigation finds that across all three soil attribute data sets (i.e., HWSD, SoilGrids, and interpolated field data) LCC values are high (meaning poor suitability for crops) in the Dosso region (Table 3). For the interpolated field data assessment, the majority of the region (95.1%) is ranked with a LCC value of 4 - Very severe limitations with fewer cropping options and/or requiring extensive conservation practices. In addition, in the interpolated field data assessment a small portion of the region (1.5%) falls into capability Class 5 - Not suitable to crop cultivation. HWSD also assesses that a large majority of the region is classified as LCC of 4 (87.5%) and that a small portion (3%) is unsuitable for agriculture. We investigated the LCC values and limitations of subdominant soils (<50% of soil mapping unit) in the HWSD dataset and found only minor differences in severity of LCC classes or limitations. Due to the limited number of soil mapping units within the HWSD dataset, the LCC analysis is unable to detect the spatial heterogeneity of LCC severity and limitations. SoilGrids assessments provide the most optimistic evaluation with 53.9% of the region classified as LCC of 4 and 44.6% classified as LCC of 3. None of the assessments generate LCC values with no (Class 1) or moderate (Class 2) limitations to agriculture.

The spatial distributions of LCC assessments also vary across the three soil data sources (Figure 2). In all of the assessments, the southernmost tip of the Dosso region has lower LCC classes indicating better potential for agriculture. Furthermore, all of the maps have LCC values of 5 or above (i.e., unsuitable for agriculture) on the southeastern border of the region. The differences between spatial distributions of the underlying soil data attributes is mimicked in the spatial distribution of LCC values (Figure 2). The interpolated field data does not have a substantial amount of spatial variation in LCC values. SoilGrids has a high amount of spatial variability while HWSD has large polygons which underlie the assessments.

When we remove the primary limitation, AWC, from LCC calculation, LCC values decline across the region and across assessments (Table 3). In the assessments of interpolated field data, the removal of AWC shifts to a majority (92.3%) of the region classified as LCC of 3 instead of LCC of 4. While an LCC of 3 still denotes severe limitations to agriculture, this is a movement in a positive direction for agricultural development. Furthermore, a portion of the region (6.1%) moves into an LCC of 2 - moderate restrictions to agriculture. HWSD and SoilGrids assessments also move to the majority of the region classified as LCC of 3. While HWSD evaluates the region as 97.05% LCC value of 3, SoilGrids classifies 66.4% of the region as an LCC of 3 with 32% of the region classified as LCC of 2.

Across all three assessments, the primary limitation for the majority of Dosso is available water-holding capacity. In the interpolated field data assessment, 98.5% of the region has AWC as a primary limitation and 1.5% with a primary limitation of surface stoniness (recall that there can be multiple primary limitations if multiple subclasses have maximum LCC values). SoilGrids has an identical breakdown of primary limitations which is the same as that of the field data since both share the same surface stoniness data. HWSD has slightly higher rates of surface stoniness as a primary limitation (7%) but still assesses the majority of the region (93%) as limited by AWC.

The spatial patterning of limitations is similar across all three assessments with the southeastern tip of the Dosso region showing primary limitation of surface stoniness (Figure 3). HWSD has less spatially detailed limitations due to the polygon soil mapping unit structure of the underlying soil data. Subdominant soil mapping units did not produce substantial differences in limitation with the exception of one polygon in the southeastern tip where the primary soil unit denotes an impermeable petroferric layer while subdominant units do not. Furthermore, when considering subdominant soils we found little within-map heterogeneity with respect to AWC and as a result subdominant soils provided little benefit to our analysis.

When we remove the primary limitation (AWC) from the LCC calculation, we investigate the soil suitability if land-planners were to manage for this limitation with irrigation technology. We find that in the interpolated field data assessment, the primary limitation shifts to lime requirement (28.5%), surface stoniness (10.4%) or a combination of both (55%) with the remaining 6.1% being a combination of many limitations. In the SoilGrids assessment, we find that 58% of the region is limited by surface stoniness, 28.5% is limited by texture and surface stoniness, and the remaining parts of the region are limited by a combination of subclasses. In HWSD, 100% of the region is limited by surface stoniness.

4. DISCUSSION

Niger's agricultural system has low adaptive capacity in the face of a changing climate due to limited irrigation capacity and low economic development. It serves as a case study for other parts of SSA that face similar constraints. The analysis approach presented in this paper highlights the broad challenges to agricultural development in Niger. However, the constraints on agriculture in Niger are multifaceted and spatially varied and potential interventions and responses may be more effective if these complexities are addressed.

As Niger is projected to reach a population of 65.6 million by 2050 (medium-variant estimate, United Nations 2019), there is a growing population of Nigeriens who will need food and employment - both of which can be supported by a strong agricultural system. One of the main solutions presented to stabilize the Sahel region of SSA is to improve agricultural systems and natural resource management (Potts, 2013). Furthermore, improving agriculture may also help prevent civil unrest as conflict often stems from natural resource scarcity and lack of arable land (Shettima and Usman, 2008). The combined challenges of social conditions and biophysical conditions which limit or stress agricultural production underpin the need for thoughtful management practices.

When land management plans are created, there are considerations external to the biophysical properties which need to be considered. For example, while irrigation may greatly reduce the limitation of AWC, this is an expensive and possibly impossible investment for many farms (Nakawuka et al., 2018). There may not be groundwater available or infrastructure in place to utilize this strategy. In many parts of SSA, land tenure may pose challenges to management plans (Barrows and Roth, 1990; Schuck, E. C., Nganje, W., & Yantio, D., 2002). In addition, the prevalence of pastoralism may impact decision-making as conflicts between grazing and crop production can be significant in this region (Shettima & Usman, 2008; Muhammed et al., 2015). The best management for given limitations must be feasible. What is pinpointed by LCC analysis as the most impactful intervention may not be an option and this is important to recognize early in the planning process. Sub-optimal farming conditions will also persist if individuals lack the capacity or capital to change their practices or when social conditions prevent adaptations of new techniques (Lal, 2007; Bryan et al., 2013). Despite the various constraints identified above, the LCC analysis is a reasonable first step toward improved management of the physical environment. The LCC framework allows for a highly customized approach to management that can then be modified based on additional physical, financial, or social constraints.

