The State of Land Use in Northern Nigeria

A Landsat-Based Mapping Framework

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Abstract

This study developed a land cover and land use mapping framework specifically designed for agricultural systems in the Sudan-Sahel region. The mapping approach extracts information from inter- and intra-annual vegetation dynamics from dense stacks of Landsat 8 images. The framework was applied to create a 30-meter spatial resolution land use map focusing on the 2015 agricultural landscapes in northern Nigeria. The map provides up-to-date information with a high level of spatial and thematic detail, resulting in a more precise characterization of agriculture in the region. The map reveals that agriculture is the main land use in the region. Arable land represents on

average 52.5 percent of the area, which is higher than the reported national average for Nigeria (38.4 percent). Irrigated agriculture covers nearly 2.2 percent of the total area, reaching nearly 20 percent of the cultivated land when traditional floodplain agriculture systems are included, which is above the reported national average (0.63 percent). There is significant variability in land use in the region. This study demonstrates the feasibility of multitemporal medium-resolution remote sensing data to provide detailed, up-to-date information on agricultural systems in the arid and sub-arid landscapes of the Sahel region.

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The State of Land Use in Northern Nigeria: A Landsat-Based Mapping Framework

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Introduction

Over the last 30 years, earth observation remote sensing for the monitoring of land use and agricultural development has grown significantly. Remote sensing-based cropland monitoring is rapidly becoming operational in different parts of the world (Gumma et al. 2014; Ozdogan 2010; Ozdogan and Gutman 2008; Thenkabail and Wu 2012). A number of agricultural monitoring systems started forecasting crop yields and production. But the advances have been geographically uneven, and the Sudan-Sahel region of Sub-Saharan Africa is one of them. Beginning with Tucker et al. (1985), a number of initiatives have studied land-cover and land-use (LCLU) trends in the region using Earth observation data (Brink and Eva 2009; CILSS 2016, 219; Fensholt et al. 2013; Herrmann, Anyamba, and Tucker 2005; Knauer et al. 2014; Spiekermann, Brandt, and Samimi 2015). But the use of remote sensing monitoring systems in the region has been sluggish. Availability and quality of land-use data have therefore been limited due to limited agricultural production, technical challenges, and slow adoption of remote sensing monitoring systems.

Despite its relevance for human development and poverty alleviation, there is a lack of basic information on the distribution of cultivated land and the main land processes in the Sudan-Sahel. The region is expected to experience major changes in the near future, and land-use information remains crucial because agriculture represents the main source of livelihoods. The region's fertility rates are among the highest in the developing world (Bertoni et al. 2016), and rural population growth will accelerate the expansion of cultivated land for subsistence farming. Likewise, the steady growth of the urban population will fuel the demand for agricultural products, which is a major driver of land-use change (DeFries et al. 2010). The consequences of climate change will likely disrupt regional agricultural practices and production. Expected temperature increases by 2050 will shorten crop-growing cycles, leading to severe yield reductions and threatening food production systems (Cervigni, Valentini, and Santini 2013; Jones and Thornton 2003; Porter et al. 2014). Coping strategies for the changing conditions may lead to progressive land degradation, further compromising rural livelihoods and increasing their vulnerability to future internal and external shocks (Leichenko and O'Brien 2008). For instance, as productivity decreases due to climate change, farmers may overexploit soil or expand cultivated lands into more marginal lands.