Our results show that in the Dosso region there are very severe limitations to agriculture. All 3 LCC assessments show a majority of the region ranking as LCC Class 4. This indicates that limitation-specific intervention strategies will be needed in order to improve the capability of land for agricultural use. In addition, all three approaches indicate that over 90% of land in the Dosso region is primarily limited by AWC and is thus vulnerable to drought. While there is broad agreement that there are severe limitations to agriculture, there is a notable amount of spatial heterogeneity in both the severity and type of limitations when we remove AWC form LCC calculation. This has implications for management as this heterogeneity will affect which intervention strategies are suitable or chosen across the region.

In the Dosso region of Niger, the primary LCC analysis identified AWC, which is a function of soil texture (sand, silt, and clay content), volumetric gravel content, organic matter content and soil depth, as the most prevalent limitation. Since the textures in this region are high in sand content, water infiltration rates are high and retention is relatively low which means that water management is critical to long-term agricultural success. In rainfed agricultural systems, the ability of soil to hold water is crucial in the face of drought events (Cornelis, 2019) and variation in AWC can be a key factor in determining whether a site is more or less vulnerable to drought conditions. Soils that hold more water may support plant growth for longer periods of time when rainfall is sparse. Possible management responses to the widespread AWC limitation are irrigation, use of drought tolerant crop varieties, and use of land for grazing rather than cropping systems. Improvements in soil structure and organic matter content can increase AWC, though this is quite challenging in dryland annual cropping systems. These are additionally subject to the economic, social, and land tenure constraints identified previously.

There is disagreement between the three analyses when investigating secondary limitations and these differences could be important especially if additional irrigation is developed in the region. Most notably, SoilGrids and HWSD fail to detect the widespread soil pH issues identified from field sampling that would need to be mitigated through the addition of lime. The other key issue that varies between the input datasets is soil texture which has important implications for soil water holding capacity, erosion potential, and other factors. In our analysis of the Dosso region, we find that HWSD texture values are closer to that of the field data than SoilGrids. SoilGrids under-predicts the high levels of sand content and thus presents texture as more favorable to agriculture than the field data suggests. Upon removing AWC as a limitation, SoilGrids continues to underestimate overall LCC constraints while HWSD tends to overestimate the severity of limitations to agriculture. Both HWSD and SoilGrids fail to detect the nuances of secondary limitations to agriculture and particularly the presence of low pH soils in the region that was identified in field sampling. These differences are large enough to generate more favorable LCC ratings for the Dosso region overall.

Both HWSD and SoilGrids lack the detail which is shown in the field data assessments and this region of Niger may be a uniquely challenging location for the use of both of these products. In the case of HWSD, the large spatial scale is a challenge for a regional analysis like this. It is possible that improved consideration of subdominant soils within HWSD could provide useful information which could be incorporated into LCC analysis for added robustness but spatial attribution of dominant and sub-dominant soil properties remains a challenge with this product. While SoilGrids provide higher spatial resolution, there are also large differences between the SoilGrids attributes and field data. In Niger, this may be due to the small amount of training points available in the region as inputs to the SoilGrids models. As was noted by Hengl et al. (2017), semi-arid and arid areas are often undersampled . It is possible that in other areas of the world, where there are more training samples, SoilGrids would result in estimates that are closer to actual field conditions. In addition to textural limitations, the depth of soils also affects available water holding capacity as deeper soils can hold more water but at present we lack sufficient information to evaluate this factor at a regional scale. For our analyses, we did not have soil depth data collected at the field sites or depth attributes in the publicly-available datasets. However, root-limiting layers including hardpans have been widely documented in Niger and some field evaluation should be considered to improve estimation of this potential limitation.

While it is ideal, field data is expensive and time consuming to collect. Despite the dense field measurements available for this analysis, these data are still incomplete in a number of important ways. Many of the attributes which are needed for LCC analysis (volumetric gravel content, soil depth, etc.) were not measured. Since soil was only sampled to a depth of 20 cm at the field sites, we used the 0-20 cm soil depth measurements for the 20-100 cm depth attributes that are necessary for calculating LCC for the full profile. This can be an issue as subsurface texture can be an important constraint to agriculture and surface textures tend to be more coarse than subsurface textures. Clay content typically increases with depth, which in these coarse-textured soils would generally improve AWC, potentially reducing this limitation. When exposed at the soil surface by erosion, these clay-rich layers can limit infiltration. Furthermore, volumetric gravel content was not measured at the field sites thus data from SoilGrids was used to augment the field data. The limitations in the field data in this study are a common issue across many or most field measurement campaigns as there are economic and logistical constraints to field sampling in all regions and especially in a field setting as challenging as Niger. In virtually all cases, there is rarely sufficient detail in field sampling to create high resolution management strategies. As a result some combination of field data collection and incorporation of existing geospatial resources may be the most effective near term regional analysis and mapping strategy.

There are many ways to improve LCC predictions. Most notably, additional, more complete site level data with a wide variety of attributes and a variety of sampling depths would yield higher confidence in the resulting LCC analysis. In the absence of such data, we suggest that the combination of this type of analysis and targeted field assessment could yield a viable hybrid approach. The broad scale analysis here has identified AWC (soil texture) and pH as two key variables. Given this information, high resolution site level data in areas of interest could be obtained to identify these limitations. This might include field determination of pH values, and hand textures of soil supported by the use of a mobile application such as LandPKS. If the texture analysis was extended to include both surface and subsurface soils, and combined with the spatial data developed here, a reasonably accurate site-scale analysis could be rapidly developed and deployed in conjunction with agricultural interventions such as micro-scale irrigation. At a larger scale, information on water table depth could be used in conjunction with this mapping exercise to localize and prioritize irrigation strategies.

5. CONCLUSIONS

The LCC provides a first-step assessment of agricultural potential and identifies the limitations which may impact the usage of land for agriculture at a regional scale. While this provides a starting point for devising a management strategy, it is not sufficient for making farm-level decisions. Even on small farms, there is often a substantial amount of heterogeneity in soil attributes and management concerns. Furthermore, when using public datasets, the resolution will not provide information at a scale which is compatible with smallholder systems. In order to fully understand the management considerations, there must be some way of locally assessing capability or input soil attributes. Field sampling at the farm level is one way to do this. Other methods of local assessment include using mobile apps such as LandPKS. Understanding the key underlying limitations to land capability is critical in attempting to improve agricultural outcomes and to build resilience to climate change and extreme weather events. Furthermore, understanding the spatial variation in limitations can lead to improved allocation of resources and interventions. Land management plans must be as varied as the landscape itself in order to be efficient and effective. When resources are scarce, targeting high risk areas with low cost interventions can maximize outcomes.

Data Availability Statement

Source code is available for download at https://github.com/taraippolito/nigerLCC. These data were derived from the following resources available in the public domain: https://soilgrids.org/ and http://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/.

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Tables

TABLE 1: Abbreviated Land Capability Classification Ranking System (USDA)

Capability class codes†	**Soil limitations for agricultural use**
LCC class 1	Most suitable for cropping systems with few limitations to crop growth
LCC class 2	Suitable for agriculture with moderate limitations that may restrict crop selection or require specific management practices
LCC class 3	Severe limitations that will significantly reduce cropping options and/or require extensive conservation practices
LCC class 4	Very severe limitations with fewer cropping options relative to class 3 and/or more extensive conservation practices
LCC classes 5-8	Not suitable to crop cultivation

† *Class codes are used to represent both irrigated and non-irrigated land capability classes.*

TABLE 2: Land Capability Classification Subclass Limitations and possible interventions. For more interventions see www.wocat.net.

Subclass		**Potential interventions**
Erosion		Stone lines; halfmoon; grass bands; zai; reduced tillage; agroforestry; pasture; hay; conservation
Soil		
	Depth	Zai; halfmoon; tied ridges; possibly deep tillage (only where depth to a non-bedrock root-limiting layer that can be broken and erosion risk is low); agroforestry; pasture; hay; conservation
	Surface soil texture	Increase organic amendments such as manure, compost and crop residues to support seedling establishment; leave crop residues or use cover crops to protect soil surface from wind and water erosion
	Salinity	Plant salinity tolerant crops; modify irrigation schedule and amount to mitigate near-surface salt accumulation from both

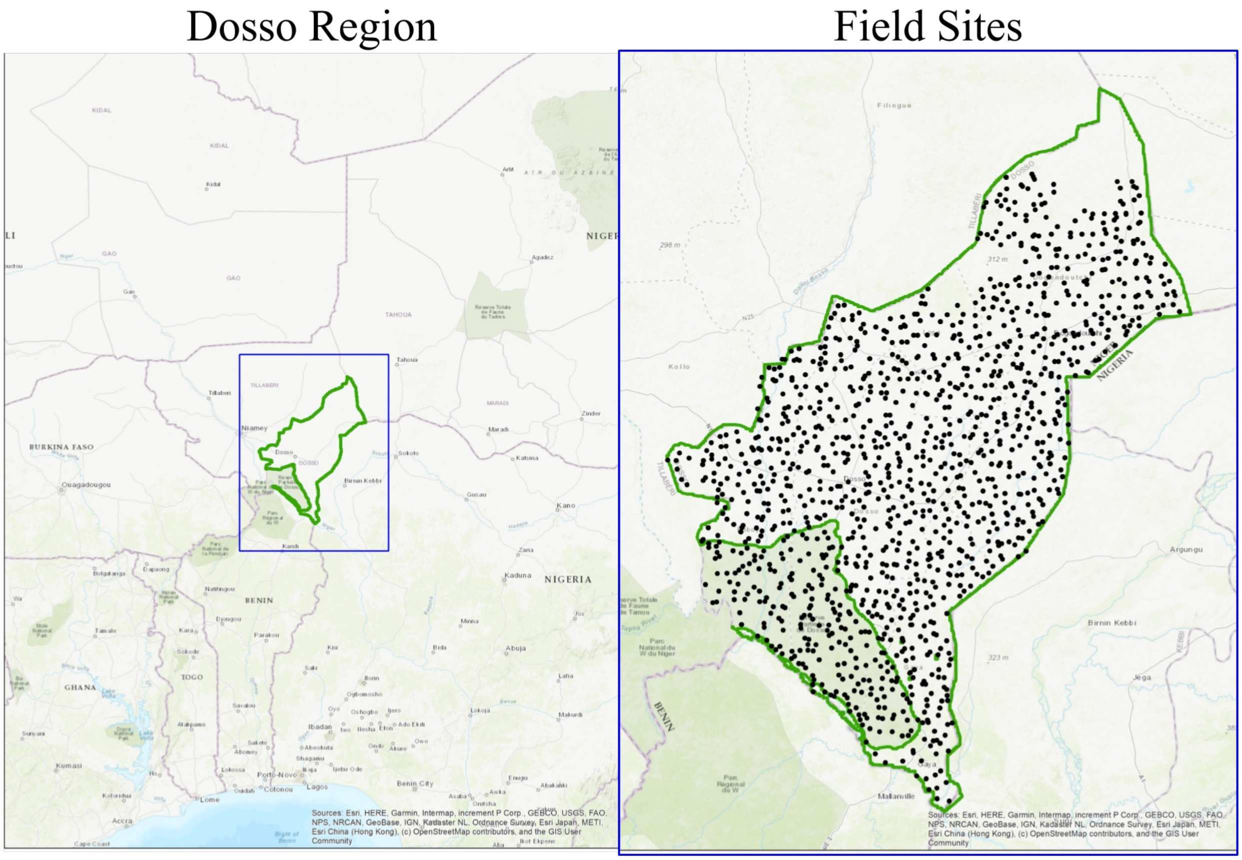
	soil parent material and salts in irrigation water.
Surface stoniness	Remove stones or use planting methods that are not limited by surface stones
Soil water storage capacity	Increase organic amendments such as manure and crop residues; use drought tolerant crops including pasture and hay species; use zai, stone lines, grass bands, tied ridges, contour ridges and half moon for rainwater capture; install irrigation; keep soil surface covered; reduce planting density
Lime requirement	Add lime; some biochars in some cases; use non-acidifying fertilizers
Wetness	
Flooding	Communal level dams, use flood tolerant crops
Water table depth	Conservation; pasture; hay
Permeability	Increase organic amendments such as manure and crop residues; use zai, stone lines, tied ridges, contour ridges, grass bands, and half moon for slowing surface runoff; some tillage