Global remote sensing-based LCLU change products include coarse-resolution land-use information for the Sudan-Sahel region (for example, MODIS MCS12Q1 and GlobCover 2005 and 2009). These products have been integrated with national statistics to generate a more robust outcome (Ramankutty et al. 2008). However, although coarse spatial resolution data meet the observational requirements for the world's large agricultural regions, they are not well suited for monitoring crops in regions with highly heterogeneous agricultural landscapes dominated by smaller farms, such as those in the Sudan-Sahel region. Furthermore, the static nature of these products fails to capture changes over time (Leroux et al. 2014; Pittman et al. 2010). The opening of the Landsat archive in 2008–09 (Woodcock et al. 2008) and, more recently, the launch of new medium-resolution sensors (Landsat 8, Sentinel-2 Disaster Monitoring Constellation, and so forth) offers unprecedented opportunities to study LCLU change at higher spatial resolution. Several initiatives are already exploiting these new data with increasing processing capabilities to map agricultural landscapes with higher spatial detail at scales more relevant to African agricultural processes. For example, Gong et al. (2013) created a global LCLU map at 30-meter spatial

resolution, which included a cropland class. Xiong et al. (2017) produced a nominal 30-meter cropland extent map of continental Africa by using Sentinel-2 and Landsat 8 data (GFSAD30AFCE). From an African context, this product represents a major improvement for food and water security assessments and is a first step for exploring not only cropland extent but also crop type, intensity, and change. The European Space Agency released a prototype land-cover 20-meter map of Africa for 2016 with cropland as one of its classes.¹

However, these products still present some limitations that hamper the extraction of information on land-use dynamics for specific regions of Africa. Cropland systems across the continent are highly diverse and are often adapted to very specific environmental conditions. The phenological signatures of the different land-use types in a region can be very similar (Xiong et al. 2017). As a consequence, mapping croplands at the continental level requires large, up-to-date training and validating data sets (Xiong et al. 2017). Although high-resolution imagery and crowdsourcing (Fritz et al. 2015) are gaining ground as sources of training and data validation, these remain scarce in remote regions, constraining the precision of supervised learning algorithms. Consequently, continental and global medium-resolution products that implement a single mapping approach are not always flexible enough to accurately characterize land-use processes in specific regions of the continent.

Northern Nigeria presents a concrete example of a data-poor region where land-use information is crucial for human development. Poverty indicators over the last decade show a growing north-south divide (World Bank 2016). Although poverty rates are only 16 percent in the southern part of the country, an estimated 50.2 percent of the population lives below the poverty line in northern Nigeria, where up to 70 percent of households rely primarily on agriculture (World Bank 2016). Ongoing land-cover change and land-use processes compromise households' main livelihood strategies, reduce their adaptation alternatives, and thus increase their vulnerability. Yet the lack of consistent and reliable land-use information hinders the accurate characterization of northern Nigeria's agricultural sector. As the links between climate change, crop failures, poverty, migration, and conflict become more explicit in the research literature, it becomes urgent to monitor land-use processes in the region to inform decision makers and design and implement efficient policy interventions in agricultural development and poverty alleviation.

This work proposes a mapping approach specifically designed for the agricultural systems of the Sudan-Sahel region. It aims to overcome some of the limitations in the region of the global and continental remote sensing products. The approach makes extensive use of expert knowledge and exploits dense stacks of Landsat 8 imagery to capture inter- and intra-annual vegetation dynamics and better characterize the study region's main land-use types. The proposed mapping framework is flexible and robust enough to operate with limited imagery, and can be easily and rapidly updated in successive years. We have applied this approach to produce a 30-meter spatial resolution LCLU map that emphasizes agricultural classes. This work aims to fill a gap of information and provide a precise, up-to-date assessment of agricultural systems in northern Nigeria.

¹ For more information, see the European Space Agency's "CCI Land Cover—S2 Prototype Land Cover 20m Map of Africa 2016," <http://2016africallandcover20m.esrin.esa.int>.