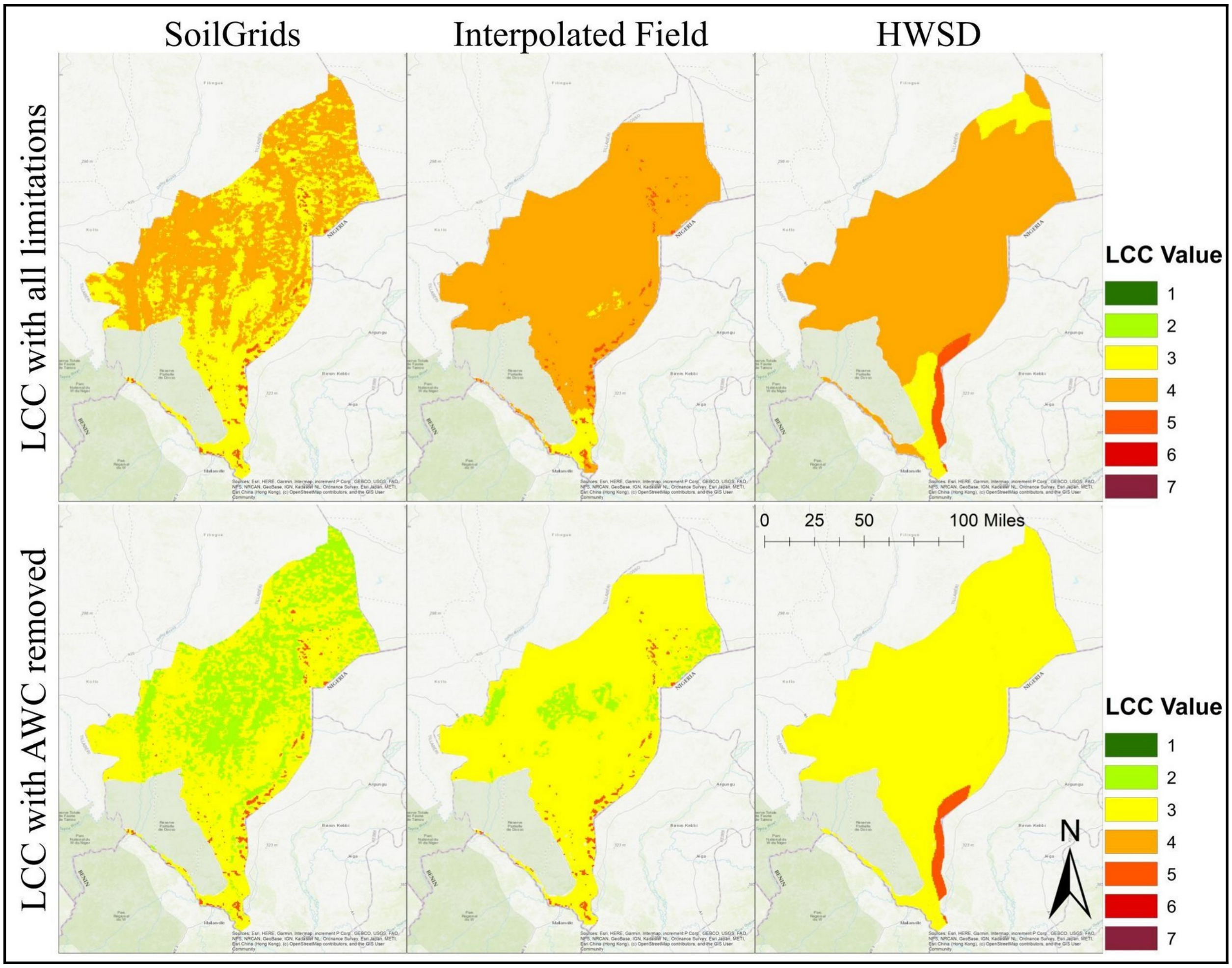
TABLE 3: Land Capability Classification breakdown with all limitations considered

LCC results with all limitations considered					
Input soil dataset	LCC class 1	LCC class 2	LCC class 3	LCC class 4	LCC class 5
Interpolated field data	0%	0%	3.4%	95.1%	1.5%
FAO Harmonized World Soil Database	0%	0%	9.5%	87.5%	3%
ISRIC SoilGrids	0%	0%	44.6%	53.9%	1.5%
LCC results with available water holding capacity removed as a limitation					
Input soil dataset	LCC	LCC	LCC	LCC	LCC

	class 1	class 2	class 3	class 4	class 5
Interpolated field data	0%	6.1%	92.3%	.04%	1.5%
FAO Harmonized World Soil Database	0%	0%	97.05%	.05%	2.9%
ISRIC SoilGrids	.003%	32%	66.4%	.04%	1.5%

Figures




SoilGrids
Interpolated Field
HWSD
LCC with all limitations
LCC with AWC removed
LCC Value
1
2
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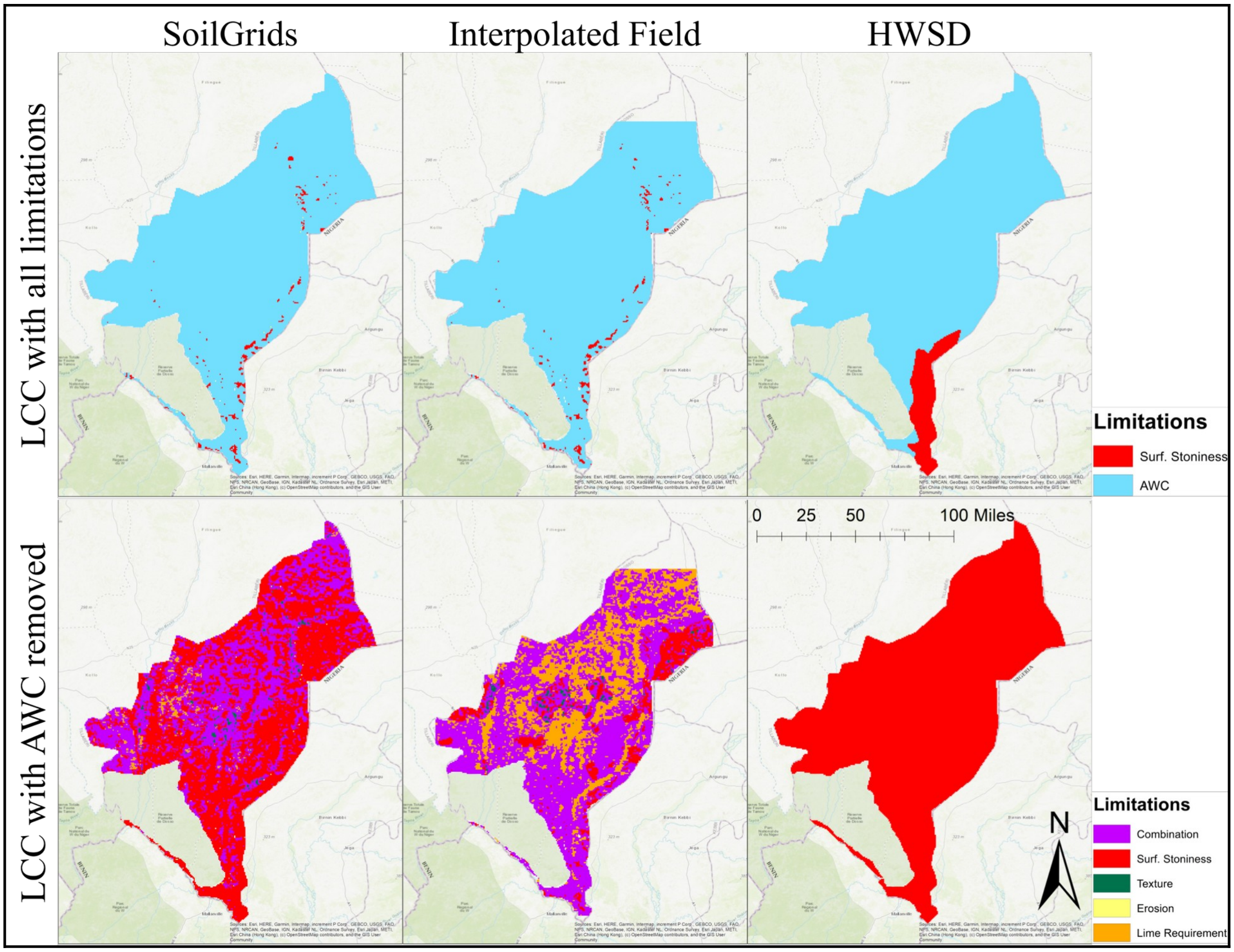


FIGURE 1 *(A): Boundary of the Dosso region of Niger. Dosso reserve has been removed from Land Capability Classification assessment as it is not considered potential agricultural land; and (B): 1308 field Sites in the Dosso Region*

FIGURE 2*: Land Capability Classification (LCC) maps for SoilGrids, Field Data, and Harmonized World Soil Database (HWSD). LCC ranges from 1 to 8 and is calculated on a per pixel basis*

FIGURE 3*: Limitation maps for SoilGrids, interpolated field data and Harmonized World Soil Database (HWSD). Note that the field data image uses surface stoniness inputs from SoilGrids resulting in the similar spatial patterning*

Supporting Information

Methods

The LCC approach typically includes the evaluation of climatic conditions (primarily mean rainfall) as one of the factors influencing agriculture. We did not include this limitation in our LCC analysis for two reasons. First, the majority of this region (with the exception of the southern portion of Dosso) is very low rainfall and crop growth is understood to be constrained by rainfall amounts. Second, rainfall in this region has high interannual variability making a characterization of average rainfall less valuable for the prediction of cropping potential than it might be in a more stable climatic region. Lastly, the relatively constraint of precipitation depends on the crop and is best evaluated through a crop suitability analysis. Our approach to LCC (excluding climate) provides a physical system/soil baseline for capability analysis. It also allows identification of some key modifiers of site capability including the water holding capacity of soils.

To calculate LCC for each pixel, we modified the resolution to be uniform across datasets and layered soil attributes with slope data so each pixel had all attributes needed for LCC calculation. In order to layer soil attributes with slope data, all datasets had to be processed in ArcGIS to ensure pixel alignment and to modify resolution as needed. The ArcGIS "Spatial Join" tool was used during data processing in order to layer data. All input datasets were projected onto the same coordinate system in order to ensure there is no geographical displacement between datasets (i.e. all pixel boundaries need to perfectly overlap). Each input dataset was trimmed to the area of analysis - the Dosso region.

In kriging first order trends for sand, silt, and clay values, were removed as there is a North/South trend in texture values. Trend removal is a key component of ordinary kriging so that the kriging model is built on the autocorrelation structure of the data; thus the spatial relationship between sites is understood and used in prediction of texture values. The North/South trend in texture values is still preserved in resulting predictions. Kriging was implemented within ArcGIS using the Geostatistical Wizard tool.

Data

FAO Harmonized World Soil Database (30 arc-second) -

HWSD global soil data attributes are derived from analyzed profile data which were obtained from a wide range of countries and sources (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009). There are soil attributes for the 0-30cm horizon (topsoil) and the 30-100cm horizon (subsoil). Since these profiles are unevenly distributed across the globe, there are large gaps in the measured data. HWSD includes 15,773 soil mapping units globally where each soil mapping unit is attributed with a number of soil properties for each soil in the unit, including topsoil texture, pH, and volumetric gravel content. Each soil mapping unit can include up to 9 unique soils, where soil units each is assigned an average (across all occurrences of that unit) share (from 0 to 100%) of the overall soil mapping unit. In Niger, there were 62 soil mapping units and in the Dosso region there were 16 polygons, associated with a total of 13 unique mapping units (figure 3). This scarcity of soil mapping units presents a limitation to accurately assessing and mapping the LCC of the region. We chose to use only the primary or dominant soils for each soil mapping unit (i.e. the soil unit with over 50% of the share in the soil mapping unit).