Materials and Methods

The area of study is northern Nigeria, which is defined as the region located on the 9.3 degrees latitude line and borders Niger to the north, Cameroon and Chad to the east, and Benin and Niger to the west. The region covers an area of 494,000 square kilometers and includes the states of Bauchi, Borno, Gombe, Jigawa, Kano, Katsina, Kebbi, Sokoto, Yobe, and Zamfara as well as parts of Adamawa, Kaduna, Kwara, Niger, and Plateau. Northern Nigeria is part of the Sudan and Sahel savannas agroecological zones (figure 1). These warm, tropical arid and semiarid zones are characterized by clearly defined dry and rainy seasons, which follow a strong rainfall latitudinal gradient. Annual precipitation ranges from below 400 millimeters in the northeast to 1,500 millimeters per year in the higher elevations of the southern part. The elevation in the study area ranges between 100 and 1,300 meters above sea level. Lower elevations are found in the Benue River valley to the west and the Gongola River valley and the Lake Chad depression to the east. The highest elevations are found to the south in the Jos Plateau.

Figure 1. States included in this work and Landsat scenes used in the study

Note: The dark gray shading represents the states included in this study; the red line represents the Landsat scenes used.

The study area was covered by 21 Landsat scenes (paths 185–191; rows 51–52). The analysis included close to 1,450 Landsat 8 Collection 1, Tier 1 calibrated top-of-atmosphere (TOA) reflectance acquired between 2014 and 2016 (Chander, Markham, and Helder 2009). The inclusion of images for a three-year period served to capture interannual dynamics required to characterize some land surfaces in the study area. For each Landsat scene, approximately 69 images were stacked during this period. A dust-laden air mass from the Sahara Desert (known as the harmattan wind) can occur up to 100 days per year during the region's dry season. This dust modifies the spectral signatures of land surfaces and results in lower vegetation index values. In this context, given the difficulties of accurately estimating aerosol properties and their spatial distribution, TOA images were chosen over top-of-canopy images (Liang 2003, 196–226). Images were not discarded based on cloud coverage because cloud-free pixels in densely clouded images could still provide valuable information within the proposed mapping framework. Digital elevation data from the

Shuttle Radar Topography Mission (SRTM) (Farr et al. 2007), at 30-meter spatial resolution were used to define floodplains. Given its focus on agricultural landscapes, urban areas were not directly mapped. Instead, urban pixels were extracted from Landsat's Global Human Built-up and Settlement Extent (HBASE) Dataset (Wang et al. 2017). The HBASE provides global 30-meter spatial resolution information on settlement extent for 2010.

Using these data, we developed an LCLU mapping framework adapted to the region's agricultural landscapes to produce a 30-meter resolution map of northern Nigeria for the baseline year 2015. The framework implemented a knowledge-based expert system (KBES) that relied on dense stacks of Landsat 8 images and exploited inter- and intra-annual vegetation dynamics and contextual information to map the main components of the study region's land surfaces (Srinivasan and Richards 1990). Recent research highlights the role of expert knowledge to advance remote sensing-based agricultural monitoring (Bégué et al. 2018), even if such experts lack remote sensing experience (for example, field extension agents). These systems constitute a useful alternative when the lack of consistent training and validation data limit the use of supervised learning systems. Expert knowledge is commonly stored as a set of rules in a knowledge base. Subsequently, the information is passed to an inference mechanism that interprets and assigns class memberships to pixels. A KBES has been successfully implemented in a number of applications, such as protected areas conservation (Szantoi et al. 2016), crop classification (Choudhury et al. 2012; Cohen and Shoshany 2002; El Hajj et al. 2009; Janssen and Middelkoop 1992), and urban mapping (Amarsaikhan et al. 2013).