Each type of polygon may repeat in different parts of the landscape where soil forming factors (climate, organisms, topography, parent material and time) are similar. Traditional soil maps are based on a combination of remote sensing and field data, field observations, and the mapper's understanding of soil processes, and soil-landscape relationships, and is often also informed by local knowledge. Thus it often results in a relatively accurate product, but due to the scale of mapping, can be quite imprecise at point locations, particularly when only the dominant soil for the map unit is considered. It is also both less accurate and less precise than the local to national maps from which it is derived for a number of reasons, particularly the presentation of soil properties for just 2 standard depths: 0-30cm and 30-100cm. HWSD is used as an input in a wide range of products such as NASA Soil Moisture Active Passive Product (SMAP, 2014).

ISRIC SoilGrids (250m) -

ISRIC's SoilGrids dataset is a 250m resolution gridded dataset with predicted soil attributes from 0 to 200m. Each discrete horizon (0cm, 5cm, 15cm, 30cm, 60cm, 100cm, 200cm) has independently predicted attributes Predictions for SoilGrids are generated by a tree-based non-linear machine learning model with soil profiles from 150,000 unique sites distributed across the globe (Hengl, 2017). There is significant undersampling in some areas, including where there are extreme climatic conditions and/or restricted access and that semi-arid or arid landscapes are common locations where this occurs (2017). The Dosso region of Niger is semi-arid, in Figure 2 we see very few samples in the Dosso region which likely had an effect on the accuracy of the SoilGrid predictions in this region.

Summary of Data Inputs -

One of the main differences between the soil datasets is the topsoil texture (SI Table 1). Texture is particularly important in this assessment because of its role in water holding capacity and soil drainage conditions. HWSD has far less variability in topsoil texture than SoilGrids or the field data. Across all three datasets, sand content is high with many topsoils classified as sand, loamy sands, or sandy loams. This high prevalence of sand content is reflected in low available water-holding capacity and high permeability of the soils.

SI Table 1: breakdown of topsoil textures in each dataset

Input soil dataset	sand	loamy sand	sandy loam	sandy clay loam	loam
Interpolated Field Data (0-20cm)	66.3%	30.7%	3%	0%	0%
FAO Harmonized World Soil Database (0-30cm)	87%	0%	5%	.5%	7.5%
ISRIC SoilGrids (0-15cm)	16.5%	32.3%	49.3%	1%	1%

Slopes in the region are mostly flat with mean slope across the region equal to 2.79% (Maximum slope 29.88%, minimum slope 0%, standard deviation 1.70%). While there are some areas of the region with steeper slopes, the majority of the region has slopes which do not negatively affect land capability classification. Slope of the landscape, when compounded with texture, plays a role in erosion risk which can reduce the capability of land for agricultural usage.

SI Table 2: LCC calibration - Data Source Attributes

Input data source	**Variables needed for LCC**	**Attributes used from data set**
FAO Harmonized World Soil Database	Soil depth	Phases - *binary indicators based on characteristics which are significant for land management* Roots - *depth class of an obstacle to roots*
	Surface Soil Texture	Sand, silt, and clay percentages for 0-30cm
	Salinity	Electrical conductivity 0-30cm
	Surface Stoniness	Volumetric gravel (particles >2mm) content of 0-30cm
	Soil Water Storage Capacity	Calculated for 0-30cm and 30-100cm horizons using texture, organic matter, and rock fragment, summed over horizons
	Lime Requirement	pH value 0-30cm
	Water Table Depth	*Attribute unavailable*
	Flooding	Phases - *binary indicators based on characteristics which are significant for land management*
	Permeability	Calculated for 0-30cm and 30-100cm horizons using texture, organic matter, and rock fragment, minimum permeability value of all horizons used
Input data source	**Variables needed for**	**Attributes used from data set**

	LCC	
ISRIC SoilGrids	Soil depth	Depth to Bedrock
	Surface Soil Texture†	Sand, silt, and clay percentages of 0-15cm horizon ‡
	Salinity	*attribute unavailable*
	Surface Stoniness	Volumetric gravel (particles >2mm) content of 0-5cm horizon ‡
	Soil Water Storage Capacity	Calculated for each horizon using texture, organic matter, and rock fragment, summed over horizons ‡
	Lime Requirement	pH value 0-30cm horizon ‡
	Water Table Depth	*Attribute unavailable*
	Flooding	*Attribute unavailable*
	Permeability	Calculated for each horizon using texture, organic matter, and rock fragment, minimum permeability value of all horizons ‡ used
Input data source	**Variables needed for LCC**	**Attributes used from data set**
Field Data	Soil Depth	*Attribute unavailable*
	Surface Soil Texture	Sand, silt, and clay percentages from 0-20cm
	Salinity	*Attribute unavailable*
	Surface Stoniness §	Volumetric gravel content of 0-5cm horizon ‡ from SoilGrid dataset
	Soil Water Storage Capacity	Calculated for 0-20cm using texture, organic matter, and rock fragment, multiplied by 5 to have 100cm of soil water storage

		capacity
	Lime Requirement	pH value from 0-20cm
	Water Table Depth	*Attribute unavailable*
	Flooding	*Attribute unavailable*
	Permeability	Calculated using texture, organic matter, and rock fragment §
Sentinel-2 Digital Elevation Model	Slope	Calculated using ArcGIS

† *Since SoilGrids attributes are predicted independently, textures were normalized to 100% as sand, silt and clay percentages often do not add to 100%*

‡ *SoilGrids has attributes for discrete layers (e.g. 60cm) rather than attributes for horizons. To calculate attributes for horizons, we took weighted averages of discrete layers as is recommended by Hengl 2017 Citation - Hengl, Tomislav, et al. "SoilGrids250m: Global gridded soil information based on machine learning." PLoS one 12.2 (2017).*

§ *Surface Stoniness was added to field data through spatially joining Surface stoniness measurements from SoilGrids*

Data limitations and implications -

It is important to note that of the modifications in the LandPKS LCC algorithms, the difference in measurement of surface stoniness has notable implications for LCC analysis. In LandPKS LCC analysis, surface stoniness is measured by visually inspecting the surface of the land and reporting the percentage of land which is covered by stones or boulders which are greater than 25cm. Since this measurement was not available in the field data, SoilGrids, or HWSD, we used topsoil volumetric gravel content (percentage of materials in soil which are greater than 2mm). For this reason, mapping of limitations due to surface stoniness should be treated as having a high degree of uncertainty.