We built a knowledge base that established production rules using spectral, temporal, and spatial constraints to identify the main agricultural systems and natural vegetation types in the study area (Cohen and Shoshany 2002). The production rules were not necessarily conclusive, but they provided a degree of evidence in favor of some class labels (Richards and Jia 2006, 342–55). These rules were defined from the analysis of the spectral profiles during the vegetative cycles of the different land-use types. Specific temporal windows were selected to maximize the separability between classes using expert knowledge in the seasonal dynamics of the land surfaces in the study area (figure 2, panel a). Similar strategies have been previously used for LCLU in tropical environments (Hansen et al. 2008; Sedano, Gong, and Ferrao 2005). The numerical values in the spectral rules were provided as thresholds that were empirically generated from observed data (Hodgson et al. 2003). These spectral thresholds were defined based on a training data set of 1,750 points of known land-use types randomly searched using visual interpretation of a combination of Landsat and very high-resolution imagery (Google Earth) for the period of study. The thresholds for each land-use class were calculated from the statistical distribution of pixel values in the training data set. The spectral rules were built based on Normalized Difference Vegetation Index (NDVI) images (Tucker 1985) calculated from each image in the original data set. The NDVI was chosen because, besides data compression, it facilitates the interpretation of land surface dynamics over time and the definition of spectral thresholds. The presence of burnt areas in natural vegetation surfaces within the three-year imagery epoch was interpreted as a sign of land-cover transition, supporting the labeling as nonstable natural vegetation pixels.

Figure 2. Temporal windows and seasonal vegetation dynamics

Note: Adapted from temporal profiles at known locations for visualization purposes. Specific temporal windows maximize separability between land-cover and land-use classes.

The rules in the knowledge base were designed to identify the following agricultural systems and natural vegetation types: stable natural vegetation, nonstable natural vegetation, rain-fed agriculture, irrigation agriculture, bare soil, and rivers and water bodies. Each of these components presents distinct seasonal dynamics (figure 2, panel b). For instance, the vegetative cycle of natural vegetation and rain-fed agriculture closely follows rain patterns, with higher NDVI values during the rainy season (July–October) and low values during the dry season (Sedano, Gong, and Ferrao 2005). However, there are distinct differences between them. The rainy season NDVI values of rain-fed agriculture are comparatively lower than those of natural vegetation because planting densities do not commonly cover the ground completely. Equally, during the dry season, the exposed soil of cultivated lands results in lower NDVI values than natural vegetation, where dormant and dry vegetation covers the ground, resulting in higher NDVI values. Irrigation agriculture relies on groundwater aquifers and irrigation systems that can result in extended growing seasons and several vegetative cycles within a year. Because of its higher planting densities, NDVI values are commonly higher than those of rain-fed agriculture. Bare soil presents

very low NDVI values year-round, and rivers and water bodies have negative NDVI values during the rainy season. Irrigation agriculture was mapped through a combination of spectral and contextual constraints as cultivated areas within floodplains whose vegetative cycle did not follow annual precipitation. A digital elevation model (SRTM) identified floodplains as areas of low slope located along rivers and water bodies.

Table 1. Description of mapped classes

Class Type	Description
Stable natural vegetation	Surfaces with natural vegetation that were never cultivated during the 2014–16 period.
Nonstable natural vegetation	Surfaces that were not cultivated in 2015 but were likely to have been under cultivation in previous or subsequent years (fallow lands). Also, land that is undergoing cover conversion. This class includes areas of sparse tree cover.
Rain-fed agriculture	Cultivated land that relies solely on rainfall for water supply.
Irrigation agriculture	Cultivated land that uses mainly irrigation for water supply (groundwater, irrigation channels, and so forth).
Bare soil	Surfaces without vegetation cover.
Rivers and water bodies	Surfaces covered by water during more than 6 months per year in the 2014–16 period.

Figure 3. Flowchart of mapping framework for LCLU map based on dense stacks of Landsat 8 imagery

Note: LCLU = land-cover and land-use; NDVI = Normalized Difference Vegetation Index; SRTM = Shuttle Radar Topography Mission; TOA = top-of-atmosphere.

The rules were applied to all available images during the defined temporal windows and imposed initial preconditions for class membership. The KBES inference mechanism analyzed the set of rules, resolved potential redundancies and inconsistencies, and made decisions about class membership using a majority rule criterion (Srinivasan and Richards 1990) (figure 3). This approach reduced the potential impact of individual aerosol-contaminated images in the mapping process.

An uncertainty flag was raised when the number of available observations during the temporal window was below a preestablished number due to cloud coverage ($n=5$). This was often the case for rain-fed agriculture based on observations during the rainy season. In these cases, we used an alternative approach and applied the rules of the knowledge base to an NDVI maximum value composite from all images available during the temporal window.

The map was validated against an independent data set of 754 ground points spread over the study region. Validation points were identified by visually interpreting images with very high resolution for the year 2015 (Google Earth) and combining these with known locations in true color Landsat 8 images. The analysis was carried out on a per-scene basis. Outputs from individual scenes were subsequently mosaicked in a final map at 30-meter resolution covering the whole study area. The implementation of the KBES and data processing was carried out in the Google Earth Engine cloud-based platform.

Figure 4. Examples of existing medium-resolution remote sensing LCLU products for northern Nigeria

Note: A. False color composition (754) of Landsat 8 image; B. European Space Agency land-cover 20-meter map of Africa; C. GFSAD30AFCE; D. Tsinghua University 30-meter resolution land-cover and land-use (LCLU) map; E. northern Nigeria 30-meter resolution Landsat 8-based LCLU map. Green: natural vegetation; light yellow: cropland.

Figure 5. Examples of 30-meter resolution Landsat 8–based LCLU map for northern Nigeria

Note: Google Earth high resolution imagery (left side) and the corresponding 30-meter resolution Landsat 8–based land-cover and land-use (LCLU) map for northern Nigeria (right side). Dark green: stable natural vegetation; light green: nonstable natural vegetation; light yellow: rain-fed agriculture; red: irrigation agriculture.

Results

We created a 30-meter spatial resolution LCLU map focusing on the agricultural landscapes of northern Nigeria for the year 2015. Validating the map against an independent data set of ground points resulted in an overall accuracy of 0.91 and a kappa coefficient of 0.89. Accuracies were consistent throughout the classes, with individual user and producer accuracies above 0.82 and 0.85, respectively (table 2).

Table 2. Accuracy matrix

	Nonstable Natural Vegetation	Stable Natural Vegetation	Irrigated Agriculture	Rain-fed Agriculture	Water	Bare Soil	User Accuracy
Nonstable natural veg.	117	13	0	12	0	0	0.82
Stable natural veg.	13	236	1	0	0	0	0.94
Irrigated ag.	0	1	85	0	0	0	0.99
Rain-fed ag.	8	3	13	180	0	1	0.88
Water	0	0	0	0	38	0	1
Bare soil	0	0	0	1	0	32	0.97
Producer accuracy	0.85	0.93	0.86	0.93	1.00	0.97	

Figure 6. LCLU distribution by state**Land use in Nigeria (landscape level)**

The map shows that agriculture is the dominant land use in northern Nigeria, with more than 52 percent of the land under cultivation. The largest proportion corresponds to rain-fed agriculture (50 percent), and irrigation agriculture covers about 2 percent of the land. Natural vegetation occupies 46 percent of the land, from which 14 percent corresponds to stable natural vegetation cover and 24 percent to areas of nonstable natural vegetation cover. From the latter, 7.2 percent corresponds to land that burned at least once during the 2014–16 period, suggesting an ongoing land transformation process. The remaining 16.8 percent of nonstable vegetation cover corresponds to land that, although covered by natural vegetation, was cultivated at some point during the period of study and is likely to be associated to fallow fields. Other surfaces, such as bare soil and water, occupy less than 2 percent of the total land (figure 6).

The map illustrates the geographical variability of land uses within the region, which are closely related to precipitation and are controlled by latitudinal and elevation gradients. The northern section of the study region consists of large expanses of croplands, with cultivated fields dominating the landscape and patches of trees, shrubs, and fallow land covering no more than 10–20 percent. Natural vegetation is restricted to isolated remnants in marginal agricultural lands. In contrast, the southern section includes larger proportions of natural vegetation. Cropland is less dominant and is often part of a mosaic of cultivated fields and natural vegetation. Although the proportion of land under cultivation in the southern states is below 50 percent, it can exceed 80 percent in some of the northern states (Jigawa, Kano, and Katsina).