A major issue in most soil analyses is the presence of varied conditions in the subsurface. Soils often have textural changes from the surface to deeper layers and these changes can have major impacts on agriculture, particularly when subsurface soils contain fine textures layers that have low infiltration or are in some cases impermeable. The soil sampling done in this project was just to 20 cm and so we assumed similar conditions at depth. For the soil products, we use the mapped properties of deeper layers but these are likely not highly accurate, especially at finer spatial resolutions. These are limitations that are present in most soil analysis efforts but should be noted as a source of uncertainty in these map products and an area where more detailed analysis would be required prior to any land planning activity.

In the Dosso region there are large areas covered by shallow soils that are not fully captured in the field data or the global scale map products. These soils are naturally occupied by shrubs. However, due to land pressure, farmers may clear these shrubs but then later abandon the fields due to sudden decrease in soil fertility. Such practices leave hardpan and stony areas behind especially in the northern and central part of the region. These degraded landscapes cannot be fully captured in this initial mapping approach and should be considered in any field-scale application of LCC. Similarly other areas that have been heavily degraded due to land use will not be represented in the HWSD or Soil Grid based products.

Results

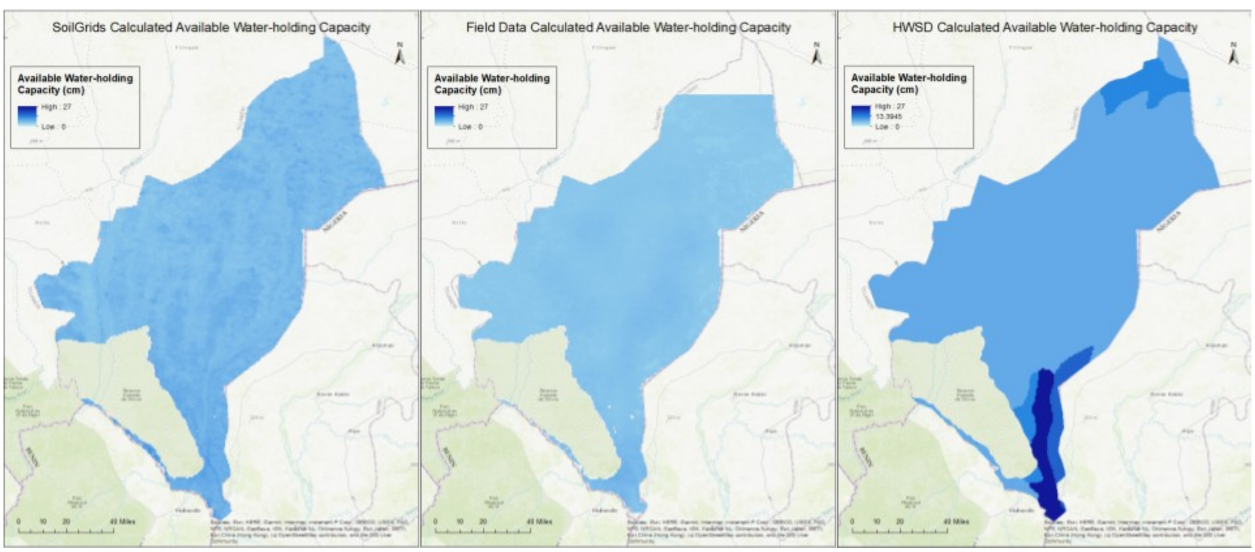
As with SoilGrids sand content values, there is a North-South trend in AWC values where there are lower AWC values in the northern part of the region and higher AWC values in the southern tip of the region. SoilGrids has a mean AWC value of 6.0cm (maximum 11.3cm, minimum 3.8cm). In HWSD, we see this same trend but with far less spatial variation due to the small number of soil mapping units in the region. HWSD has a higher mean AWC value of 9.4cm (maximum 25.4cm, minimum 8.2cm). For the interpolated field data, there are lower AWC values in the North and lower AWC values in the South, but there are pockets in the center of the region with both high and low AWC values. The interpolated field data shows a mean AWC value of 4.6cm (maximum 7.2cm, minimum 3.3cm).

Our analysis highlights the distinct differences between publicly available soil datasets and their limitations in usage for land-use management decisions. Both HWSD and SoilGrids accurately identified available water capacity as the primary limitation in the Dosso region. Neither HWSD nor SoilGrids identified lime requirement as a limitation when AWC was removed from the LCC calculations. Since surface stoniness was not measured at field sites, we cannot assess how accurate HWSD and SoilGrids were at detecting this limitation. Furthermore, in terms of capability classes, both HWSD and SoilGrids assessments underestimate the severity of limitations to agriculture when LCC is calculated with AWC as a limitation. When AWC is removed as a limitation, SoilGrids underestimates severity of limitations while HWSD overestimates severity of limitations. While SoilGrids does not perfectly assess the capability classes, it picks up on the spatial variation in the region that HWSD does not identify. Since HWSD is only made up of 13 unique soil mapping units, the region gets split into blocks which preclude the development of management strategies at a finer resolution. Given that many farms in this region are a few hectares in size, finer resolution capability assessment is highly useful.