Floodplains represent the most fertile agricultural land in arid and subarid ecosystems. Irrigated agriculture in the region is confined to river floodplains. Up to 74 percent of these floodplains are cultivated, from which 19 percent is associated to major irrigation schemes, and the remaining 55 percent applies traditional forms of water management. States with complex hydrographic networks or large floodplains associated with the region's main rivers have significantly higher irrigated areas than the regional average. Thus, although on average irrigation agriculture covers 2.2 percent of the land, it reaches up to 5 percent in Kaduna.

Figure 7. Proportion of natural vegetation in agriculture-dominated areas

Note: One-kilometer (km) spatial aggregation. Color bar represents proportion of natural vegetation within agriculture-dominated 1 km grid cells (geographic projection, WGS84).

The spatial aggregation of the original 30-meter product provides additional information about the landscape structure in the study region and shows that areas dominated by croplands can still contain a significant share of natural vegetation (figures 7 and 8). In the southern part of the study area, this landscape fragmentation is associated with a mosaic structure; in the northern part, it is related to agroforestry systems in which cultivated fields and low-density trees share the land.

Discussion

Our LCLU mapping framework relies on dense stacks of Landsat 8 imagery and seasonal metrics to address the peculiarities of the Sudan-Sahel region. It is flexible, robust, and can operate with a limited number of observations due to cloud and dust contamination. To overcome the scarcity of reliable in situ data, this mapping framework uses extensive knowledge of phenological cycles and ecosystem processes in the Sudan-Sahel region; it also relies on temporal windows that maximize the spectral separability of the relevant land surfaces (Porter et al. 2014). Finally, it applies an acquisition window of several years to allow a solid characterization of dynamic land-use types that involve a multiyear cycle. This framework has been applied to produce a 30-meter spatial resolution map for northern Nigeria, a region that lacks a comprehensive land survey scheme to collect agricultural data. As a consequence, LCLU information in the region is scarce and outdated. Without specific, up-to-date information on the state of agriculture, preexisting and misguided narratives—based on limited and uncertain data—shape the discussion in the development community. The resulting map provides information about spatial distribution of land use in northern Nigeria with higher spatial resolution and thematic detail than existing remote sensing–based products. Mapping features more closely linked with the livelihood of the rural population provides valuable information with which to design and implement effective rural development and poverty alleviation interventions. The framework can potentially be expanded to other areas within the Sudan-Sahel ecozone and replicated in successive years to monitor the evolution of agricultural systems over time, setting the basis for an agricultural monitoring.

Figure 8. LCLU map showing distribution of natural vegetation

b. Distribution of permanent natural vegetation

Note: One-kilometer spatial aggregation. The upper plate shows the distribution of temporary natural vegetation; the lower plate shows the distribution of permanent vegetation. The color bar represents the percentage of natural vegetation. LCLU = land-cover and land-use.

Figure 9. Comparison of farming intensity

a. Drylands, late 1970s

b. Rain-fed agriculture, 2015

Source: Hodgson et al. 2003.

Note: One-kilometer spatial aggregation. The color bar represents the percentage of land under cultivation.

The map describes a region of intense agricultural use in which most land suitable for agriculture is already under cultivation. Historical evidence (Mortimore 1989) reveals that large areas of Nigeria's drylands already had high farming intensities by the late 1970s. A cautious visual comparison between the historical farming density map and the 2015 rain-fed agriculture map

(figure 9) shows that the farming area has increased and areas of high farming intensity have expanded considerably over the last 30 years. The present spatial distribution of farming intensity underscores a limited potential for further agricultural expansion into new lands and suggests that further increases in farming intensities are likely to take place in current agricultural landscapes.

The map shows that production systems that have adapted to arid conditions in marginal and less productive areas (for example, mosaics of cultivated fields and scattered trees) can reach 30 percent of the land at lower elevations. It also highlights the distinct characteristics of land-use dynamics in northern Nigeria when compared with the rest of the country. For instance, whereas cropland represents on average 52.5 percent of total land in the northern part of the country—reaching 80 percent in some states—the reported national average for Nigeria is 38.4 percent. From these figures we estimate that there are 0.31 hectares of cultivated land per person in northern Nigeria, but the national average remains at 0.193 hectares per person (World Bank 2014). The map also questions the existing assessments of irrigated agriculture, covering nearly 2.2 percent of the land and 4.4 percent of the cultivated land in northern Nigeria (figure 10), which is considerably higher than the national average (0.63 percent) (World Bank 2014). These intranational differences highlight the need to establish monitoring systems to provide region-specific, reliable, up-to-date information for designing and implementing interventions.

Figure 10. LCLU map showing distribution of agriculture

a. Distribution of rain-fed agriculture

b. Distribution of irrigated agriculture

Note: One-kilometer spatial aggregation. The color bar represents the percentage of cultivated land. LCLU = land-cover and land-use.

The current map improves the spatial detail of LCLU information extracted from remote sensing products with coarser resolution. Its higher spatial detail allows a more realistic characterization of complex landscapes. Coarse-resolution pixels are the result of mixing spectral signatures from different features. LCLU products from moderate sensors cannot accurately map heterogeneous landscapes and complex land-use types of arid and semiarid African regions. The spatial aggregation from a 30-meter resolution map charts landscape features with consistent spectral signatures and allows flexible spatial aggregations to answer specific questions and define classes with additional value.

This map also improves the thematic detail of existing medium-resolution remote sensing–based products with cropland information for northern Nigeria. Continental and global remote sensing products commonly apply a uniform mapping framework that aims to retrieve consistent products and maximize overall accuracies over large regions. The application of empirical models to large regions implies a lack of flexibility to adapt to subregions’ specific features and dynamics. By restricting the geographical extent of the mapping area, we adapt the framework to chart relevant land uses specific to the ecoregion and thus improve thematic detail.

The advancement of cloud storage and computing capabilities and the increase in imagery from medium-resolution sensors have led to the recent emergence of global-scale analysis and products with global medium spatial resolution. Yet there are significant advantages of using cloud storage and computing capabilities for the study of smaller and coherent ecoregions because it can enable the development of regional-based products that identify relevant key land-use classes and land-use processes, targeting specific questions and bringing analysis closer to managers and decision makers.

Conclusions

This work presents a mapping approach specifically designed for the agricultural systems of northern Nigeria. This approach has the potential to be replicable in successive years and expanded to other locations within the Sudan-Sahel ecozone. The present work underscores the relevance of incorporating expert knowledge in the design-mapping strategies in regions where other data sources are scarce. It also highlights the importance of interannual land surface dynamics to achieve a robust characterization of land use in the study area. Likewise, it demonstrates the potential of dense stacks of medium-resolution imagery to capture these dynamics.

The mapping framework was applied to produce a 30-meter spatial resolution LCLU map focusing on the agricultural landscapes of northern Nigeria for 2015. The map provides up-to-date information at higher spatial resolution and better characterizes agriculture in a region with limited land-use information, where agriculture is the main livelihood strategy. The map shows a high farming intensity and a cropland area that is significantly higher than in the rest of the country. Rain-fed agriculture systems already occupy most of the landscapes—at the expense of natural vegetation—and the majority of floodplains suitable for irrigation agriculture are already under use. The map also identifies the landscape variations associated with the region's well-defined north-south gradients.

In a region under increasing environmental and demographic stress, this work highlights the potential of multitemporal medium-resolution satellite data to generate detailed, up-to-date land-use information. This type of information is essential for designing efficient policy interventions, improving famine-related early warning and response systems, and understanding the links between land use and agricultural development, migration, and conflict.

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