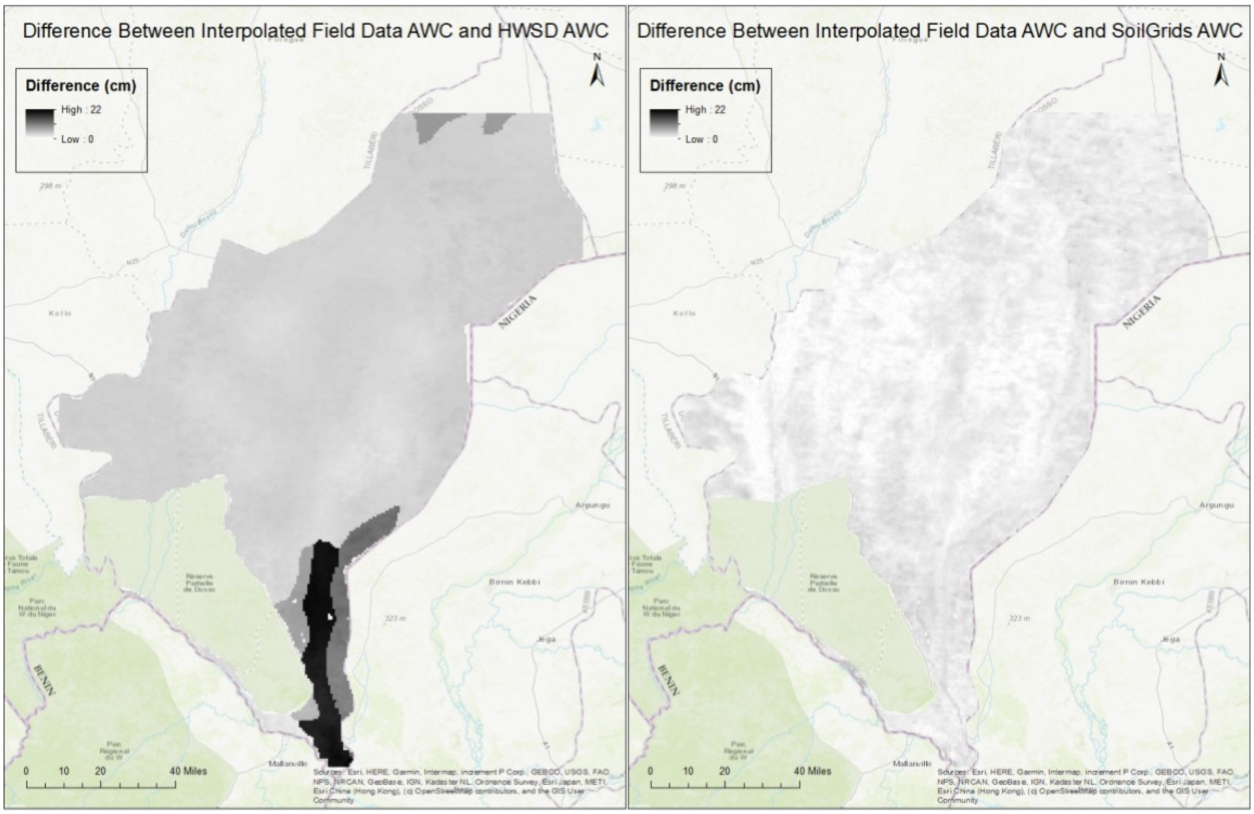
The most notable difference between these three assessments is in the values of soil water storage capacity. Soil water storage capacity is expressed as AWC which is a function of sand, silt and clay content, organic matter, and volumetric gravel content (% of soil with particles >2mm). In general, higher sand content yields lower AWC values (depending on the relative ratio of silt to clay) and higher organic matter content yields higher AWC. Due to the high sand content values across the region in all three input soil data sets, all three assessments have low AWC values. There are some notable differences between the AWC values of each of the data sets (see supporting information for spatial analyses of AWC). High sand content in the region leading to low water storage capacity is an relatively immutable characteristic of the soils in the Dosso region over management time scales, except where soil loss exposes a layer with different texture, or tillage, termites, ants or burrowing animals result in mixing of different layers. Given the low level of rainfall in this semi-arid area, low water storage capacity would be detrimental to crop productivity during most if not all years.

SI Table3: LCC limitation breakdown with AWC removed

Input Soil Dataset	LCC primary limitation
Interpolated Field Data	55% lime requirement and surface stoniness 28.5% lime requirement 10.4% surface stoniness 6.1% erosion, texture, lime requirement, and/or surface stoniness
FAO Harmonized World Soil Database	100% surface stoniness
ISRIC SoilGrids	58% surface stoniness 28.5% texture and surface stoniness 7.9% lime requirement and surface stoniness 3.9% erosion, texture, lime requirement, and/or surface stoniness 1.7% lime requirement



SI Figure 1: Calculated AWC for SoilGrids, Field Data, and HWSD. AWC is a function of soil texture, rock fragment content, and organic matter. AWC is measured in centimeters and is calculated to 100cm depth.



SI Figure 2: Difference between Interpolated Field Data AWC values and HWSD and SoilGrids AWC values. Difference is measured in cm and is the absolute value of Field data AWC minus HWSD or SoilGrids AWC

<u>SI Table 4: AWC Descriptive Statistics</u>

Input Soil Dataset	AWC descriptive statistics (cm /m soil)	
FAO Harmonized World Soil Database	Minimum	8.2 cm
	Maximum	25.4 cm
	Mean	9.4 cm
	Standard Deviation	3.7
ISRIC SoilGrids	Minimum	3.8 cm
	Maximum	11.3 cm
	Mean	6.0 cm
	Standard Deviation	.9
Interpolated Field Data	Minimum	3.3 cm
	Maximum	7.2 cm
	Mean	4.6 cm
	Standard Deviation	.5

Discussion

Through the addition of irrigation infrastructure, water storage capacity could be removed as a limitation to these soils. Irrigated agriculture represents less than 1% of the total cultivated area and all agriculture contributes to 38% of the GDP (FAO, 2016, World Bank, 2019). There is tremendous potential to expand irrigation and improve agricultural outcomes across the region which, in turn, improves the livelihoods of smallholder farmers. The USDA highlights a number of practices which lead to poor water storage capacity such as conventional tillage operations, low residue crop rotations, heavy equipment traffic on wet soils, and grazing systems which allow loafing areas and livestock trails (USDA, 2008). There are methods which can be used to improve low water storage capacity such as conservation crop rotation, growing cover crops, and prescribed grazing (USDA, 2008) as well as stone lines, grass bands, half moon, and Zai (Traore et al., 2020). Farmers can also plant drought-tolerant crops thereby reducing the need for stored water. While the stoniness of soils has limited management options, the lime requirement can be modified through targeted lime application. However, most applications of lime in the region are cost prohibitive due to high lime prices, low crop yields, and low crop market prices.